THE RISK-RELATED BEHAVIOUR OF FINANCIAL INTERMEDIARIES

by

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To my wife LiXian Catherine Chen,

our parents and our daughter Aimee and son Ethan…

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DECLARATION

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ABSTRACT

The following thesis contains four empirical chapters focusing on the contagion, interest rate, foreign exchange rate, and investment risk exposures of financial institutions, respectively. Chapter 1 provides an overarching view of the four empirical chapters and the main objective of the thesis. Chapter 2 examines the return and volatility spillovers among the financial sector portfolios across the global financial markets from an US investor's perspective. The potential influence of the recent financial crisis on the return and risk interdependence among these sector portfolios has also been evaluated. Financial institutions with different characteristic and size have been examined separately as well as jointly. Chapter 3 and 4 investigate the interest rate and foreign exchange rate risk exposures of financial institutions, respectively. In chapter 3, we evaluate the impact of changes in term structure on the equity value of financial intermediaries across major economies. In chapter 4, the influences of both domestic and foreign currency fluctuations on the equity value of financial intermediaries are explored. Furthermore, we split the sample period into pre- and post-crisis period to investigate the potential impact of recent financial crisis on the interest rate and foreign exchange rate risk exposure of these financial intermediaries under examination. Chapter 5 focuses on the investment risk faced by financial institutions (mainly non-banking financial service firms, e.g. mutual funds, pension funds and hedge funds). We shed light on the economic value of correlation timing for dynamic asset allocation strategies. In order to further evaluate the influence of the rebalancing frequency on the economic value of the correlation timing, we assess the performance of the dynamic asset allocation strategy on both daily and monthly basis. Finally, chapter 6 provides the concluding remarks that summarize the thesis.

CHAPTER 1

INTRODUCTION

1.1. INTRODUCTION

Financial intermediaries (*i.e.* banks and insurers) play an important role in the in the transmission of monetary policy, maturity transformation, and the mobilization of financial resources. Therefore, the stability and prosperity of these financial intermediaries – especially the systemic important ones[1] – is vital from a social as well as regulatory perspective since it directly affects the supply of credit in financial market, which in turn supports the growth of real economy.

Deregulation (*e.g.* the Gramm Leach Bliley Financial Modernisation Act in 1999) and consolidation/globalization in the financial sector have changed the landscape of the global financial industry dramatically over the recent decades. As the financial sector becomes increasingly concentrated and interconnected, the systematic risk of the failure of these consolidated financial institutions has also increased. In other words, the failure of large and well-connected institutions will have a significant and lasting impact on the rest of the global financial system. Besides, through the establishment of financial holding companies and financial innovations,[2] financial institutions that specialize in different areas (*i.e.* banks and insurers) can expose to similar risk factors. That means the modern financial industry is more vulnerable to systemic shocks than ever before, as one common systematic event (*e.g.* credit crisis) can influence all the institutions in a similar fashion.

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[1] The Financial Stability Board defines systemic important financial institution as the one "whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activities". This definition is provided in the *Policy Measures to Address Systemically Important Financial Institutions* (2011) report issued by Financial Stability Board in November 2011.

[2] For instance, the creation of insurance linked securities by insurance companies in the last decade exposes insurers to credit risk, which previously only face by banks.

Therefore, from a regulatory perspective, the risk transmission across financial institutions is an important issue, especially during periods of financial distress.

In order to better regulate the financial intermediaries to prevent failures and/or contagions due to systemic distress events, it is important to first identify the risk factors and interdependences of financial institutions and quantify their magnitudes. We employ asset pricing models to fulfil our research purpose as they provide a measure of the relationship between risk and changes in equity value of the firm (portfolio) under examination. Better understanding of these relationships provides crucial insight about the risk management practice currently implemented by financial institutions and the effectiveness of the existing regulatory framework. In addition, the recent financial turmoil starts from 2007 provides us a unique opportunity to evaluate the risk factors of financial sector across major economies and the spillover effect among them.

Furthermore, financial institutions, especially non-banking financial service firms (e.g. mutual funds, pension funds and hedge funds), are also major providers of investment management/consultant services. Large financial intermediaries across the global are offering fund management/advisory services for their wealth clients to generate income in the form of performance and/or management fees. Asset allocation strategies, therefore, play an important role in the success of fund management/advisory business. The recent empirical studies on the behaviour of asset returns has identified numerous stylized facts (*e.g.* asymmetry effect between positive and negative shocks) regarding the conditional correlations among financial assets. The implementation of these stylized facts (*i.e.* dynamic correlation timing), therefore, could be valuable for the success of portfolio management practise.

1.2. OBJECTIVE OF THE THESIS

The objective of the thesis is to empirically examine the interconnectedness and major risk factors faced by financial intermediaries across major markets. Additionally, we investigate whether correlation timing strategy is able to provide enhanced risk adjusted performances for financial institutions that offer fund management services.

Firstly, we assess the return and risk interdependence among financial intermediaries before and during the recent financial turmoil. Existing literatures that focus on the spillover effect failed to capture the full extent of the recent crisis. By employing a more comprehensive sample period with sector level portfolios, the current study is able to provide a more general picture regarding the interactions across financial sectors. Next, we investigate the two major risk exposures, the interest rate and foreign exchange rate risk, of financial intermediaries separately. The two empirical studies distinguish themselves from the previous literatures by adopting new estimation frameworks (*i.e.* modified VAR-BEKK model) and alternative pricing models (*i.e.* the incorporation of home and foreign currency value). Finally, we compare the risk adjusted performances of dynamic correlation timing with the one based on static models. This study aims to address the question of whether incorporating the stylized facts of conditional variance and correlation into the estimation framework will improve the investor's utility.

The empirical studies carried out in this thesis try to shed light on four research questions. Each question provides some insight information regarding the risk related behaviour of financial intermediaries. The first question focuses on the interconnectedness within the global financial market, and its impact during the recent crisis. By analysing the risk and return spillovers across financial sector portfolios from different countries, we show the interactions among global financial markets. Furthermore, we investigate the difference in spillover pattern between the banking and insurance industry during the financial turmoil by conducting cross-sector spillover analyses.

The second and third question investigates the return sensitivity of financial intermediary upon changes in the interest rate environment and currency value, respectively. Previous empirical studies based on these two research questions find mixed results. On one hand, the theoretical framework suggests that changes in interest rate environment/currency value will influence the value of assets and liabilities, which in turn has a significant impact on financial intermediaries' equity value. On the other hand, however, operational and financial hedging practise carried out by financial institution mitigates the impact of these risk factors. In this thesis, we try to capture the relationship between fluctuations in interest rate/currency value and changes in equity value of financial intermediaries through alternative model settings. For instance, instead of measuring the changes in interest rate environment with changes in a given bond index or interest rates with a certain maturity; we describe the former based on term structure model (*i.e.* Nelson-Siegel three factor model), which is able to accurately illustrate the shape changes in the entire yield curve. For the third research question (*i.e.* the relationship between currency value and equity value of financial intermediaries), we incorporate both home and foreign currency value changes into the estimation framework. We argue that despite hedging activity being able to mitigate the currency effect, it is true for home currency value only but not for the foreign one.[3] The proposed model not only enables us to shed light on the relationship between the home/foreign currency value and the equity value of financial intermediaries, but also provides us a reasonable explanation.

[3] The currency value is defined as the trade weighted currency price index. A detailed explanation of the latter is given in chapter 3.

Furthermore, we try to reveal and justify the potential changes in the relationship between interest rate environment/currency value fluctuation and equity value of financial intermediaries during the recent financial turmoil.

The final research question focuses on the risk adjusted performances of various asset allocation strategies. Volatility and correlation among asset returns are central inputs to portfolio selection and risk management. In theory, the model that captures more stylized facts of returns' second moment should provide more accurate variance-covariance matrix estimations in statistical merits. However, without transforming this superior performance into economic value, the former is of little use. In the current study, we compare asset allocation strategies based on various conditional correlation estimation frameworks (*i.e.* dynamic/static correlation timing) in terms of the investor's utility and risk adjusted reward they are able to generate.

1.3. CONTRIBUTION AND IMPLICATION

In general, the first three empirical chapters in this thesis contribute to the existing literature in three ways. First, the first three empirical studies employ up-to-date multinational dataset covering both banking and insurance institutions, while previous literatures have ether focused on one particular type of financial institutions, or within one national market. Second, to our knowledge, this thesis is the first empirical study to shed light on the impact of current financial crisis on the risk characteristic (both systemic risk and firm specific) of financial institutions. Third, the empirical studies presented in this thesis adopt an alternative empirical framework based on multivariate GARCH models. The alternative framework takes into account the time-varying conditional variance as well as correlation among the assets, which can improve the estimation efficiency and the accuracy of the estimated parameters.

The contribution of the final empirical chapter to the existing literature is twofold. First, the benefits of correlation timing vis-à-vis the static constant covariance strategy are explored and the impact of transaction costs and rebalancing frequency on the strategy performance is assessed. Second, the role of asymmetries and structural breaks in sector correlations is statistically and economically evaluated.

Our empirical findings have potential implications from the perspective of regulation, risk management, asset pricing and portfolio management. The first empirical chapter (i.e. chapter 2) is important from a regulatory point of view. The current financial crisis shows the importance of improving the resilience of financial institutions during stress market condition, and how collapse in a small corner of the financial market could tumble the stability of the entire global financial system through interdependence among these institutions. Therefore, a crisis-led regulation framework targeting the interdependence across financial institutions/markets is vital to the stability of global financial system.

The second and third empirical chapter (i.e. chapter 3 and 4) have important implications in the area of regulation, risk management and asset pricing. First, the characterisation of the risk profile of banks in terms of observable macro-variables – namely, the stock market and the yield curve/currency value – has important implications for bank regulators seeking to foster stability in the banking industry via market discipline. Second, better understanding of the risk characteristic of financial institution is important for improving the risk management effectiveness. Finally, the yield and currency value sensitivity is crucial in the context of asset pricing and the existence of industry specific return generating process.

The findings obtained from the final empirical chapter (i.e. chapter 5) could be valuable from a portfolio/asset management perspective. As reducing risk while maintaining a desirable level of return becomes increasingly important in the asset management industry, better understanding the conditional volatility as well as correlation among financial assets – especially their asymmetry and structural break nature - is key for controlling/reducing the overall risk of the portfolio through diversification.

1.4. LAYOUT OF THE THESIS

There are four empirical chapters within the thesis with each of them concentrating on one aforementioned research question. Generally, the thesis can be separated into three parts. In chapter 2, which consists the first part, we investigate the interactions among global financial sectors before and during the recent financial turmoil. The second part (*i.e.* chapter 3 and 4) analyses the relationship between changes in interest rate environment/ currency value and equity return of financial intermediaries across major markets. The final part examines the economic value of various correlation timing strategies, and the empirical results are presented in chapter 5.

Chapter 2 concentrates on the interconnectedness across the global financial industries. By adopting a new estimation framework (i.e. modified VAR-BEKK model with return and volatility transmission), we can identify the pattern of return and volatility spillovers among financial intermediary types (*i.e.* banks and insurers) across major markets and quantify their magnitude before and during the recent financial turmoil in a more accurate manner. Moreover, the size effect of the return and volatility transmission has also been taking into account by re-sampling the financial intermediaries according to their market capitalization. Finally, various reports from academics and practitioners alike have emphasised on the difference in the behaviour of equity return of banks and insurers during the recent financial crisis due to their different business models and risk characteristics. In order to investigate this phenomenon, we further analyse the cross-sector return and risk transmission between the banking and insurance industries across markets and on a global level.

The second empirical study (chapter 3) examines the interest rate risk exposure of financial intermediaries. We measure changes in the interest rate environment as changes in the factor loading of Nelson-Siegel three-factor model, which is capable of accurately capturing the shape of an entire yield curve. The new interest rate change measure enables us to investigate the impact of long-term, short-term interest rate changes as well as changes in the slope of yield curve on the equity value of financial intermediaries across major markets. In order to evaluate the effectiveness of various market interventions carried out by central banks/governments across major economies, we also incorporate these intervention events into our empirical framework to directly measure their influences on the equity value of financial intermediaries in different markets.

In chapter 4, the relationship between fluctuations in currency value and changes in equity value of financial intermediaries has been scrutinized. Unlike the conventional approach that only focuses on the impact derived from home value fluctuations, changes in foreign currency value have also be involved into our estimation framework. Our empirical framework is based on the "flight-to-quality" hypothesis, which suggests that investors prefer asset with higher credit quality compared to the lower ones. Financial assets are usually traded in home currency terms and thus the need to obtain that currency is apparent. Currency value, therefore, can be used as an indirect measure of investor's sentiment. Given that changes in home currency value are usually hard to detect due to operational/financial hedging activities, the "flight-to-quality" effect is, therefore, more likely to be captured by changes in foreign currency value.

We focus our attention on various correlation timing strategies and their economic value in chapter 5. The risk adjusted performance of an asset allocation strategy is the key element for the success of portfolio managers. As major players in the fund management/advisory industry, the economic value of different correlation timing strategies, therefore, provides valuable information for financial intermediaries. In this study, we measure the economic value of dynamic correlation timing strategies based on the performance fee they are able to generate over the static asset allocation strategies. The influence of transaction cost on the economic value of dynamic correlation timing strategy has also been taking into account, and we further examine the impact of rebalancing frequency on their break-even transaction costs.

Finally, chapter 6 concludes the thesis by providing an overview of our research and a general summary of the issues examined. In addition, the chapter discuss and identifies a number of issues for risk management of financial intermediaries that worth further investigation.

CHAPTER 2

INTERDEPENDENCE AMONG GLOBAL BANKING AND INSURANCE INDUSTRY

2.1. INTRODUCTION

The sub-prime crisis in 2007 has led to the most severe post-war financial market crisis in recent history. Despite the relative size of the problematic sub-prime mortgages is small compares to US economy, the impact of the crisis is devastating not only to the US financial market, but across the global[4]. Researchers argue that the contagion effect from the US market to the rest of the global financial market is mainly through the channel of the banking sectors (Adrian and Shin, 2008; De Grauwe, 2008; Kollmann and Malherbe, 2011). The argument is based on the fact that the liquidity of banks suffered from the sudden decrease in asset price at the beginning of the crisis, which caused a liquidity and loss spiral and developed into a full blown financial crisis.[5]

Several empirical studies have focused their attention on the contagion effect during the recent financial crisis.[6] However, they failed to capture either the whole extent of the crisis period, or the impact across global financial markets. For instance, Pukthuanthong

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[4] Eichengreen et al (2009) suggest that the total value of subprime mortgage related securities is only 3% of the US financial assets. Adrian and Shin (2008) further argue that the total value of US subprime mortgage lending in 2006 and 2007 is only equivalent to 1% of the US equity market value, and it is less than 0.2% of the US household net wealth. Brunnermeier (2009) shows that the stock market losses in the US alone is around 8 trillion US Dollar from October 2007 to October 2008.

[5] The shape fall in asset prices and liquidity condition around the global financial markets is due to the deleveraging process of the banks during the crisis period. As banks suffer losses from their subprime mortgage lending, they are forced to sale their asset holdings to maintain their leverage ratio (Adrian and Shin, 2010) and become more cautious about lending (Acharya and Merrouche, 2009). The crowded trades on financial assets cause asset price drop and the precautionary hoarding on lending activities reduces the market liquidity. The asset price fall reduces the asset value of the banks, and force banks to sale even more assets to maintain the leverage ratio, which makes banks even more cautious about their lending activities. This vicious cycle is also called “liquidity spiral” or “loss spiral”. For further discussion on the two “spirals” and development of the recent financial crisis, please refer to Blackburn (2008), Brunnermeier (2009), Brunnermeier and Pedersen (2009), De Grauwe (2008) and Frank et al (2008).

[6] The contagion effect refers to the increase in linkages among the financial sectors or markets during the economic downturn or crisis period. Please refer to Kaufman (1994), Dornbusch et al (2000), Kaminsky and Reinhart (2000) and Kaminsky et al (2003) for excellent reviews on the topic.

and Roll (2009) examine the correlations among 81 financial markets across the global with a sample period over thirty years which ends at *8 February 2008*. Another study by Diebold and Yilmaz (2009) investigate the connections across the returns and volatilities of major financial markets from *January 1992* to *November 2007* based on weekly returns of local currency stock market indices. Despite these studies find empirical evidence which supports the contagion effect among financial markets during the crisis period, they fail to capture the full picture of the crisis due to the sample period they employed. Brunnermeier (2009) claims that the recent financial crisis has two phases, it started with a subprime mortgage crisis since early 2007 and turned into a full blown global financial crisis in late 2008 after the collapse of Lehman Brothers.[7] This argument is supported by Eichengreen et al (2009), who also show that the failure of Lehman Brothers is a critical turning point in the recent financial crisis, from which a relative small US housing market crisis became a global financial crisis.[8] Since banks are the main channel through which the US subprime mortgage crisis transformed into a global financial market meltdown, some researchers refer the second phase of the financial crisis as a global "banking crisis" [9].

For empirical studies which do cover the entire crisis period, they fail to investigate the impact of the crisis across the global financial markets. For instance, Longstaff (2010) examine the spillover effects from the collateralized debt obligations (CDO) market to the bond and equity markets from late 2006 to the end of 2008. However, he restricted his

[7] In Brunnermeier (2009), the subprime mortgage crisis is defined as the increasing default rate of the subprime mortgage loans, and the massive credit rating downgrades of the mortgage backed securities since early 2007. The full blown global financial crisis refers to the sudden liquidity dry up in the wholesale and interbank funding market follows the bankruptcy of Lehman Brother on *15 September 2008*. Eling and Schmeiser (2010) divide the crisis period into two phases in a similar fashion. The first phase is from *September 2007* till *August 2008*, and the second phase is from *September 2008* till early 2009.

[8] Eichengreen et al (2009) suggest that the total value of subprime mortgage related securities is only 3% of the US financial assets. Adrian and Shin (2008) further argue that the total value of US subprime mortgage lending in 2006 and 2007 is only equivalent to 1% of the US equity market value, and it is less than 0.2% of the US household net wealth.

[9] See, for instance, Eichengreen et al (2009), De Grauwe (2008) and Honohan (2008). Since the consequence of the recent financial crisis is a sudden liquidity dried up in the global financial market, Adrian and Shin (2008) also refer the crisis as a "credit crisis".

study solely on the US market. Similarly, the empirical study by Goldsmith-Pinkham and Yorulmazer (2010) only captured the contagion effect within the UK banking industry.

To our knowledge, the only exception comes from a working paper by Eichengreen et al (2009) which provide an empirical study on the contagion effect across the global financial market which covers most of the crisis period. Their sample finishes at the *28 November 2008*. However, they only focus on the contagion of the bank's default risk as the study is based on weekly credit default swap (CDS) spreads of the 45 world largest banks. The study does not provide any information on the return interdependence among the banking sectors across the financial markets, and ignore the impact of the crisis on the risk and return of small banks and other type of financial institutions.

In this chapter, we contribute to the existing literature in four different ways. First, we examine the return and risk interdependence among financial institutions over the full extent of the recent financial crisis.[10] The sample period used in this empirical chapter starts from the *January 1, 2003* till *9 March 9, 2009*, which includes both the first and the second phase of the recent financial crisis. Second, the current study investigates the contagion effect for more than one type of financial institutions across major financial markets. Existing literatures often emphasis on the one type of financial intermediaries (banking sector by Elyasiani and Mansur, 2003, insurance companies by Carson et al, 2008), or one single economy (financial sectors within US market by Elyasiani et al, 2007). Our sample covers both banks and insurers from the world's major economies. Finally, the study sheds light on the different impact of current crisis on the spillover effects of banking and insurance institutions. It is commonly believed that the recent financial crisis has a far greater impact on the banking industry compare to the insurance sector. Harrington (2009) and Eling and Schmeiser (2010) argue that the insurance companies

[10] Please find further discussion in Section 2.3.

perform relatively well during the recent financial crisis compare to banks. The reports from CEA and The Geneva Association support the argument, as they both suggest that insurers have gone through the crisis in a better shape due to the nature of their business model.[11] According to the report from CEA, most insurance companies, especially the European ones, are affected by the recent financial crisis through mark-to-market losses of their financial assets due to the depressed financial market and liquidity shortage, but not because their direct involvement in the subprime mortgage lending. Banks are the main driving force for the collapse of asset prices and the liquidity dried up across the global financial markets. Therefore, one would expect the performance of the banking industry can influence the performance of the insurers, but not vice versa. The enriched sample set also enables us to explore the difference in the interdependence among different type of financial intermediaries across the global markets, especially during the recent financial crisis.

Third, the current study contributes to the existing literature by proposing a new model structure for the examination of return and volatility interdependence among multiple assets, which named VAR-BEKK model. The models used by early empirical studies only focuses on the linkage within the returns of the financial assets but not their volatilities (Karolyi and Stulz, 1996). Later, the estimation framework has been improved to examine both the return and volatility linkages at the same time (Elyasiani and Mansur, 2003). However, the bivariate GARCH employed by Elyasiani and Mansur (2003) can only investigate the return and volatility spillover effects between two assets at one time. Elyasiani et al (2007) proposed the multivariate GARCH framework to estimate the return

[11] The report from Geneva Association is under the title *Systemic Risk in Insurance, An analysis of insurance and financial stability* (2010), see: www.genevaassociation.org. The report from CEA is under the title *Eight Key Messages on the Financial Turmoil*(2008), see: www.cea.eu. They claim that insurance companies are less exposed to the credit risk and liquidity risk compares to banks, and the insurance industry is less involved in the mortgage related security market.

and volatility spillover effects across more than two assets. However, the model used by Elyasiani et al (2007) assumes the conditional correlations among the involving assets are constant over the estimation period. This assumption is in contrary to the existing literature on conditional correlation, which shows that the correlations among financial assets are actually time-varying.[12]

In comparison to the models used in the previous studies, our model has three improvements. The first improvement is that our model is multivariate, which enables us to evaluate the interdependence across multiple assets at the same time instead of only two assets such as the bilateral estimation framework. Secondly, our model enables us to investigate the return as well as the volatility spillover effects among the financial institutions simultaneously. The above two improvements help to increase the estimation efficiency of the model as we can use less estimations and less parameters to increase the degree of freedom of the model. Finally, the proposed VAR-BEKK model is more flexible in terms of the parameterization for conditional variance-covariance equations. In our model we do not impose restriction on the time-varying dynamics of the conditional correlations among the financial institutions. Therefore, our model should fit the return series of involved financial institutions better and provide higher estimation accuracy compares to the one proposed by Elyasiani et al (2007). We provide a detail explanation of our model in the methodology section.

Our empirical findings bear important implications in terms of improving the resilience of financial institutions during volatile market conditions. The significant rise in cross-market dependence across banking sectors shows the importance to embed the systemic risk into the risk assessment and management regulation framework for banking

[12] Please refer to Ramchand and Susmel (1998), Ang and Bekaert (1999), Longin and Solnik (2001), and Cappiello et al (2006) for further discussion on time-varying conditional correlations.

institutions. Besides, enhanced interdependence between global bank and insurance portfolios during the recent financial crisis also indicates the need of regulatory initiatives for enhanced risk coverage and reduction of systemic risk.

The rest of the chapter is organized as follow. The following section provides a brief literature review on contagion and spillover effects. Section 2.3 describes the dataset we used in the current study. Section 2.4 outlines the new model structure we proposed in detail and discuss the estimation procedure used. Section 2.5 presents the discussion on the result of our empirical study. Finally, section 2.6 concludes the study.

2.2. LITERATURE REVIEW

This section presents a brief overview of the literature with no intention to lessen the importance of any excluded studies. The cross-border linkage among financial markets can be measured by the transmission of return and volatility across these markets (Forbes and Rigobon, 2001). Early studies of return and volatility transmissions primarily focus on the contagious spillovers across advanced financial markets during crises periods. For instance, Hamao et al (1990) and King and Wadhwani (1990) demonstrate the volatility spillover effects from the US to Japan and the UK during the 1987 stock market crash. However, these studies focus on return and volatility spillover separately, rendering their results unreliable and inaccurate. Subsequently, Koutmos and Booth (1995) and Karolyi (1995) examine both the return and volatility spillovers across major financial markets with simultaneous equation system during the 1987 market crash. Recently, Dungey and Martin (2007) look into the price transmission among Asian financial markets during the 1997 Asian financial crisis. The rapid transmission of the price and risk information across financial markets during economic downturn is also known as contagion effect (Kodres and Prisker, 2002; Kyle and Xiong, 2001). Since the return and volatility spillover could have a catastrophic impact on the stability of global financial market, the information about the spillover mechanism is highly valuable to regulators, hedging strategists and investment advisors interested in accurate asset pricing models as better understanding the transmission mechanism can be helpful in designing regulatory restrictions to prevent intensification of financial crises, in risk management practices, and for formulation of successful investment strategies (Karolyi, 1995; Summers, 2000). In the current study, we define the spillover effect as the transmission of first and second moment of price information from one sector/market to another.

The spillover effect is not only sensitive to market conditions/business cycles, but also sensitive to the size of the involved economies and the changes in regulatory frameworks. Eun and Shim (1989) provide the first empirical study on the size effect of spillovers. They show that the price information generated from the US stock market – the largest in the world - plays a dominate role in return spillovers among the world's nine major stock markets in the early 1980s.[13] The finding is later supported by Koutmos and Booth (1995), Karolyi (1995) and Bekaert et al (2005). Changes in regulatory frameworks also have a significant impact on the spillover effect across financial markets. The empirical studies by Bartram et al (2007) and Asgharian and Nossman (2011) indicate that the spillover effect among the European countries has increased since the introduction of Euro in 1999.[14] However, Bekaert et al (2005), Bartram et al (2007) and Asgharian and Nossman (2011) all use regionally syndicated indices to evaluate the spillover effects

[13] The remaining eight stock markets are Australia, Japan, Hong Kong, the UK, Switzerland, France, Germany and Canada.

[14] Please refer to Hartmann et al (2003) for further discussion on how the introduction of European Monetary Union increases the financial system integration among the Euro zone countries.

among the regional markets. Therefore, they fail to identify the direction and magnitude of spillovers across each individual markets.

The return and volatility transmissions not only exist at market level, but also at sector/firm level. Financial institutions play an important role in the modern financial system as they act as the collector and distributor of public financial resource (Saunders and Cornett, 2010). Therefore, studies on sector/firm level spillover effects primarily focus on the financial institutions like banks and insurers. Lang and Stulz (1992) shows that bankruptcy announcement of a bank can have a negative spillover effect on the rest of the banks in the same financial system. This finding is reinforced by Kaufman (1994), who shows that the failure of one bank can spread to the rest of the banking system through banks runs in a contagious manner. Furthermore, Slovin et al (1992) and Bessler and Nohel (2000) claim that the liquidity (secondary equity offering) and profit (dividend cut) related announcement issued by a bank also can influence the equity value of other banks in a contagious manner. Elyasiani et al. (2007) and Carson et al. (2008) focus, respectively, on the return and volatility spillover among banks, insurers and investment bankers and among different types of insurers (accident and health, life, property and casualty) within the US market during 1991-2001. The former study finds that return (volatility) spillovers among the small institutions are stronger (weaker) compared to large ones; while the latter shows strong (weak) return (volatility) spillover among insurers. However, after the sample has been categorized according to size and degree of diversification (in terms of product and geographic), the volatility spillover effect becomes significant.

The financial crisis in 2007-2009 provides a unique opportunity for researchers to investigate the spillover effect across financial industries. To investigate how a relative small fragment of the financial market (the US sub-prime mortgage market) can bring down the entire global financial system provides valuable insight for regulators and investors to prevent and hedge for future crises.[15] Blackburn (2008) and Frank et al (2008) suggest that the crisis is transmitted from the US banking sector to the rest of the global financial markets through liquidity and credit channels and amplified by the sudden dry-up in the interbank loan market. Eichengreen et al (2009) examine the contagious spillover of default probability among the world's largest 45 banks during the recent financial crisis. The default probability is measured by the spread of credit default swap contracts. The empirical result suggests that the risk profile of these large international banks is closely related especially after the collapse of Lehman Brother. Goldsmith-Pinkham and Yorulmazer (2010) investigate the bank run in the UK during the failure of Northern Rock[16] and reinforce Kaufman's (1994) theory of transmission of bank failures to other banks through liquidity shortage.

It is worth noticing that the negative shocks generated by one sector/firm can transmit to the other sectors/firms in a positive manner instead of negative as discussed above. In other words, firms can benefit from the adverse shocks experienced by the other players in the same market/industry. This positive spillover effect is also known as competitive effect (Lang and Stulz, 1992).[17] Slovin et al (1999) show that profit related announcement (dividend cut) by the US regional banks has positive competitive effect on their geographic rivals from 1975 to 1992. The finding indicates that regional competitors

[15] Eichengreen et al (2009) suggest that the total value of subprime mortgage related securities is only 3% of the US financial assets. Adrian and Shin (2008) further argue that the total value of US subprime mortgage lending in 2006 and 2007 is only equivalent to 1% of the US equity market value, and it is less than 0.2% of the US household net wealth. Brunnermeier (2009) shows that the losses in the US stock market alone is around 8 trillion US Dollar from October 2007 to October 2008.

[16] In September 2007, Northern Rock - the fifth largest mortgage lender in the U.K. - experienced an old-fashioned bank run, the first bank run in the U.K. since the collapse of City of Glasgow Bank in 1878. The run had been contained by the government's announcement that it would guarantee all deposits in Northern Rock.

[17] Lang and Stulz (1992) argue that the distress or bankruptcy of one firm can improve the competitive position of the other firm in the same industry since the distressed or bankrupted firm will offer profitable opportunities to other competitors.

benefit from their rival's profit loss or deterioration in cash flows/loan values. Elyasiani et al (2011) also find positive competitive effect among the US financial institutions during the recent financial crisis. Their result indicates that the financial institution who accepted the government rescue funding has a positive impact on the ones who did not.[18] Instead of examining spillovers of financial institutions within the same market, Elyasiani and Mansur (2003) investigate the return and volatility transmission across banking sectors of Japanese, German and the US market from 1986 to 1995. Their result also confirms the existence of competitive effects by showing that an adverse shock to the US banking sector will benefit banks in the other two markets in terms of lower unsystematic risk.

Overall, the existing literature has identified a number of interdependencies, but at the same time, some studies have failed to investigate the return and volatility interdependencies simultaneously; some have employed modified regional indices (rather than country/sector portfolios) to investigate the integration among equity markets;[19] and those focusing on financial intermediaries have concentrated on a single market and/or industry.

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[18] In their study, the government rescue funding refers to the injection of government capital under the Troubled Asset Relief Program (TRAP).

[19] Several empirical studies examining the spillover effects among a regional market (e.g. the Europe, Latin America, and Asia regional markets in Bekaert et al., 2005) by investigate the influence of regional market on the individual national market. However, the conventional regional market indices usually contain all the national market indices within the region, which will introduce biasness to the analysis of spillover effects. Therefore, modified regional market indices are employed where the country under examination is excluded from the index. Asgharian and Nossman (2011) and Bartram et al. (2007) also adopt similar approach for their empirical studies.

2.3. DATE COLLECTION

2.3.1. Equity Portfolios And Explanatory Variable

In the current study, we investigate the interdependence among the banking and insurance (both life and non-life) sectors from the US, Japanese and seven Western European countries. The seven EU countries are UK, France, German, Italy, Spain, Portugal and Greece. Despite the rapid expansion of the financial sectors in emerging markets in past two decades, the major developed economies are still the dominate force of the global financial market. The report from International Monetary Fund (IMF) shows that the combined bank assets of the US, UK, Japan, and European Union (EU) countries take over more 60% of the asset of global banking sectors in total.[20] The study by Swiss Re also claims that more than 75% of the insurance premiums is generated by the insurers come from North America, Western Europe and Japan in 2009.[21]

In order to eliminate the cross-sectional spillover due to the multiple-listed companies across different markets,[22] we only select the financial institutions which are listed in the market where they are basesd. For each of the markets, we collect the daily price information for all the domestic listed companies within the banking, life and non-life insurance sectors.[23] All the price information is in the local currency units.[24] We use local currency price in this study to avoid the potential biasness in the interdependence across different markets due to the fluctuations of relative currency value of these markets. The idea can be better illustrated with a simplified scenario. Assuming that the stock price

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[20] The report from IMF is under the title *Global Financial Stability Report* (2010), see: www.imf.org.
[21]The data is collected from the *SIGMA Report* (2010) by Swiss Re, see: www.swissre.com.
[22] Eun and Shim (1989) and Karolyi (1995) suggest one should exclude the multiple- and/or double-listed stocks from the sample to prevent interdependence due to stocks which are double counted across the financial markets.
[23] We use the sector category provided by DataStream International to ensure consistency across the financial markets.
[24] Studies like Eun and Shim (1989), Diebold and Yilmaz (2009) and Karolyi (1995) also use price information in local currency terms in their studies.

of a US bank is one dollar, and the price of a Japanese bank is one Yen, and both remain constant over the sample period. Assuming that the stock price of the two banks is represented in local currency terms, then there will not be any relative movements between the two stocks regardless of the changes in the exchange rates between the two currencies. However, assuming that the value of US Dollar increases against Japanese Yen, and both stock prices are represented in a common currency terms, say US Dollar. In this case, the relative movement between the two stock prices will be negative even though the stock prices in local currency terms remain constant. The reason is because the stock price for Japanese bank has decreased relative to the US bank in terms of US Dollar. Therefore, if the stock prices of financial institutions are all dominated in one currency across different countries, the returns of these institutions may be related even without fundamental linkages. In order to eliminate the issue of survivorship bias while maximizing the sample size, the dataset for each day contains all the listed institutions whose stocks are actively traded on that particular day.

The daily information of the equity market price index, long-term benchmark bond yield, and the trade-weighted foreign exchange rate index have also been collected for each financial market.[25] All the information is obtained from DataStream International. In order to eliminate the potential influence from the Dot-Com Bubble which has a lasting impact on global financial market till late 2002, we start our sample period from the *January 1, 2003* and finishes on the *March 9, 2009*. To ensure the same number of daily return observations across all the markets, we exclude the days when any of the markets is

[25] For the European market, we collect the syndicate long-term benchmark bond yield for European markets constructed by DataStream International. We collect the trade-weighted foreign exchange rate index for the Euro, Japanese Yen, British Pound and US Dollar. The trade-weighted foreign exchange rate index is provided by Bank of England.

closed.[26] In other words, we drop the daily return observation if there is no trading activity on any of the markets. The total number of daily return observations for each price series is 1437 after the non-trading adjustment.

2.3.2. *Define the Crisis Period*

In order to investigate the impact of the recent financial crisis on the risk and return interdependence among the financial sectors across the major economies, we need to specify the crisis period for the empirical study. In this chapter, we define the crisis period from the *April 2, 2007* to the *March 9, 2009*. The recent financial crisis starts to show its sign in early 2007, when the US housing market begins to decline with a number of small sub-prime lenders suffered huge losses in February and March. On the *April 2, 2007*, the crisis claimed its first major victim as the largest US sub-prime lender, New Century Financial, filed for bankruptcy. The event is followed by a series credit rating downgrades on structured financial products (mainly asset backed securities backed by subprime loans).[27] Although the asset backed security markets are still expending in the first half of 2007, the pace of the expansion slowed since *April* and eventually collapsed in *August 2007*.[28]

The bankruptcy of New Century Financial put serious doubt on the "originate and distribute" business model of banks, which shaken the investor's confidence in the banking sector (Blackburn, 2008).[29] The banking sector from the major economies started

[26] The structure of the VAR-BEKK model requires the return series of involved assets have the same number of observations.
[27] Moody's has downgraded 131 asset backed securities which are backed by subprime mortgage loans in *June 2007*. For detail timeline of the events during the recent financial crisis, please refer to Guillén (2009).
[28] Please find the diagram represents the monthly outstanding volume of the asset backed security markets in the Appendix A.1.
[29] Banks with "originate and distribute" business model do not hold the loans they generated but sale it to other investors once these loans are generated. Since the banks pass the credit risk to other parties through securitizing the loans into structured financial assets, they on longer care about the quality of the loans. The

to collapse following the event.[30] The value of banks decreased because the structured financial products they were holding is highly sensitive to market conditions.

It is worth mentioning that structured products are hard to value as they are complex in nature and traded over-the-counter (OTC). Under the fair value accounting standard, the structured products are categorized as "Level 3" assets.[31] That means, the fair value of structured products is based purely on models, and has no directly tradable elements. Therefore, during extreme market conditions (economic downturn, or collapse of the housing market), the value of these OTC structured products is simply "a wish and a prayer" (Blackburn, 2008). Banks are the most active investors in the structured financial products (Duffie, 2008), and they need to mark the financial assets on their balance sheet to the market price/fair value of the assets according to the fair value accounting standard. Therefore, the dramatic price drop in structured financial products forces banks to write-off large amount of value on their balance sheet, and makes the liquidity situation within the banking sector even worse. In order to ease the liquidity shortage, banks forced to sell their liquid assets which driven the asset price down further. This vicious circle is also known as liquidity and/or loss spiral (Blackburn, 2008). The insurance sectors were also suffered during the crisis due to the fair value accounting standard. Eling and Schmeiser (2010) claim that the negative impact on the value of insurance companies was "unavoidable" since insurers are the largest institutional investors on the financial market.

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structured financial assets are off-balance sheet items, which means banks can create a "shadow banking system" and take on as much credit risk as they want.

[30] Please find the diagram for daily movement of the equity value for different sector portfolios in the Appendix A.2.

[31] The fair value accounting standard is according to the Statement of Financial Accounting Standards No. 157: Fair Value Measurement (FAS 157), which is issued by the US Financial Accounting Standards Board (FASB). For further discussion on the fair value accounting rule and its impact on the current financial crisis, please refer to the *Global Financial Stability Report* (2008) issued by the IMF. The GFSR is issued on an annually basis and available from IMF's website: www.imf.org.

Some researchers suggest alternative starting dates for the recent crisis. For instance, Brunnermeier (2009) argues the event that BNP Paribas ceases the redemptions for three of its investment funds on the *August 9, 2007* should be the starting date of the crisis, as it triggered the collapse of the wholesale funding market. He suggests that the event indicates that even large financial institutions cannot value the structured products properly, which severely damaged the investor's confidence in the structured financial products. However, we do not fully agree with this argument. The BNP Paribas event is just the last straw since which the whole global economy started to crumble due to credit and liquidity shortage. However, it is the bankruptcy of New Century Financial that triggered the chain reaction which eventually led to the melt down of the global financial market.

We specify the end of the recent financial crisis at the *March 9, 2009*. On this day, the equity markets of the selected markets reach their lowest point during the recent financial crisis.[32] After that, these stock markets experience the biggest single rally since the start of the crisis, which shows a strong recovery of the global financial market.[33]

2.3.3. Equity Portfolios And Explanatory Variable

There is one issue for using the daily frequency data to investigate the interdependences among financial sectors across different markets, which is the nonsynchronous trading time. Stock markets in different countries are operating in diverse time zones with different opening and closing times. In order to better illustrate the idea, we draw the following diagram which presents the nature of nonsynchronous trading periods for the stock markets in our sample.

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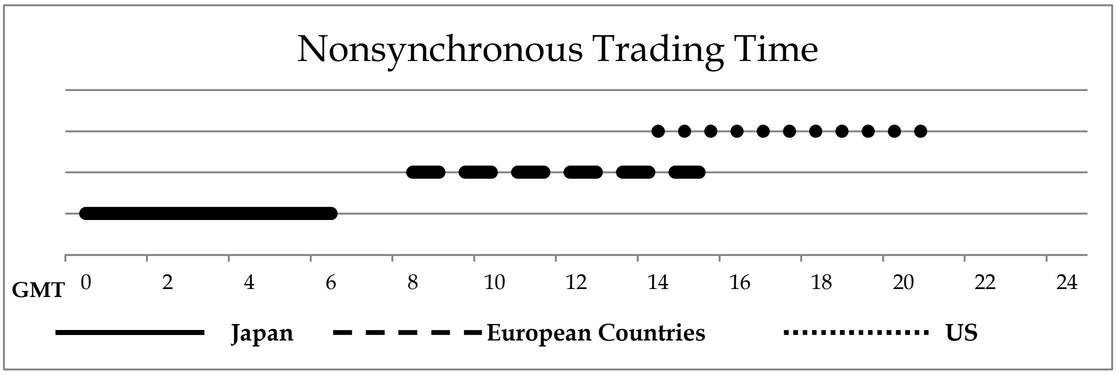
[32] Please find the diagram for daily movements of the stock market indices represented in the Appendix A.3.
[33] The S&P 500 Financials index is increased by 16% on the *March 10, 2009* alone.

Figure 2.1 **Nonsynchronous Trading Time across Stock Markets**[34]



From the above diagram (Figure 2.1), one can see that simply using the lagged price information to investigate the cross-sectional spillover effects could be misleading. For instance, one should use the same day price information instead of the price information of previous trading day from the Japanese market to evaluate its spillover effect towards the US market. Since the Japanese market finishes trading before the US market opens, the price information generates from the Japanese market is fully disclosed to the US investors on the same trading day.

In order to overcome this issue, some researchers use low frequency data such as weekly (Baele, 2005, Bekaert et al, 2005) or monthly (Peek and Rosengren, 1997) price information. However, using low frequency data may fail to capture the spillover effects as they usually last for a short period of time (Eun and Shim, 1989). In the current study, we fix the nonsynchronous trading time by adjusting the time lag for different markets.

Our approach is similar to the one used by Eun and Shim (1989) and Hamao et al (1990). Given the trading sequence of the different stock markets, it is reasonable to assume that the return and volatility information from a market that finishes its trading activity earlier in the calendar day is likely to transmit to other markets that operate later

[34] The GMT refers to the Greenwich Mean Time. The figure illustrates the opening and closing time of the major stock exchange in each region. Tokyo Stock Exchange in the Japanese market opens at GMT 0:00 and closes at GMT 6:00. The London Stock Exchange in UK shares almost the same trading period with most of the European stock exchanges, which operates between GMT 8:00 till 16:30. The New York Stock Exchange in the US market opens the latest at GMT 14:30 and finishes at GMT 21:00.

in the same trading day, but not vice versa. For instance, it is very likely that the trading information from the Japanese market will transmit to the markets in the European countries and US on the same trading day. However, the Japanese market would only respond to the price information generated from the European and US markets over the previous trading day.

2.3.4. *Financial Sector Portfolio*

We construct equally weighted sector portfolios for different types of financial institutions within a market.[35] For each market, two financial sector portfolios are constructed, namely the banking and the insurance portfolio. The insurance portfolio contains both life and non-life insurance companies. We also group the six Western European countries as one market. The six Western European countries are France, German, Italy, Spain, Portugal and Greece. We treat the six countries as one market due to the fact that these countries are all members of the European Monetary Union (EMU) and they are highly integrated in terms of financial market movements.[36] We exclude UK from the group as it is the only major European country which is not belongs to the EMU. We label the group of six Western European countries as EU market in the current study.

We focus on the interdependence among financial sectors instead of individual financial institutions across the global financial markets. Therefore, we would like the firm specific information to be removed from the financial sector portfolio through diversification. It is well-known that the portfolio size has a significant impact on the diversification effectiveness. Previous studies suggested that a portfolio with 28 to 60

[35] The size weighted portfolio will represent the performance of the large institutions, while the equally weighted portfolio will provide a more general performance measure across all institutions involved. We focus on the return performance of a financial sector rather than a group of individual institutions. Therefore, we employ equally weighted portfolios in this chapter.

[36] For further discussion on the impact of the introduction of Euro on the EMU member states, and their market integration, please refer to Bartram et al (2007), and Christiansen (2007) among others.

securities is only 20% to 10% higher than the universal minimum risk portfolio, which indicates that most of the diversification benefits can be achieved when the portfolio size is above 20 (Evans and Archer, 1968, Elton and Gruber, 1977, Shawky and Smith, 2005) . In order to illustrate the diversification effectiveness of the financial sector portfolios we constructed for the current study, the number of financial institutions in each market is presented in Table 2.1 as follow.

Table 2.1 Time-Varying Size of the Financial Sector Portfolios

The following table contains the size of the financial sector portfolios over the sample period on an annually basis. The sample period used in the current study is from the *1 January 2003* till *9 March 2009*.

	EU				Japan			
Date	Small Banks	Large Banks	Bank	Insurance	Small Banks	Large Banks	Bank	Insurance
2003	52	17	69	24	59	20	79	3
2004	53	17	70	25	60	20	80	3
2005	53	18	71	25	61	20	81	3
2006	55	18	73	26	62	21	83	3
2007	57	19	76	26	63	21	84	3
2008	58	19	77	26	63	21	84	3
2009	58	19	77	26	65	21	86	3

	UK		US			
Date	Bank	Insurance	Small Banks	Large Banks	Bank	Insurance
2003	6	19	65	21	86	61
2004	7	22	74	24	98	66
2005	7	26	76	25	101	67
2006	8	27	79	26	105	69
2007	8	33	83	28	111	73
2008	8	34	83	28	111	75
2009	8	34	84	28	112	75

The above table illustrates the number of institutions for different financial sectors within each market. The number of institutions in the all the insurance sectors, as well as the banking sector in the UK market is comparatively small over the sample period. In order to obtain the maximum diversification benefits, we only construct one portfolio for each of these financial sectors. We named these portfolios which contain all the financial institutions within the same industry as all size financial sector portfolios.

The number of institutions in the EU, Japanese and US banking sector is more than 70 during the sample period. Existing literature shows that financial institutions with different sizes react differently to the market risk factors, especially for banks.[37] In order to examine the potential size effect for the banks in our sample while maintain a reasonable level of diversification effectiveness, we construct two additional size portfolios for the EU, Japanese and US banking industries, namely the large and small size banking portfolios.

In order to categorize banks into different size groups, we collect the market capitalization for banks in these three markets on a monthly basis. The size of the financial institution fluctuates as time elapses, which might cause the change of the firm's size category over the sample period. To ensure the institutions in the large size portfolio consistently have a higher market capitalization compares to ones from the small size portfolio, we rebalance our size portfolio on a monthly basis. At the start of each calendar month, we rank financial institutions within the same financial sector for each market from large to small according to their average market capitalization over the year. The institution within the top 25% region will be picked as the large banks for that month,

[37] For further discussion on the size effect of the banking industry, please refer to Demsetz and Strahan (1997), De Nicoló et al (2004), and Elyasiani et al (2007).

while the remaining ones will be treated as small banks. The number of institutions in each size portfolios is also illustrated in Table 2.1.

2.3.5. Descriptive Statistics and Diagnostic Analysis

Table 2.2 illustrates the descriptive statistics for the portfolio return series. In order to investigate the impact of the recent crisis on the return performance of these sector portfolios, we provide three panels in Table 2.2. Panel A summarizes the distributional statistics of the sector portfolio returns over the entire sample period, while Panel B and C contains the distributional statistics of the sector portfolio returns over the pre-crisis and crisis period, respectively. The result indicates that the mean returns for all the sector portfolios are negative over the entire sample period. The result is well expected as the financial markets across the global experienced a tough time during the last three years of our sample period.[38] In fact, as one can see in Panel B, the mean returns of all the sector portfolios are positive over the pre-crisis period. In addition, the mean returns of the banking sector portfolios are lower than the mean return of the insurance sectors over the entire sample period. The finding is consistent with the previous studies suggesting that the current financial crisis has a much significant impact on the banks compares to insurers (Eling and Schmeiser, 2010).

Furthermore, the result indicates that large size banks are outperformed by their smaller counterparts over the entire sample period, as the mean returns of the small size banking sector portfolios are higher than the large size ones, especially for the US market. By examining the result in Panel B and C, one can see that the relative poor return

[38] From the figures illustrate of the daily movement of the financial sector portfolio values in Appendix A.2, one can see that the value of all the value of financial sector portfolios increased steadily before the crisis. However, the value of these financial sector portfolios dropped dramatically during the crisis period, which wiped out all the gains they previous earned. None of the portfolios recover back to its original level at the end of the sample period.

performances of large size banking portfolios is mainly due to the huge losses they suffered during the crisis period. In Panel B, one can see that large banks enjoy higher mean return compare to small banks before the crisis. The reason is because large banks are more likely to enhance their return performance by diversifying their business across regional markets and/or take on more risk (Demsetz and Strahan, 1997; De Nicoló et al, 2004). However, during the crisis period, the losses suffered by large banks are much higher than the small ones. From Panel C, the mean returns of large size banking portfolios are much lower than the ones of small size banking portfolios. One possible explanation of this phenomenon is that large size banks are more aggressive in terms of risk appetite and financial leveraging (Demsetz and Strahan, 1997). Since liquidity is low during the crisis period, so a bank with higher leverage is more risky. Therefore, one can see that the standard deviation of the large bank returns is also higher than the small ones in all the three panels, which is similar to the findings by Elyasiani et al (2007). In addition, De Nicoló et al (2004) argued that large banks are more likely involve in internationalization and consolidation, which makes large banks vulnerable to contagion effects during the financial crisis since they are well integrated across the global markets.

Table 2.2 Distributional Statistics of the Financial Sector Portfolio Returns.

The sample period used in the current study is from the *January 1, 2003* till *March 9, 2009*.

Panel A: Distributional statistics over the entire sample period.

Bank	EU			Japan			UK	US		
Raw Return (%)	All	Small	Large	All	Small	Large	All	All	Small	Large
Mean	-0.048	-0.037	-0.088	-0.024	-0.024	-0.029	-0.083	-0.093	-0.086	-0.105
Maximum	6.615	4.864	13.289	13.467	13.207	15.026	15.174	10.811	9.770	14.029
Minimum	-6.627	-5.694	-10.825	-8.665	-8.006	-12.262	-11.634	-13.951	-12.675	-18.092
Std. Dev.	0.872	0.723	1.642	1.571	1.504	1.970	1.768	1.434	1.278	2.197
Distribution Property										
Skewness	-0.940	-1.350	-0.215	0.193	0.270	0.069	0.038	-1.469	-1.959	-0.765
Kurtosis	13.237	14.097	13.514	9.559	9.828	9.181	17.499	28.416	34.583	19.062
Normality Test	6486 ***	7810 ***	6630 ***	2585 ***	2809 ***	2289 ***	12588 ***	39196 ***	60643 ***	15587 ***
ADF Test	-21.738 ***	-20.431 ***	-35.468 ***	-39.144 ***	-39.645 ***	-37.782 ***	-24.010 ***	-12.089 ***	-7.449 ***	-9.632 ***

Insurance	EU	Japan	UK	US
Raw Return (%)	All	All	All	All
Mean	-0.041	-0.021	-0.010	-0.075
Maximum	6.009	12.328	5.202	8.781
Minimum	-7.770	-17.581	-5.054	-16.563
Std. Dev.	1.108	2.487	0.876	1.727
Distribution Property				
Skewness	-0.695	-0.382	-0.188	-1.729
Kurtosis	9.305	9.863	7.272	21.164
Normality Test	2496 ***	2855 ***	1101 ***	20469 ***
ADF Test	-22.648 ***	-37.749 ***	-36.653 ***	-9.330 ***

Note: The normality Test is conducted following the Jarque-Bera test. The ADF Test refers to the Augmented Dickey-Fuller Unit Root test. The test statistics under the serial correlation test is conducted from the Ljung-Box serial correlation test. Q(n) represents the n-lagged serial correlation of the return series, Q(n)^2 represents the n-lagged serial correlation of the squared return series. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

Panel B: Distributional statistics over the pre-crisis period, *January 1, 2003* to *April 1, 2007*.

Bank	EU						Japan						UK		US					
Raw Return (%)	All		Small		Large		All		Small		Large		All		All		Small		Large	
Mean	0.060		0.065		0.043		0.040		0.032		0.060		0.003		0.009		0.008		0.017	
Maximum	2.150		1.972		5.112		4.607		4.741		5.384		5.123		1.624		1.704		2.939	
Minimum	-3.811		-3.618		-4.557		-6.476		-6.036		-8.110		-9.298		-2.726		-2.582		-3.017	
Std. Dev.	0.532		0.459		0.968		1.197		1.155		1.493		1.056		0.426		0.336		0.805	
Distribution Property																				
Skewness	-0.845		-0.899		-0.491		-0.054		0.000		-0.039		-0.272		-0.717		-1.217		-0.097	
Kurtosis	7.945		9.340		6.205		4.962		4.973		5.072		11.266		6.690		11.849		3.918	
Normality Test	1127	***	1793	***	464	***	159	***	161	***	177	***	2833	***	647	***	3478	***	36	***
ADF Test	-18.928	***	-18.517	***	-29.806	***	-29.896	***	-30.535	***	-29.123	***	-30.874	***	-29.842	***	-28.063	***	-33.026	***

Insurance	EU	Japan	UK	US
Raw Return (%)	All	All	All	All
Mean	0.055	0.101	0.048	0.039
Maximum	4.553	12.238	3.313	3.322
Minimum	-3.854	-9.060	-3.336	-3.312
Std. Dev.	0.824	1.839	0.687	0.744
Distribution Property				
Skewness	-0.332	0.269	-0.381	-0.147
Kurtosis	6.489	5.620	5.874	4.944
Normality Test	521 ***	295 ***	365 ***	160 ***
ADF Test	-28.105 ***	-30.864 ***	-19.553 ***	-30.916 ***

Note: The normality Test is conducted following the Jarque-Bera test. The ADF Test refers to the Augmented Dickey-Fuller Unit Root test. The test statistics under the serial correlation test is conducted from the Ljung-Box serial correlation test. Q(n) represents the n-lagged serial correlation of the return series, Q(n)^2 represents the n-lagged serial correlation of the squared return series. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

Panel C: Distributional statistics over the crisis period, *April 2, 2007* to *March 9, 2009*.

Bank	EU						Japan						UK		US					
Raw Return (%)	All		Small		Large		All		Small		Large		All		All		Small		Large	
Mean	-0.288		-0.263		-0.378		-0.166		-0.150		-0.229		-0.275		-0.321		-0.295		-0.375	
Maximum	6.615		4.864		13.289		13.467		13.207		15.026		15.174		10.811		9.770		14.029	
Minimum	-6.627		-5.694		-10.825		-8.665		-8.006		-12.262		-11.634		-13.951		-12.675		-18.092	
Std. Dev.	1.319		1.071		2.547		2.178		2.075		2.741		2.748		2.481		2.227		3.745	
Distribution Property																				
Skewness	-0.292		-0.663		0.168		0.391		0.457		0.251		0.246		-0.639		-0.912		-0.290	
Kurtosis	7.315		7.997		7.252		7.417		7.786		6.969		9.184		9.949		11.728		7.161	
Normality Test	352	***	497	***	338	***	374	***	441	***	297	***	715	***	928	***	1477	***	328	***
ADF Test	-12.595	***	-11.807	***	-20.007	***	-23.187	***	-23.367	***	-22.246	***	-20.191	***	-19.424	***	-18.010	***	-22.341	***

Insurance	EU	Japan	UK	US
Raw Return (%)	All	All	All	All
Mean	-0.254	-0.294	-0.139	-0.328
Maximum	6.009	12.328	5.202	8.781
Minimum	-7.770	-17.581	-5.054	-16.563
Std. Dev.	1.545	3.511	1.185	2.880
Distribution Property				
Skewness	-0.418	-0.355	0.138	-0.950
Kurtosis	6.461	6.918	5.563	8.403
Normality Test	236***	295***	124***	610***
ADF Test	-12.952***	-21.386***	-20.954***	-24.396***

Note: The normality Test is conducted following the Jarque-Bera test. The ADF Test refers to the Augmented Dickey-Fuller Unit Root test. The test statistics under the serial correlation test is conducted from the Ljung-Box serial correlation test. Q(n) represents the n-lagged serial correlation of the return series, Q(n)^2 represents the n-lagged serial correlation of the squared return series. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

For all portfolios, the unconditional distributions of returns are non-normal. The non-normality is supported by the high kurtosis figures as well as the noticeable deviation of the skewness statistics from zero. The result is reinforced by the Jarque-Bera normality test, where the statistics for all the portfolios are significantly above the critical value at 1% confidence level. In order to identify whether the portfolio returns series are stationary, we perform the Augmented Dickey-Fuller unit root test. For all portfolios, the test statistics reject the null hypothesis that the portfolio return has a unit root at 1% confidence level. The result of the Ljung-Box serial correlation test indicates that the return and squared return series are highly autocorrelated for all portfolios. This finding suggests that a dynamic variance-covariance estimation framework (see Section 3) is indeed appropriate for modeling the returns of financial sector portfolios across the four markets.

In order to investigate the potential multicolinearity issue within our sample, we estimate the unconditional correlation among the sector portfolios. In the current study, we examine the return and risk spillover effect across the financial sectors over the entire sample period, and the changes in spillover magnitude during the crisis period. Previous empirical studies suggest that correlation among financial assets will increase during the crisis periods (Koutmas and Booth, 1995, Forbes and Rigobon, 2002, Bekaert et al, 2005). In order to ensure the multicolinearity issue will not arise over the sample period, we generate the correlation matrix across the financial sector portfolios over the pre-crisis period (*January 1, 2003* to *April 1, 2007*) as well as the crisis period (*April 2, 2007* to *March 9, 2009*). The correlation matrix across the portfolios is illustrated in Table 2.3.

Table 2.3 Unconditional Correlation of the Financial Sector Portfolio Returns.

The following table contains the unconditional correlation coefficients between the financial sector portfolio return across the national markets. In order to adjust the non-synchronize trading time issue, we adjusted the time lag of the return series before the correlation estimation.

The sample period is from the *January 1, 2003* to the *March 9, 2009*.

Panel A: Unconditional correlation before the financial crisis from *January 1, 2003* to *April 1, 2007*.

	Bank				Insurance			
	EU	**Japan**	**UK**	**US**	**EU**	**Japan**	**UK**	**US**
EU		0.277	0.013	0.216		0.208	0.039	0.275
Japan	0.149		0.061	0.260	0.147		0.115	0.272
UK	0.050	0.186		0.139	0.110	0.221		0.269
US	0.309	0.083	0.209		0.421	0.053	0.296	

	Large Banks			Small Banks		
	EU	Japan	US	EU	Japan	US
EU		0.242	0.168		0.242	0.185
Japan	-0.024		0.245	0.117		0.222
US	0.426	0.066		0.180	0.089	

Panel B: Unconditional correlation during the financial crisis from *April 2, 2007* to *March 9, 2009*.

	Bank				Insurance			
	EU	**Japan**	**UK**	**US**	**EU**	**Japan**	**UK**	**US**
EU		0.451	0.141	0.367		0.412	0.041	0.338
Japan	0.188		0.205	0.337	0.252		0.244	0.570
UK	0.013	0.320		0.282	-0.045	0.400		0.323
US	0.487	0.154	0.489		0.332	0.049	0.328	

	Large Banks			Small Banks		
	EU	Japan	US	EU	Japan	US
EU		0.447	0.328		0.432	0.365
Japan	0.134		0.244	-0.068		0.461
US	0.469	0.190		0.414	0.026	

From Panel A Table 2.3, one can see that most correlations across the financial sectors are positive during the entire sample period. The only exception comes from the correlation between the large size banking sector portfolios from Japanese and the EU market (-2.4%). During the crisis period, the correlation correlations across the financial sector portfolios have increased.[39] The result is consistent with the previous literature on contagion effects, as the linkage across financial assets increased during the crisis period (Kaufman, 1994; Dornbusch et al, 2000; Kaminsky et al, 2003). However, none of the correlation coefficient is above the 80% level.[40]

2.4. METHODOLOGY

2.4.1. VAR-BEKK Estimation Framework

In this study, we contribute to the existing literature by proposing a new model structure for examining the cross-sectional return and volatility spillover across multiple assets. In the proposed model, the mean returns and variance-covariance matrices of the involved financial sector portfolios are represented by a modified VAR-BEKK(1,1) process.[41] We modify the original diagonal BEKK model to capture the volatility spillover effects in the conditional variance equation. We employ the BEKK parameterization in the current study due to its less restrictive nature compared to the framework used by previous empirical studies. For instance, Elyasiani et al (2007) pose a constant correlation restriction on their empirical framework. However, empirical studies on dynamics of correlation

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[39] The two exceptions are the correlation between UK and EU insurance portfolios, and the correlation between small Japanese and EU banking portfolios.

[40] The 80% threshold is derived from the variance inflation factor (VIF) test, which suggests the multicolinearity issue will only arise if the R squared of the regression among the independent variables is higher than 80%. Since the R squared of a regression with one independent and one dependent variable is equal to the square of correlation coefficient between the two variables, we use 80% as the threshold for correlation coefficient among the variables as critical value to detect the existence of multicolinearity.

[41] For more information on the technical detail of the BEKK model, please refer to the work by Baba et al (1989) which first introduced the parameterization.

show that correlation among the financial asset returns do vary as time elapses.[42] The BEKK parameterization used in our model poses no restriction on correlation dynamics. Therefore, it should fit the data in a better way and provides higher efficiency. In addition, the VAR-BEKK model enables us to estimate the return and volatility spillover effects among multiple financial sector portfolios simultaneously, which also increase the estimation efficiency.

The proposed VAR-BEKK model has two components: a VAR system of conditional mean equations and conditional variance-covariance equations with BEKK parameterizations. We specify the mean equation in the VAR system as a multi-factor model similar to the previous studies on asset pricing of financial institutions (Prasad and Rajan, 1995, Chamberlain et al, 1997, Elyasiani et al, 2007). The factors include the changes in interest rate, changes in foreign exchange rate, as well as the equity market portfolio return.[43] However, the movements in market return, foreign exchange rate and interest rate are usually highly related.[44] Therefore, it is not suitable to estimate the multi-factor model with these three macroeconomic factors without any adjustment as they may introduce multicolinearity into the mean equation. In the current study, we avoid this issue by constructing the unexpected changes of the foreign exchange rates and interest rate index from autoregressive moving average (ARMA) models.[45] Given the fact that the errors generated from the ARMA process are independent and uncorrelated within

[42] For discussions on time-varying conditional correlation among financial assets, please refer to Ang and Bekaert (1999) and Cappiello et al (2006) among others.
[43] For discussions on the influence of interest rate changes on the performances of financial institutions, please refer to the survey paper by Staikouras (2003 and 2006a). For discussions on the relationship between currency value changes and the equity value of financial institutions, please refer to the empirical studies by Adler and Dumas (1985), Eun and Resnick (1988), and Wetmore and Brick (1994 and 1998) among others.
[44] Please refer to Choi et al (1992) among others.
[45] The orthogonalization method used by Stone (1974) and Flannery and James (1984) can also remove the linear dependence among the three variables. However, the orthogonalized risk factors may introduce bias into the model estimation (Giliberto, 1985).

themselves and with the original series,[46] the estimated unexpected changes of the foreign exchange rate and interest rate index are, therefore, independent from each other, as well as from the market return.

In order to capture the return spillover effects among the financial sector portfolios, we also include the returns of involved financial sector portfolios into the mean equation. For instance, the mean equation for US banking portfolio will include the return of US market portfolio, the changes in US interest and exchanges rates, and the returns of banking portfolios from the remaining three markets. In order to examine the influence of the current financial crisis on the interdependence among the global financial markets, we also introduce a dummy variable into the estimation framework. The dummy variable takes value 1 from *April 2, 2007* till *March 9, 2009*, which represents the crisis period, and zeros elsewhere. The dummy variable helps us to capture the potential changes in the return and volatility spillover effects across the sector portfolios. The VAR system of conditional mean equations can be demonstrated in matrix form as follow.[47]

$$R_t = \beta \circ MF_t \cdot 1 + I \cdot [\Theta \cdot R_t^*] + DUM \cdot I \cdot [\Gamma \cdot R_t^*] + \varepsilon_t$$

$$\varepsilon_{i,t} \sim N(0, h_{ii,t}) \; i \text{ and } j \in [EU, JP, UK, US], \qquad i \neq j.$$

with:

$\circ$ is the Hadamard product,[48] 1 is a vertical vector of ones which matches the vertical dimension of β

$$R_t^* = \begin{bmatrix} r_{JP,t} & r_{UK,t-1} & r_{UK,t-1} \\ r_{EU,t-1} & r_{UK,t-1} & r_{US,t-1} \\ r_{EU,t-1} & r_{JP,t} & r_{US,t-1} \\ r_{EU,t} & r_{JP,t} & r_{UK,t} \end{bmatrix}$$

[46] For further discussion about the property of the ARMA estimation, please refer to Greene (2008).
[47] The system demonstrated is a four equation scenario, with financial sector portfolios from EU, Japanese, UK and US market, respectively.
[48] The Hadamard product is a special operator for matrix multiplication. It refers to the element-by-element multiplication of two matrices with the same dimension.

$$\Theta = \begin{bmatrix} \theta_{EU,JP} & \theta_{EU,UK} & \theta_{EU,US} \\ \theta_{JP,EU} & \theta_{JP,UK} & \theta_{JP,US} \\ \theta_{UK,EU} & \theta_{UK,JP} & \theta_{UK,US} \\ \theta_{US,EU} & \theta_{US,JP} & \theta_{US,UK} \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} \gamma_{EU,JP} & \gamma_{EU,UK} & \gamma_{EU,US} \\ \gamma_{JP,EU} & \gamma_{JP,UK} & \gamma_{JP,US} \\ \gamma_{UK,EU} & \gamma_{UK,JP} & \gamma_{UK,US} \\ \gamma_{US,EU} & \gamma_{US,JP} & \gamma_{US,UK} \end{bmatrix}$$

$$\mathrm{I} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where:

R_t = a [k x 1] matrix represents the return of financial sector portfolios over day t. k is equal to the number of financial sector portfolios involved in the VAR-BEKK system.

β = a [k x 4] parameter matrix where the first column represents the constants, the second to fourth column represent market, foreign exchange rate and interest rate betas for the corresponding financial sector portfolios, respectively.

MF_t = a [k x 4] matrix contains ones for the first column which represent the constants for conditional mean equations. The second to fourth column of the matrix contains the market, foreign exchange rate and interest rate risk factors for the corresponding financial sector portfolios over day t, respectively. The market risk factor is represented by the return of stock market index, the foreign exchange rate risk factor is represented by the unexpected changes in trade weighted currency price index, and the interest rate risk factor is represented by the unexpected changes in long-term benchmark bond yields.[49]

R_t^* = a [k x k-1] return matrix for the involved financial sector portfolios which has been adjusted for nonsynchronous trading time.

I = a [k x k] identity matrix.

Θ = a [k x k-1] parameter matrix represents the return spillover effects among the financial sector portfolios. $\theta_{i,j}$ represents the return spillover effect from portfolio in market j to portfolio in market i over the entire sample period, with $i, j \in$ [*EU, JP, UK, US*]. *JP* represents the Japanese market.

Γ = a [k x k-1] parameter matrix represents the changes in the return spillover effects over the crisis period. $\gamma_{i,j}$ represents the changes in return spillover effect from portfolio in market j to portfolio in market i over the crisis period.

DUM = a dummy variable represents the potential structural break for the crisis period. *DUM* = *0* before the *April 2, 2007*, and *DUM* = *1* afterwards.

The estimated residuals $\varepsilon_{i,t}$ from each mean equation are assumed to have a multi-normal distribution, which has zeros mean and conditional variance represented by $h_{ii,t}$. We further assume the $h_{ii,t}$ is derived from a conditional variance-covariance matrix H_t, whose time-varying dynamic follows a modified BEKK framework.

We employ a diagonal BEKK multivariate GARCH model as the base setting for our conditional variance-covariance matrix among the financial sector portfolios (H_t). In the current study, we extend the conventional diagonal BEKK model of Engle and Kroner

[49] Follows the previous empirical studies on the effects of interest rate, the interest rate index employed in the current study is the yield relative $-[(Y_t-Y_{t-1})/Y_{t-1}]$, Y_t is the yield of long-term benchmark bond of the corresponding markets over day t. For further detail please refers to Flannery and James (1984).

(1995) to incorporate the volatility spillover effects into the conditional variance equation.[50] The modified BEKK MGARCH model can be described as follow:[51]

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + I \cdot [G \cdot H_t^{*}{}'] + D \cdot I \cdot [Z \cdot H_t^{*}{}']$$

with:

$$H_t^* = \begin{bmatrix} h_{JP,t} & h_{UK,t-1} & h_{US,t-1} \\ h_{EU,t-1} & h_{UK,t-1} & h_{US,t-1} \\ h_{EU,t-1} & h_{JP,t} & h_{US,t-1} \\ h_{EU,t} & h_{JP,t} & h_{UK,t} \end{bmatrix}$$

$$G = \begin{bmatrix} g_{EU,JP} & g_{EU,UK} & g_{EU,US} \\ g_{JP,EU} & g_{JP,UK} & g_{JP,US} \\ g_{UK,EU} & g_{UK,JP} & g_{UK,US} \\ g_{US,EU} & g_{US,JP} & g_{US,UK} \end{bmatrix}$$

$$Z = \begin{bmatrix} z_{EU,JP} & z_{EU,UK} & z_{EU,US} \\ z_{JP,EU} & z_{JP,UK} & z_{JP,US} \\ z_{UK,EU} & z_{UK,JP} & z_{UK,US} \\ z_{US,EU} & z_{US,JP} & z_{US,UK} \end{bmatrix}$$

$$\mathrm{I} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where:

H_t = a [k x k] conditional variance-covariance matrix of the estimated residuals at day t; k is equal to the number of financial sector portfolios involved in the VAR-BEKK system.

ε_t = a [1 x k] vector contains the estimated residuals from the mean equation of the VAR system for day t.

C = a [k x k] lower triangle matrix. The product of CC' represents the unconditional part of the time-varying variance-covariance matrices;

A and B = [k x k] diagonal parameter matrices represents the multivariate ARCH and GARCH effect of the conditional variance-covariance matrices. The

[50] The technical details of the BEKK model are available in the Appendix A.4.

[51] The system demonstrated is a four equation scenario, with size portfolios from EU, Japanese, UK and US market, respectively.

parameters represent the ARCH and GARCH effects are on the main diagonal of the matrix A and B, respectively.

H_t^* = a [k x k-1] modified conditional variance matrix for the involved financial sector portfolios which has been adjusted for nonsynchronous trading time.

I = a [k x k] identity matrix.

G = a [k x k-1] vector parameter matrix represents the volatility spillover effect among the financial sector portfolios. The parameter g_{ij} represents the volatility spillover effects from portfolio in market j to portfolio in market i over the entire sample period, with $i, j \in$ [*EU, JP, UK, US*]. *JP* represents the Japanese market.

Z = a [k x k-1] vector parameter matrix represents the changes in volatility spillover effect among financial sector portfolios during the crisis period. The parameter z_{ij} represents the changes in the volatility spillover effects from portfolio in market j to portfolio in market i during the financial crisis.

D = the dummy variable represents the crisis period. *DUM* = *0* before the *April 2, 2007*, and *DUM* = *1* afterwards.

In the proposed model, the parameter for volatility spillover is not a full matrix. In other words, the volatility oriented from financial sector portfolio in one market can only influence the volatility of portfolios in the other markets but not the covariance or correlation between these portfolios. The reason that we do not use full matrix is twofold. First, the empirical study by Bekaert et al (2005) argued that change in correlations among the financial markets is the result of common risk factor but not of volatility spillovers. Therefore, it is unnecessary to introduce full matrix parameter to incorporate volatility spillover effect for correlation. Second, the main purpose of the current study is to investigate the cross-sectional return and volatility spillovers across the financial markets, not changes in correlations due to volatility spillover effects. By employing a vector matrix parameter for volatility spillovers instead of a full matrix can reduce the number of parameters, which increases the efficiency of the estimation.

In order to better illustrate the conditional mean and the variance of each individual portfolio return under the VAR-BEKK system, we also represent the conditional mean and variance equation for each financial sector portfolio in a multi-equation format as follow. In the following demonstration, we assume there are four portfolios in the system, one from each of the four markets.

Conditional Mean Equation:

$$\begin{aligned}
r_{EU,t} = \beta_{EU} + \beta_{EU,MKT} MKT_{EU,t} &+ \beta_{EU,FX} FX_{EU,t} + \beta_{EU,IR} IR_{EU,t} + \gamma_{EU,JP} r_{JP,t} \\
&+ \gamma_{EU,UK} r_{UK,t-1} + \gamma_{EU,US} r_{US,t-1} \\
&+ D\left[\theta_{EU,JP} r_{JP,t} + \theta_{EU,UK} r_{UK,t-1} + \theta_{EU,US} r_{US,t-1}\right] + \varepsilon_{EU,t}
\end{aligned}$$

$$\begin{aligned}
r_{JP,t} = \beta_{JP} + \beta_{JP,MKT} MKT_{JP,t} &+ \beta_{JP,FX} FX_{JP,t} + \beta_{JP,IR} IR_{JP,t} + \gamma_{JP,EU} r_{EU,t-1} + \gamma_{JP,UK} r_{UK,t-1} \\
&+ \gamma_{JP,US} {r^*}_{US,t-1} + D\left[\theta_{JP,EU} r_{EU,t-1} + \theta_{JP,UK} r_{UK,t-1} + \theta_{JP,US} r_{US,t-1}\right] + \varepsilon_{JP,t}
\end{aligned}$$

$$\begin{aligned}
r_{UK,t} = \beta_{UK} + \beta_{UK,MKT} MKT_{UK,t} &+ \beta_{UK,FX} FX_{UK,t} + \beta_{UK,IR} IR_{UK,t} + \gamma_{UK,EU} {r^*}_{EU,t-1} \\
&+ \gamma_{UK,JP} r_{JP,t} + \gamma_{UK,US} r_{US,t-1} \\
&+ D\left[\theta_{UK,EU} r_{EU,t-1} + \theta_{UK,JP} r_{JP,t} + \theta_{UK,US} r_{US,t-1}\right] + \varepsilon_{UK,t}
\end{aligned}$$

$$\begin{aligned}
r_{US,t} = \beta_{US} + \beta_{US,MKT} MKT_{US,t} &+ \beta_{US,FX} FX_{US,t} + \beta_{US,IR} IR_{US,t} + \gamma_{US,EU} r_{EU,t} + \gamma_{US,JP} r_{JP,t} \\
&+ \gamma_{US,UK} r_{UK,t} + D\left[\theta_{US,EU} r_{EU,t} + \theta_{US,JP} r_{JP,t} + \theta_{US,UK} r_{UK,t}\right] + \varepsilon_{US,t}
\end{aligned}$$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$ with, i and $j \in [EU, JP, UK, US]$, $i \neq j$. JP represents the Japanese market.

where:

$r_{i,t}$ = the return for financial sector portfolio in market i over day t.

$MKT_{i,t}$ = the market portfolio return for market i, over day t;

$FX_{i,t}$ = the unexpected changes of the foreign exchange rate for market i, over day t.

$IR_{i,t}$ = the unexpected changes of the long-term benchmark bond yield for market i over day t.

$\gamma_{i,j}$ = the coefficient for return spillover effect from financial sector portfolio in market j to portfolio in market i over the entire sample period.

$\theta_{i,j}$ = the coefficient for the changes in return spillover effect from financial sector portfolio in market j to portfolio in market i during the crisis period.

$h_{ii,t}$ = the conditional variance of financial sector portfolio in market i over day t.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio in market i over day t.

D = the dummy variable represents the crisis period. $DUM = 0$ before the *April 2, 2007*, and $DUM = 1$ afterwards.

Conditional Variance Equation:

$$h_{EU,t} = c_{EU} + a_1^2 \varepsilon^2{}_{EU,t-1} + b_1^2 h_{EU,t-1} + g_{EU,JP} h_{JP,t} + g_{EU,UK} h_{UK,t-1} + g_{EU,US} h_{US,t-1} + D\left(z_{EU,JP} h_{jp,t} + z_{EU,UK} h_{UK,t-1} + z_{EU,US} h_{US,t-1}\right)$$

$$h_{JP,t} = c_{JP} + a_2^2 \varepsilon^2{}_{JP,t-1} + b_2^2 h_{JP,t-1} + g_{JP,EU} h_{EU,t-1} + g_{JP,UK} h_{UK,t-1} + g_{JP,US} h_{US,t-1} + D\left(z_{JP,EU} h_{EU,t-1} + z_{JP,UK} h_{UK,t-1} + z_{JP,US} h_{US,t-1}\right)$$

$$h_{UK,t} = c_{UK} + a_3^2 \varepsilon^2{}_{UK,t-1} + b_3^2 h_{UK,t-1} + g_{UK,EU} h_{EU,t-1} + g_{UK,JP} h_{JP,t} + g_{UK,US} h_{US,t-1} + D\left(z_{UK,EU} h_{EU,t-1} + z_{UK,JP} h_{JP,t} + z_{UK,US} h_{US,t-1}\right)$$

$$h_{US,t} = c_{US} + a_4^2 \varepsilon^2{}_{US,t-1} + b_4^2 h_{US,t-1} + g_{US,EU} h_{EU,t} + g_{US,JP} h_{JP,t} + g_{US,UK} h_{UK,t} + D\left(z_{US,EU} h_{EU,t} + z_{US,JP} h_{JP,t} + z_{US,UK} h_{UK,t}\right)$$

$$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$$

with, i and $j \in [EU, JP, UK, US]$, $i \neq j$. JP represents the Japanese market.

where:

$h_{ii,t}$ = the conditional variance of financial sector portfolio in market i over day t.

$h_{i,i,t}$ = the conditional covariance between the financial sector portfolio in market i and market j over day t.

$\varepsilon_{i,t}$ = the estimated residuals from the conditional mean equation of financial sector portfolio in market i from the VAR system for day t.

$c_{i,j}$ = the $[i, j]^{th}$ element of the CC' matrix, which is the unconditional part of the time-varying variance-covariance matrices.

a_i and b_i = the i^{th} element on the main diagonal of the ARCH and GARCH effect parameter matrix A and B, respectively.

$g_{i,j}$ = the parameter represents the volatility spillover effects from financial sector portfolio in market j to portfolio in market i.

$z_{i,j}$ = the parameter represents the changes in spillover effects from financial sector portfolio in market j to portfolio in market i during the financial crises.

D = the dummy variable represents the crisis period. $DUM = 0$ before the *April 2, 2007*, and $DUM = 1$ afterwards.

2.4.2. *Model Estimation*

We estimate the models for the first moment simultaneously with those for the second moment. Despite the large amount of parameters involved in the modified VAR-BEKK system,[52] the simultaneous estimation process will increase the accuracy and efficiency of the model (Elyasiani and Mansur, 2003).

[52] The total number of parameters needs to be estimated for a k-portfolio system is $3k^2+3k+k(k+1)/2$.

We follow the quasi-maximum likelihood estimation (QMLE) process developed by Bollerslev and Wooldridge (1992) for the parameter estimation of the proposed modified VAR-BEKK MGARCH model.[53] We assume the residuals generated from the mean equations follow a multi-normal distribution with zero mean and a variance-covariance matrix equals to Ω. We further assume that for every observation point $t \in [0, T]$ the estimated residual vector ε_t is also a multi-normal distribution $N(0, H_t)$. Due to the fact that Ω is unobservable, we will use H_t to estimate Ω as for every t, where the estimated residual vector ε_t can be observed. Under the multi-normality assumption of ε_t, we can specify the quasi-conditional log-likelihood as follow.

$$l_t = -\frac{1}{2}[k\ln(2\pi) + \ln|H_t| + \varepsilon'_t H_t \varepsilon_t]$$

where:

k = the number of portfolios in the VAR-BEKK system.

H_t = a $[k \times k]$ variance-covariance matrix for portfolio returns at day t.

ε_t = a $[1 \times k]$ vector contains the estimated residuals from the mean equation of the VAR system for day t.

We use numerical maximization techniques to estimate the model. The parameter is estimated via maximizing the sum of l_t over the normal period.

One major challenge of estimating a system of non-linear equations with substantial amount of parameters is the initial value setting of the parameters before the estimation. Given the non-linear nature of the VAR-BEKK system, a sub-optimal initial parameter setting might lead the log-likelihood maximization process to a local maximum instead of

[53] We generate the QML standard errors for the estimated parameters based on the VAR-BEKK model. The QML standard error is generated based on the quasi-maximum likelihood function instead of variance of the estimated residuals. The QML standard error is also known as the robust Bollerslev-Wooldridge standard error.

a global one. In the current study, we propose to estimate the initial value setting of the parameters in a two-step framework.

In the first step, we separate the mean equations from the VAR-BEKK system, and estimate the parameters for each mean equation separately via OLS. The estimated parameters are later been used as the initial value setting for the mean equations in the VAR-BEKK system. In the second step, we generate the residual series $\varepsilon_{i,t}$ from each individual mean equations we estimated in the first step. Then, we model the time-varying variance-covariance dynamics of the estimated residuals with a diagonal BEKK framework. The estimated parameters from the variance-covariance model are deployed as the initial value setting for the parameter *C*, *A* and *B* in the VAR-BEKK system.

In case the value of the ARCH and GARCH effect parameters (represented by *A* and *B*) change dramatically after introducing the volatility spillovers across the markets, we introduce two more initial value settings for parameter *A* and *B* of the proposed VAR-BEKK system. We assume the unconditional part (represented by the product of CC') of the variance-covariance matrix among portfolio return residuals will not be affected by the introduction of cross-sectional volatility spillover, and only the time-varying dynamic (the ARCH and GARCH effect represented by parameter *A* and *B*) will be influenced. Under the first additional initial value setting, we restrict all the elements in parameter *A* and *B* to be equal to $(0.05)^{1/2}$ and $(0.95)^{1/2}$, respectively. For the second additional setting, we set the value of parameter *A* and *B* as the estimated ARCH and GARCH effect from the scalar BEKK model over the residuals generated from the individual mean equations.

In the current study, we estimate the proposed VAR-BEKK models with all the three initial parameter value settings for parameter *A* and *B*, and select the one that provides the highest log-likelihood value. All the estimation result presented in the empirical section is based on the model that enjoys the highest estimated log-likelihood figure.

2.5. EMPIRICAL RESULT

In the current study, we focus on the return and volatility interdependence among the financial sector portfolios across four markets, namely EU, Japan, UK and US markets. We perform three tests to investigate the linkages among these portfolios based on the proposed VAR-BEKK model. The first test (Test 1) evaluates the return and volatility spillovers among the same type of financial sector portfolios across the markets. We estimate the VAR-BEKK model for each of the two types of financial sectors, namely the banking and insurance sector portfolios from the four markets.

The recent financial crisis is originated from the US subprime mortgage lending crisis, and it spreads to the rest of the world through the US banking industry. Therefore, we focus on the interdependence between the US banking portfolio and the insurance portfolios from the remaining markets in Test 2.[54] We only focus on the insurance sectors from the other markets in the second test because the relationship between US banks and the banks from other markets is already evaluated in the first test.

The final test (Test 3) examines the interdependence between the global banking portfolio and the global insurance portfolio. Since insurance companies perform relatively well during the recent financial crisis compare to banks (Eling and Schmeiser, 2010, and Harrington, 2009), it is reasonable to argue that the insurers should enjoy a competitive advantage against banks in terms of portfolio returns over the crisis period. The global

[54] We select the US banking sector as it is the most important channel through which the US subprime mortgage lending crisis transforms into a global financial crisis. For further discussion on the issue, please refer to Blackburn (2008), Brunnermeier (2009) and Dymski (2007).

banking and insurance portfolio used in the present study are also equally weighted portfolios.

We discuss the estimation output of the three tests from a US point of view because US financial market plays an important role in the development of the crisis. Thus, it is more valuable to focus on the return and volatility spillovers between the US financial sectors and the sectors from the rest of the markets. Because the first two tests are based on VAR-BEKK model with all the available financial sector portfolios across the markets, the number of estimated parameters is large.[55] In order to illustrate the estimation result from Test 1 and 2 in a clear manner, we spilt the result into three sub-tables, namely i) macroeconomic factors and GARCH effects, ii) return spillover effects, and iii) volatility spillover effects.

In the first sub-table, we summarize the estimated coefficients for market, interest rate and foreign exchange rate betas of the financial sector portfolios in the mean equations, as well as the parameters for ARCH and GARCH effects in the conditional variance equations.[56] The levels of volatility persistence for each individual variance equations, and the value of log-likelihood function of the estimation are also presented. The other two sub-tables summarize the estimated coefficients for return and volatility spillovers among the financial sector portfolios, respectively. For each spillover effects, the coefficient estimated over the entire sample period and its potential changes during the crisis period are reported separately.

[55] For a four-asset case, the total number of estimated coefficients is *82*, while the number of coefficients for risk and return spillover effects is *48*.

[56] We skip the coefficients for the constants from the summary table to save space as they are non-significant and/or very close to zero.

2.5.1. *Impact of Macro Economic Factor*

Before we discuss the cross-sectional spillover effects among the financial sector portfolios, we first examine the impact of macroeconomic risk factors on the performances of these financial sector portfolios. We discuss the impact of market, interest rate and foreign exchange rate risk factors based on the estimation results generated from Test 1.[57] Three VAR-BEKK models have been estimated under Test 1 for the all, large and small size financial sector portfolios, respectively.[58] The result of these three models is presented in Table 2.4 – 2.6. Table 2.4 contains the estimated coefficients of VAR-BEKK model based on all size financial sector portfolios, while Table 2.5 and 2.6 summarize the estimation output based on the large and small size banking sector portfolios, respectively.

[57] We based our discussion on the estimation result from Test 1 as it is the only test investigates the macroeconomic risk factors for all the financial sector portfolios across the markets. In addition, the estimated coefficients for the macroeconomic risk factors from Test 1 are consistent with the ones from Test 2 for all size banking and insurance portfolios across markets.

[58] As mentioned in Section 2, the large and small size portfolios only applicable to banking sectors.

Table 2.4 VAR-BEKK Model based on All Size Financial Sector Portfolios.

The following tables summarize the estimation output of the VAR-BEKK models based on all size financial sector portfolios across the markets. The all size financial sector portfolio is an equally weighted portfolio with all the corresponding financial institutions from a given market. The estimated coefficients from the model have been categorized into three sub-tables: i) Macroeconomic Factors and GARCH Effects, ii) Return Spillover Effects and iii) Volatility Spillover Effects.

i) Macroeconomic Factors and GARCH Effects

The following table summarizes the estimated coefficients for all the $\beta_{i,x}$, a_i, and b_i in the mean and variance equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RF(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N\left(0, h_{ii,t}\right)$, with $i, j \in [EU, JP, UK, US]$, $i \neq j$.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1}\, h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$. *JP* represents the Japanese market.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for national market *i* over the day *t*. $X \in$ [*MKT, FX, IR*] which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D= the dummy variable represents the crisis period. *D = 1* from *2 April 2007 to 9 March 2009*, and *D = 0* for elsewhere.

Markets	**EU**			**Japan**			**UK**			**US**		
Bank - All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Market ($\beta_{i,MKT}$)	0.523	34.223	***	0.799	36.454	***	0.956	16.218	***	0.451	39.264	***
FX ($\beta_{i,FX}$)	0.199	6.095	***	-0.004	-0.094		0.235	3.697	***	-0.017	-1.084	
IR ($\beta i_{,IR}$)	-0.025	-2.342	**	0.011	1.101		-0.006	-0.166		0.049	6.088	***
GARCH Effects												
ARCH (a_{ii}^2)	0.034	4.833	***	0.051	8.330	***	0.133	8.422	***	0.096	9.132	***
GARCH (b_{ii}^2)	0.933	145.150	***	0.934	180.810	***	0.774	60.324	***	0.756	73.566	***
Persistence	0.968			0.985			0.907			0.852		
Log-Likelihood	21733.0											
Insurance – All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Market ($\beta_{i,MKT}$)	0.726	42.232	***	0.970	28.916	***	0.562	34.753	***	0.857	41.942	***
FX ($\beta_{i,FX}$)	0.248	5.438	***	-0.020	-0.279		0.126	3.683	***	0.005	0.173	
IR ($\beta i_{,IR}$)	0.010	0.615		-0.022	-1.557		-0.019	-1.239		-0.002	-0.202	
GARCH Effects												
ARCH (a_{ii}^2)	0.004	2.695	***	0.058	6.822	***	0.001	2.750	***	0.110	7.759	***
GARCH (b_{ii}^2)	0.982	688.230	***	0.897	108.990	***	0.997	2582.000	***	0.600	37.212	***
Persistence	0.987			0.955			0.998			0.710		
Log-Likelihood	20688.0											

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

ii) Return Spillover Effects

The following table summarizes the estimated coefficients for all the $\gamma_{i,j}$ and $\theta_{i,j}$ in the mean equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RiskFactor(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, UK, US]$, $i \neq j$. JP represents the Japanese market.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

$\gamma_{i,j}$= the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$= the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to the portfolio *i* during the crisis period.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

Markets	**EU**			**Japan**			**UK**			**US**		
Bank - All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Return 1 (γ_{i1})	**0.024**	**2.203**	**	**0.031**	**0.560**		**0.151**	**2.459**	**	**-0.069**	**-2.972**	***
Cross-Return 2 (γ_{i2})	**0.033**	**2.514**	**	**-0.066**	**-2.515**	**	**0.005**	**0.150**		**0.002**	**0.224**	
Cross-Return 3 (γ_{i3})	**-0.021**	**-0.815**		**0.046**	**0.717**		**-0.161**	**-2.556**	**	**0.015**	**1.124**	
Change in Cross-Return 1 (θ_{i1})	**0.014**	**0.630**		**-0.075**	**-0.905**		**-0.090**	**-0.890**		**0.298**	**2.698**	***
Change in Cross-Return 2 (θ_{i2})	**-0.024**	**-1.233**		**0.075**	**2.097**	**	**-0.027**	**-0.542**		**-0.042**	**-1.132**	
Change in Cross-Return 3 (θ_{i3})	**0.115**	**3.668**	***	**-0.031**	**-0.465**		**0.273**	**2.776**	***	**0.136**	**2.314**	**
Insurance – All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Return 1 (γ_{i1})	**0.022**	**2.360**	**	**0.109**	**1.781**	*	**0.072**	**2.978**	***	**0.056**	**2.399**	**
Cross-Return 2 (γ_{i2})	**0.073**	**2.712**	***	**-0.146**	**-1.815**	*	**0.036**	**3.744**	***	**0.008**	**0.957**	
Cross-Return 3 (γ_{i3})	**0.043**	**1.956**	*	**0.110**	**1.604**		**0.048**	**1.985**	**	**-0.036**	**-1.371**	
Change in Cross-Return 1 (θ_{i1})	**-0.018**	**-1.052**		**0.000**	**0.009**		**-0.045**	**-1.256**		**-0.009**	**-0.116**	
Change in Cross-Return 2 (θ_{i2})	**-0.034**	**-0.874**		**0.025**	**0.225**		**-0.059**	**-1.602**		**-0.024**	**-1.114**	
Change in Cross-Return 3 (θ_{i3})	**0.005**	**0.155**		**0.092**	**1.158**		**0.013**	**0.420**		**0.033**	**0.412**	

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The magnitude of the cross-sectional return spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $\gamma_{i,j}$) and the change in spillover effect over the crisis period (represented by $\theta_{i,j}$).

iii) Volatility Spillover Effects

The following table summarizes the estimated coefficients for all the $g_{i,j}$, and $z_{i,j}$ in the variance equations of the VAR-BEKK model:

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1}\, h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$. JP represents the Japanese national market.

where,

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio j to the portfolio i over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio j to portfolio i during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio i over day t.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio i over day t.

D = the dummy variable represents the crisis period. $D = 1$ from *April 2, 2007 to March 9, 2009*, and $D = 0$ for elsewhere.

Markets	**EU**			**Japan**			**UK**			**US**		
Bank – All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Volatility 1 (g_{i1})	-0.002	-1.265		0.008	1.848	*	0.050	1.844	*	0.039	1.610	
Cross-Volatility 2 (g_{i2})	0.005	1.977	**	0.012	1.203		0.038	1.088		0.006	2.885	***
Cross-Volatility 3 (g_{i3})	0.013	3.225	***	0.062	3.019	***	0.089	3.467	***	0.002	0.725	
Change in Cross-Volatility 1 (z_{i1})	0.008	1.927	*	-0.019	-4.258	***	0.044	1.443		0.013	0.534	
Change in Cross-Volatility 2 (z_{i2})	-0.007	-2.315	**	0.000	0.729		0.005	0.929		0.040	0.561	
Change in Cross-Volatility 3 (z_{i3})	-0.006	-1.023		0.016	0.768		0.027	1.777	*	0.057	1.681	*
Insurance – All	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Volatility 1 (g_{i1})	0.000	0.830		0.168	0.916		0.007	1.123		0.096	2.233	**
Cross-Volatility 2 (g_{i2})	-0.011	-2.276	**	0.067	0.831		0.001	0.397		0.003	0.574	
Cross-Volatility 3 (g_{i3})	0.024	4.824	***	0.183	1.111		-0.001	-0.649		0.094	2.510	**
Change in Cross-Volatility 1 (z_{i1})	-0.006	-2.656	***	0.003	0.575		0.004	1.130		0.113	2.535	**
Change in Cross-Volatility 2 (z_{i2})	0.042	1.954	*	-0.038	-0.597		-0.014	-1.724	*	0.022	2.368	**
Change in Cross-Volatility 3 (z_{i3})	-0.001	-0.575		0.036	0.539		0.000	0.732		0.015	0.541	

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The magnitude of the cross-sectional volatility spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $g_{i,j}$) and the change in spillover effect over the crisis period (represented by $z_{i,j}$).

Table 2.5 VAR-BEKK Model based on Large Banking Sector Portfolios

The following tables summarize the estimation output of the VAR-BEKK models based on large size banking portfolios across the markets. The large size banking portfolio is an equally weighted portfolio with banks above the top 25 percent market size threshold from a given market. The estimated coefficients from the model have been categorized into three sub-tables: i) Macroeconomic Factors and GARCH Effects, ii) Return Spillover Effects and iii) Volatility Spillover Effects.

The following table summarizes the estimated coefficients for all the estimated parameters in the mean and variance equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RF(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, US]$, $i \neq j$. JP represents the Japanese national market.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1} h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for market *i* over the day *t*. $X \in [MKT, FX, IR]$ which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

$\gamma_{i,j}$= the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$= the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* during the crisis period.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio *j* to portfolio *i* during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

Markets	**EU**			**Japan**			**US**		
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Macroeconomic Factors									
Market ($\beta_{i,MKT}$)	1.006	60.275	***	0.961	42.068	***	0.956	47.135	***
FX ($\beta_{i,FX}$)	0.374	9.124	***	0.027	0.569		-0.001	-0.042	
IR ($\beta_{i,IR}$)	-0.017	-1.244		-0.016	-1.068		0.051	3.967	***
GARCH Effects									
ARCH (a_{ii}^2)	0.012	2.065	**	0.075	9.441	***	0.056	6.144	***
GARCH (b_{ii}^2)	0.934	149.070	***	0.897	128.640	***	0.822	100.260	***
Persistence	0.946			0.971			0.877		
Log-Likelihood	15401.0								
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Return Spillover									
Cross-Return 1 (γ_{i1})	0.021	2.181	**	-0.029	-0.767		-0.037	-1.987	**
Cross-Return 2 (γ_{i2})	-0.062	-3.630	***	0.023	0.560		-0.015	-1.350	
Change in Cross-Return 1 (θ_{i1})	-0.025	-1.089		0.077	1.478		0.147	2.452	**
Change in Cross-Return 2 (θ_{i2})	0.140	5.611	***	0.021	0.467		-0.020	-0.416	
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Volatility Spillover									
Cross-Volatility 1 (g_{i1})	-0.005	-1.972	**	-0.020	-0.220		0.060	2.551	**
Cross-Volatility 2 (g_{i2})	0.064	4.475	***	0.074	0.738		0.010	2.639	***
Change in Cross-Volatility 1 (z_{i1})	0.006	1.186		0.025	0.273		0.299	3.777	***
Change in Cross-Volatility 2 (z_{i2})	-0.045	-3.097	***	-0.065	-0.556		-0.004	-0.102	

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The shadings in the above table means the corresponding size portfolio is not available within the national group for the given financial sector. The magnitude of the cross-sectional return spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $\gamma_{i,j}$) and the change in spillover effect over the crisis period (represented by $\theta_{i,j}$).The magnitude of the cross-sectional volatility spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $g_{i,j}$) and the change in spillover effect over the crisis period (represented by $z_{i,j}$).

Table 2.6 VAR-BEKK Model based on Small Banking Sector Portfolios

The following tables summarize the estimation output of the VAR-BEKK models based on small size banking portfolios across the markets. The large size banking portfolio is an equally weighted portfolio with banks below the top 25 percent market size threshold from a given market. The estimated coefficients from the model have been categorized into three sub-tables: i) Macroeconomic Factors and GARCH Effects, ii) Return Spillover Effects and iii) Volatility Spillover Effects.

The following table summarizes the estimated coefficients for all the estimated parameters in the mean and variance equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RF(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, US]$, $i \neq j$. JP represents the Japanese national market.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1}\, h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for market *i* over the day *t*. $X \in$ [*MKT, FX, IR*] which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

$\gamma_{i,j}$= the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$= the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* during the crisis period.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio *j* to portfolio *i* during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

Markets	**EU**			**Japan**			**US**		
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Macroeconomic Factors									
Market ($\beta_{i,MKT}$)	**0.340**	**15.387**	***	**0.773**	**35.546**	***	**0.292**	**18.871**	***
FX ($\beta_{i,FX}$)	**0.112**	**3.014**	***	**-0.016**	**-0.377**		**-0.032**	**-2.203**	**
IR ($\beta_{i,IR}$)	**-0.010**	**-0.841**		**0.042**	**3.559**	***	**0.041**	**5.402**	***
GARCH Effects									
ARCH (a_{ii}^2)	**0.123**	**7.434**	***	**0.042**	**9.077**	***	**0.254**	**10.273**	***
GARCH (b_{ii}^2)	**0.766**	**69.241**	***	**0.901**	**170.860**	***	**0.687**	**36.617**	***
Persistence	**0.889**			**0.943**			**0.940**		
Log-Likelihood	**16922**								
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Return Spillover									
Cross-Return 1 (γ_{i1})	**0.061**	**5.475**	***	**0.000**	**-0.047**		**-0.005**	**-0.191**	
Cross-Return 2 (γ_{i2})	**-0.002**	**-0.042**		**0.035**	**0.414**		**0.017**	**2.012**	**
Change in Cross-Return 1 (θ_{i1})	**0.015**	**0.684**		**-0.070**	**-1.149**		**0.506**	**1.926**	*
Change in Cross-Return 2 (θ_{i2})	**0.096**	**2.080**	**	**-0.053**	**-0.604**		**-0.054**	**-0.791**	
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Volatility Spillover									
Cross-Volatility 1 (g_{i1})	**0.013**	**3.669**	***	**-0.009**	**-0.814**		**0.006**	**1.260**	
Cross-Volatility 2 (g_{i2})	**0.029**	**4.184**	***	**0.160**	**2.958**	***	**0.002**	**1.848**	*
Change in Cross-Volatility 1 (z_{i1})	**-0.001**	**-1.517**		**-0.009**	**-1.226**		**0.127**	**3.453**	***
Change in Cross-Volatility 2 (z_{i2})	**-0.009**	**-1.299**		**0.063**	**0.687**		**0.032**	**5.741**	***

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The shadings in the above table means the corresponding size portfolio is not available within the national group for the given financial sector. The magnitude of the cross-sectional return spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $\gamma_{i,j}$) and the change in spillover effect over the crisis period (represented by $\theta_{i,j}$).The magnitude of the cross-sectional volatility spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $g_{i,j}$) and the change in spillover effect over the crisis period (represented by $z_{i,j}$).

As mentioned above, we spilt the estimation output for Test 1 into three sub-tables. From Table 2.4, one can see that the market beta is always positive and statistically significant for all the financial sectors portfolios. However, by comparing the market beta across different size portfolios in Table 2.5 and 2.6, one can see that the market beta for large size banking portfolios is noticeably higher than the small size ones across the markets. The estimated coefficient for market risk is 1.006, 0.961 and 0.956 for large banks from EU, Japan and US market, respectively. In contrast, the market betas of small banks in these three markets are 0.340, 0.773 and 0.292, respectively. The size effect on market beta is mainly due to the different risk appetite of the large and small banks. Demsetz and Strahan (1997) suggest that large banks tend to be better diversified than the small banks, but it not necessarily translate into risk reduction. They claim that large banks or bank holding companies tend to use their diversification advantage to increase risky lending and to operate with lower capital ratio instead of operating at lower levels of overall risk. Their argument is later reinforced by the empirical study of De Nicoló et al (2004). Elyasiani et al (2007) further argued that large banks is likely to have higher market beta due to their "assumption of greater credit risk, higher financial leverage, more extensive engagement in risky off balance sheet activities, and more aggressive attitudes of their managers towards risk".

The impact of the foreign exchange rate on the equity value of financial institutions has been well explored in the previous literature.[59] Financial institutions play an important role in the foreign exchange rate market, as they conduct a large proportion of the total foreign currency trading volume (Saunders and Cornett, 2010). Since most financial institutions involved in the foreign currency transactions, the foreign exchange

[59] For foreign exchange rate risk on banks, please refer to Choi et al (1992), Chamberlain et al (1997) and Tai (2000) among others. For foreign exchange rate risk on insurance companies, please refer to Mange (2000) and Elyasiani et al (2007).

rate fluctuation can be regarded as a translation of risk for financial institutions that process non-zero net foreign lending/borrowing (Choi et al, 1992). In the case of increase of foreign exchange rate where the relative value of domestic currency increases against foreign currencies, the financial institution with net foreign currency borrowing will benefit from the relative value decrease of its foreign debts, and vice versa.

The sign of the exchange rate coefficient of the financial sector portfolio depends on the net foreign currency position of each individual financial institution within the portfolio. Positive sign indicates that the financial sector portfolio benefits from home currency appreciation. In other words, the financial institutions within the portfolio are on average net foreign asset borrowers since the appreciation of home currency value will benefit the net foreign asset borrower by decreasing the value of foreign obligation in home currency terms. In contrast, negative sign shows the financial institutions within the portfolio are on average net foreign asset lenders.

From Table 2.4, one can see that the foreign exchange rate beta is positive and statistically significant for both banking and insurance sector portfolios in EU and UK markets. One possible explanation could be that banks and insurers in these two markets are on average net foreign asset borrowers. For EU market, the estimated foreign exchange rate betas are 0.199 and 0.248 for the banking and insurance sector portfolios, respectively. The foreign exchange rate bates for the banking and insurance portfolios in UK market are 0.235 and 0.126, respectively. However, none of the financial sector portfolios in Japanese and US market is influenced by the fluctuation of home currency value.

Previous empirical studies have shown that there is a relationship between the interest rate variation and the value of financial institutions. The changes in interest rate affect the profitability of the banks and insurers through two channels. i) Mismatch of the asset and liability's maturity within the institution. Flannery and James (1984) showed that interest rate risk of the financial institution is linked to the maturity composition of the firm's net asset holding. Similarly, Elyasiani et al (2007) showed that US life insurance companies exposed to interest rate risk due to the longer duration of their bond investments relative to their liabilities. ii) Leverage ratio of the institution and its sensitivity to changes in interest rate. Staking and Babbel (1995) showed that for non-life insurance companies, the interest rate fluctuation has a negative impact on firm's value when the leverage of the firm is low.[60]

In the current study, the interest rate risk is represented by the unexpected changes in the yield relative calculated based on the long-term benchmark bond yield. Previous empirical studies show that the unexpected changes in the yield relative have a positive impact on the financial institutions' performance (Flannery and James, 1984, and Carson et al, 2008).[61] Since a positive yield relative indicates a decrease in the long-term bond yield, which means a decrease in long-term bond yield will benefit the financial institution. However, from Table 2.4 sub-table i), one can see that the estimated interest rate beta shows mixed result. The interest rate beta of US banking sector portfolios is positive and statistically significant, which equals to 0.049. The positive interest rate beta may due to the long-term assets hold by the US banks. Therefore, a decrease in long-term bond yield

[60] The authors argue that leveraged insurer is concentrated in long-term, fixed-income securities. Interest rate changes, therefore, will have a negative impact on the market value of insurers as the discount factor of future cash flows generated from their long-term assets will increase. However, limited evidence has been found by the authors indicating that at high levels of leverage, market value of insurers begins to increase. They argue the phenomenon could be interpreted as stemming from the put option value of increasing volatility associated with insurers who are able to expropriate value from policyholders and/or their competitors through state guarantee programs.

[61] Carson et al (2008) use the simple difference of long-term benchmark bond yield as interest rate risk factor instead of yield relative. By taking into account the difference in the sign of simple difference of bond yield and the yield relative, the empirical result by Carson et al (2008) is consistent with the one by Flannery and James (1984).

will increase the value of long-term asset and benefit the value of these financial institutions. However, the interest rate betas of EU banking portfolio is negative and statistically significant, which equals -0.025. The result suggests that the banking sector in EU market seems to put most of their asset into short term investments. In addition, the result indicates that the financial institutions in Japanese market seem to hedge their foreign exchange and interest rate exposures effectively, as none of the two financial sectors has a significant coefficient for the two risk factors.

From Table 2.5 and Table 2.6, one can see that the size effects also exist for the foreign exchange and interest rate risk factors. For instance, large banking portfolios are more likely to benefit from the domestic currency appreciation than the small ones. The foreign exchange rate betas of the large EU and US banks are 0.374 and zero compares to 0.112 and -0.032 for the small banks in these two markets, respectively. Since positive currency exposure shows the financial institutions in the portfolio are net foreign asset borrowers, the result indicates that large EU and US banks are more likely to require financial resources from foreign markets compare to the small ones. The finding is consistent with the study by Chamberlain et al (1997) which suggests that large size financial institutions are indeed more likely to be involved in foreign activities relative to small institutions.

However, the result for interest rate beta is less decisive. The only notable difference comes from the banking sector in Japanese market, where small banks suffer from interest rate changes but not the large ones. The interest rate beta is 0.042 for the small Japanese banks, but is no significant for the large ones. We argue the difference in interest rate exposure between the large and small Japanese banks is mainly due to the fact that financial institutions with different sizes have different incentives to hedge their risk exposures. The cost efficiency of the hedging activity is positively related to the size of the risk exposure (Nance et al, 1993). Therefore, large size firms enjoy higher cost efficiency compare to small size firms when they hedge their risk exposures. Thus, large size firms have higher motivation to hedge their risk exposures compare to small size ones. The argument is supported by Mian (1996) based on the annual reports of 3022 firms in the US market. He shows that the economics of scale also exists for hedging activities where large size firms are indeed more likely to be involved into the hedging activities against foreign exchange and interest rate risk factors against the small ones. Although the finding of two papers mentioned above is based on non-financial multi-national corporations (MNC) instead of financial institutions, the concept about economics of scale for hedging activity still holds regardless of the nature of the business.[62] Furthermore, Crabb (2002) claims that hedging activity reduces the risk exposure of MNC, which makes the risk beta of the company insignificant. Therefore, it is reasonable for one to assume that the lower interest rate beta of the large size Japanese banks is due to their higher incentive to hedge against the fluctuation of long-term interest rates.

2.5.2. *Joint-Hypotheses Test*

Before we move into the detail discussion of the return and volatility spillover effects among financial sectors, we first investigate the overall significance of the risk and return interdependence among these portfolios. Previous empirical studies show that the linkage among the global financial markets has increased over the last two decades.[63] Financial sectors across markets are no longer isolated from each other. Previous empirical studies provide several stylized factors on the interdependence among global financial markets.

[62] Nance et al (1993) suggests that a risk exposure with market value less than 5 to 10 million US Dollar is not cost efficient for a firm to hedge against it. Therefore, regardless of the business model of the firm, it will not hedge against a risk exposure if the market value of the exposure is smaller than a certain amount.

[63] For further discussion on integration and globalization of the world financial markets, and its implication on risk and return spillover effects, please refer to Agenor (2003), Bekaert et al (2005), Berger et al (1999), and De Nicoló and Kwast (2002) among others.

For instance, Eun and Shim (1989) show the return of US financial market has a significant impact on the other major financial markets. Other studies suggest that the return and volatility spillovers among closely related financial markets are significant and positive (Jeong, 1999, Karloyi, 1995). Recently, researchers find the interdependences among the financial markets tend to be higher during the economic downturns, which is also known as "contagion" effects (Forbes and Rigobon, 2002; Tai, 2007). In addition, Bekaert et al (2005) and Baele (2005) suggest the linkages among the developed financial markets have increased over time.

The linkages across financial markets can be established through various channels. Dornbusch et al (2000) and Kodres and Pritsker (2002) claim that markets move together because they share the similar macroeconomic and financial risk factors. Glick and Rose (1999) suggest the interdependences are mainly due to the trade linkages across the involved countries. Other studies focus on the financial linkages across the markets. De Nicoló et al (2004) argue that the connections among major financial markets are caused by the consolidation of global banking industry. Dornbusch et al (2000) argue that the interdependence among global financial markets is mainly due to the fact that they have a common creditor, known as global investors.[64] They claim that the dynamic movements among financial markets are simply because global investors shift their investments across these markets.[65]

We design four hypotheses tests (H1 – H4) in the current study to investigate the existence of return and volatility interdependence among the financial sector portfolios. The first two hypotheses tests, H1 and H2, focus on the overall return and volatility

[64] The global investor can be an individual investor who hold a diversified portfolio with assets from different national market, or an institutional investor (banks, or investment funds) who invest in multiple countries.

[65] The global investor may shift their investments across national financial markets as they want to seek for assets with higher liquidity (Vayanos, 2004) or higher credit quality (Eichengreen et al, 2009).

spillover effect among the financial sector portfolios over the entire sample period, respectively.

In addition, theory on contagion effects argues that the return and volatility spillover across the financial markets will increase during financial crises (Allen and Gale, 2000; Elyasiani et al, 2007). Therefore, we design another two hypotheses test, H3 and H4, to investigate whether the return and risk spillover effects across the financial sector portfolios have changed during the recent financial crisis from *April 2, 2007* to *March 9, 2009*. The description of the four null hypotheses tests are listed as follow:

Return and volatility spillovers over the entire sample period:

H1: No return spillovers exist across financial sector portfolios.

H2: No volatility spillovers exist across financial sector portfolios.

Changes in return and volatility spillovers over the crisis period:

H3: No changes in return spillover during financial crisis.

H4: No changes in volatility spillover during financial crisis.

The hypothesis test is based on log-likelihood (LLR) ratio test, which evaluates the difference between the log-likelihood statistics of the restricted and non-restricted VAR-BEKK models.[66] The null hypothesis assumes that the corresponding spillover parameters are all equal to zero, so no spillover effects during the entire sample period (H1 and H2), or no changes in the spillover effects during the crisis period (H3 and H4). Therefore, we force the corresponding parameters for return/volatility spillover effect to be zeros in the restricted model. If the LLR test result rejects the null hypothesis, we claim the corresponding cross-sectional return/volatility spillover effect is statistically significant

[66] For detail explanation of the LLR ratio test, please refer to Appendix A.5.

over the corresponding period. Table 2.7 summarizes the result of the four joint hypotheses tests.

Table 2.7 Joint-Hypotheses Test Result for Return and Volatility Interdependence among Financial Sector Portfolios

The following table summarizes the test statistics of the log-likelihood ratio (LLR) test for the four hypotheses on the interdependence among financial sector portfolio.
The VAR-BEKK Model is estimated as follow:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RF(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, UK, US]$, $i \neq j$.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1}\, h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$.

Where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for market *i* over the day *t*. *X* ∊ [*MKT, FX, IR*] which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

$\gamma_{i,j}$= the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$= the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* during the crisis period.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio *j* to portfolio *i* during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

Joint Hypotheses:		Log-likelihood Ratio Test Statistics (LLR) and Degrees of Freedom (DF)								
Interdependence over entire sample period:		All			Large			Small		
H1: No return spillovers exist across sector portfolios.		DF	LLR		DF	LLR		DF	LLR	
$\gamma_{i,j} = 0$ and $\theta_{i,j} = 0$, with $i \neq j$. x∊[1,2].	Bank	24	990	***	12	66	***	12	74	***
	Insurance	24	108	***						
H2: No volatility spillovers across sector portfolios.	Banks	24	144	***	12	106	***	12	26	**
g(i,j) = 0 and z(i,j) = 0, with i≠j.	Insurance	24	208	***						
Change in the interdependence over the crisis period.										
H3: No change in return spillovers over the crisis period.		DF	LLR		DF	LLR		DF	LLR	
γ(i,j,2) = 0, with i≠j.	Banks	12	914	***	6	100	***	6	12	*
	Insurance	12	12							
H4: No change in volatility spillovers over the crisis period.	Banks	12	338	***	6	42	***	6	16	**
z(i,j) = 0, with i≠j.	Insurance	12	36	***						

Note: the LLR represents the test statistics of the log-likelihood ratio test. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The unrestricted model for H1-H4 is the original VAR-BEKK model proposed in the methodology section, which without restrictions on any of the parameters.

The test statistics for H1 and H2 are highly significant at 1% confidence level for all the financial sector portfolios, which suggests that the return and volatility spillovers do exist among these portfolios over the entire sample period.

From the test result of H1, one can see the return spillovers effects among the small size banking sector portfolios is higher compares to the large ones. Given the same degrees of freedom, the statistics of the LLR test for small size portfolios (74) is higher than the large portfolios (66). The result suggests the return linkages among the small size banks across the financial markets are higher compares to the large size banks. One possible explanation for this phenomenon is the "herding" effect introduced by Calvo and Mendoza (2000). They argue that investors' incentive to collect price information to form their own trading strategy will decrease as the cost of collecting the information increases. When the cost of collecting price information is higher than the potential return one can earn from forming his/her own trading strategy, the investor will have a high incentive following other traders to save cost. Small banks have more firm-specific risk compare to large banks, which make their price information hard to collect. Therefore, investors have higher incentive to follow the decisions made by investors in the other markets when they trade the stock of small banks than large ones. Thus, the returns of small banks across the financial markets are more likely to be connected compared to large banks. Similar finding have been documented by Elyasiani et al (2007) for the small US banks. However, it is worth mentioning that since Elyasiani et al (2007) only focused on financial institutions within US market, their explanation on the phenomenon is not suitable for the current study.[67]

[67] Elyasiani et al (2007) provide three possible explanations for the higher interdependence among small size financial institutions. First, the competition among small financial institutions is higher as their products are substitutable with each other. Second, small financial institutions are more likely to be influenced by national economic factor. Thus, small financial institutions are more likely to be correlated within the same region. Third, small financial institutions are less able to bypass regulations and earn differential returns compare to large ones.

The test result for H2 also indicates that volatility spillover effects are different for different size portfolios. The LLR test statistics for the large and small banking portfolio is 106 and 26, respectively. The empirical evidence suggests that the risk linkage among the large banks is stronger compares to small banks, which is consistent with the previous studies. The integration among global financial market is mainly due to the consolidation and globalization of large financial institutions (De Nicoló et al, 2004, DeYoung et al, 2009). So, the large financial institutions should be share more common risk factors compare to the small ones. Therefore, one would expect higher risk interdependence across large banks than small banks.

The remaining two hypotheses, H3 and H4, test whether the magnitude of return and volatility spillover effects has changed during the recent financial crisis. The hypothesis test rejects the null hypothesis that "no changes in return/volatility the spillovers during financial crisis" at 1% confidence level for most of the financial sector portfolios.[68] The result shows that the return and volatility spillover effects among the financial sector portfolios have changed significantly during the crisis period. This finding is in line with the pervious empirical studies on contagion effect during the crisis period.[69]

We believe the reason behind the changes in return and volatility spillover effects during the crisis period is threefold. First, the increased market integration reinforced the contagion effect during the crisis period. According to the *Group of Ten* report by IMF and De Nicoló et al (2004), the integration among global financial market has increased over the last two decades due to the consolidation and globalization of the

[68] The only exceptions are come from the insurance sector for H3.

[69] Empirical studies like Koutmos and Booth (1995) on the 1987 US crisis, Forbes and Rigobon (2002) on the 1987 US crisis, 1994 Mexico crisis and 1997 Asian crisis, and Bekaert et al (2005) on the 1994 Mexico and 1997 Asian crisis also find significant increase in return and volatility spillover effects during the crisis periods.

financial institutions.[70] This increase in the level of concentration among large global financial institutions significantly increases their risk similarities (Carey and Stulz, 2006). The test result of H3 and H4 bases on the large and small banking portfolios also support the argument. From Table 2.7, one can see that the LLR test statistics of the large banking portfolio is consistently higher than the ones of the small banking portfolios for both H3 and H4. That means the changes in risk and return spillover effects of the large banking portfolios are more significant compare to the small banks.

Second, according to the theory of "flight-to-quality" proposed by Lang and Nakamura (1995), the changes in the return and volatility spillovers might be due to changes in investor's preference towards risk during the crisis period. The quality of sub-prime mortgage related structured financial products are poor and very risky during the crisis period (Demyanyk and Hemert, 2009). Financial institutions, especially banks, are the major investors in these structured financial products (Duffie, 2008). In addition, Gonzalez-Hermosillo (2008) shows the risk appetite of the global investor decreased dramatically during the crisis period. Since investors are no longer willing to assume risk, it is reasonable for investors to sell off their holdings in these financial sectors during the crisis period and increase the interdependence among these financial institutions across the markets.

The final reason for the increased risk and return interdependence among financial sectors during the crisis is the fair value accounting standard. The fair value accounting standard is procyclical. As the financial assets across the global markets deteriorated during the crisis period, the financial institutions are forced to write-down massive value from their balance sheet which led to a dramatic decrease in the value of these institutions over the crisis period (De Grauwe, 2008). Since all the financial institutions

[70] The full title of the report is: *Group of Ten - Report on Consolidation in the Financial Sector (2001)*, which is available to general public via IMF's website: www.imf.org.

suffer from the decrease in financial asset value simultaneously as the global financial market deteriorates, this synchronized decrease in the value of financial institutions increases the return interdependence among the financial sectors during the crisis period.

2.5.3. Test 1: Interdependence among Financial Sectors Portfolios

In this section, we discuss the return and volatility spillover effects across the financial sector portfolios. In order to demonstrate the spillover effects in a clear manner, we select the estimated coefficients for the return and risk spillover effects from Table 2.4 – 2.6 which are statistically significant and summarize them into Table 2.8.[71] Table 2.8 is divided into three panels, Panel A – C. The first two panels (Panel A and B) present the selected coefficients estimated based on the all size banking and insurance portfolios, while the final one (Panel C) contains the parameters for the significant return and volatility spillover effects among the large and small size banking portfolios. Each panel splits into two sub-tables which contains the selected coefficients for the return and volatility spillover effects, respectively. The spillover effects estimated over the entire sample period are represented by the coefficient $\gamma_{i,j}$ and $g_{i,j}$ for return and volatility spillovers, respectively. The spillover effects over the crisis period are combinations of the spillover effects estimated over the entire sample period and the changes in spillover effects over the crisis period. The latter is represented by coefficients $\theta_{i,j}$ and $z_{i,j}$ for the return and volatility spillover effects, respectively.

[71] The selected coefficient is statistically significant at 10% significance level or lower.

Table 2.8 Summary of the Significant Spillover Effects based on Table 2.4 – 2.6.

The table below summarizes the selected estimated return and volatility spillover effects which are statistically significant above 10 percent significance level. The estimated coefficients for return and volatility spillovers are selected from Table 2.4 – 2.6. The table is divided into four panels. Panel A – B represent the significant return and volatility spillover effects among the all size banking and insurance sector portfolios, respectively. Panel C represents the significant return and volatility spillover effects among the large and small size banking portfolios across the markets. Both the estimated coefficients of the statistically significant spillover effects and their z-Statistics is presented in the following table.

Panel A: Return Spillover Effects among All Size Banking Portfolios

	Entire sample period ($\gamma_{i,j}$)			Changes during the crisis period ($\theta_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Banks			-0.161	0.115		0.273
z-Stat.			*-2.556*	*3.668*		*2.776*
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Banks	-0.069			0.298		0.136
z-Stat.	*-2.972*			*2.698*		*2.314*

Volatility Spillover Effects among All Size Banking Portfolios

	Entire sample period ($g_{i,j}$)			Changes during the crisis period ($z_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Banks	0.013	0.062	0.089			0.027
z-Stat.	*3.225*	*3.019*	*3.467*			*1.777*
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Banks		0.006				0.057
z-Stat.		*2.885*				*1.681*

Panel B: Return Spillover Effects among All Size Insurance Portfolios

	Entire sample period ($\gamma_{i,j}$)			Changes during the crisis period ($\theta_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Insurers	0.043		0.048			
z-Stat.	*1.956*		*1.985*			
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Insurers	0.056					
z-Stat.	*2.399*					

Cross-Sectional Volatility Spillover Effects among All Size Life Insurance Sector Portfolios

	Entire sample period ($g_{i,j}$)			Changes during the crisis period ($z_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Insurers	0.024					
z-Stat.	*4.824*					
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Insurers	0.096		0.094	0.113	0.022	
z-Stat.	*2.233*		*2.510*	*2.535*	*2.368*	

Panel C: Return Spillover Effects among Large and Small Banking Portfolios

	Entire sample period ($\gamma_{i,j}$)			Changes during the crisis period ($\theta_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Large Size Banks	-0.062			0.140		
z-Stat.	*-3.630*			*5.611*		
Small Size Banks				0.096		
z-Stat.				*2.080*		
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Large Size Banks	-0.037			0.147		
z-Stat.	*-1.987*			*2.452*		
Small Size Banks		0.017		0.506		
z-Stat.		*2.012*		*1.926*		

Volatility Spillover Effects among Large and Small Banking Portfolios

	Entire sample period ($g_{i,j}$)			Changes during the crisis period ($z_{i,j}$)		
	To			To		
From US	EU	Japan	UK	EU	Japan	UK
Large Size Banks	0.064			-0.045		
z-Stat.	*4.475*			*-3.097*		
Small Size Banks	0.029	0.160				
z-Stat.	*4.184*	*2.958*				
	From			From		
To US	EU	Japan	UK	EU	Japan	UK
Large Size Banks	0.060	0.010		0.299		
z-Stat.	*2.551*	*2.639*		*3.777*		
Small Size Banks		0.002		0.127	0.032	
z-Stat.		*1.848*		*3.453*	*5.741*	

Note: The shadings in the above table means the financial sector portfolio is not available within the corresponding national market. The magnitude of spillover effect over the entire sample period is represented by the estimated parameter $\gamma_{i,j}$ and $g_{i,j}$ for the return and volatility spillovers, respectively. The changes in spillover effect during the crisis period is represented by the estimated parameter $\theta_{i,j}$ and $z_{i,j}$ for the return and volatility spillovers, respectively. The magnitude of spillover effect during the crisis period is the sum of the spillover effect over the entire sample period ($\gamma_{i,j}$ or $g_{i,j}$) and the changes in spillover effect during the crisis period ($\theta_{i,j}$ or $z_{i,j}$).

Panel A summarizes the significant spillover effects across the all size banking portfolios. Generally, the empirical result indicates that the return and volatility interdependence between the US banks and banks from EU and UK market increased dramatically during the crisis period.

The result for return spillover effects over the entire sample period indicates the existence of competitive effects between the banks in EU and US market, as well as the banks in US and UK market. The return spillover from US banks to UK ones is -0.161, while the return spillover from EU banks to US ones is -0.069 over the entire sample period. The spillover effect estimated over the entire sample period is mainly representing the spillover effect over the pre-crisis period, as the spillover effect over the crisis period is the sum of the former and the changes in spillover effect during the crisis period. Therefore, the finding indicates that EU banks perform better compare to US banks, and latter performs better compare to the UK banks. The finding is consistent with the result from Panel B Table 2.2. The mean return of EU banking portfolio (0.060%) is indeed higher than the one of US banks (0.009%). UK banks also perform poorly compare to US ones. The average daily return of UK banking portfolio is only 0.003% during the pre-crisis period from *January 1, 2003* to *April 1, 2007*. The low mean return of UK banking sector is mainly due to the sudden stock price decrease of one UK banks, named the European Islamic Investment Banks. On the *May 17, 2006*, the company's stock price experienced a 47.8% drop, which led to a 9.3% decrease in the UK banking portfolio on that day.

The volatility spillovers estimated over the entire sample period show that US banks are the main information provider in terms of volatility innovations. The volatility innovation generated from US banking portfolio has a significant and positive impact on the volatility of the banking sectors from the remaining three markets. However, the volatility spillover towards the US banking portfolio from the other market is negligible.[72] The finding is consistent with the empirical studies by Eun and Shim (1989) and Hamao et al (1990), which also show that US financial market is the main information provider in terms of volatility innovations.

During the crisis period, the return interdependence between US banking portfolio and the banking portfolio from EU and UK markets has increased dramatically. The changes in return spillover from US banking portfolio towards EU and UK banking portfolios are 0.115 and 0.273 during the crisis period, respectively. And the return spillovers from the banking sector in EU and UK market towards US market have also increased by 0.298 and 0.136, respectively. The enhanced return interdependence among these three banking portfolios has transformed the competition effects among them during the pre-crisis period into contagion effects over the crisis period.[73] The finding is consistent with the previous empirical studies on contagion effects, which showed that linkages among financial markets increased during the crisis period (Koutmos and Booth, 1995; Forbes and Rigobon, 2002; Bekaert et al, 2005).

In addition, the volatility spillover effects between the banking portfolios from US and UK markets have also enhanced during the crisis period. The volatility spillover effects from the US banks towards UK banks have increased from 0.089 before the crisis to 0.116 during the crisis, while the spillovers from UK to US have increased from zero to 0.057.[74] In other words, both the return and volatility linkages between US and UK banking sectors have increased during the recent financial crisis.

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[72] The only significant volatility spillover towards US banking sector portfolio is oriented from Japanese banks, but the magnitude of the spillover effect is very small at 0.006.

[73] The spillover effect during the crisis period is the sum of the spillover effect estimated over the entire sample period plus the changes in spillover effect during the crisis period. Therefore, the return spillover effect from US to UK banking portfolio has changed from -0.161 during the pre-crisis period to 0.112 over the crisis period. And the return spillover effect from EU to US banks has changed from -0.069 during the pre-crisis period to 0.229 over the crisis period.

[74] The spillover effect during the crisis period is the sum of the spillover effect estimated over the entire sample period plus the changes in spillover effect during the crisis period. Therefore, the volatility

The reason behind the strong return and volatility interdependence between the two banking sector portfolios is twofold. First, banks from both UK and US markets are severally damaged during the crisis period as they suffered from massive value write-offs as the global financial market deteriorates and the liquidity shortage in the interbank funding markets (Blackburn, 2008, Brunnermeier, 2009, De Grauwe, 2008).[75] The massive write-offs during the crisis period by US and UK banking sectors would lead to a synchronized drop in the value of both banking portfolios, which will increase the return interdependence bewteen the returns of the two portfolios. Second, the UK banking sector was heavily involved in the US sub-prime mortgage market. According to the *Financial Stability Report* (FSR) issued by Bank of England, the UK banks had USD 192 billion investments in the US structured financial products which was under threat during the crisis period, while the exposure of US banks towards the structured financial products is USD 195 billion.[76] In other words, UK and US banking sectors share the same risk factors during the crisis period. Besides, since the size of the risk exposure is also similar for both banking sectors, the riskiness of the two banking sector should also similar to each other. The FSR shows that the spreads of credit default swap (CDS) of UK and US banking sectors were indeed closely related during the crisis period.[77] Therefore, one should expect strong risk interdependence between the two banking portfolios during the crisis period.

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spillover effect from US banks to UK banks during the crisis period is equal to 0.089 plus 0.027, while the spillover from UK banks to US banks is equal to zero plus 0.057.

[75] The current financial crisis has forced a number of UK banks into nationalization due to liquidity shortage, such as Northern Rock, Lloyds TSB, and Royal Bank of Scotland. HSBC and Barclay have also forced to enhance their liquidity by conducting emergency right issue during the current financial crisis. In the US, a series bankruptcies and government bailouts among the banking industry happened during the crisis period, which includes the Bear Stearns, Lehman Brothers, Merrill Lynch, and JPMorgan. For detail information on these events, please refer to Guillén (2009).

[76] The *Financial Stability Report* (FSR) is issued by Bank of England on a bi-annually basis, see: http://www.bankofengland.co.uk/publications/fsr/index.htm. The information used in the present study is provided by the FSR issued in April 2008.

[77] Please refer to FSR issued in October 2008. The asset-weighted CDS spreads for the UK and US banking sector is illustrated in Chart 3.1 on Page 17.

In contrast to the previous empirical studies,[78] the result shows no return transmissions between US and Japanese banking portfolios over the estimation period. In addition, the volatility spillover effect between the two banking sectors is also low. The volatility spillover effect between the two is 0.062 from US banks to Japanese banks and only 0.006 for the opposite direction over the entire sample period, and both spillover effects have not increased during the crisis. We believe the lack of interdependence between the two banking sectors is due to the structural differences of the financial system in these two markets. As discussed in the previous literature, the financial system in the US market is commonly regarded as market-oriented, while the Japanese financial system is bank-oriented.[79] Thakor (1996) showed that the type of financial system is distinguished by the way the financial resources is been collected and distributed. In a market-oriented financial system, the demand for capital investments is most likely to be fulfilled by the supply of money market instruments and/or by the investments in equity market directly. In contrast, under a bank-oriented financial system, banks play a dominate role in collecting and re-distributing the financial recourses in the capital market. Empirically, Hartmann et al (2003) claim the main source of financing for financial institutions is also different in markets with different financial systems based on accounting data from EU, Japanese and US markets. They show that financial institutions in Japanese market are mainly financed through loans and deposits and, therefore, heavily relied on banks. However, the main funding channel in the US financial market is market-based securities, such as bonds and equities. In other words, the funding sources for banks in a bank-oriented system are more

[78] Karolyi and Stulz (1996) show positive return interdependence between the returns of Japanese stocks which traded on the US market through American Depository Receipts (ADRs) and the returns of a matched peer group with US stocks from 1988 to 1992. Peek and Rosengren (1997) show that Japanese banks which operate in the US market can significantly influence the return and risk performances of the US banks through interbank loan market. Their sample period is from 1988 to 1995.

[79] For further discussion on the types of financial systems, and the classifications across major economies, please refer to Beck and Levine (2002), and Wang and Ma (2009).

secured as they act as the main finding channel for the whole financial system. In comparison, investors in a market-oriented system have more investment options apart from bank deposits, such as market-based securities. Therefore, banks in a market-oriented financial system need to compete for funding with other participants in the markets, while banks in a bank-oriented financial system hold most of the funding in the market. In other words, banks in a bank-oriented financial system enjoy a better liquidity position compare to the ones in a market-oriented system. Therefore, the liquidity shortage should have a larger impact on banks in a market-oriented financial system than the ones in a bank-oriented financial system. Thus, return and volatility performances of the banks in the Japanese and US markets should not be closely related.

The significant spillover effects for insurance portfolios are represented in Table 2.8 Panel B. From the table one can see strong return spillover effects from US insurers to insurers in EU and UK markets over the entire sample period. The estimated parameter for return spillover from US insurers to EU and UK ones is 0.043 and 0.048, respectively. The return spillover effects between the US insurance industry and insurance sectors from the rest of the markets have not experienced any significant changes during the crisis period. The finding is consistent with the result from hypotheses test H3, where the null hypothesis cannot be rejected for insurance portfolios.[80]

We argue that the unchanged return spillovers among the insurance sector portfolios during the crisis period are mainly due to the fact that the nature of the common risk factor shared by the insurance companies has not changed during the crisis period. The common risk factor shared by the insurance companies from different markets is the deterioration in financial asset value across the global financial markets. Insurance companies do not invest heavily into the structured financial products; they suffer from the current financial crisis by value write-offs due to the sharp decrease in financial asset

[80] The null hypothesis for H3 is "no changes in the return spillover during the crisis period".

value around the global (Harrington, 2009). However, the nature of this risk factor does not change for insurers during the crisis period, which means the decrease in financial asset prices has the same effect on the equity value of insurers before and during the crisis period. Thus, the return interdependence among these insurance portfolios is likely to remain constant during the crisis period.

For volatility spillover effects, the result shows that US insurance sector has a strong linkage with the insurance sectors from EU and UK markets. There is a significant volatility spillover from US to EU insurance portfolio over the entire sample period, which equals to 0.024. The volatility of US insurance sector is also influenced by the volatility from EU and UK insurance sectors. The volatility spillover effect from EU and UK insurance portfolio towards US market is 0.096 and 0.094 over the entire sample period, respectively. During the crisis period, the volatility spillover effect from EU and Japan insurance portfolio towards US insurance portfolio has increased. The changes in the spillover effect towards US insurance sector are 0.113 and 0.022 for EU and Japanese insurance portfolios, respectively.

The fair value accounting standard may be the main reason behind the stronger risk interdependence among the insurance portfolios during the crisis period. As mentioned in the previous section, the fair value accounting standard requires financial institutions to mark the value of financial assets on their balance sheet to the market price/fair value of the assets. Since insurance companies are the major investors on capital market, the insurers across the markets have similar risk exposures as global financial markets deteriorated during the crisis period.[81] Decreasing in asset value increases the default risk of the firm, and the volatility of a firm's equity return can be used as a proxy for its

[81] For further discussion on the influence of fair value accounting standard on the performances of insurance companies during the crisis period, please refer to Eling and Schmeiser (2010), and Harrington (2009).

default risk (Zhang et al, 2009).[82] Therefore, stronger volatility spillover from one to another represents higher linkages in default probabilities between the two. In other words, the volatility innovation generated from EU and Japanese insurance sectors can be treated as a risk indicator for insurers in US market as they all expose to similar risk factors during the crisis period. In addition, EU and Japanese equity markets open early in each calendar day compare to US market. Therefore, it is reasonable that the volatility innovations of EU and Japanese insurance portfolios can transmit to US insurers in a positive manner during the crisis period.

Panel C represents the return and risk spillovers across the large and small size banking portfolios. From the table, one can see that the competitive effects between EU and US all size banking portfolios which we find in Table 2.8 Panel A is mainly coming from the large size banks. The return spillover from large US banking portfolio towards large EU banks is -0.062 over the entire sample period while the spillover effect for the opposite direction is -0.037.

The volatility interdependence among the large banking portfolios is stronger compare to small ones. The volatility spillover from large US banks to EU ones is 0.064, while for small banks the figure is 0.029 over the entire sample period. Similarly, the volatility spillovers from large EU and Japanese banking portfolios to large US banks are 0.060 and 0.010 over the entire sample period, respectively. However, for small banks, the volatility spillover is not significant from EU to US market, and 0.002 from Japanese to US market. We believe the main reason behind the phenomenon is the higher level of integration and globalization among the large size banks compares to the small ones. According to the special report by IMF, the integration among global financial market is

[82] Zhang et al (2009) claim that the volatility of equity return can explain around 50% of the default risk of the firm measured by the spread of CDS.

mainly due to the consolidation and globalization of large financial institutions.[83] This finding is reinforced by the survey paper conducted by DeYoung et al (2009). This increase in the level of concentration among global large financial institutions significantly increases their risk similarities. As discussed in the Carey and Stulz (2006), these trends have led to common sources of underlying risk, as well as adoption of similar models for risk assessment and management. As a result, the possibility of risk spillovers across global large financial institutions increased, especially during the crisis period. However, the small size banks are more likely to operate within the markets. Therefore, the linkages among the small size banking sector portfolios from different markets are weak.

During the crisis period, the return and volatility spillover effects between large and small EU and US banking portfolios increased significantly. Since the large banks are more internationally integrated and more involved in the global financial markets, the changes in return and volatility spillover effects for large banks are higher compare to small ones[84]. The only exception comes from the volatility transmission from the US large banking sector portfolio towards large EU banking portfolio during the crisis period. The volatility spillover effect has decreased by 0.045 from 0.064 to -0.019[85]. The result indicates that the risk linkage between the two financial sectors has decreased during the crisis period. We argue that the main reason for this phenomenon is due to the different financial structures of the two financial markets. As a major player in the EU market, German is also regarded as a market with bank-oriented financial system. So,

[83] The report is conducted by IMF under the title: *Group of Ten - Report on Consolidation in the Financial Sector (2001)*, which is available to general public via IMF's website: www.imf.org.

[84] The return spillover from small EU banks to US ones has increased by 0.506 during the crisis period, which seems higher than the changes in return spillover from large EU banks to large US banks (0.147) in numerical terms. However, the changes in return spillover for the small banks is only statistically significant at 10% level, while the changes in return spillover for the large banks is statistically significant at 1% level. In other words, if we choose a more conservative significance level, the increase in the return spillover among small banks during the crisis period will not be statistically significant.

[85] The volatility spillover effect over the crisis period is the sum of spillover effect overt the entire sample period (0.064) and the changes in spillover effect during the crisis period (-0.045).

we are able to find an argument for decrease volatility spillover from large US banks to large EU banks just like the one we made for Japanese banks. However, it will be hard to justify the increase in volatility spillover effect from large EU banks to large US banks (0.299) during the crisis period along the same line.

2.5.4. Test 2: Interdependence Between US Banking Portfolio and Insurance Portfolios From Other Markets

Apart from examining the interdependence among the same type of financial sectors across the markets, we investigate the interdependence between different financial sectors in the second test. As mentioned in the previous section, the current financial crisis is oriented from the US financial market, where banks play an important role in the build-up and spread of the crisis to the rest of the world (Kollmann and Malherbe, 2011). In addition, insurance companies are influenced by the current financial crisis as they are the main institutional investor in the financial markets. During the crisis period, the sharp decrease in the value of financial assets forces insurers to write-down large amount of their asset holding. Although insurers are not directly involved in the recent financial crisis, their values are still damaged during the crisis period. Since the US banking sector is the main driver of the sharp decrease in the value of financial asset through liquidity and loss spiral (Blackburn, 2008; Brunnermeier, 2009), we would like to investigate the return and risk interdependence between the US banking portfolio and the insurance portfolios from the rest of the markets. To our knowledge, the current study is the first one to investigate the relative performance of the US banking sector and insurance sectors of the major financial markets. The estimated result is represented in Table 2.9.

Table 2.9 Interdependence between US Banking Portfolio and the Insurance Portfolios from the rest of the Markets

The following tables summarize the estimation output of the VAR-BEKK models based on US banking portfolios and the insurance sector portfolios of the remaining three markets, namely EU, Japanese and UK market. The insurance portfolio used in this test is an equally weighted portfolio with both life and non-life insurance companies from a given market. The estimated coefficients from the model have been categorized into three sub-tables: i) Macroeconomic Factors and GARCH Effects, ii) Return Spillover Effects and iii) Volatility Spillover Effects.

The following table summarizes the estimated coefficients for all the estimated parameters in the mean and variance equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RF(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, UK, US]$, $i \neq j$.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1} h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for market *i* over the day *t*. $X \in [MKT, FX, IR]$ which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

$\gamma_{i,j}$ = the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$ = the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* during the crisis period.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio *j* to portfolio *i* during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

Markets	**EU-Insurance**			**Japan-Insurance**			**UK-Insurance**			**US-Bank**		
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-**	
Macroeconomic Factors												
Market ($\beta_{i,MKT}$)	**0.726**	**42.326**	***	**0.989**	**32.246**	***	**0.562**	**34.526**	***	**0.468**	**41.014**	***
FX ($\beta_{i,FX}$)	**0.199**	**4.464**	***	**-0.033**	**-0.481**		**0.112**	**3.400**	***	**-0.042**	**-2.736**	***
IR ($\beta_{i,IR}$)	**0.011**	**0.675**		**-0.024**	**-1.693**	*	**-0.012**	**-0.787**		**0.054**	**7.270**	***
GARCH Effects												
ARCH (a_{ii}^2)	**0.033**	**9.192**	***	**0.030**	**8.672**	***	**0.014**	**9.318**	***	**0.162**	**13.021**	***
GARCH (b_{ii}^2)	**0.927**	**284.680**	***	**0.948**	**325.250**	***	**0.978**	**1012.800**	***	**0.754**	**91.219**	***
Persistence	**0.960**			**0.977**			**0.992**			**0.916**		
Log-Likelihood	**21116.0**											
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-**	
Return Spillover												
Cross-Return 1 (γ_{i1})	**0.040**	**3.468**	***	**0.100**	**1.445**		**0.082**	**3.629**	***	**-0.005**	**-0.271**	
Cross-Return 2 (γ_{i2})	**0.089**	**3.433**	***	**-0.154**	**-1.868**	*	**0.036**	**3.399**	***	**-0.001**	**-0.230**	
Cross-Return 3 (γ_{i3})	**0.039**	**0.961**		**0.221**	**1.834**	*	**0.080**	**1.895**	*	**-0.013**	**-0.659**	
Change in Cross-Return 1 (θ_{i1})	**-0.003**	**-0.141**		**-0.009**	**-0.077**		**-0.074**	**-2.154**	**	**0.075**	**1.047**	
Change in Cross-Return 2 (θ_{i2})	**-0.087**	**-2.245**	**	**-0.040**	**-0.273**		**-0.032**	**-1.757**	*	**0.008**	**0.340**	
Change in Cross-Return 3 (θ_{i3})	**0.036**	**0.784**		**0.056**	**0.434**		**-0.030**	**-0.637**		**0.259**	**3.094**	***
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-**	
Volatility Spillover												
Cross-Volatility 1 (g_{i1})	**-0.001**	**-0.466**		**0.084**	**0.125**		**0.009**	**2.349**	**	**0.020**	**1.610**	
Cross-Volatility 2 (g_{i2})	**0.047**	**1.738**	*	**0.027**	**0.755**		**0.001**	**1.134**		**0.000**	**0.980**	
Cross-Volatility 3 (g_{i3})	**0.004**	**0.552**		**0.104**	**0.167**		**0.000**	**-0.282**		**0.005**	**0.415**	
Change in Cross-Volatility 1 (z_{i1})	**-0.002**	**-0.609**		**0.000**	**-0.362**		**-0.005**	**-1.224**		**-0.001**	**-0.469**	
Change in Cross-Volatility 2 (z_{i2})	**0.001**	**0.201**		**-0.005**	**-0.487**		**-0.028**	**-0.585**		**0.017**	**2.474**	**
Change in Cross-Volatility 3 (z_{i3})	**0.006**	**2.045**	**	**0.017**	**0.230**		**0.003**	**0.440**		**-0.001**	**-0.681**	

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The magnitude of the cross-sectional return spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $\gamma_{i,j}$) and the change in spillover effect over the crisis period (represented by $\theta_{i,j}$).The magnitude of the cross-sectional volatility spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $g_{i,j}$) and the change in spillover effect over the crisis period (represented by $z_{i,j}$).

Table 2.9 summarizes the estimated coefficients from the proposed VAR-BEKK model. In this model, US banking portfolio and the insurance portfolios from EU, Japanese and UK markets are the four portfolios involved in the model. Similar to Table 2.8, we summarize the parameters for spillover effects which are statistically significant into Table 2.10 to better illustrate the return and volatility interdependence across these portfolios.

From Table 2.10, one can see that the return innovation from US banking portfolio has a significant impact on the return of Japanese and UK insurance portfolios. The return spillover effect from US banks towards Japanese and UK insurance sectors are 0.221 and 0.080 over the entire sample period, respectively. However, none of the insurance portfolios can influence the return of US banking portfolio over the entire sample period. Furthermore, there is not volatility interdependence between the US banking portfolio and the insurance portfolios from the rest of the markets as none of the estimated volatility spillover effects is significant over the entire sample period.

During the crisis period, the volatility spillover from US banks to insurers in EU market has only increased by 0.006, and there is no increase in return spillover effects from US banks to other insurance portfolios. The volatility spillover from insurers to US banks is also minimal during the crisis period, with the spillover oriented from Japanese insurance portfolio the only significant one which is equals to 0.017. Similarly, apart from the insurers in UK market, there is no return spillover towards the US banks from the insurance sectors during the crisis period. The return spillover from UK insurance portfolio to US banking portfolio has increased from zero to 0.259 during the crisis period.

Table 2.10 Summary of the Significant Spillover Effect based on Table 2.9.

The table below summarizes the selected estimated return and volatility spillover effects which are statistically significant above 10 percent significance level. The estimated coefficients for return and volatility spillovers are selected from Table 2.9. The table is divided into two panels. Panel A represents the significant return spillover effects between US banking sector portfolio and the insurance sector portfolios of the remaining three markets, while Panel B summarizes the significant volatility spillover effects between the two.

Panel A: Cross-Sectional Return Spillover Effects

	Entire sample period ($\gamma_{i,j}$) To Insurers in			Changes during the crisis period ($\theta_{i,j}$) To Insurers in		
From US	EU	Japan	UK	EU	Japan	UK
Banks		0.221	0.080			
z-Stat.		*1.834*	*1.895*			
	From Insurers in			From Insurers in		
To US	EU	Japan	UK	EU	Japan	UK
Banks						0.259
z-Stat.						*3.094*

Panel B: Cross-Sectional Volatility Spillover Effects

	Entire sample period ($g_{i,j}$) To Insurers in			Changes during the crisis ($z_{i,j}$) To Insurers in		
From US	EU	Japan	UK	EU	Japan	UK
Banks				0.006		
z-Stat.				*2.045*		
	From Insurers in			From Insurers in		
To US	EU	Japan	UK	EU	Japan	UK
Banks					0.017	
z-Stat.					*2.474*	

Note: The shadings in the above table means the financial sector portfolio is not available within the corresponding national market. The magnitude of spillover effect over the entire sample period is represented by the estimated parameter $\gamma_{i,j}$ and $g_{i,j}$ for the return and volatility spillovers, respectively. The changes in spillover effect during the crisis period is represented by the estimated parameter $\theta_{i,j}$ and $z_{i,j}$ for the return and volatility spillovers, respectively. The magnitude of spillover effect during the crisis period is the sum of the spillover effect over the entire sample period ($\gamma_{i,j}$ or $g_{i,j}$) and the changes in spillover effect during the crisis period ($\theta_{i,j}$ or $z_{i,j}$).

The finding provides some interesting insights about the interactions between US banks and insurers from other markets. First, the result suggests that insurers from other markets and US banking sector share similar risk factor as the return of US banks do have influential power over the return of insurance companies in the other markets. The risk is the fluctuation of financial asset price. Both banks and insurers are major institutional investors in the financial markets. Therefore, they will both be influenced by the changes in financial asset price due to fair accounting standard. Since US financial market is the main information provider in terms of price innovations (Eun and Shim, 1989), the return performance of US financial institutions should have a positive impact on the financial institutions in other markets. In addition, as discussed in the above section, the nature of this risk factor does not change during the crisis period. Therefore, there is no change in return spillover effects from US banks towards insurers in other markets during the crisis period.

Second, the return and risk performances of US banks are only influenced by insurers from other markets during the crisis period but not before. That means these insurance companies also share some kind of risk factor with US banks which is only observable during the financial crisis. We argue this risk factor is the sharp decrease in the demand and value of the structured financial products. Insurance companies also issue insurance related structured financial products such as insurance-linked securities (ILS).[86] Cummins and Trainar (2009) argue that insurance related structured products helps insurer to reduce insurance risk exposure by passing the risk to boarder capital markets. Therefore, the cost of capital will be more economical. Since late 1990s, the insurance securitization market grows rapidly from less than USD 2 billion in 1998 to nearly USD 23

[86] For further discussion on the development of structured products issued by the insurance companies, please refer to the *Securitization – New Opportunity for Insurers and Investors* (2006) by Swiss Re, which is available to general public via Swiss Re's website: http://www.swissre.com/r/sigma7_2006_en.pdf.

billion in 2006.[87] The structured financial product market credit risk starts to during the crisis period and takes its toll on financial institutions which generate profits from producing and distributing these products. That is why US banks are barely influenced by the return or volatility innovations generated from these insurance sectors before the financial crisis.

Finally, the volatility spillover effect from US banks to insurers in other markets is negligible over the sample period. The empirical result is well expected as banks and insurers have totally different business models and core risk factors. Insurance companies mainly expose to insurance risk within their home country as they mainly operate in their home market, while banks have no insurance risk exposure embedded in its business model. Furthermore, insurance companies mainly rely on insurance premiums for liquidity instead of interbank funding market (Eling and Schmeiser, 2010), which makes them less risky over the crisis period compare to banks. Therefore, it is reasonable that the volatility innovation of US banking portfolio have no influential power over the volatility of insurance portfolios from other markets.

2.5.5. *Test 3: Interdependence between Global Banking and Insurance Portfolios*

In order to investigate the return and risk interdependence between the global banking and global insurance industry during the current financial crisis, we perform another test based on global banking and global insurance portfolios. Our motivation comes from the studies examining the performance of insurance companies during the recent financial crisis (Eling and Schmeiser, 2010; Harrington, 2009). These studies show that insurance companies perform relative well compare to banks during the recent financial crisis as

[87] The data for insurance securitization market is collected from the report named *The Essential Guide to Reinsurance (2010)* by Swiss Re, which is available on Swiss Re's website: www.swissre.com.

they were well funded, and less involved in the risky structured financial products compare to banks. The report from The Geneva Association[88] also confirms that most of the insurers were able to absorb the losses within their own balance sheets during the crisis, but banks struggled with funding. This argument is further supported by the report from the US treasury,[89] which shows that around US 600 banks have been rescued by the TARP[90] program while only three insurance companies need the funding from the central government. Therefore, according to "flight-to-quality", investors should prefer insurance sector over banking sector during the crisis period. In other words, insurers should benefit from the bad return performance of banks during the crisis period.

The idea of "flight-to-quality" is first proposed by Lang and Nakamura (1995). They argued that investors' risk aversion increased dramatically during the crisis period. Instead of following the "rumor" to adjust their portfolios irrationally, investors sell off risky assets and invest the proceedings into high quality asset. Caramazza et al (2004) provide the empirical evidence for the existence of "flight-to-quality" during the three previous crises episodes.[91]

Due to the lack of direct information on the investment flows between the two global financial sectors, we investigate the existence of "flight-to-quality" though the return spillover effects between the two sectors.[92] The global sector portfolios used in this test

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[88] The report is under the title of *Systemic Risk in Insurance, An analysis of insurance and financial stability*, which is available to general public via its website: www.genevaassociation.org.

[89] A series of special reports is been conducted by the US Department of Treasury under the title of *Financial Stability Transactions Report.* The article quoted here is for the period ending July 2009, which is available to general public via its website: http://www.financialstability.gov.

[90] TRAP refers to the Troubled Asset Relief Program provided by the US central government.

[91] The three crises episodes are the 1987 US crisis, 1994 Mexican crisis and 1997 Asian crisis.

[92] "Flight-to-quality" refers to the phenomenon that investors prefer high risk quality asset over low risk quality asset by shifting their investments from the latter to the former. Therefore, the ideal dataset for the investigation of "flight-to-quality" would be the information about the investment flow going in and out of the two assets.

include the corresponding financial institutions from all the markets. The estimation result is represented in Table 2.11.

Table 2.11 Return and Volatility Spillovers between the Global Banking Sector and the Global Insurance Sector.

The following tables summarize the estimation output of the VAR-BEKK models. The estimated coefficients from the model have been categorized into three sub-tables: i) Macroeconomic Factors and GARCH Effects, ii) Return Spillover Effects and iii) Volatility Spillover Effects.

The following table summarizes the estimated coefficients for all the estimated parameters in the mean and variance equations of the VAR-BEKK model:

Mean Equation: $r_{i,t} = \beta_i + \sum \beta_{i,x} RiskFactor(X)_{i,t} + \sum \gamma_{i,j} r_{j,t} + D \sum \theta_{i,j,} r_{j,t} + \varepsilon_{j,t}$

$\varepsilon_{i,t} \sim N(0, h_{ii,t})$, with $i, j \in [EU, JP, UK, US]$, $i \neq j$.

Variance Equation: $h_{i,t} = c_i + a_i^2 \varepsilon^2{}_{i,t-1} + b_i^2 h_{i,t-1} + \sum g_{i,j} h_{j,t-1} h + D \sum z_{i,j} h_{j,t-1}$

$h_{i,j,t} = c_{i,j} + a_i \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_j + b_i h_{i,j,t-1} b_j$, with i and $j \in [EU, JP, UK, US]$, $i \neq j$.

where,

$r_{i,t}$ = the return for financial sector portfolio *i* over day *t*.

RF(X) = the three macroeconomic risk factors for market *i* over the day *t*. $X \in$ [*MKT, FX, IR*] which represents the market, foreign exchange rate, and interest rate risk factor, respectively.

$\beta_{i,x}$ = the coefficient that represents the sensitivity of corresponding risk factor *RF(X)* for financial sector portfolio *i*.

$\gamma_{i,j}$= the coefficient for cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$\theta_{i,j}$= the coefficient for the changes in the magnitude of the cross-sectional return spillover effect from financial sector portfolio *j* to portfolio *i* during the crisis period.

a_i and b_i = the coefficients that represent the ARCH and GARCH effect of the conditional variance equation for financial sector portfolio *i*.

$g_{i,j}$ = the parameter represents the cross-sectional volatility spillover effects from financial sector portfolio *j* to portfolio *i* over the entire sample period.

$z_{i,j}$ = the parameter represents the changes in the magnitude of cross-sectional spillover effects from financial sector portfolio *j* to portfolio *i* during the financial crises.

$h_{ii,t}$ = the conditional variance of financial sector portfolio *i* over day *t*.

$\varepsilon_{i,t}$ = the residuals from the mean equation of financial sector portfolio *i* over day *t*.

D = the dummy variable represents the crisis period. *D = 1* from *April 2, 2007 to March 9, 2009*, and *D = 0* for elsewhere.

National Markets	**Global-Bank**			**Global-Insurance**		
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**	
Macroeconomic Factors						
Market ($\beta_{i,MKT}$)	**0.605**	**36.863**	***	**0.725**	**38.780**	***
FX ($\beta_{i,FX}$)	**-0.017**	**-0.171**		**0.090**	**0.684**	
IR ($\beta_{i,IR}$)	**0.015**	**1.635**		**0.039**	**3.319**	***
GARCH Effects						
ARCH (a_{ii}^2)	**0.097**	**9.758**	***	**0.069**	**8.751**	***
GARCH (b_{ii}^2)	**0.886**	**106.810**	***	**0.916**	**135.070**	***
Persistence	**0.983**			**0.985**		
Log-Likelihood	**11642.0**					
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Sectional Return Spillover						
Cross-Return 1 (γ_{i1})	**0.038**	**1.825**	*	**-0.001**	**-0.043**	
Change in Cross-Return 1 (θ_{i1})	**0.103**	**3.240**	***	**-0.126**	**-3.242**	***
	Coeff.	**Z-stat.**		**Coeff.**	**Z-stat.**	
Cross-Sectional Volatility Spillover						
Cross-Volatility 1 (g_{i1})	**0.015**	**4.484**	***	**0.019**	**3.368**	***
Change in Cross-Volatility 1 (z_{i1})	**0.000**	**-0.891**		**0.015**	**1.361**	

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. The magnitude of the cross-sectional return spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $\gamma_{i,j}$) and the change in spillover effect over the crisis period (represented by $\theta_{i,j}$).The magnitude of the cross-sectional volatility spillover effect over the crisis period is the sum of the spillover effect over the entire sample period (represented by $g_{i,j}$) and the change in spillover effect over the crisis period (represented by $z_{i,j}$).

From the above table, one can see that during the crisis period, the return transmission from the global banking sector portfolio towards the global insurance sector portfolio is significant but negative. The return spillover from global banking portfolio to global insurance portfolio has decreased from zero to -0.126 over the crisis period, while the return spillover effect from global insurance portfolio to global banking portfolio have increased from 0.038 to 0.141 during the crisis period.[93]

Since the mean returns of both the banking and insurance sectors are negative during the crisis period from Table 2.2 Panel C, the negative return spillover from global banking portfolio to global insurance portfolio indicates the insurers enjoy a competitive advantage over the banks on a global level. Therefore, the empirical evidence proves the existence of "flight-to-quality" between the global banking and insurance portfolios during the recent financial crisis. In other words, the investors did shift their investments away from the risky banking sectors into the insurance sectors which were less risky in terms of liquidity and funding risk during the crisis period.

However, from Test 2, we find no competitive effect between US banks and insurers from other markets. That means the competitive effect is not because of the relative better return performances of insurance portfolios from other markets against banks in US market. Combining the result from Test 2 and Test 3, we argue that the competitive effect between the global banking and insurance portfolios during the crisis period is mainly coming from the relative higher return of insurers against banks within each market, but not against banks from another market.

[93] The return spillover effect from global insurance to global banking portfolio over the crisis period is equal to the sum of return spillover during the entire sample period (0.038) plus the changes in spillover effect over the crisis period (0.103), which is 0.141. However, it is worth mentioning that the return spillover from global insurance portfolio to global banking portfolio is only statistically significant at 10% confidence level. In other words, if one choose a more conservative confidence level, there will be no return spillover from global insurance portfolio to global banking portfolio, which is consistent with the finding from Test 2.

In addition, there is a bidirectional volatility spillover effect between the global banking and global insurance portfolio over the entire sample period. The magnitude of the volatility spillover effect from global banking to global insurance portfolio is 0.019, while the spillover effect for the opposite direction is 0.015. Since we do not find any significant volatility spillover effects estimated over the entire sample period in Test 2, once again we argue this bidirectional volatility spillovers is mainly coming from the risk interdependence between banks and insurers within the sample market. The magnitude of this bidirectional volatility spillover effect has not increased during the crisis period.

2.6. CONCLUSION

The current study investigates the interdependencies among the banking and insurance industries by examining the interactions among banks/insurers between the EU, Japanese, U.K. and U.S. markets. Transmissions of shocks in returns and in volatility are both considered. We also look at the potential changes in the magnitude of these cross-sectional return and volatility transmissions during the recent financial market turmoil (2007-2009), to shed some light on the impact of the crisis on global financial dynamics.

In general, the empirical evidence shows return contagion among the banking industries of the EU, U.K. and U.S. markets, especially during the crisis period. This calls for regulatory attention in designing a coordinated regulatory landscape as well as the need for co-ordination of monetary policy across the industrialized world. As an exception, the connections between the banking sectors in the Japanese and the U.S. markets seem to be weak as no return spillover is recorded between these two markets even during the crisis period. One source of dissimilarity in effects across different regional banking markets is their structural differences. To elaborate, since U.S. is a market-oriented economy while Japan is a bank-oriented economy, banks in these two countries are operating in different environments and consequently have different attitudes towards competition and risk taking. Our findings also document the prominence of the U.S. banking sector as the main origin of volatility information to its EU, Japanese and U.K. counterparts demonstrating its continuing leadership role in global financial markets.

For the insurance sectors, once again the EU, U.K. and U.S. markets show a strong linkage with one another. Positive and significant return spillovers are registered on the EU and U.K. markets while the effects on U.S. and Japan are more limited. Unlike banks, the magnitudes of the return spillovers across insurance markets remain unaltered during the crisis period, perhaps because the risk factors faced by the insurers were not affected by the turmoil. However, volatility spillovers to the U.S. and EU insurance sectors do intensify during the crisis period raising concerns about contribution of the insurance sector to systemic risk. The U.S. insurance sector receives contagion type volatility spillovers from the U.K. and the EU insurance markets with the former intensifying during the crisis. The increase in default probability due to the sharp decrease in asset values could be the reason behind the stronger volatility linkage across the insurance portfolios during the crisis. As an exception, Japanese insurers appear to be mostly insulated from shocks originating in other markets even during the crisis, reflecting the segmented nature of the Japanese markets.

In regards to interdependence among banks and insurers at a global level, we show risk and return interdependence between the U.S. banking sector and insurers within the EU and U.K. markets during the crisis period. The same phenomenon is registered for the aggregated banking and insurance portfolios. This finding is in line with the current trend of integration between the two financial intermediary types over the last two decades.

There is also evidence of contagious volatility transmission between the two industries. The spillover in returns, mostly evident during the crisis, is of a competitive nature and favors the insurance industry in the sense that when banks suffer, insurers benefit by attracting their customers ('flight-to-quality' effect). Industrial reports and empirical studies on the general performance of the global banking and insurance sectors also confirm our empirical results.[94] Our findings highlight the importance of monitoring and managing the contagion effects at the international level and the need to design an appropriate regulatory framework to curb it. Further globalization of financial markets, advancement of technology and the consolidation trend among "Systemically Important Financial Institutions" intensify this necessity.

[94] For industrial reports, please refer to report *Systemic Risk in Insurance, An analysis of insurance and financial stability* (2010) by from Geneva Association, and the report *Eight Key Messages on the Financial Turmoil* (2008) by CEA among others. Both reports claim that insurance companies are less exposed to the credit risk and liquidity risk compares to banks, and the insurance industry is less involved in the mortgage related security market. For empirical studies, please refer to Cummins and Phillips (2008), Harrington (2009) and Eling and Schmeiser (2010) among others.

Chapter 3

The Evolution of Term Structure and the Return Sensitivity of Financial and Non-Financial Institutions

3.1. Introduction

In this chapter, we investigate the relationship between changes in the term structure and the equity value of financial (banks and insurers) and non-financial institutions across major economies from 2003 to 2010. The sensitivity of equity value for financial and non-financial institutions upon changes in the term structure has been scrutinized by both academics and practitioners since early 1970s, when Merton (1973) and Long (1974) provide the first insight about the potential relationship between the two. Comparatively, the interest rate risk of financial institutions has received more attention, especially from a regulatory perspective. The capital adequacy of financial institutions plays a vital role in the stability of the financial system (Basel Committee, 2004) since the failure of financial institutions (*e.g.* banks) has a significant negative impact on the economic development (Staikouras, 2006b). IFRI-CRO (2007) classifies interest rate risk as the most significant source of market risks for banks; while Drehmann et al (2010) show that the interaction between interest rate risk and credit risk is important for the overall assessment of the bank's capital adequacy. Despite the less economic significance and smaller impact (Saunders and Yourougou, 1990),[95] the interest rate fluctuation can still influence the equity value of industrial firms through its impact on the inflation expectations and real interest rates (Sweeney and Warga, 1986).

[95] Saunders and Yourougou (1990) argue that securities which are claim on real assets (*e.g.* non-financial institution stocks) have lower sensitivity upon changes in nominal interest rates.

The current study contributes to the existing literature in four ways. First, we shed light on how the recent financial turmoil influences the yield curve exposure of financial intermediaries.[96] Second, we use the first order difference in the Nelson-Siegel (1987) (hereafter NS) *level*, *slope* and *curvature* factor to measure changes in the yield curve.[97] Third, we propose a different empirical framework, namely the VAR-BEKK multivariate-GARCH (*hereafter* MGARCH) model, to investigate whether the financial intermediaries are rewarded by exposing to yield curve changes. The proposed VAR-BEKK model not only resolves the issue of heteroskedasticity, while maintain the desire feature of investigating multiple assets simultaneously, but also takes into account the time-varying conditional correlations among assets (Engle and Kroner, 1995). The latter is often ignored by previous studies (*i.e.* the constant conditional correlation MGARCH model in Elaysiani et al., 2007), which reduces estimation efficiency. Finally, previous studies on the interest rate risk of financial intermediaries focus either on one type of institution (Flannery and James, 1984; Viale et al., 2009) or on a single market (Dinenis and Sotiris, 1998; Elyasiani et al., 2007). The current study fills this gap by using a global dataset with both banking and insurance (life/non-life) firms across major market-oriented (the U.S./UK) and bank-oriented (Japan) financial systems.

There are five main findings in this empirical chapter. First, the equity value of banks is positively related to changes in long-term interest rates while negatively related to short-term rate fluctuations over the pre-crisis period. This finding suggests that changes in term structure influence the equity value of banks through their impact on the profitability of the banking sector. Second, the relationship between long-term rates and

[96] The most recent empirical study on interest rate risk of financial institutions (English et al., 2012) employs a sample period from July 1997 to June 2007, which failed to cover the recent economic downturn (*i.e.* the 2007-08 financial crisis) which started in the late 2007.
[97] We will discuss the technical aspects of the NS model in the methodology section.

the equity value of banks has increased during the crisis period, which may attribute to the "flight to quality" hypothesis. Third, insurance firms show similar interest rate risk patterns as banks suggesting that the two financial intermediary share similar risk exposures over the sample period. Fourth, industrial firms' exposure to yield curve changes in a similar fashion as banks. Finally, the results show that market interventions (*e.g.* government bailouts and stimulus packages) have a significant impact on the equity value of both financial and non-financial institutions during the recent financial turmoil.

The empirical findings of this chapter could potentially have important implications on the asset pricing, risk management and regulation. First, banks/insurers hold asset/liability across various maturities. Therefore, the asset pricing model for financial intermediaries should take changes in the entire yield curve into account, instead of changes in interest rate/term spread with fixed maturity (Flannery and James, 1984; Bae, 1990; Viale et al., 2009). Second, being able to precisely identify yield curve exposures is crucial for any interest rate hedging/mitigating strategies, which in turn can improve the effectiveness of financial institutions' risk management. Finally, Adrian and Shin (2008) show that monetary policy is an important determinant of financial intermediaries' balance sheet size. The latter is further signalling the future real activity. Thus, the monetary policy and financial stability policy are closely related. A better understanding of the relationship between the shape of yield curve and financial intermediaries' equity value/profitability is, therefore, vital for designing effective monetary/financial stability policies.

The remainder of the chapter is organized as follow. The following section provides a brief literature review on the interest rate risk of financial and non-financial institutions. Section 3.3 presents the dataset employed in the current study. Section 3.4 illustrates the technical detail of the proposed VAR-BEKK empirical framework. Section 3.5 discusses the result of our empirical study. Finally, section 3.6 concludes the study.

3.2. LITERATURE REVIEW

This section provides a brief review on the interest rate risk of financial and non-financial institutions with no intention to lessen the importance of any excluded studies. The literature is categorized based on whether it focuses on the importance of interest rate risk for financial institutions, the interest rate exposure of industrial firms, and the estimation framework for interest rate risk.

3.2.1. Interest Rate Risk of Financial Institutions and its Importance

Interest rate risk is the most significant source of market risk for banks (IFRI-CRO, 2007). Furthermore, Jarrow and Turnbull (2000) suggest that credit risk exposure and interest rate risk exposure is intrinsically related. That means changes in interest rate can also influence the bank's exposure on credit risk. Based on the result of a hypothetical stress test on banks, Drehmann et al (2010) show that the interaction between interest rate risk and credit risk is important for the overall assessment of the bank's capital adequacy. They reveal that interest rates are an important determinant of defaults which will further influence the net interest income of the bank.

In addition, the liquidity condition in the financial market is also driven by the perceptions of credit and interest rate risks (Basel Committee, 2009). The fluctuation of interest rates will influence the credit risk of financial assets, which has an impact on investor's appetite for these assets.[98] An increase in asset's credit risk will reduce its

[98] For further discussion on changes in investors' risk appetite during the recent financial turmoil, please refer to Gonzalez-Hermosillo (2008).

market liquidity and value as investors pull their investments away and demand higher premiums. Therefore, financial products with higher credit risk (*e.g.* CDOs), *inters alia*, suffer from greater losses when market liquidity deteriorates. Furthermore, for institutional investors (*e.g.* banks) the perceived losses due to credit risk will be rapidly priced in through the fair-value accounting, which has an instant impact on the equity value and the capital adequacy of these institutions.

Based on the aforementioned studies, the credit, interest rate and liquidity risks are three highly integrated and important sources of risk for the capital adequacy of banks. Besides, both the credit and liquidity risk exposures seem to be driven by the fluctuation of interest rates. Therefore, the relationship between changes in the interest rate or its term structure and performances of financial institutions has great importance from a regulatory perspective (Drehmann et al, 2010).[99]

According to the maturity model, changes in term structure (*e.g.* parallel shifts or "twists") can influence the economic value of financial institution's assets and liabilities, which will have an further impact on its equity value (Saunders and Cornett, 2010). The maturity model (also known as duration mismatch/gap) was first proposed by Grove (1974) based on the Hicks-Samuelson Duration Theorem (Hicks, 1946; Samuelson, 1945). The maturity model argues that due to the maturity (or duration) mismatch of asset and liability, changes in interest rates have different impact on financial institution's asset and liability position. According to the duration theory, securities with longer duration have higher sensitivity upon changes in interest rates. A financial institution with positive duration mismatch (*i.e.* the average duration of asset is longer than the one of liability), therefore, has a negative relationship with changes in the yield curve.

[99] According to regulators, the capital adequacy of financial institutions matters most (Basel Committee, 2004).

Alternatively, changes in the term structure can also influence the equity value of a financial institution by affecting its profitability. For instance, the net profit margin of banks is sensitive to interest rate fluctuations as they increasingly rely on short-term liabilities and long-term investments (Ho and Saunders, 1981). The changes in the long-term and short-term interest rate (*i.e.* fluctuations in the term structure), therefore, will directly influence the profitability of bank through altering its net interest margin. According to the profitability argument, increase (decrease) in long-term (short-term) interest rate will benefit banks in terms of enhancing their profitability (*i.e.* higher net interest margin). This earning perspective is a traditional approach for interest rate risk analysis for many banks, as fluctuations in earnings can threaten the stability of an institution by reduces capital adequacy and market confidence (Basel Committee on Banking Supervision, 2003).

Empirically, Flannery (1983) is among the first empirical studies to investigate the net interest rate margin of the U.S. commercial banks from 1960 through 1978, and finds no significant relationship between the interest rate changes and the profitability of banks. The following study by Flannery and James (1984), however, find significant and negative relationship between the equity value of U.S. banking institutions and changes in interest rates over the period from 1976 to 1981.[100] Recently, Elyasiani et al (2007), Carson et al (2008) and Viale et al (2009) have examined the interest rate risk factors of financial institutions within the U.S. market with updated sample sets. Elyasinai et al (2007) show that apart from large insurance companies, the equity value of U.S. financial institutions is not sensitive to changes in the long-term (*i.e.* the 10-year U.S. Treasury bond) yield from

[100] In interest rate risk factor used in Flannery and James (1984) is the holding period return of a bond index with certain maturity. The empirical result indicates that holding period return of a bond index is positively related to changes in bank equity return, which indicates that the equity value of banks has a negative relationship with interest rate changes.

1991 to 2001. They argue that result is mainly due to the duration mismatch of the asset and liability hold by the large U.S. insurers. This finding is supported by Carson et al (2008), which focus solely on the U.S. insurance industry with a sample period span from 1991 to 2001. They also find negative relationship between the insurance firms (life, accident & health, and property & casualty) and changes in long-term (10-year) government bond yields. Viale et al (2009) investigate the bank stock return and changes in the term spread (*i.e.* the yield difference between the government bond with maturity >25 years and one-month) from 1986 through 2003. The empirical findings suggest that fluctuations in term spread significantly influence the bank's equity value but the impact is different for banks with different sizes. They argue that large (small) banks are negatively (positively) related to changes in the term spread due to positive (negative) duration mismatch.

The interest rate exposure of German and Japanese financial institutions have been covered by Czaja et al (2009) and Oyama and Shiratori (2001), respectively. The former shows that the equity return of German banks are negatively related to changes in long-term and medium-term rates while the short-term rate changes have a minimal impact from 1974 to 2002. The latter shows that changes in the short-term rate have no impact on the profitability of Japanese banking sector in the 1980s and 1990s.

On a global scale, Elyasiani and Mansur (2003) and English (2002) investigate the interest rate risk of large banking portfolios across different markets. Elyasiani and Mansur (2003) assess the equity return sensitivity of the U.S., German and Japanese banks upon changes in long-term bond yields from 1986 to 1995, and find no significant relationship between the two. English (2002) shows that profitability of banks from the G-

8 countries is not strongly related to changes in the yield curve from 1979 to 1999[101] apart from the U.S. market, where net interest margin of banks is positively related to steepening yield curve (*i.e.* widening term spread). He argues that the lack of relationship in the European countries is mainly due to the increasing competition within the European banking sector during the sample period.

3.2.2. Interest Rate Risk of Non-Financial Institutions

Previous empirical studies suggest that non-financial institutions also expose to interest rate fluctuations. Financial theory suggests that changes in macroeconomic factors should have a systemic influence on the return of stock market. Among various macroeconomic factors, Chen et al (1986) show that changes in the term structure (*e.g.* "twist" in the yield curve) and unexpected changes in inflation will have a significant impact on the stock market return. They argue that changes in term structure affect the discount rate for financial assets, which have a direct impact on the valuation of these assets. The unexpected change in inflation (usually represented by changes in long-term interest rate[102]), on the other hand, will affect the performance of the stock market through its influence on the nominal expected cash flows.

Early studies on industrial firms, however, show mixed result. For instance, Sweeney and Warga (1986) investigate the interest rate risk of the U.S. sector portfolio from 1960 to 1979. They find the sensitivity of utility firm's equity value on changes in interest rate is much higher than the average.[103] They claim that the negative relationship

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[101] The G-8 refers to U.S., Canada, the UK, Germany, Sweden, Japan, Australia, Switzerland, Italy and Norway.

[102] Please see Sweeney and Wara (1986) and Bartram (2002), among others, also argue that changes in long-term interest rates are a measure of unexpected changes in inflation.

[103] There are three alternative interest rate measures used in Sweeney and Warga (1986), which are the 20-year government bond yield, 3-month Treasury bill yield and a set of indices approximating the shape of yield curve.

between the interest rate changes and utility firms is mainly through three channels: a) inflation channel, b) real interest-rate changes, and c) mismeasurement in the market index. The first channel mainly refers to the "regulatory lag" effect, which means the regulated industries (i.e. utility firms) cannot adjust the price of their services in a quick manner under sudden increase in inflation. The second channel suggests that the value of stock will change given fluctuations in interest rates based on the dividend discount model. The final channel claims that the significant interest rate risk of utility firms might due to their sensitivity to the lack of an interest rate component in the market return used in their model. Contrary to the previous findings, Yourougou (1990), however, finds no interest rate sensitivity for industrial firms in the U.S. market from 1977 to 1981. He argues that the lack of significant interest rate beta is mainly due to the low sensitivity of interest rate risk for the industrial firms. This finding is supported by Bae (1990).

Recently, Bartram (2002) examines the interest rate exposure for German non-financial institutions from 1987 to 1995. The empirical findings suggest that German industrial firms expose to changes in long-term rates, short-term rates as well as the term spread. The author argues that the liquidity condition of the firms is the main driving force behind the interest rate risk. Besides, a large number of firms show non-linear relationship with the interest rate changes (i.e. positive and negative interest rate shocks have different impact), which the author claims is attributed to the non-linear payout of hedging activities. The interest rate risk exposure of the UK institutions has been revealed by Staikouras (2005). By investigating the equity return sensitivity of both financial and non-financial institutions upon changes in the short-term interest rate from 1989 to 2000, the finding shows that the non-financial institutions are significantly influenced by changes in interest rates. Additionally, the author claims that the impact of interest rate fluctuation on the equity value is opposite for financial and non-financial institutions.

With a multinational dataset covering financial and non-financial institutions across major European countries (*i.e.* France, Germany, Switzerland, and the U.K.) from 1982 through 1995, Oertmann et al (2000) claim that industrial as well as financial firms are negatively related to changes in domestic long-term interest rates. The magnitude of the interest rate effect of financial institutions, however, is comparatively higher than industrial ones. However, given the orthogonalization process of the explanatory variables used in their study,[104] the authors claim that the significant impact of interest rate changes on industrial firm value is mainly due to its influence through market return. In order words, interest rate changes first affect the stock market, while the changes in the stock market further influence the equity value of industrial firms.

3.2.3. Estimation Framework of Interest Rate Risk

Conventional studies (*e.g.* Lloyd and Shick, 1977; Flannery and James, 1984; Choi et al, 1992; Tai, 2000) usually use the unexpected changes in a given bond index or interest rates based on a given maturity to evaluate the interest rate sensitivity of financial institutions. However, by measuring yield effects through interest rates with certain maturity cannot reveal the changes in the slope of the term structure or the effect of "twist" (Staikouras, 2003). Other studies try to involve interest rates with multiple maturities (*e.g.* Lynge and Zumwalt, 1980), or short-term rates plus term spreads (*e.g.* English, 2002; Viale et al, 2009) into the asset pricing model to tickle the issue of twist in the yield curve[105]. However, they

[104] The finding is based on the following orthogonalization ordering: domestic interest rate changes are defined as the prime risk factor prior to the international interest rate and domestic market return.

[105] In English (2002), the term spread is defined as the difference between the yield on 10-year government securities and three-month government bills. In Viale et al (2009), the term spread is defined as the

failed to recognize the potential relationship between interest rates with different maturities and the term spread. Bliss (1997) shows the long-term and short-term interest rates are highly related.[106] Therefore, by involving these interest rate measures into the pricing model without orthogonalization may introduce biasness into the parameter estimation due to multicollinearity.

Czaja et al (2009), to our knowledge, is the only existing study investigates the interest rate exposure of financial institutions based on the three factors estimated from the NS model. However, since their study is solely focused on the German financial market from 1974 to 2002, they failed to capture the interest rate sensitivity of financial institutions during the recent financial turmoil. The latest study by English et al (2011) investigates the relationship between "slope surprise" of the yield curve and the banks equity value from July 1997 till June 2007.[107] But their sample period fails to capture the full impact of the recent financial turmoil. McAndrews (2009) shows that the deterioration of liquidity condition in major financial markets (*e.g.* the UK, the U.S. and European countries) accelerated after the freeze of redemptions for three investment funds by BNP Paribas on the *August 9, 2007* as the level and volatility of overnight interbank borrowing rates within these markets increased dramatically. The sudden increase in short-term interest rate following the BNP Paribas event and its impact on financial institutions' interest risk exposure, therefore, is ignored by Czaja et al (2009). In the current study we extend the sample period to early 2010, which allow us to investigate the full impact of the

difference between the yield on a portfolio of long-term government bonds with more than 25 years maturity and the one-month Treasury bill.

[106] In his study, he claims that the level, slope and curvature factor in the three factor model proposed by Litterman and Scheinkman (1991) are highly interdependent. Since the level, slope and curvature factor represents the yield with long-term, short-term and medium-term maturity, the result indicates that the changes of yields with different maturities are related.

[107] The slope surprise is defined as the difference between a medium (*e.g.* 2- and 5-year) or long-term (*e.g.* 10-year) Treasury yield and the federal fund rates.

recent financial turmoil on the interest rate risk exposure of financial and non-financial institutions.

Additionally, early studies on interest rate risk usually base their empirical framework on simple regression (*e.g.* OLS) model.[108] The simple OLS model is easy to implement but can only estimate the risk exposure of an individual or a group of similar assets/firms at a time. Recently, Scott and Peterson (1986), Yourougou (1990) and Staikouras (2005) adopt a multivariate estimation framework based on seemingly unrelated regression estimation (SURE) model to investigate the interest rate risk of financial institutions. The SURE model not only can evaluate the risk exposure of multiple firms/groups of firms simultaneously to increase the estimation efficiency but also takes the potential correlation across the firms/groups of firms into account. However, the SURE model ignores the time-varying nature of the variance-covariance information across the firms/groups of firms, which could reduce the estimation efficiency of the model. In the current study, we propose our own VAR-BEKK model to resolve the issue of heteroscedasticity while maintain the desired feature of a multivariate framework that enables us to estimate the interest rate risk of multiple asset series simultaneously.

3.3. DATA

The current study investigates the relationship between the changes in the term structure of interest rates and the equity value of financial (banks and insurers) and non-financial institutions across the U.S., the UK and Japanese markets. We focus on these three countries as they are the dominate force in the global financial market. According to International Monetary Fund (IMF), 69% of the total global financial assets are managed

[108] Please refer to Staikouras (2003) for a detailed review of empirical studies on interest rate risk of financial institutions.

by financial institutions from these three countries in 2009.[109] Besides, the three countries contribute more than 36% of the global GDP and total bank assets, and around 45% of the total stock market capitalization in 2009.[110] The following table summarizes the number of institutions selected under each category across the three markets.

Table 3.1 Number of Financial and Non-Financial Institutions across Markets

The table below summarizes the number of institutions within the sector portfolios across the three markets. Size portfolios have been formed for financial and non-financial sector according to their capital value (financial institutions) and market capitalization (non-financial institutions).

Institutions	U.S.	UK	Japan
Systemic Important Financial Institutions	8	4	3
Medium Banks (U.S.)/Regional Bank (Japan)	28	-	54
Small Banks (U.S.) /Secondary Bank (Japan)	29	-	26
Large Insurers	11	6	5
Small Insurers	64	25	4
Large Industrial Firms	26	26	24
Small Industrial Firms	96	65	175

From Table 3.1, one can see that the financial and non-financial institutions have been divided into sub-groups according to their size. The size effect of risk factors among financial and non-financial institutions due to difference in hedge incentive and/or operation structure has been discussed extensively in the previous literatures (Graddy and Karna, 1984; Jorion, 1990; Nance et al, 1993). Therefore, by categorizing institutions into size groups enables us to investigate the potential size effect in interest rate risk across different types of institutions.

For the banking sector, institutions categorized as SIFI (*i.e.* systemically important financial institutions) are selected according to the announcement made by Financial

[109] The information is collected from the IMF report "*Global Financial Stability Report*" (*hereafter* GFSR) issued in September 2011. The data on assets of institutional investors by country is obtained from the *Figure 2.2* within the GFSR 2011, see: http://www.imf.org/External/Pubs/FT/GFSR/2011/02/c2/figure2_2.csv.

[110] The information is collected from the GFSR issued in October 2010. The data presented in the current study is obtained from the *Table 3. Selected Indicators on the Size of the Capital Markets* within the GFSR 2010, see: http://www.imf.org/External/Pubs/FT/GFSR/2010/02/pdf/statappx.pdf.

Stability Board (FSB).[111] We isolate the SIFIs as one sub-group as they are important to the stability of the financial markets. According to FSB, the failure of these SIFIs will incur significant disruption into the wider financial system and economic activities, which has deleterious consequences for both private and public interests. Therefore, a better understanding of the equity return sensitivity of these SIFIs to changes in yield curves has great value from a regulative perspective. In the FSB announcement 29 bank holding companies have been identified as global SIFIs due to their importance to the stability of the global financial market, out of which 15 are based in the U.S., the UK and Japanese markets.[112] It is worth mentioning that since all the four listed banks in the UK market are identified as SIFIs, there is only one sub-group for the UK banking sector.

The medium and small banks for the U.S. market are selected according to their asset value. We define medium banks according to the bank holding corporations (BHC) ranking provided by the Federal Deposit Insurance Corporation (FDIC).[113] The top 50 BHCs which are not identified as SIFI are categorized as medium banks in the current study.[114] We use the remaining banks listed on the New York Stock Exchange (*i.e.* the ones are not identified as SIFI and/or medium banks) as small banks. The medium and small banks in Japanese market are selected according to the according to the institution classification provided by the Japanese Bankers Association (JBA). According to JBA, Japanese banks are categorized into three groups according to their business functions,

[111] The list of SIFIs is reported in the FSB announcement "*Policy Measures to Address Systemically Important Financial Institutions*" on *November 4, 2011*, see: http://www.financialstabilityboard.org/publications/r_111104bb.pdf. The FSB was established in April 2009 as the successor to the Financial Stability Forum (FSF). The FSF was founded in 1999 by the G7 Finance Ministers and Central Bank Governors following recommendations by Hans Tietmeyer, President of the Deutsche Bundesbank.
[112] The selected SIFIs are listed in Appendix B.1.
[113] The ranking of the U.S. BHCs is based on the bank's total assets. The ranking is available from the Federal Deposit Insurance Corporation, which can be found as follow: http://www.fdic.gov/bank/statistical/. The ranking used in the current study is updated on the 31 December 2010.
[114] The selected banks have to be listed on stock exchange within the U.S. market.

namely the city banks, regional banks and secondary banks.[115] We specify the regional and secondary banks which are listed on the Tokyo Stock Exchange as medium and small banks for Japanese market, respectively. It is worth noticing that banks under the city bank classification of JBA are also SIFIs according to FSB.[116]

Given the comparatively small sample size of the insurance firms across the three markets, only two size groups have been specified for insurance companies, namely large and small size insurers. It is worth noticing that the insurance sector SIFIs have not been officially identified yet.[117] In the current study, we try to match the systemic importance of large insurers and banking sector SIFIs by matching their relative size. We define large and small insurers in a three-step process. First, we collect all the insurance companies listed on the respective main stock exchange for each market.[118] Second, we choose institutions whose asset value is greater than $100 billion as large insurers in the respective market.[119] We set the entry level for large insurers at $100 billion based on the relative size of the large insurance companies compared to banking sector SIFIs. For instance, the asset value of the largest U.S. insurer *MetLife* is only one third of the size of the largest U.S. banking sector SIFI *Bank of America*.[120] Therefore, given that the lowest entry level on total

[115] According to JBA, city banks are large in size, with headquarters in major cities and branches in Tokyo, Osaka, other major cities, and their immediate suburbs. Regional banks are usually based in the principal city of a prefecture and they conduct the majority of their operations within that prefecture and have strong ties with local enterprises and local governments. Secondary banks usually serve smaller companies and individuals within their immediate geographical regions.

[116] Due to space limits, the name of the selected medium (regional) and small (secondary) banks from the U.S. (Japanese) market is not reported. Further information is available from the author upon request.

[117] According to FSB, the International Association of Insurance Supervisors (IAIS) is expected to complete its assessment methodology for identifying global systemically important insurers in June 2012.

[118] In the current study, we specify the New York Stock Exchange, London Stock Exchange and Tokyo Stock Exchange as the main stock exchange for the U.S., the UK and Japanese market, respectively.

[119] The asset value of insurers is collected from Thomson Routers DataStream®. The latest available information on financial institution's total asset is updated on the *December 31, 2010*. For insurance companies from the UK and Japanese market we convert their total asset value figure from local currency (*e.g.* British Pound and Japanese Yen) into the U.S. dollar based on the corresponding bilateral exchange rates observed on the 31 December 2010.

[120] The asset value of *MetLife* and *Bank of America* is $730.906 billion and 2,264.909 billion on the *December 31, 2010*, respectively.

asset for the banking sector SIFIs is around $300 billion, the $100 billion entry level for insurance firms seems consistent and reasonable.[121] The selection criterion yields 22 large insurers across the three markets.[122] Finally, we categorize the remaining insurance companies from each market as small insurers.

For non-financial institutions, we define large firms as the non-financial components from the TOPIX Core 30, Financial Times 30 (FT 30), and Dow Jones Industrial Average (DJIA) index for the Japanese, the UK and the U.S. market, respectively.[123] We choose the non-financial components from the three aforementioned indices as large non-financial institutions for two reasons. First, these indices are commonly regarded as the measure of overall performance of their respective markets[124], the non-financial institutions from these indices should reflect the general performance of the industrial sector of these markets. Therefore, we can match the systemic importance of large non-financial institutions with their large financial counterparts in the current study. Second, the components of these indices are usually firms with the highest market value.

Given the large number of non-financial institutions listed across the three markets, the small non-financial institutions are selected via a two-step process. First, we collect all the firms from non-financial industries listed on the respective main stock exchange for each market. The number of non-financial institutions for the U.S., the UK and Japanese market is 1212, 682 and 1750, respectively. In the second step, we rank non-financial institutions according to their market value from each market and pick up the firms within

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[121] In our sample, *U.S. Bancorp* and *Bank of New York Mellon*, ate the two banking sector SIFIs with the lowest asset value, which is $307.786 billion and $247.259 billion on the *December 31, 2010*, respectively.
[122] The selected large across the three markets are listed in Appendix B.2. Due to space limits, the name of the small insurers is not reported. Further information is available from the author upon request.
[123] The selected large industrial firms are listed in Appendix B.3.
[124] For further detail of the three indices please refer to the description provided by their providers. For TOPIC Core 30, see: http://www.tse.or.jp/english/market/topix/; for FT 30, see: http://www.ft.com/cms/78c12166-0773-11db-9067-0000779e2340.html; and for DJIA, see: http://www.djaverages.com/?go=industrial-overview.

the bottom 20% to bottom 10% threshold.[125] We eliminate the firms within the bottom 10% threshold as firms very low market value/price (*i.e.* micro-cap firms) usually suffer from non-frequent trading and market-microstructure problems (*e.g.* Brennan and Subrahmanyam, 1996; Amihud, 2002; Gray and Johnson, 2011) which might produce unsmooth return series. Therefore, we skip the micro-cap firms by eliminating the bottom 10% of the sample and select firms within the bottom 10% to 20% range as small non-financial institutions for each market.[126]

The daily price information of the selected financial and non-financial institutions along with the equity market index is collected in local currency terms from Thomson Routers DataStream® for each market.[127] The daily term structure of interest rates of the three countries is represented by the zero-yield curve with 15 maturities from 3-month to 30-year[128], which are collected from the Bloomberg®. The sample period starts from the *March 31, 2003* due to the availability of the yield curve data on Japanese market, while stops at the *January 31, 2010*. We stop the sample period at the end of January 2010 for two reasons. First, the sample period covers the full extent of the recent financial crisis which started in 2007 and had a lasting impact through 2008 and early 2009.[129] Second, by stopping the sample period at the end of January 2010 we avoid the potential influence of the recent European sovereign debt crisis on the equity return of financial and non-

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[125] The market value is represented by the non-financial institution's market capitalization which is collected from Thomson Routers DataStream®. In order to match the selection criterion for financial institutions, we use the market capitalization information updated on the 31 December 2010.

[126] Due to space limits, the name of the selected small non-financial institutions is not reported. Further information is available upon request from the author.

[127] The equity market indices used in the current study are NIKKEI 225, FTSE 100 and S&P 500 for Japanese, the UK and the U.S. market, respectively.

[128] The 15 maturities are: 3-, 6-, 9-, 12-month, 2-, 3-, 4-, 5-, 7-, 8-, 9-, 10-, 15-, 20-, 25-, and 30-year. Please find the daily term structures of interest rates over the sample period plotted in a 3-demtional manner for the three markets in Appendix B.4.

[129] Please refer to Batram and Bodnar (2009) for further discussion on the general performance of global financial markets during the crisis period.

financial institutions.[130] Although no consensus has been reached on the starting date of the recent sovereign crisis, a series sovereign debt warnings issued by the Standard and Poor's to Spain, Greece and Portugal in December 2009 and/or the austerity program announced by the Greece government on the *February 2, 2010* to cut government debt should be treated as clear indications for the crisis.

Equally weighted portfolios are constructed for financial and non-financial institutions within each sub-group across the three markets.[131] For each market, the non-trading days are eliminated from the dataset, which ends up with 1761, 1770 and 1719 daily observations for the U.S., the UK and Japanese market, respectively. In order compare the return sensitivity of sector portfolios upon changes in yield curve before and after the financial crisis, we divide the sample into two parts, namely the pre- and post-crisis periods. We define the starting date of the recent financial crisis on the *August 9, 2007* when BNP Paribas stopped the redemption of its investment funds as this event has a significant impact on the borrowing cost of banks across the global markets. The BNP Paribas event signalled the inability to correctly evaluate toxic sub-prime related assets by large financial institutions and intensified the credit and liquidity risk within the financial market. Bartram and Bodnar (2009) show that the borrowing cost between financial institutions increased dramatically following this liquidity squeeze in August 2007. The two sub-sample periods contain 1138/1143/1115 and 624/627/604 daily observations for the U.S./UK/Japanese market before and after the crisis, respectively. Table 3.2 illustrates

[130] The sovereign debt crisis influences the financial market through its negative impact on the economy growth of certain regions instead of the liquidity shortage within the financial markets. Therefore, the negative shocks on financial and non-financial institutions' equity value may not due to changes in interest rates.

[131] The size weighted portfolio will represent the performance of the large institutions, while the equally weighted portfolio will provide a more general performance measure across all institutions involved. We focus on the return performance of a sector rather than a group of individual institutions. Therefore, we employ equally weighted portfolios in this chapter. The time series of sector portfolios' value over the sample period is presented in Appendix B.5.

the statistical and distributional properties of the returns of these financial and non-financial sector portfolios over the sample period.

Table 3.2 Summary Statistics of Sector Portfolio Returns.

The table below summarizes the distributional statistics of sector portfolio returns from the three markets. The *pre-crisis* period represents the 6-year period from October 1, 2002 to August 8, 2007 and the *post-crisis* period represents the remaining of the sample from August 9, 2007 to January 31, 2010.

Panel A: The U.S. Sector Portfolios

	Banks			Insurers		Industrial Firms	
Raw Return (%)	SIFIs	Money-Center	Small	Large	Small	Large	Small
Mean	-0.010	-0.026	-0.037	-0.015	0.009	0.017	0.004
Std. Dev.	2.846	2.451	2.127	2.896	1.751	1.253	1.855
Skewness	0.302	-0.053	-0.136	-0.229	-0.575	0.193	-0.490
Kurtosis	20.2	15.4	13.6	19.0	18.9	15.0	11.2
Normality	-0.010	-0.026	-0.037	-0.015	0.009	0.017	0.004
Pre-Crisis							
Mean	0.051	0.027	0.013	0.056	0.047	0.048	0.052
Std. Dev.	0.969	0.811	0.821	0.883	0.736	0.760	0.929
Post-Crisis							
Mean	-0.121	-0.121	-0.127	-0.144	-0.060	-0.040	-0.084
Std. Dev.	4.602	3.972	3.399	4.721	2.771	1.838	2.854
ADF	-44.8	-46.4	-45.8	-43.4	-33.6	-24.9	-43.4
ARCH	381.3	440.8	436.7	539.9	534.1	685.6	611.1

Note: Normality refers to the Jarque-Bera normality test statistics. ADF refers to the Augmented Dickey-Fuller unit root test statistics. ARCH refers to the ARCH-LM test statistics with 21 lags. Std. Dev. stands for the daily standard deviation of the sector portfolio. All reported test statistics are significant at the 99% confidence level.

Table 3.2 Summary Statistics of Sector Portfolio Returns. (CON'T)

Panel B: The UK Sector Portfolios

	Banks	Insurers		Industrial Firms	
Raw Return (%)	SIFIs	Large	Small	Large	Small
Mean	-0.054	0.007	0.015	0.020	-0.060
Std. Dev.	2.859	2.385	0.725	1.302	0.661
Skewness	-1.345	-0.076	0.067	-0.269	-0.287
Kurtosis	44.0	14.8	6.1	9.0	6.0
Normality	124621.0	10210.4	711.9	2650.8	709.9
Pre-Crisis					
Mean	0.038	0.059	0.046	0.061	-0.013
Std. Dev.	1.043	1.436	0.662	0.895	0.605
Post-Crisis					
Mean	-0.221	-0.089	-0.041	-0.053	-0.147
Std. Dev.	4.591	3.506	0.825	1.821	0.745
ADF	-18.8	-19.8	-39.4	-43.0	-12.4
ARCH	327.3	414.2	129.5	512.1	175.8

Note: Normality refers to the Jarque-Bera normality test statistics. ADF refers to the Augmented Dickey-Fuller unit root test statistics. ARCH refers to the ARCH-LM test statistics with 21 lags. Std. Dev. stands for the daily standard deviation of the sector portfolio. All reported test statistics are significant at the 99% confidence level.

Panel C: Japanese Sector Portfolios

	Banks			Insurers		Industrial Firms	
Raw Return	SIFIs	Regional	Secondary	Large	Small	Large	Small
Mean	0.010	-0.009	-0.032	0.001	0.012	0.017	0.001
Std. Dev.	2.700	1.520	1.190	1.946	3.522	1.474	1.145
Skewness	0.245	0.199	0.439	-0.196	0.368	-0.326	-0.806
Kurtosis	6.1	8.7	11.0	7.2	6.3	10.4	19.3
Normality	720.2	2319.5	4682.2	1265.9	839.4	3950.5	19295.5
Pre-Crisis							
Mean	0.114	0.033	0.009	0.065	0.030	0.074	0.063
Std. Dev.	2.252	1.164	0.951	1.486	4.024	1.047	0.993
Post-Crisis							
Mean	-0.183	-0.088	-0.109	-0.117	-0.022	-0.089	-0.114
Std. Dev.	3.368	2.016	1.535	2.585	2.327	2.037	1.377
ADF	-38.4	-43.5	-42.9	-26.4	-38.3	-42.9	-33.2
ARCH	298.4	519.5	338.3	478.8	230.1	643.9	322.7

Note: Normality refers to the Jarque-Bera normality test statistics. ADF refers to the Augmented Dickey-Fuller unit root test statistics. ARCH refers to the ARCH-LM test statistics with 21 lags. Std. Dev. stands for the daily standard deviation of the sector portfolio. All reported test statistics are significant at the 99% confidence level.

The summary statistics indicate that the average daily returns of these financial and non-financial sector portfolios typically range between 1.7 to -6.0 bps per day over the whole sample period. The riskiness of financial institutions is much higher than those of non-financial ones across the three markets.[132] For instance, the standard deviation of the U.S. banking and insurance portfolio is between 1.751% and 2.896%, while the standard deviation of the industrial portfolio is between 1.253% and 1.855%. The daily return series for all the sector portfolios are stationary according to the Augmented Dickey-Fuller (*ADF*) test.

Based on the result of the *Normality Test*, the unconditional distribution of all the daily return series is non-normal as the skewness and kurtosis of the sector portfolio return are noticeably deviated from their mean. Finally, all the return series reject the null hypothesis of the *ARCH Test*. Given the variance of the return series is not constant over time, the result suggests the estimation framework for portfolio returns should take the non-linear return generating process and time-varying conditional variance into account.

In order to investigate the impact of the credit crunch on the equity return of these sector portfolios during the recent financial crisis, we further investigate the performance of these sector portfolios before and after the August 9, 2007. The result shows that before the crisis (*i.e.* pre-crisis period), all the sector portfolios enjoy a positive average return.[133] The liquidity squeeze triggered by the BNP Paribas event dramatically increased the riskiness of these sector portfolios as their standard deviation increased noticeably during the *post-crisis* period. Besides, all sector portfolios experienced negative averages daily

[132] The only exception comes from the UK market, where the portfolio of small insurance companies has the lowest standard deviation over the sample period.
[133] The only exception comes from the small industrial portfolio in the UK market, where the average daily return over the pre-crisis period is -0.9 bps.

return during the crisis. Furthermore, compared to non-financial institutions, the equity value of financial sector portfolios suffered bigger losses during the crisis.

Finally, we collect all the major announcements by the central bank/government/Treasury department of each market to evaluate the potential influence of market interventions on the equity returns of financial and non-financial institutions during the crisis period. It is worth noting that some market interventions have a lasting impact on the global financial market until the early 2010. For instance, the Foreign-Currency Liquidity Swap Lines proposed by the Federal Reserve and other major central banks in the late 2007 were effective until the end of January 2010. Similarly, the Quantitative Easing program introduced by Bank of England in early 2009 had a lasting impact until early 2010 through a series of extension announcements.[134] Therefore, by employing a sample period from early 2003 to early 2010 we are able to show a more general picture of how the equity value of financial and non-financial institutions reacts to market interventions, which is valuable from a regulatory perspective. We classify these announcements into different categories according to their characteristics. The number of announcements made under each category is illustrated in Table 3.3 for each market.

[134] The Quantitative Easing program had been extended for three times with the latest one on *November 5, 2009*. The Bank of England issued an announcement on the *February 4, 2010* to signal the program will no longer be extended. For further information of the Quantitative Easing program, please refer to Joyce et al (2011).

Table 3.3 Summary of Market Intervention Announcements

The table below summarizes the number of market intervention announcements made by the central bank/government/Treasury department of the three markets considered. The counting of announcements starts in August 2007, when the recent financial turmoil begins to impact the global financial market. These market intervention announcements have been categorized into different types according to their main function and property. In general, five main categories have been identified in the current study, namely rate cuts, liquidity injection, joint market intervention, government bailouts, and special measures. The categorization of announcements might be different across markets.

	Rate Cuts		Liquidity Injection	Joint Market Intervention	Government Bailouts	Special Measure	
	Fed Funds	*Discount*				*TARP*†	*Stimulus*
U.S.	10	12	9	8	5	1	3
						QE††	
UK	9		19	8	4	4	
						ORP†††	*Stimulus*
Japan	2		19	8	-	3	1

† *TARP* refers to the Trouble Asset Relief Program introduced by the U.S. government in September 2009.
†† *QE* refers to the quantitative easing program introduced by the Bank of England since early 2009.
††† *ORP* refers to the outright purchase of government/corporate bonds by the Bank of Japan since early 2009.

Note: The announcement for rate cuts refers to decisions made by central banks to reduce the short-term borrowing rate for financial institutions. There are two different types of rate cut announcements for the U.S> market, namely *Fed Funds* and *Discount* rate cuts. The former refers to deductions in federal fund rates, while the latter refers to deductions in discount window rate.
Liquidity injection related announcements refer to actions taken by central banks to enhance liquidity condition of the financial system.
Joint market intervention refers to coordinated actions taken by more than one major central bank to stabilize the financial market on a global scale.
The government bailouts refer to the government rescue of financial institutions (*i.e.* nationalization or direct capital injection) during the crisis period.
Special measure refers to the additional market interventions apart from rate cuts, liquidity injections and government bailouts (*i.e.* quantitative easing, TRAP, out-right purchase, and stimulus)

In general, there are five categories of announcements, namely rate cuts, liquidity injections, joint market interventions, government bailouts and special measures. The announcement for rate cuts refers to decisions made by central banks to reduce the short-term borrowing rate for financial institutions. For the U.S. market, there are two different types of rate cut announcements namely *Fed Fund* rate cuts and *Discount* rate cuts. The former refers to deductions in federal fund rates, while the latter refers to deductions in discount window rate.[135]

For liquidity injections, we select announcements which are related to liquidity enhancement of the financial system.[136] For instance, the asset backed commercial paper money market mutual fund liquidity facility (AMLF) introduced by the Federal Reserve on the *September 19, 2008*, and the special liquidity scheme launched by the Bank of England on the *April 21, 2008* which allows banks swap their high quality securities for government bonds on a temporary basis.

The third category is announcements regarding the joint market interventions. Since late 2007, major central banks around the world started to coordinate their intervention actions in order to better stabilize the global financial market. For instance, on the 12 December 2007, the Federal Reserve initiated the Foreign-Currency Liquidity Swap Lines with the Bank of England, the European Central Bank, the Bank of Japan, and the Swiss National Bank to provide liquidity for the U.S. dollar across the global financial market.[137]

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[135] Both rates are tools of monetary policy used by the Federal Reserve to influence the supply and demand of funding in the U.S. financial market. For further information of the federal rate, please refer to http://www.federalreserve.gov/monetarypolicy/openmarket.htm; for further information of the discount window rate, please refer to http://www.federalreserve.gov/monetarypolicy/discountrate.htm. In the current study, we only select the announcement date for primary discount rates.

[136] The related announcements include unscheduled auctions of overnight funds injecting liquidity into the financial market, and special liquidity scheme for financial institutions aiming to improve their liquidity situations.

[137] For further information about the liquidity swap lines, see:
http://www.federalreserve.gov/newsevents/press/monetary/20071212a.htm, and,
http://www.federalreserve.gov/monetarypolicy/bst_liquidityswaps.htm.

We isolate these joint market interventions from the ones carried out by individual markets to investigate whether financial and non-financial institutions react differently to these two types of actions during the crisis period.

In the current study, the government bailouts refer to the government rescue of financial institutions (*i.e.* nationalization or direct capital injection) during the crisis period. The nationalization of AIG by the U.S. government in September 2008 and the capital injection by the UK government into three major banks in October 2008 are two vivid examples of government bailouts during the recent financial turmoil. It is worth noticing that there is no major bailout on financial institutions by Japanese government during the recent crisis.

The final category is special measures. We refer special measures as additional market interventions apart from rate cuts, liquidity injections and government bailouts. During the crisis period, governments may take extreme measures to restore the stability of financial system and/or prevent economic recession. From Table 3.3, one can see that different markets have implemented different special measures during the crisis period. For instance, the U.S. government has introduced the Troubled Asset Relief Program (TARP) in September 2009 in order to rescue the entire financial system. Similar actions like Quantitative Easing (QE) and outright purchase of government/corporate bonds have been taken by the Bank of England and Bank of Japan in early 2009, respectively. Furthermore, in order to stop the economy contraction, the U.S. and Japanese government have introduced a series of stimulus packages aiming to revival their economy in 2009.[138]

In the current study, we create one intercept dummy variable for each announcement category within a market. For instance, there will be 7 announcement

[138] The U.K. government did not propose additional stimulus package but extended the magnitude of QE for three times following the initial introduction in March 2009.

dummies for the U.S. market, while 5 announcement dummies for Japanese market. We incorporate these intercept dummies into the estimation framework to evaluate the impact of different types of market interventions on financial and non-financial institutions across markets.

3.4. Estimation Framework

3.4.1. Nelson-Siegel Term Structure Model

In the current study, we investigate the equity return sensitivities of large financial and non-financial institutions upon the changes in the term structure of interest rates. Inspired by Czaja et al (2009), we also use the estimated factor loadings from NS model to represent fluctuations in the term structure. In the following section, we briefly introduce the NS model and its estimation method.

In the NS model developed by Nelson and Siegel (1987), the term structure of interest rate is decomposed into three factors, namely the level, slope and curvature factors. The NS three-factor model is popular among practitioners and policy makers as it uses a flexible and smooth parametric function to replicate the term structure at any given time (Svensson, 1995; Bank for International Settlements, 2005; Gurkaynak et al, 2007; Christensen et al, 2011; Sekkel, 2011). Although the NS model lacks of theoretical backup compares to affine class models, they provides an excellent fit to the term structure of interest rate.[139] Empirically, Diebold and Li (2006), De Pooter (2007) and Yu and Zivot (2011) all show that NS class models fit the real term structure well in both in-sample and out-of-sample period. Despite the desirable arbitrage-free property enjoyed by the affine

[139] The NS model has no restrictions to eliminate opportunities for riskless arbitrage. As the technical detail is beyond the discussion of current paper, we refer interested readers to studies by Filipovic (1999), Diebold et al (2005) and Christensen et al (2011) among others. Recently, Christensen et al (2011) propose a new set of NS models with an additional "yield-adjustment" term which will ensure the arbitrage-free property.

class models introduced by Vasicek (1977) and Cox et al (1985), Duffee (2002) argues that they perform poorly with real yield curve data. However, based on US Treasury yield curves, Coroneo et al (2011) show that the NS model is compatible with the arbitrage-free constraints on the US market. In other words, even without the arbitrage-free setting build-in, the NS class models are capable to provide a yield curve estimation which is free from arbitrage.[140]

The NS model is based on *Laguerre* functions which consist of product between a polynomial and an exponential decay terms. The basic three-factor NS model can be treated as the solution to a second order differential equation with equal roots for spot rates. The spot rate curve can be illustrated as follow:

$$y_t(\tau) = \beta_{1,t} + \beta_{2,t}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_t}\right)}{\left(\frac{\tau}{\lambda_t}\right)}\right] + \beta_{3,t}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_t}\right)}{\left(\frac{\tau}{\lambda_t}\right)} - \exp\left(-\frac{\tau}{\lambda_t}\right)\right] \tag{1}$$

where $y_t(\tau)$ is the spot rate with maturity τ at time t; $\beta_{1,t}$, $\beta_{1,t}$ and $\beta_{1,t}$ are the three factor loadings[141] estimated from NS model at time t; λ_t is the decay factor which optimize the model fitting at time t. There are three reasons for the NS class model's popularity. First, it provides a parsimonious approximation of the yield curve using only four parameters to estimate the shape of yield curve. The three components $\{1, [1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t), [1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t) - \exp(-\tau/\lambda_t)\}$ provide the model enough flexibility to capture a range of monotonic, humped and S-type shapes commonly observed in the yield curve data. Second, the model enjoys a desirable property of starting off from an easily computed

[140] Svensson (1995) propose an extended four-factor model based on the original NS three-factor model by adding an additional curvature factor. In this study, we choose to use the NS three-factor model to avoid the potential difficulties of interpreting the two curvature factors. In addition, Diebold et al (2008) show that even adopting a NS model with only level and slope factor could well explain the dynamic in the term structure of interest rates.

[141] A graphical presentation of the three loading factors and their changes upon time to maturity is illustrated in Appendix B.6.

instantaneous short rate value of [$\beta_{1,t}$ + $\beta_{2,t}$], and levelling off at a finite infinite-maturity value of [$\beta_{1,t}$], which is constant:

$$\lim_{\tau \to 0} y_t(\tau) = \beta_{1,t} + \beta_{2,t}; \qquad \lim_{\tau \to \infty} y_t(\tau) = \beta_{1,t}$$

There are two different approaches can be employed to estimate the NS model. The first one is a simple OLS approach, while the second one is a nonlinear least square (NLS) approach. The OLS approach estimates the term structure of interest rate for any given time t while fixing the decay factor λ_t to a pre-specified figure which is constant for every t. In this way, the non-linear exponential measurement equation reduces to a linear framework (Diebold and Li, 2006). Therefore the NS model can be estimated using standard cross-sectional OLS approach over the estimation period.

The decay factor λ_t determines the maturity at which the *curvature* factor loading reaches its maximum. The pre-specified value used in their study is λ_t = 16.42, which means that the curvature factor loading reaches its peak at a 30-month maturity. A smaller value for λ_t produces faster decaying factor loadings with the *curvature* factor reaching its maximum at a shorter maturity and vice versa.

The NLS approach estimates the decay parameters alongside the other factors makes the estimation procedure more challenging and therefore requires for NLS. However, it also increases the flexibility of the model since the assumption on constant decay parameter over time is dismissed. In the current study, we use the NLS approach to estimate the parameters from NS model.

However, the nonlinear estimation procedure can sometimes produce extreme results (Gimeno and Nave, 2006; Bolder and Streliski, 1999). The nonlinear structure of the model seems to pose serious difficulties for optimization procedure to arrive at reasonable estimates. De Pooter (2007) showed that when the decay parameters take on extreme values the behavior of the factor loadings will introduce multicolinearity problems. Therefore, some of the factors are no longer uniquely identified. The demonstration of this extreme decay parameter problem is showed as below:

$$\lim_{\lambda \to 0}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_{1,t}}\right)}{\left(\frac{\tau}{\lambda_{1,t}}\right)}\right] = 0; \quad \lim_{\lambda \to 0}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_{1,t}}\right)}{\left(\frac{\tau}{\lambda_{1,t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1,t}}\right)\right] = 0$$

$$\lim_{\lambda \to \infty}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_{1,t}}\right)}{\left(\frac{\tau}{\lambda_{1,t}}\right)}\right] = 1; \quad \lim_{\lambda \to \infty}\left[\frac{1-\exp\left(-\frac{\tau}{\lambda_{1,t}}\right)}{\left(\frac{\tau}{\lambda_{1,t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1,t}}\right)\right] = 0$$

The above results imply that for very small value of λ_t the *slope* and *curvature* factors will be near non-identifiable which can result in extreme estimation results. While for large values of λ_t the *curvature* factors are nearly non-identified. In addition, this means the *level* and *slope* factors can only be estimated jointly, but no longer individually.

In order to prevent these unfavourable extreme estimates, we follow the idea of De Pooter (2007) to impose restrictions on the estimation of decay parameters. By assuming the *curvature* factor loading will reach its peak for a maturity between 1 and 5 years, the decay parameter for NS three-factor model are restricted to within the domain of [6.69, 33.46].

The three components provide a clear interpretation as *long*, *short*, and *medium-term* components, which also can be named as *level* ($\beta_{1,t}$), *slope* ($\beta_{2,t}$) and *curvature* ($\beta_{3,t}$) factor loadings, respectively.[142] The *level* effect represents the level of entire yield curve and/or the long-term interest rate as $\beta_{1,t}$ is constant for all maturities and the last two components of the NS model, $[1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t)$ and $[1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t) - \exp(-\tau/\lambda_t)$, become zero when maturity τ approaches infinity. The *slope* effect indicates the level of short-term interest rate as the second component, $[1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t)$, gradually decays to zero from one as the maturity τ increases. Finally, the *curvature* effect, the loading attached to the third component $[1 - \exp(-\tau/\lambda_t)] / (\tau/\lambda_t) - \exp(-\tau/\lambda_t)$, reflects the magnitude of the

[142] See Diebold and Li (2006) for further discussion.

hump above the *slope* effect as the maturity τ grows from zero to infinity.[143]

3.4.2. *VAR-BEKK Model for Interest Rate Risk*

As discussed in the introduction, conventional approach on interest rate risk exposure is to measure the interest rate sensitivity of stock returns based on on the changes in interest rates with a constant maturity, or the spread of a pair of long-short interest rates.[144] The most common approach to quantify interest rate risk is the two-factor model proposed by Stone (1974). In his paper, Stone suggested extending the basic Capital Asset Pricing Model (CAPM) to a two-factor model by including a debt or interest rate factor. The basic two-factor model can be described as follow:

$$r_t = \beta_0 + \beta_M \cdot r_{M,t} + \beta_D \cdot r_{D,t} + \varepsilon_t; \qquad (2)$$

where r_t is the return of an asset/portfolio in period *t*; β_0 is a constant; $r_{M,t}$ is the return on the market portfolio on time *t*; $r_{D,t}$ is the return of a bond index or changes in interest rate with a constant maturity on time *t*; the β_M and β_D is the sensitivities of the stock returns upon changes in the market return and bond index, respectively. However, the return on equity and interest rates are not independent. Hirtle (1997) claimed that the interest rate coefficient β_D can only partially gauge the interest rate risk exposure of the asset/portfolio return since the changes in interest rates affect the market factor as well.

Recently, Czaja et al (2009) proposed a new interest rate risk pricing model by integrating Willner's (1996) bond pricing framework into the Stone (1974) model. They used the estimated *level*, *slope* and *curvature* factors from the NS model as interest rate risk

[143] Given the constant decay factor employed in our OLS estimation framework, the maximum hump occurs at the same maturity for all the daily yield curves. The fixed decay factor for the U.S. (20.44), UK (42.33), and Japanese (39.07) indicates that the maximum hump will occur at the maturity τ equals to 36, 72 and 70 months, respectively. Therefore, we claim the *curvature* effect in our study can be treated as an indicator for medium-term rates as the maximum hump always occurs within the 3 to 6 year-maturity range across the three markets.

[144] Please refer to Staikouras (2003 and 2006a) for excellent review for empirical studies on the interest rate risk exposure of financial institutions.

factors. This approach can capture the changes in the whole term structure instead of changes on one part of the yield curve (*e.g.* a bond index with a given maturity). In the current study, we also include intercept dummies representing the market intervention announcements to capture the potential influences of these intervention events on the equity value of financial and non-financial institutions under consideration.[145] The proposed pricing model can be presented as follow:

$$r_t = \beta_0 + \beta_M r_{M,t} + \beta_L \Delta L_t + \beta_S \Delta S_t + \beta_C \Delta C_t + \sum \beta_{i,DUM} DUM_i + \varepsilon_t \quad (3)$$

where r_t is the sector portfolio return over period t; $r_{M,t}$ is the market risk factor over period t; ΔL_t, ΔS_t and ΔC_t is the first difference of the estimated *level* ($\beta_{1,t}$), *slope* ($\beta_{2,t}$) and *curvature* ($\beta_{3,t}$) factor from NS model (*Eq.1*) over period t; DUM_i is the intercept dummy variable represents the announcement of market intervention under announcement category i; and

In the estimation framework proposed by Czaja et al (2009), a pricing model similar to *Eq.3* is estimated for all the financial sector portfolios simultaneously based on a SURE model.[146] However, their model ignores the fact that variances and interdependence among these sector portfolio returns may not be consistent over time (Ang and Bekaert, 1999; Cappiello et al, 2006). Failed to incorporate these stylized factors into the model may lead to inefficient estimation results. In order to solve this issue, we estimate the interest rate risk of the sector portfolio returns simultaneously with their time-varying variance-covariance with a diagonal BEKK model based on a modified VAR-BEKK framework.[147] By estimating the interest rate risk of all the sector portfolios within the same country with

[145] The interdependence among the market risk factors, interest rate (*i.e. level, slope* and *curvature*) risk factors, and intervention announcement dummies, as well as the interdependence among interest rate risk factors (Bliss, 1997) has been removed through a set of auxiliary regressions.
[146] In Czaja et al (2009), the market and interest rate risk factor is orthogonalized in a different order. Besides, their model does not contain any intercept dummy variable.
[147] For more information on the technical detail of the BEKK model, please refer to the work by Baba et al (1989) which first introduced the parameterization.

a system of *Eq.6* in a VAR framework, we are able to increase the accuracy and efficiency of the model (Elyasiani and Mansur, 2003). We follow the quasi-maximum likelihood estimation (QMLE) process developed by Bollerslev and Wooldridge (1992) to estimate the coefficients for the modified VAR-BEKK MGARCH model.[148]

In order to compare the interest rate risk exposure of financial and non-financial institutions before and during the recent financial turmoil, we split the sample period into two parts and estimate the VAR-BEKK model over the two estimation periods separately. The first part, namely the pre-crisis period, starts from the beginning of the sample period till the 8 August 2007. The remaining sample period is defined as the second part, namely the post-crisis period. Since all the market intervention announcements are made during the post-crisis period, we exclude announcement dummies in *Eq.3* for the pre-crisis period.[149] In addition, previous studies show that the bankruptcy of Lehman Brother's has a significant impact on the financial markets and might alter the interest rate sensitivity of the institution's equity return. Therefore, it is important to take this special event into account as failed to capture potential structural changes in the risk factor could lead to biasness in the estimated coefficient (Levi, 1994).[150] In the current study, we introduce an interactive dummy (D) to capture the potential structural break introduced by the collapse of Lehman Brother's on the *September 15, 2008*. The proposed VAR-BEKK model can be illustrated in a matrix form as follow:

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \varepsilon_t \;;$$

for $t \in$ [*January 31, 2003* : *August 8, 2007*]

[148] We generate the standard errors for the estimated parameters based on the quasi-maximum likelihood function instead of variance of the estimated residuals. These standard errors are also known as the robust Bollerslev-Wooldridge standard error, which adjust for the time-varying variance-covariance nature among the estimated residuals.
[149] During the pre-crisis period, the value of announcement dummies (D_i) is equal to zero.
[150] Despite introducing multiple interaction dummies will increase the complexity of the model and the difficulty of interpretation we still prefer the former over splitting the sample into sub-periods as the latter suffers from lower estimation efficiency by reducing the number of observations in the model.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \gamma \cdot RiskFactor_t \cdot D + \beta_{DUM} \cdot DUM + \varepsilon_t \; ;$$

for $t \in$ [*August 9, 2007* : *January 31, 2010*]

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \qquad \text{with, } \varepsilon_t \sim N(0, h_t) \tag{4}$$

where:

R_t = a [$k \times 1$] matrix represents the return of portfolios from a given market over day t. k is equal to the number of portfolios involved in the VAR-BEKK system.[151]

β_0 = a [$k \times 1$] parameter matrix represents the constants for the involved sector portfolios in a market.

$RiskFactor_t$ = a [4×1] matrix contains the *market* ($r_{M,t}$), *level* (ΔL_t), *slope* (ΔS_t), and *curvature* (ΔC_t) risk factors over day t for the corresponding market.

β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β, namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.

γ = a [$k \times 4$] parameter matrix represents the changes in return sensitivity upon the $RiskFactor_t$ after the collapse of Lehman Brother on the *September 15, 2008* (*DUM*) for the k sector portfolios in R_t. The elements within γ, namely γ_M, γ_L, γ_S, and γ_C represent the changes in *market*, *level*, *slope* and *curvature* effect of the sector portfolio return after the collapse of Lehman, respectively.

D = a dummy variable with *0* before the *September 15, 2008*, and *1* afterwards.

β_{DUM} = a [$k \times n$] parameter matrix represents the impact of different types of market intervention announcements on the portfolio returns R_t.

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[151] In the current study, $k = 3$ as we have three sector portfolios for each market, namely the banking, insurance and industrial sector portfolios.

DUM = a [$n \times 1$] intercept dummy variable matrix represents the announcement of market intervention under different category for the corresponding market; n is the number of announcement categories in the corresponding market.

H_t = a [$k \times k$] conditional variance-covariance matrix of the estimated residuals at day t; k equals to the number of sector portfolios involved in the VAR-BEKK system.

ε_t = a [$1 \times k$] vector contains the estimated residuals from the mean equation of the VAR system for day t.

C = a [$k \times k$] lower triangle matrix. The product of CC' represents the unconditional part of the time-varying variance-covariance matrices;

A and B = [$k \times k$] diagonal parameter matrices represents the multivariate ARCH and GARCH effect of the conditional variance-covariance matrices. The parameters represent the ARCH and GARCH effects are the elements on the main diagonal of the matrix A and B, respectively.

3.5. EMPIRICAL RESULT

As discussion in the above section, interest rate risks of the banking, insurance and industrial portfolios are estimated for each country with a modified VAR-BEKK framework (*Eq.4*). In the following section, we discuss the relationship between the return of these sector portfolios and fluctuations in the term structure of interest rate before and during the recent financial turmoil in detail for each market.

3.5.1. Interest Rate Sensitivity of the Banking Institutions

The estimation result for the banking portfolios across the three markets is represented in Table 3.4 and Table 3.5 for pre- and post-crisis period, respectively. Each table has three panels (*i.e.* Panel A, B and C), which contain the estimation output for institutions from the U.S., UK and Japan markets, respectively.

Table 3.4 The Return Sensitivities of Banking Sector Portfolios upon Changes in Market and Interest Rate Risk Factors before the Crisis.

The table below summarizes the estimated coefficient for market and interest rate risk factors for the banking sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinarity issue. The pre-crisis period is from *January 31, 2003* till *August 8, 2007.*

The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \varepsilon_t$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$
with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*January 31, 2003, August 8, 2007*]

R_t = a [$k \times 1$] matrix represents the return of portfolios from a given market over day t. k is equal to the number of portfolios involved in the VAR-BEKK system.

β_0 = a [$k \times 1$] parameter matrix represents the constants for the involved sector portfolios in a market.

$RiskFactor_t$ = a [4×1] matrix contains the orthogonalized *market* ($r_{M,t}^*$), orthogonalized *level* (ΔL_t^*), *slope* (ΔS_t^*), and orthogonalized *curvature* (ΔC_t^*) risk factors over day t for the corresponding market.

β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β, namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.

H_t = a [$k \times k$] conditional variance-covariance matrix of the estimated residuals at day t; k equals to the number of sector portfolios involved in the VAR-BEKK system.

A and B = [$k \times k$] diagonal parameter matrices represents the multivariate ARCH and GARCH effect of the conditional variance-covariance matrices. The parameters represent the ARCH and GARCH effects are the elements on the main diagonal of the matrix A and B, respectively.

Panel A: The U.S. Banking Portfolios

	SIFIs			Medium Banks			Small Banks		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.32		0.000	-1.26		0.000	-1.41	
β_M	1.102	50.77	***	0.891	43.37	***	0.859	32.57	***
β_L	0.094	17.53	***	0.073	11.19	***	0.071	11.82	***
β_S	-0.007	-2.42	***	-0.002	-0.79		-0.003	-0.96	
β_C	0.014	12.24	***	0.012	10.23	***	0.010	7.64	***
Cond. Variance									
A	0.011	2.83	***	0.027	4.80	***	0.017	4.21	***
B	0.978	101.49	***	0.928	68.51	***	0.956	68.67	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Banking Portfolios

	SIFIs		
Cond. Mean	*Coeff*	*t-Stat*	
Cons	0.000	0.14	
β_M	1.039	48.11	***
β_L	0.084	19.14	***
β_S	-0.005	-1.58	
β_C	0.002	2.55	***
Cond. Variance			
A	0.108	3.13	***
B	0.783	12.32	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Banking Portfolios

	SIFIs			Regional Banks			Secondary Banks		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.88		0.000	-1.71	*	0.000	-2.06	**
β_M	0.979	25.30	***	0.745	30.29	***	0.542	24.01	***
β_L	-0.024	-0.63		-0.059	-1.92	*	-0.059	-2.07	**
β_S	-0.103	-9.07	***	-0.061	-9.04	***	-0.049	-7.42	***
β_C	0.037	7.15	***	0.034	8.38	***	0.026	6.16	***
Cond. Variance									
A	0.061	10.19	***	0.082	6.57	***	0.096	5.55	***
B	0.934	175.14	***	0.857	47.77	***	0.832	39.62	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

From Panel A Table 3.4, one can see that the *market* effect of the U.S. banking portfolio is, as expected, positive and highly significant over the pre-crisis period. In addition, the result on *market* risk factor shows size effect as large size banks have a higher *market* effect compared to small ones. For instance, the *market* effect of SIFIs is 1.102 over the pre-crisis period, while the one of medium and small banks is 0.891 and 0.859, respectively. The finding is consistent with previous studies which suggest that large banks usually have higher market risk than the small ones due to their higher incentive to risky investment strategies (*e.g.* De Nicolo et al, 2004; Demsetz and Strahan, 1997).

The estimated coefficient for *level* and *curvature* factor is also positively significant for all the size portfolios showing that the U.S. banks benefit from increasing long- and medium-term interest rates over the pre-crisis period. The negative *slope* effect (-0.007) of the SIFIs indicates that increase in the short-term interest rate will reduce the equity value of large banks. Our result is in contrary to the finding by Czaja et al (2009) who find the return of German financial institutions is related to the level and curvature factor in a negative way from 1974 to 2002. Their argument rests on the duration mismatch of banks' asset and liability. By assuming a positive duration gap, they claim that bank's value drops as long- and medium-term rate increase because the latter has a higher impact on asset value compare to liability.[152]

We based our argument on the relationship between term structure fluctuation and the profitability of banks (Ho and Saunders, 1981). The return on bank's assets is closely tied to longer-term rates and the return of bank's borrowing cost is closely related to short-term rates (English, 2002). Since banks increasingly rely on short-term interbank/money market for funding and liquidity in the recent year (Blackburn, 2008; Brunnermeier, 2009),

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[152] A positive duration gap refers to the average duration of bank's asset is longer than the one of bank's liability. For further discussion on the duration gap and its implication on bank's interest rate risk please refer to Staikouras (2003 and 2006a), and Saunders and Cornett (2010).

the close relationship between short-term rates and banks' borrowing cost enhanced. Therefore, an increase in the long- and medium-term rates (*e.g.* positive *level* and *curvature* effect) will boost bank's interest related income and its value, while an increase in short-term rate (*e.g.* negative *slope* effect) pushes up bank's borrowing cost which has a negative impact on its profitability and value. In other words, the return of the banking portfolio is expected to be positively related to the *level* and *curvature* factor while negatively depended on the *slope* factor. Furthermore, Banking Supervision Committee (2000) argues that given nominal rates cannot fall below zero, if market rates are already on a low level, further decrease in market rates (*e.g.* downward parallel shift in the yield curve) will reduce bank's profitability as they cannot cut the deposit rate further to reduce their borrowing costs. Given that parallel shift of the yield curve is governing by the *level* factor in NS model, the positive relationship between the value of banking portfolio return and level factor is reinforced.

The result on interest rate related risk factors also indicates size effects. From Panel A, one can see that the *level* and *curvature* effect of large U.S. banks (*i.e.* the SIFIs) are comparatively higher than the ones of medium and small banks. For instance, the level effect of SIFIs is 0.094 during the pre-crisis period, while the ones of medium and small banks are 0.073 and 0.071, respectively. In addition, the parameter of *slope* risk factor is only significant for the U.S. SIFIs but not smaller banks. This finding suggests that large banking institutions expose to higher interest rate risk compared to small banks, which is similar to the size effect observed for the *market* effect. Our result is supported by Graddy and Karna (1984), who argue that large banks accept considerably more spread risk than smaller banks. In other words, large banks should be more sensitive to the interactions between long- and short-term rates (*i.e.* the changes in *level*, *curvature* and *slope* factor).

However, Hanweck and Ryu (2005) claim that large banks are less sensitive to interest rate and term-structure shocks in terms of net interest income due to diversification. We argue that the difference between the current finding and Hanweck and Ryu (2005) may due to the different definitions of interest rate and term-structure shocks. In Hanweck and Ryu (2005), the interest rate and term-structure shock is defined as the volatility of one-year interest rate and the difference between one- and five-year interest rate, respectively. However, in the current study, the interest rate risk is represented by the fluctuation of the entire yield curve (*i.e.* the maturity is from one-month to thirty-year). Besides, Hanweck and Kilcollin (1984) suggest that small banks can benefit from rising interest rates (*i.e.* increase in *slope* factor) compared to large ones, which may be the reason of non-significant *slope* effects for the medium and small banking portfolios.

Panel B and C in Table 3.4 represent the estimation result for banking portfolios from the UK and Japanese market over the pre-crisis period, respectively. For the table, one can see that the findings on banks in both the UK and Japanese markets are similar to the U.S. banks. For instance, banks in these two markets also positively related to the difference between short- and long-term rates (*i.e.* negative *slope* effects, and positive *level* and *curvature* effects). Despite the similarity in interest rate risk, SIFIs in the UK market are, however, not sensitive to changes in the *slope* factor. In other words, the changes in short-term interest rate will not influence the equity value of these SIFIs, which is different from their counterparts in the U.S. and Japanese market. Previous study finds that shocks in short-term interest rates were priced into the equity return for both financial and non-financial institutions in the UK (*e.g.* banks, insurers and utility firms) in a negative manner (*e.g.* Staikouras, 2005).[153] We argue that the difference results between the current and

[153] The shocks in short-term interest rates used in Staikouras (2005) are represented by the unexpected changes in the one- and three-month Treasury bill discount rates. The author claims that the negative

previous studies may due to the different sample period employed in the two papers. The sample period covered by Staikouras (2005) is between 1989 and 2000, while the sample period in this chapter spans from 2003 till 2010. One notable difference between the two periods is that the short-term rate is more volatile in the former than the latter.[154] Therefore, the insignificant return sensitivity of the UK financial institutions on changes in the *slope* factor may due to the stable short-term rates observed during the sample period.

The significant *slope* effect for Japanese banks is in conflict with Oyama and Shiratori (2001) who find Japanese banks are not sensitive to short-term rates.[155] We argue that the different results may due to the different specifications of short-term rate risk factors employed in the two studies. In our study, the short-term rate risk factor is represented by the changes in *slope* loading factor from NS model, which is a direct measure of the interest rates with a short maturity (3-month in our study). However, the short-term rate variable employed in Oyama and Shiratori (2001) is orthogonalized short-term interest rates based on term spread.[156] Thus, the insignificant short-term rate risk factor may simply due to the orthogonalization, as the valuable information of short-term interest rates has already been captured by the term spread. Besides, similar size effects for both *market* and interest rate related factors have been observed for Japanese banking portfolios. For instance, the

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exposure to short-term rates of the financial institutions shows that stock market perceives these stocks as insurance against high yield surprise.

[154] The short-term rates in the UK market are presented in Appendix B.7 on a monthly basis from 1978 to 2011. From the graph, one can see the short-term rates, especially the 3-month Treasury bill rates, are much volatile in the late 1980s and late 1990s, but they are almost constant after 2003 until the sudden drop to near zero level in late 2007.

[155] Oyama and Shiratori (2001) argue that the profitability of Japanese financial institutions is not sensitive to short-term rate changes in the 1980s and 1990s. They argue that the absence of short-term rate risk factor is due to the near zero market rates since the middle 1980s. Since banks cannot reduce the deposit rate below zero, the fluctuation in the near zero short-term rates should not influence the financial institution's profitability.

[156] The short-term interest rate variable used in Oyama and Shiratori (2001) is the residual of the regression of short-term interest rate by long and short-term interest rate spread. The long and short-term interest rate is represented by the 5-year bank debenture yield and 3-month certificate deposit (CD) rate.

market effect of Japanese SIFIs is 0.979 over the pre-crisis period, while the one of regional and secondary banks is 0.745 and 0.542, respectively.

Besides, banks in Japanese market react to changes in *level* factor in a different manner (Panel C) compared to their counterparts in the other two markets. For SIFIs, changes in long-term rates (*i.e.* the *level* risk factor) have not influential power on their equity value before the crisis period. We argue that the insignificant level effect is mainly due to the relative low level and volatility of long-term rates in Japanese market compared to the U.S. and the UK.[157] The *level* effect for regional and secondary banks in Japanese market is negative and significant (both are -0.059) over the pre-crisis period which suggests increase in long-term interest rate will reduce the equity value of these banks. There are two possible explanations behind this size effect: a) SIFIs are more likely to diversify away the inverse impact of unfavorable long-term interest rate movements than regional and secondary banks, and b) large banks (*i.e.* SIFIs) are more likely to pass the increase in interest rate to borrowers given their competitive advantage and stronger bargaining power compared to small banks.

Table 3.5 summarizes the estimation output of the VAR-BEKK model for banking portfolios across the three markets during the recent financial turmoil.

[157] From figures in Appendix B.4, one can see that the average long-term rate (*e.g. level* factor) in Japanese market is around 2.5% compared to 5%/4.6% in the U.S./UK market.

Table 3.5 The Return Sensitivities of Banking Sector Portfolios upon Changes in Market and Interest Rate Risk Factors during the Crisis

The table below summarizes the estimated coefficient for market and interest rate risk factors for the banking sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinarity issue. The post-crisis period is from *August 9, 2007* till *January 31, 2010*.

The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \gamma \cdot RiskFactor_t \cdot D + \beta_{DUM} \cdot DUM + \varepsilon_t \;;$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$
with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*August 9, 2007, January 31, 2010*]

β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β, namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.

γ = a [$k \times 4$] parameter matrix represents the changes in return sensitivity upon the $RiskFactor_t$ after the collapse of Lehman Brother on the *September 15, 2008* for the k sector portfolios in R_t. The elements within γ, namely γ_M, γ_L, γ_S, and γ_C represent the changes in *market*, *level*, *slope* and *curvature* effect of the sector portfolio return after the collapse of Lehman, respectively.

D = a dummy variable with *0* before the *September 15, 2008*, and *1* afterwards.

β_{DUM} = a [$k \times n$] parameter matrix represents the impact of different types of market intervention announcements on the portfolio returns R_t.

DUM = a [$n \times 1$] intercept dummy variable matrix represents the announcement of market intervention under different category for the corresponding market; n is the number of announcement categories in the corresponding market.

Due to space limits, the explanation of variables above is not complete. For further detail please refer to Eq.4 in Page 126.

Panel A: The U.S. Banking Portfolios

	SIFIs			Medium Banks			Small Banks		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	-0.001	-1.24		-0.001	-1.54		-0.001	-1.43	
β_M	1.615	19.68	***	1.435	16.71	***	1.243	16.71	***
β_L	0.142	9.05	***	0.130	7.86	***	0.121	9.13	***
β_S	-0.010	-1.30		-0.011	-1.04		-0.014	-1.68	*
β_C	0.022	8.07	***	0.018	6.24	***	0.015	6.11	***
γ_M	0.010	0.09		0.004	0.03		0.059	0.58	
γ_L	0.013	0.34		-0.041	-1.29		-0.067	-2.53	***
γ_S	0.024	1.73	*	0.007	0.41		-0.003	-0.19	
γ_C	0.006	0.87		0.006	0.84		0.001	0.25	
DUM1 (Fed Fund)	0.010	2.23	**	0.003	0.73		0.004	0.97	
DUM2 (Discount)	0.014	2.96	***	0.009	1.34		0.008	1.46	
DUM3 (Liquidity)	-0.047	-5.33	***	-0.030	-2.95	***	-0.033	-2.98	***
DUM4 (JMI†)	0.021	2.66	***	0.017	1.36		0.025	2.30	***
DUM5 (Bailouts)	0.047	3.02	***	0.030	2.53	***	0.017	1.55	
DUM6 (TARP)	0.186	7.81	***	0.099	3.38	***	0.092	4.95	***
DUM7 (Stimulus)	0.144	6.78	***	0.110	7.73	***	0.079	5.01	***
Cond. Variance									
A	0.291	10.82	***	0.091	13.78	***	0.081	11.98	***
B	0.691	38.21	***	0.878	119.72	***	0.896	121.18	***

† *JMI* refers to the announcements related to joint market intervention.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Banking Portfolios

	SIFIs		
Cond. Mean	*Coeff*	*t-Stat*	
Cons	-0.002	-3.08	***
β_M	1.380	20.13	***
β_L	0.094	4.63	***
β_S	-0.008	-0.89	
β_C	0.014	3.16	***
γ_M	0.082	0.70	
γ_L	0.031	0.82	
γ_S	-0.025	-1.12	
γ_C	-0.005	-0.87	
DUM1 (Rate Cuts)	-0.025	-5.45	***
DUM2 (Liquidity)	-0.012	-0.96	
DUM3 (JMI†)	-0.002	-0.25	
DUM4 (Bailouts)	0.044	5.73	***
DUM5 (QE††)	0.020	2.74	***
Cond. Variance			
A	0.378	4.48	***
B	0.668	13.53	***

† *JMI* refers to the announcements related to joint market intervention.
†† QE refers the quantitative easing program introduced by the Bank of England.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Banking Portfolios

	SIFIs			Medium Banks			Small Banks		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	-0.001	-0.64		0.000	-0.47		-0.001	-2.03	**
β_M	1.464	18.24	***	0.910	18.14	***	0.641	16.98	***
β_L	-0.027	-0.43		-0.025	-0.60		-0.012	-0.39	
β_S	-0.178	-7.03	***	-0.108	-6.55	***	-0.088	-6.59	***
β_C	0.049	4.29	***	0.026	4.42	***	0.017	3.50	***
γ_M	-0.402	-4.05	***	-0.227	-3.71	***	-0.116	-2.35	***
γ_L	-0.042	-0.47		-0.011	-0.22		0.003	0.08	
γ_S	0.043	1.03		0.031	1.37		0.034	1.75	*
γ_C	0.009	0.39		0.004	0.42		0.002	0.27	
DUM1 (Rate Cuts)	0.000	-0.01		-0.025	-2.85	***	-0.019	-1.74	*
DUM2 (Liquidity)	-0.002	-0.22		0.008	1.38		0.009	1.55	
DUM3 (JMI†)	0.020	3.45	***	0.013	1.73	*	0.014	2.42	***
DUM4 (ORP††)	0.004	0.45		0.010	3.20	***	0.009	2.66	***
DUM5 (Stimulus)	0.062	71.60	***	0.018	42.28	***	0.013	38.14	***
Cond. Variance									
A	0.131	4.61	***	0.070	8.30	***	0.029	6.52	***
B	0.521	5.69	***	0.884	47.86	***	0.938	99.47	***

† *JMI* refers to the announcements related to joint market intervention.
†† ORP refers to the outright purchase of government/corporate bonds introduced by the Bank of Japan.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

From Panel A Table 3.5, one can see that the *market* risk factor of the U.S. banking sector has increased following the freeze of redemption by BNP Paribas on *August 9, 2007*. For instance, the market effect of SIFIs has increased from 0.979 during the pre-crisis period to 1.464 over the post-crisis period, while for medium/small banks the *market* risk has raised from 0.891/0.859 to 1.435/1.243. The raise in *market* risk indicates that the turmoil in the banking sector starts to influence the economy since August 2007, which enhances the interdependence between the two. Previous studies claim that banking crises will decelerate real economy, as decrease in credit supply and aggregated demand leading firms to cut investment and working capital, which will decelerate the real economy further in a vicious circle.[158] Similar to pre-crisis period, the *market* risk factor during the crisis period also shows size asymmetry (*i.e.* large banks suffer from higher market effect compared to small ones) indicating that the recent financial turmoil had a stronger impact on large banks than the small ones.

By comparing Table 3.4 and 3.5, one can see that the *level* and *curvature* effect (*i.e.* sensitivity upon changes in long-term rates) of the U.S. banking sector has also increased during the crisis period, while the *slope* effect was almost unobserved. We argue the increase in the impact of long-term rate related risk factors (*i.e. level* and *curvature* effects) is mainly due to changes in investors' sentiment during the crisis period. Chari et al (2008) claim that "flight to quality" usually observed in financial crises as investors seeking for safe securities (*e.g.* Treasury bonds).[159] In addition, Li et al (2009) show that the demand for Treasury bond is closely related to the liquidity conditional in the stock market.[160]

158 For further discussion on the relationship between banking crises and real economy, please refer to Kaminsky and Reinhart (1999), Kroszner et al (2007) and Dell'Ariccia et al (2008) among others.

159 The "flight to quality" refers to the phenomenon that investors move away from high credit risk assets to lower ones. For further discussion on the topic, please refer to Vayanos (2004) among others.

160 They claim that when there is high selling pressure in the stock market, liquidity drops in the stock market but increases in the Treasury bond market as the buying pressure in the latter will also be high.

Given that the return of U.S. financial sector suffered a notable drop combined with a huge increase in volatility during the August 2007 credit/liquidity squeeze (Bartram and Bodnar, 2009),[161] investors are likely to substitute their holdings in the banking portfolio into safe securities (*e.g.* Treasury bonds). This "flight to quality" effect will push down the equity value of banking portfolio as well as the interest rate of Treasury bonds (*e.g.* long-term rates). Therefore, the linkage between banking portfolio return and *level* factor increased following the BNP Paribas event in August 2007. Moreover, the *slope* (*level*) effect of the U.S. SIFIs (small banks) has increased (decreased) by 2.4% (6.7%) points after the collapse of Lehman in September 2008.

In addition, the collapse of Lehman significantly alters the *slope* effect of the U.S. banking portfolio by 2.4% points. We believe the sharp decrease in the magnitude of banks' return sensitivity upon changes in the short-term rate (*e.g. slope* effect) is due to the change in their investment strategy following the Lehman event. According to the *Flow of Funds* data from Federal Reserve, the net lending for mortgages has changed from positive to negative following the third quarter of 2008 and remain negative till the end of the sample period.[162] Since mortgage is usually provided through banks, the negative net mortgage lending means banks were actively reducing their reliance on mortgage related long-term assets after the Lehman collapse. In addition, Afonso et al (2011) show that large U.S. banks reduce their daily borrowing from the interbank market after the Lehman event and their borrowing cost goes down. Combining the reduced reliance on long-term assets and reduced short-term funding with a lower borrowing cost, banks should be less

[161] In addition, Bartram and Bodnar (2009) argue that the credit/liquidity squeeze is mainly due to the crisis in quantitative hedge funds, which force them to liquidize their assets and squeeze the market liquidity.
[162] The net mortgage lending in the U.S. is illustrated in Appendix B.8. The relevant data is collected from the two *Flow of Funds* reports issued by Federal Reserve on the *June 11, 2009* and *June 10, 2010*, see: http://www.federalreserve.gov/releases/z1/20090611/ for the *June 11, 2009* issue and http://www.federalreserve.gov/releases/z1/20100610/ for the *June 10, 2010* issue.

sensitive to the slope of the yield curve. Therefore, the magnitude of the *slope* effect for the U.S. banking portfolio decreased following the bankruptcy of Lehman.

The market interventions carried out by the U.S. government/Federal Reserve has a huge impact on the equity performance of the U.S. banking industry. From Panel A Table 3.5, one can see that, announcements regarding *Fed Fund* and *Discount* rate reduction have a significant and positive impact (0.010 and 0.014, respectively) on the U.S. SIFIs equity returns during the crisis period. The Federal and Discount Window rate represents the benchmark lending rate in the short-term wholesale and interbank funding markets. That means the SIFIs benefit from the decrease in *Fed Fund* and *Discount* rates as the latter reduces the borrowing cost of these institutions. The borrowing rate reduction by the central bank, however, does not have a positive impact on medium and small banks in the U.S. market given the insignificant coefficient for *DUM1* and *DUM2*. We argue that this size effect is mainly due to the funding characteristic of banks with different size. Craig and von Peter (2010) show that the structure of interbank funding market has multiple tiers, where small banks require interbank funding from large (money centre) banks. During the crisis period, large (money centre) banks are reluctant to provide funding for smaller banks due to counterparty risk and liquidity hoarding (*e.g.* Heider et al, 2009; Acharya and Merrouche, 2010). Thus, the benefit of reduced borrowing cost is only enjoyed by large (money centre) banks but not the small ones.

The joint market intervention, government bailout, TRAP rescue plan and economy stimulus plan announcements all have a positive and significant impact on the equity return of the U.S. banking sector. Especially the TRAP rescue plan and the economy stimulus plan announced by the U.S. government in late 2008 and early 2009.[163] The equity return of SIFIs/Medium/Small banks had increased by 18.6%/9.9%/9.2% upon the

[163] Due to space limits, the exact dates of these announcements are available from the author upon request.

announcement of TRAP rescue plan (*DUM6*), while the economy stimulus plan (*DUM7*) boots the equity return of SIFIs/Medium/Small banks by 14.4%/11.0%/7.9% during the crisis period. The only exception is the liquidity related announcements (*DUM3*), which have a negative and significant impact on the U.S. banking industry. The possible explanation behind this phenomenon could be that these announcements (*i.e.* liquidity related) signalling the lack of funding liquidity within the U.S. banking system. Given the funding liquidity is the main driving force behind the recent financial turmoil (*e.g.* Blackburn, 2008; Brunnermeier, 2009), it is reasonable for investors to be sensitivity about the funding liquidity situation of the banking system.

The return sensitivity of the U.K. and Japanese banking sector during the crisis period is reported in Panel B and C in Table 3.5. Similar to the finding observed from the U.S. banking sector, the *market* effect during the crisis period (Table 3.5) for both UK and Japanese banking portfolios is higher compared to the pre-crisis period (Table 3.4). For the UK banking sector, one possible explanation of the enhanced *market* sensitivity could be the bailout on Northern Rock in early 2008. The British government nationalized Northern Rock on *February 17, 2008* as a temporary measure to prevent a bank run spreading to other financial institutions (Goldsmith-Pinkham and Yorulmazer, 2010). This event is likely to strike uncertainty into the UK banking sector and may have a further impact on the whole economy, which is likely to increase the interdependence between the two during the crisis period. In addition, the size effect of *market* effect (*i.e.* large banks have higher *market* effect than small ones) has also been registered for the Japanese banking portfolios (Panel C). This size effect might attribute to the difference between the risk characteristic of the large and small Japanese banks as well as the currency value movements during the crisis period. Melvin and Taylor (2009) show that the Japanese Yen had appreciated dramatically since the collapse of Lehman due to unwinding of currency carry trade and the "safe-haven" status enjoyed by the Japanese Yen. Given that large banks (*e.g.* banking SIFIs in our sample) are more likely to invest into foreign markets Chamberlain et al (1997), the further losses suffered by Japanese banks in our sample may be caused by the decrease in their foreign asset value due to the appreciation in Yen. Moreover, the collapse of Lehman in late 2008 seems to have significantly reduced the *market* effect of Japanese banking portfolios but not the UK ones.[164] We claim the reason for this "roller coaster" movement of the *market* effect for Japanese banking sectors is twofold. First, despite the sharp fall following the Lehman collapse in late 2008, the equity market in Japan has gradually recovered since early 2009. Second, banks from Japanese banking sector suffer further losses in the second half of 2009. For instance, from Panel C Table 3.2, one can see that the average daily return of Japanese SIFIs over *Sub-Period 3* (*i.e.* post-Lehman) is -22.4 bps, which is lower than the -13.3 bps average return over *Sub-Period 2* (*i.e.* pre-Lehman). The reduced market effect over the post-Lehman period, therefore, may attribute to the divergence in performances between the two.[165]

The return sensitivity of the UK banking sector upon changes in the term structure shows similar pattern as their U.S. counterpart during the crisis period. From Panel B, Table 3.5, one can see that the *level* (9.4%) and *curvature* (1.4%) effect of the UK SIFIs are positive and significant during the crisis period, and are considerably higher than their pre-crisis level (*i.e.* 8.4% and 0.2% for *level* and *curvature* effect, respectively). We argue the increase in long-term rates related risk factors (*i.e. level* and *curvature* effect) is mainly due

[164] It is worth noting that the *market* effect after the collapse of Lehman Brother is equal to the *market* effect over the crisis plus the change in *market* effect after the Lehman event (*i.e.* the parameter attached to the interactive dummy for *market* risk factor). For instance, the market effect of Japanese SIFIs after the Lehman collapse is equal to the sum of 1.464 (*i.e. market* effect over the crisis period) and -0.402 (*i.e.* the change in *market* effect after the Lehman event), which is 1.062.

[165] Please find the daily value changes of the equity market (*e.g.* NIKKEI 225) and SIFI portfolio of Japanese market in Appendix B.9.

to the “flight to quality” phenomenon during the crisis period. As discussed in the previous sections, investors prefer Treasury bonds than equity of banks during the crisis, which pushes down the equity value of banking portfolio and the interest rate of Treasury bonds (*e.g.* long-term rates). Therefore, the linkage between banking portfolio return and *level/curvature* factors increased following the BNP Paribas event in August 2007. However, the collapse of Lehman seems to have no influence on the sensitivity of SIFIs regarding the term structure related risk factors.

The market interventions carried out by the UK and Japanese governments and central banks also have a significant impact on the equity return of their banking sectors. From Panel B and C Table 3.5, one can see that interest rate related (*DUM1*) and special measure related (*DUM 4-5*) announcements are statistically significant for most banking portfolios across the two markets. In specific, the interest rate related announcements have a negative impact on the equity return of the UK SIFIs and Japanese regional/secondary banks, while the special measures (*i.e.* the bailouts and QE in the UK, and out-right purchase and stimulus in Japan) have a strong and positive impact on all banks in the two markets. The negative and significant coefficients for interest rate related announcements (*DUM1*) suggest that investors treat short-term interest rate cuts by the central bank as unfavorable signals for the UK and Japanese banking sector. This finding is supported by Taylor (2009), who argues that rapid interest rate reduction by central banks might prolong the crisis through currency depreciation and surge in commodity prices.

Similar to the findings on U.S. banking portfolios, the larger Japanese banks benefits more from stimulus packages (*i.e.* larger coefficient for *DUM5*) than small banks. The announcements regarding the joint market intervention (*DUM3*), however, only influence the performances of Japanese banks but not the U.K. ones. In other words, the Japanese banks treat joint market interventions as positive signals for potential market recovery. In general, our finding is supported by Ait-Sahalia et al (2010), who also show that market interventions (*i.e.* liquidity supports, liability guarantees, and recapitalization) by the U.S., UK and Japanese governments have a positive impact on their respective banking sector.

3.5.2. Interest Rate Sensitivity of the Insurance Institutions

The estimated parameters based on insurance portfolios across the three markets during the pre- and post-crisis period are presented in Table 3.6 and 3.7, respectively. Once again, we separate the estimation output for the three markets into three panels (*i.e.* Panel A, B and C for the U.S., UK and Japan, respectively).

Table 3.6 The Return Sensitivities of Insurance Sector Portfolios upon Changes in Market and Interest Rate Risk Factors before the Crisis.

The table below summarizes the estimated coefficient for market and interest rate risk factors for the insurance sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinarity issue. The pre-crisis period is from *January 31, 2003* till *August 8, 2007.* The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \varepsilon_t$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$
with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*January 31, 2003, August 8, 2007*]

R_t = a [$k \times 1$] matrix represents the return of portfolios from a given market over day t. k is equal to the number of portfolios involved in the VAR-BEKK system.

β_0 = a [$k \times 1$] parameter matrix represents the constants for the involved sector portfolios in a market.

$RiskFactor_t$ = a [4×1] matrix contains the orthogonalized *market* ($r_{M,t}^*$), orthogonalized *level* (ΔL_t^*), *slope* (ΔS_t^*), and orthogonalized *curvature* (ΔC_t^*) risk factors over day t for the corresponding market.

β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β, namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.

H_t = a [$k \times k$] conditional variance-covariance matrix of the estimated residuals at day t; k equals to the number of sector portfolios involved in the VAR-BEKK system.

A and B = [$k \times k$] diagonal parameter matrices represents the multivariate ARCH and GARCH effect of the conditional variance-covariance matrices. The parameters represent the ARCH and GARCH effects are the elements on the main diagonal of the matrix A and B, respectively.

Panel A: The U.S. Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	0.64		0.000	0.47	
β_M	0.928	43.37	***	0.797	44.32	***
β_L	0.087	16.35	***	0.075	15.56	***
β_S	-0.008	-3.20	***	-0.007	-3.14	***
β_C	0.012	11.33	***	0.011	11.70	***
Cond. Variance						
A	0.115	7.43	***	0.035	5.08	***
B	0.731	24.34	***	0.919	66.26	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	0.76		0.000	1.98	**
β_M	1.229	32.74	***	0.430	14.04	***
β_L	0.106	15.02	***	0.038	7.18	***
β_S	-0.005	-0.90		-0.001	-0.23	
β_C	0.007	4.29	***	0.001	1.05	
Cond. Variance						
A	0.063	5.81	***	0.020	3.00	***
B	0.920	87.58	***	0.960	99.92	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	0.10		-0.001	-1.37	
β_M	0.749	23.27	***	0.915	7.88	***
β_L	-0.016	-0.40		0.012	0.13	
β_S	-0.076	-7.41	***	-0.111	-2.92	***
β_C	0.028	5.83	***	0.018	1.27	
Cond. Variance						
A	0.067	6.97	***	0.064	7.83	***
B	0.901	63.34	***	0.920	82.62	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

For the U.S. insurers (Panel A), both large and small size institutions are sensitive to the *market* as well as the interest rate related (*i.e.* the *level, slope* and *curvature*) risk factors. Regarding the sign of these interest rate risk factors, changes in long-term interest rates (*i.e.* the *level* and *curvature* risk factors) have a positive impact on the U.S. insurers, while changes in short-term interest rates (*i.e. slope* risk factor) have a negative one. The findings are similar to the one observed from the U.S. banking portfolios. We argue that the reason for this similarity is twofold. First, the insurance companies have gone closer to the banking firms in terms of their products and services -and vice versa- under the umbrella of financial conglomerates in recent years (*e.g.* Saunders and Cornett, 2010). Therefore, insurers should have similar risk characteristic to banks. Second, previous studies claim that insurers are sensitive to interest rate fluctuations due to the longer duration of their investments relative to their liability (Elyasiani et al, 2007; Carson et al, 2008).[166] In other words, insurers seem to operate with a balance sheet structure similar to banks with long-term assets funded by short-term liabilities. Therefore, from a cash-flow point of view, insurers should have a similar interest rate risk exposure as banks (*e.g.* an increase in long-term/short-term rates will increase/decrease the profitability).

For the UK insurance portfolios (Panel B), there are two noticeable findings worth further discussion. First, the large insurance companies face much higher *market* effect (122.9%) during the pre-crisis period compared to small ones (43.0%). The result may attribute to the fact that the size (*i.e.* market capitalization) of large insurers is much bigger than the smaller ones.[167] Given that the market index (*i.e.* FTSE 100) employed in the current study for the UK is more focus on the performances of large firms, the index

[166] The datasets of Elyasiani et al. (2007) and Carson et al (2008) are drawn from the U.S. financial market. The interest rate risk factor used in these two studies is represented by the first difference of the 10-year U.S. Treasury bond yield.

[167] The average size of the large UK insurers is around 92 times the average size of the small ones. The detail information is available from the author upon request.

should be more representative for the large portfolio instead of the small one. Second, the UK insurers are not sensitive to the *slope* risk factor (insignificant coefficients). That means changes in short-term interest rates have no impact on the equity value of the UK insurers.

Finally, the estimation output based on Japanese insurance sector is presented in Panel C. As expected the coefficient of *market* risk factor is positive and statistically significant for both large (0.749) and small (0.915) insurance portfolios over the pre-crisis period. Besides, the negative *slope* and positive *curvature* effect for Japanese insurers are similar to findings observed from the U.S. market, which indicate that Japanese insurance sector also benefit from steepening yield curve. In addition, the coefficient for *level* risk factor is insignificant for both large and small insurers in Japanese market. We argue the result is due to the flat term structure and low long-term interest rates experienced in the Japan.[168]

The return sensitivity of insurance portfolios upon changes in the *market* and interest rate related risk factors (i.e. *level*, *slope* and *curvature* risk factors) over the crisis period is summarized in Table 3.7.

[168] The term structure of Japanese market over the sample period is presented in Panel C Appendix B.4.

Table 3.7 The Return Sensitivities Of Insurance Sector Portfolios upon Changes in Market and Interest Rate Risk Factors during the Crisis.

The table below summarizes the estimated coefficient for market and interest rate risk factors for the insurance sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinarity issue. The post-crisis period is from *August 9, 2007* till *January 31, 2010*. The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \gamma \cdot RiskFactor_t \cdot D + \beta_{DUM} \cdot DUM + \varepsilon_t \ ;$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*August 9, 2007, January 31, 2010*]

γ = a [k × *4*] parameter matrix represents the changes in return sensitivity upon the $RiskFactor_t$ after the collapse of Lehman Brother on the *September 15, 2008* for the *k* sector portfolios in R_t. The elements within γ namely γ_M, γ_L, γ_S, and γ_C represent the changes in *market*, *level*, *slope* and *curvature* effect of the sector portfolio return after the collapse of Lehman, respectively.

D = a dummy variable with *0* before the *September 15, 2008*, and *1* afterwards.

β_{DUM} = a [k × n] parameter matrix represents the impact of different types of market intervention announcements on the portfolio returns R_t.

DUM = a [n × *1*] intercept dummy variable matrix represents the announcement of market intervention under different category for the corresponding market; *n* is the number of announcement categories in the corresponding market.

Due to space limits, the explanation of variables above is not complete. For further detail please refer to Eq.8 in Page 126.

Panel A: The U.S. Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.84		0.000	-0.71	
β_M	1.193	24.88	***	0.888	20.66	***
β_L	0.105	11.20	***	0.081	10.25	***
β_S	0.001	0.20		-0.001	-0.25	
β_C	0.018	12.33	***	0.014	10.38	***
γ_M	0.899	9.34	***	0.415	6.88	***
γ_L	0.068	1.82	*	0.006	0.34	
γ_S	0.003	0.17		0.000	-0.04	
γ_C	0.017	2.38	***	0.004	1.42	
DUM1 (Fed Fund)	0.002	0.84		0.002	0.97	
DUM2 (Discount)	0.008	2.03	**	0.003	0.91	
DUM3 (Liquidity)	-0.020	-2.96	***	-0.023	-2.97	***
DUM4 (JMI†)	0.014	2.80	***	0.011	2.72	***
DUM5 (Bailouts)	0.024	1.61		0.020	3.08	***
DUM6 (TARP)	0.141	21.78	***	0.098	12.79	***
DUM7 (Stimulus)	0.121	6.78	***	0.065	14.55	***
Cond. Variance						
A	0.140	16.70	***	0.145	9.85	***
B	0.873	110.28	***	0.852	62.37	***

† *JMI* refers to the announcements related to joint market intervention.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.70		0.000	-0.80	
β_M	1.439	24.80	***	0.452	19.08	***
β_L	0.084	4.86	***	0.032	4.08	***
β_S	-0.005	-0.52		-0.005	-1.31	
β_C	0.010	2.75	***	0.002	1.49	
γ_M	-0.046	-0.52		-0.223	-6.91	***
γ_L	0.038	1.60		-0.021	-2.08	**
γ_S	-0.016	-1.03		0.003	0.51	
γ_C	-0.005	-1.20		-0.002	-0.97	
DUM1 (Rate Cuts)	-0.035	-4.84	***	-0.006	-2.72	***
DUM2 (Liquidity)	0.002	0.30		-0.002	-0.54	
DUM3 (JMI†)	0.002	0.29		-0.002	-0.75	
DUM4 (Bailouts)	0.036	2.10	**	0.009	1.69	*
DUM5 (QE††)	-0.001	-0.31		0.002	0.86	
Cond. Variance						
A	0.147	10.28	***	0.025	4.42	***
B	0.844	54.08	***	0.957	97.88	***

† *JMI* refers to the announcements related to joint market intervention.

†† QE refers the quantitative easing program introduced by the Bank of England.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Insurance Portfolios

	Large Insurers			Small Insurers		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	-0.001	-0.86		0.000	-0.01	
β_M	0.760	12.05	***	0.670	8.03	***
β_L	-0.043	-1.17		-0.053	-0.84	
β_S	-0.122	-5.31	***	-0.050	-1.82	*
β_C	0.043	6.05	***	0.012	1.20	
γ_M	0.110	1.47		-0.065	-0.70	
γ_L	-0.067	-1.04		-0.017	-0.20	
γ_S	0.013	0.39		-0.049	-1.23	
γ_C	0.000	0.00		-0.003	-0.16	
DUM1 (Rate Cuts)	-0.018	-2.07	**	-0.031	-1.54	
DUM2 (Liquidity)	0.011	2.59	***	0.021	3.22	***
DUM3 (JMI†)	0.004	1.63		0.011	3.77	***
DUM4 (QRP††)	0.026	1.92	*	0.016	2.94	***
DUM5 (Stimulus)	0.066	110.38	***	0.038	52.20	***
Cond. Variance						
A	0.075	6.97	***	0.089	7.83	***
B	0.911	63.34	***	0.849	82.62	***

† *JMI* refers to the announcements related to joint market intervention.
†† *ORP* refers to the outright purchase of government/corporate bonds introduced by the Bank of Japan.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

By comparing the estimation output from Table 3.6 (*i.e.* pre-crisis) and 3.7 (*i.e.* during the crisis), one can see that the *market* risk factor for the U.S. insurers (Panel A) has increased during the crisis period. For instance, the *market* effect of the large (small) U.S. insurance portfolio has gone up from 92.8% (79.7%) over the pre-crisis period (Table 3.6) to 119.3% (88.8%) during the financial turmoil (Table 3.7). The result suggests that insurers suffer from higher systematic risk during the crisis. The finding is supported by Harrington (2009), who argue that although insurance companies are not directly involved into the sub-prime mortgage crisis, they still suffer from the deterioration of global financial market due to mark to market. However, the incremental value of the *market* effect for insurers is relatively low compared to the banking sector. For instance, the market risk factor for the U.S. SIFIs has increased from 110.2% (Panel A Table 3.4) over the pre-crisis period to 161.5% during the crisis (Panel A Table 3.5), which is more than twice the amount of the large U.S. insurers (*i.e.* from 92.8% to 119.3%). The empirical evidence shares the view with Harrington (2009) and Eling and Schmeiser (2010), which suggest that insurers are less influenced by the recent financial turmoil compared to banks.

The return sensitivity of the U.S. insurers upon changes in the long-term interest rate related (*i.e. level* and *curvature*) risk factors has also increased. For large/small insurers, the *level* and *curvature* effect has increased from 8.7%/7.5% and 1.2%/1.1% before the crisis (Table 3.6) to 10.5%/8.1% and 1.8%/1.4% over the crisis period, respectively. The result is coincides with changes in return sensitivity of the U.S. banking sector, which also experiences enhanced long-term interest rate effect (*i.e.* higher *level* and *curvature* risk factors) during the crisis. Once again, we argue that the “flight to quality” behavior of investors during the financial turmoil may be a reasonable explanation behind the empirical finding. As investors prefer “safe haven” assets (*i.e.* long-term Treasury bills) during the crisis period than the equity of financial institutions (*i.e.* banks and/or insurers), they push down the long-term interest rate as well as the equity value of these institutions.

The collapse of Lehman has increased the systemic risk (i.e. higher *market* risk factor) of both large and small insurers in the U.S. market. Comparatively, the large insurers suffer more from the event as the incremental value in the *market* risk factor of large insurers (89.9% points) is much higher than the smaller ones (41.5% points) during the post-Lehman period.[169] The *level* and *curvature* effect of the large U.S. insurers have also increased due to the Lehman collapse but not for the smaller ones. The empirical finding suggests that investors are more concern about large insurers, which may due to their higher involvement in the credit risk insurance market (*e.g.* Cummins and Traninar, 2009; Cummins and Weiss, 2009).

By investigating the impact of market intervention related announcements on the equity value of the U.S. insurers, we document similar result as the one from U.S. banking sector. The empirical findings suggest two possibilities. On one hand, the similarity in the reaction to market interventions by the U.S. banking and insurance industry is due to the rapid convergence between the two financial intermediary types over the recent decades (Staikouras, 2006b; Saunders and Cornett, 2010). On the other hand, this similarity could attribute to the fact that the equity value of both the U.S. insurers and banks are closely related to the general economy. Thus, the market interventions influence the two sectors in similar fashion through their impact on the general economy.

In specific, the liquidity related announcements have a negative impact (-2.0%/-2.3%) on the equity return of U.S. (large/small) insurers, while the announcements regarding the

[169] It is worth noting that the total *market* effect during the post-Lehman period is the sum of the *market* coefficient before and after the Lehman event over the crisis period. For instance, the total *market* effect for the large U.S. insurers after the Lehman collapse is the sum of 1.193 (pre-) and 0.889 (post-), which equal to 2.089.

joint market intervention (1.4%/1.1%), TRAP rescue package (14.1%/9.8%) and economy stimulus package (12.1%/6.5%) have a positive one. It is worth noting that only the equity return of large insurers is sensitive to interest rate related announcements (0.8%) and only small insurers are sensitive to bailouts (2.0%).

The return sensitivity of the UK insurance portfolios during the crisis period is presented in Panel B. Similar to the finding from the U.S. market, the UK insurers also experience higher systemic risk (*i.e.* stronger *market* effect) during the crisis period compared to its pre-crisis level. Unlike the UK banking industry, the return sensitivity of the UK insurers upon changes in long-term interest rates (*i.e. level* risk factors) have decreased during the crisis period.[170] The changes in long-term interest rates may reflect the "flight to quality" behavior of investors during the crisis period. The decreased *level* risk factors for the UK insurers, therefore, could mean that investors do prefer the insurance companies compared to banks during the financial turmoil due to their relatively better performances. The collapse of Lehman has no impact (insignificant coefficients) on the return sensitivity of the large UK insurers but it significantly influences the *market* and *level* effect of the small insurance portfolio. The magnitude of the *market* and *level* risk factor for small UK insurers has dropped by 22.3% points and 2.1% points in the post-Lehman period, respectively. These findings reinforce our argument that small UK insurers perform relatively better than the large ones during the crisis period.[171]

The UK insurers (Panel B Table 3.7) and banks (Panel B Table 3.5) have similar return sensitivity pattern upon market intervention announcements. The announcement regarding interest rate cuts (*DUM1*) seem to have a negative impact on the insurance

[170] By comparing the Panel B in Table 6 and 7, one can see that *level* risk factor for the large and small UK insurance portfolio has increased from 0.106 and 0.038 to 0.084 and 0.032, respectively.

[171] The finding is supported by the summary statistics of the daily portfolio return reported in Table 2. The average daily return of the small UK insurance portfolio is higher than the large insurance portfolio over the crisis period (*Sub-Period* 2 and 3), especially after the collapse of Lehman (*Sub-Period* 3).

companies in the UK market, while the bailout related announcements (*DUM4*) have a positive one. It is worth noting that large insurers are more sensitivity to intervention announcements than smaller ones. For instance, the coefficients for interest rate (bailout) related announcements are -3.5% (3.6%) and -0.6 (0.9%) for large and small UK insurance portfolios, respectively.

Panel C Table 3.7 summarizes the estimation output of the VAR-BEKK model based on Japanese insurance portfolios over the recent financial turmoil. Unlike the result observed from the U.S. and UK markets, the *market* effect of Japanese insurers has almost unchanged during the crisis. For small insurers, the *market* risk factor has even decreased from 91.5% before the crisis (Panel C Table 3.6) to 67.0% over the crisis period (Panel C Table 3.7). The findings suggest that the systemic risk of the small Japanese insurers has decreased during the recent financial turmoil. The *market* effect of large insurers has increased slightly by 1.1% points (*i.e.* from 74.9% to 76.0%). However, it is worth noting that the magnitude of the incremental value for large Japanese insurance portfolio is negligible compared to its banking counterpart (*i.e.* Japanese SIFIs).[172]

From Panel C, one can see that the return sensitivity of Japanese insurers upon changes in the term structure has also altered during the crisis period but in different manners. Comparing to the pre-crisis period (Panel C Table 3.6), the magnitude of the *slope* (*curvature*) effect of large insurers has decreased (increased) from -7.6 (2.8) to -12.2 (4.3). For small insurers, however, the magnitude of its return sensitivity upon changes in short-term interest rates (*i.e. slope* effect) has dropped by 6.1% points (*i.e.* from -11.1% to -5.0%). The collapse of Lehman in the late 2008 does not seem to influence (insignificant

[172] By comparing Panel C in Table 4 and 5, one can see that the *market* risk factor of Japanese SIFIs has increased from 0.979 before the crisis to 1.464 during the crisis period.

coefficients) the return sensitivity of Japanese insurers upon changes in the *market* and interest rate related risk factors.

By investigating the impact of market intervention announcements on the equity performances of Japanese insurers, one can see that liquidity (*DUM2*), outright purchase (*DUM4*) and stimulus (*DUM5*) related announcements all influences the Japanese insurance industry in a positive manner. It is worth noting, however, that liquidity related announcements have no impact on Japanese banking portfolios (Panel C Table 3.5), which suggests that the liquidity injection by the Japanese central banks seems to benefit insurers only but not banks. The interest rate related announcements (*DUM1*) only affect the large insurers, but not the smaller ones, in a negative way (-1.8). The result is consistent with the enhanced *slope* risk factor for large insurers during the crisis period. In general, insurance companies across the three markets also benefit from market interventions, especially for the liquidity, bailout and special measure (*i.e.* stimulus packages) related announcements. The similarity between the banks and insurers upon their reaction to the market intervention could attribute to the rapid convergence of the two financial intermediary types (Staikouras, 2006b; Saunders and Cornett, 2010).

3.5.3. Interest Rate Sensitivity of the Non-Financial Institutions

Finally, the return sensitivities of non-financial institutions (or industrial firms) upon changes in market and interest rate related risk factors across the three markets are summarized in Table 3.8 and 3.9 for pre- and post-crisis period, respectively. Similar to tables presented in the previous sections, the estimation results based on industrial firms from different markets is presented in separate panels.

Table 3.8 The Return Sensitivities of Industrial Sector Portfolios upon Changes in Market and Interest Rate Risk Factors before the Crisis.

The table below summarizes the estimated coefficient for market and interest rate risk factors for the industrial sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinearity issue. The pre-crisis period is from *January 31, 2003* till *August 8, 2007.*
The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \varepsilon_t$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$
with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*1 January 2003, 8 August 2007*]

R_t = a [$k \times 1$] matrix represents the return of portfolios from a given market over day t. k is equal to the number of portfolios involved in the VAR-BEKK system.
β_0 = a [$k \times 1$] parameter matrix represents the constants for the involved sector portfolios in a market.
$RiskFactor_t$ = a [4×1] matrix contains the orthogonalized *market* ($r_{M,t}^*$), orthogonalized *level* (ΔL_t^*), *slope* (ΔS_t^*), and orthogonalized *curvature* (ΔC_t^*) risk factors over day t for the corresponding market.
β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.
H_t = a [$k \times k$] conditional variance-covariance matrix of the estimated residuals at day t; k equals to the number of sector portfolios involved in the VAR-BEKK system.
A and B = [$k \times k$] diagonal parameter matrices represents the multivariate ARCH and GARCH effect of the conditional variance-covariance matrices. The parameters represent the ARCH and GARCH effects are the elements on the main diagonal of the matrix A and B, respectively.

Panel A: The U.S. Industrial Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.70		0.000	0.15	
β_M	0.945	110.29	***	1.027	36.93	***
β_L	0.093	43.19	***	0.096	15.47	***
β_S	-0.008	-6.28	***	-0.008	-2.71	***
β_C	0.015	32.93	***	0.015	10.76	***
Cond. Variance						
A	0.036	4.60	***	0.068	5.96	***
B	0.890	27.90	***	0.790	18.75	***

Note: The estimated parameters are generated from Eq.8 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Industrial Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	3.64	***	0.000	-1.51	
β_M	0.968	71.73	***	0.182	8.27	***
β_L	0.075	27.61	***	0.018	2.82	***
β_S	-0.002	-0.88		0.002	0.35	
β_C	0.004	5.80	***	0.002	1.21	
Cond. Variance						
A	0.042	4.10	***	0.043	6.22	***
B	0.943	75.60	***	0.936	93.87	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Insurance Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	1.58		0.001	3.33	***
β_M	0.830	74.16	***	0.431	9.73	***
β_L	-0.027	-1.75	*	-0.038	-1.51	
β_S	-0.093	-24.25	***	-0.049	-7.73	***
β_C	0.029	16.26	***	0.014	3.86	***
Cond. Variance						
A	0.031	6.68	***	0.407	8.06	***
B	0.956	129.77	***	0.524	12.31	***

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "Cons" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Regarding the *market* risk factor, both large and small industrial firms in the U.S market (Panel A) is positively and significantly exposed to changes in equity market return over the pre-crisis period. The magnitude of the systemic risk for large industrial firms (0.945), however, is lower compared to the smaller firms (1.027), which indicate that the large industrial firms are more resilient to systemic shocks. This finding is opposite to the one based on the U.S. financial institutions, which indicates that large banks/insurers suffer from higher *market* risk compared to smaller ones. We argue that the potential reason behind this phenomenon could be twofold. First, the large firms are more likely to be diversified in terms of different business lines, which helps them to cope with unfavourable market conditions in a better manner through more steady income streams and enhanced competitive edge compared to the small firms. Second, the large firms are more likely to be multi-national corporations, which are able to diversify domestic systemic risk through international operations. Similarly, the small Japanese industrial firms (Panel C) also have higher (0.915) systemic risk (i.e. *market* risk factor) compared to the large ones. However, the large UK industrial firms have a much higher systemic risk (0.968) compare to the small ones (0.182), which might due to the use of FTSE 100 as approximation of market index.[173]

Regarding the return sensitivity upon changes in the term structure, the empirical finding indicates that the equity return of U.S. industrial sector is positively related to changes in long-term rates (i.e. positive *level* and *curvature* risk factors) and negatively related to short-term rate changes (i.e. negative *slope* risk factor) over the pre-crisis period. In other words, the U.S. non-financial institutions seem to have a similar interest rate exposure to financial institutions. Similar findings are also observed from the UK and

[173] FTSE 100 index is capitalization weighted equity market index where firms with large capitalization (i.e. large financial/industrial firms) will have a higher weighting in the index composition.

Japanese market, where industrial portfolios expose to yield curve changes in a parallel fashion compared to the financial institutions. For instance, UK industrial portfolios (Panel B) are positively related to changes in long-term interest rates (i.e. positive *level* and *curvature* risk factors for large firms; positive *level* risk factor for small firms), while Japanese industrial portfolios are negatively related to changes in short-term interest rates (i.e. negative *slope* risk factor), while large firms also positively expose to the changes in *curvature* risk factor before the recent financial crisis.

Previous studies suggest that the interest rate risk exposure of non-financial institutions is usually weak, and the impact is only found significant on utility firms (e.g. Sweeney and Warga, 1986; Staikouras, 2005). Given that only four out of the 26 industrial firms from DJIA is categorized as utility firms[174], arguments from previous studies seem unable to justify our result. One potential explanation could be that the significant impact of interest rate changes on industrial firm equity value is due to the fact that interest rate changes also have a significant impact on the equity market itself. Fluctuations in interest rates will have an impact on the value of entire equity market by changing the discount factor/require rate of return for all future cash flows derived from the equity assets. Given the explanatory variable transformation process employed in the current study, the equity value of non-financial institutions could expose to the yield changes through its exposure to the whole equity market.[175] Another potential explanation could be the use of derivative instruments. Non-financial institutions, especially large ones, are increasingly

[174] The four utility firms in the DJIA index are AT&T, Chevron Corporation, Exxon Mobile and Verizon Communications.

[175] As discussed in the methodology section, we eliminate the interdependence between the market and yield curve variables by removing the overlapping information of yield curve changes from the market risk factor. This method is supported by previous studies, such as Flannery and James (1984) and Hirtle (1997). Hirtle (1997) argues that by removing the interest rate effect from the market risk factor, the coefficient on interest rate risk factor will reflect both the direct influence of changes in interest rates on the equity value of institution under examination, as well as the indirect influences working through changes in the market rate of return.

using financial derivatives to reduce their exposures to a variety of risk (e.g. Geczy et al., 1997; Bodnar et al., 1998; Guay and Kothari, 2003). It is well known that the value of financial derivatives is sensitive to changes in interest rates. Therefore, non-financial institutions might also expose to interest rate risk via their holdings of financial derivatives. Finally, the significant interest rate risk of non-financial institutions might attribute to the international Fisher effect. As exchange rates will be influenced by changes in interest rates (Fisher, 1930), the equity value of non-financial institutions might expose to yield curve fluctuations through their foreign currency exposures.[176]

The return sensitivity of industrial portfolios upon changes in the *market* and interest rate related risk factors (i.e. *level*, *slope* and *curvature* risk factors) over the crisis period is summarized in Table 3.9.

[176] It is worth noting that since we do not have any direct measure or empirical evidence on the foreign currency exposure of non-financial institutions in our sample, the argument based on international Fisher effect can only be regarded as one of the possible explanations.

Table 3.9 The Return Sensitivities of Industrial Sector Portfolios upon Changes in Market and Interest Rate Risk Factors during the Crisis.

The table below summarizes the estimated coefficient for market and interest rate risk factors for the industrial sector portfolios across the three markets. The interest rate risk factors are represented by the level (ΔL^*_t), slope (ΔS^*_t) and curvature (ΔC^*_t) factors from the Nelson-Siegel term structure models. The risk factors used in the estimation are orthogonalized to eliminate the potential multicollinarity issue. The post-crisis period is from *August 9, 2007* till *January 31, 2010*. The coefficients reported in the table are estimated from a VAR-BEKK model with the following functional form.

$$R_t = \beta_0 + \beta \cdot RiskFactor_t + \gamma \cdot RiskFactor_t \cdot D + \beta_{DUM} \cdot DUM + \varepsilon_t \,;$$
$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$
with, $\varepsilon_t \sim N(0, h_t)$; $t \in$ [*August 9, 2007, January 31, 2010*]

β = a [$k \times 4$] parameter matrix represents the return sensitivity upon the $RiskFactor_t$ over the entire sample period for the k sector portfolios in R_t. The elements within β, namely β_M, β_L, β_S, and β_C represent the *market*, *level*, *slope* and *curvature* effect of the sector portfolio return, respectively.

γ = a [$k \times 4$] parameter matrix represents the changes in return sensitivity upon the $RiskFactor_t$ after the collapse of Lehman Brother on the *September 15, 2008* for the k sector portfolios in R_t. The elements within γ, namely γ_M, γ_L, γ_S, and γ_C represent the changes in *market*, *level*, *slope* and *curvature* effect of the sector portfolio return after the collapse of Lehman, respectively.

D = a dummy variable with *0* before the *September 15, 2008*, and *1* afterwards.

β_{DUM} = a [$k \times n$] parameter matrix represents the impact of different types of market intervention announcements on the portfolio returns R_t.

DUM = a [$n \times 1$] intercept dummy variable matrix represents the announcement of market intervention under different category for the corresponding market; n is the number of announcement categories in the corresponding market.

Due to space limits, the explanation of variables above is not complete. For further detail please refer to Eq.4 in Page 126.

Panel A: The U.S. Industrial Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	0.25		0.000	-1.35	
β_M	0.844	48.31	***	1.092	27.25	***
β_L	0.075	20.74	***	0.117	13.26	***
β_S	-0.005	-3.17	***	-0.015	-3.69	***
β_C	0.012	22.38	***	0.016	12.97	***
γ_M	0.062	2.86	***	0.252	3.71	***
γ_L	-0.001	-0.14		-0.034	-2.21	**
γ_S	-0.002	-0.81		-0.015	-1.83	*
γ_C	-0.001	-1.10		-0.003	-0.64	
DUM1 (Fed Fund)	0.004	2.73	***	0.011	4.60	***
DUM2 (Discount)	0.001	0.81		0.003	1.45	
DUM3 (Liquidity)	-0.017	-8.70	***	-0.023	-4.22	***
DUM4 (JMI†)	0.018	11.01	***	0.017	3.73	***
DUM5 (Bailouts)	0.006	1.16		0.014	3.67	***
DUM6 (TARP)	0.039	19.55	***	0.081	15.00	***
DUM7 (Stimulus)	0.029	13.33	***	0.044	9.02	***
Cond. Variance						
A	0.055	7.11	***	0.145	7.57	***
B	0.937	104.85	***	0.837	46.70	***

† *JMI* refers to the announcements related to joint market intervention.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel B: The UK Industrial Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	0.55		-0.001	-4.44	***
β_M	0.930	36.62	***	0.109	3.10	***
β_L	0.072	9.85	***	0.006	0.77	
β_S	-0.008	-1.87	*	0.004	0.90	
β_C	0.005	2.72	***	0.001	0.56	
γ_M	-0.074	-2.16	**	-0.063	-1.54	
γ_L	0.000	-0.02		0.018	1.80	*
γ_S	0.003	0.64		-0.001	-0.21	
γ_C	-0.003	-1.41		0.000	0.00	
DUM1 (Rate Cuts)	-0.022	-12.14	***	0.004	2.28	**
DUM2 (Liquidity)	0.004	2.02	**	-0.001	-0.86	
DUM3 (JMI†)	0.001	0.31		0.005	0.89	
DUM4 (Bailouts)	0.020	5.60	***	-0.006	-3.19	***
DUM5 (QE††)	0.003	0.83		0.002	0.57	
Cond. Variance						
A	0.052	7.19	***	0.195	6.40	***
B	0.944	119.22	***	0.657	15.58	***

† *JMI* refers to the announcements related to joint market intervention.
†† QE refers the quantitative easing program introduced by the Bank of England.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

Panel C: Japanese Industrial Portfolios

	Large Industrial Firms			Small Industrial Firms		
Cond. Mean	*Coeff*	*t-Stat*		*Coeff*	*t-Stat*	
Cons	0.000	-0.59		-0.001	-2.55	***
β_M	0.940	47.78	***	0.616	16.18	***
β_L	-0.045	-1.81	*	-0.006	-0.26	
β_S	-0.091	-13.38	***	-0.053	-4.73	***
β_C	0.027	9.37	***	0.012	3.44	***
γ_M	-0.099	-3.94	***	-0.198	-4.40	***
γ_L	-0.010	-0.32		-0.050	-1.07	
γ_S	-0.017	-1.54		-0.017	-0.93	
γ_C	0.006	1.04		0.012	0.99	
DUM1 (Rate Cuts)	-0.025	-5.09	***	-0.021	-2.24	**
DUM2 (Liquidity)	0.011	3.82	***	0.018	4.18	***
DUM3 (JMI†)	0.010	4.42	***	0.016	6.09	***
DUM4 (QRP††)	0.007	2.66	***	0.002	0.64	
DUM5 (Stimulus)	0.029	136.08	***	0.017	45.00	***
Cond. Variance						
A	0.070	5.11	***	0.168	3.88	***
B	0.904	41.22	***	0.714	13.95	***

† *JMI* refers to the announcements related to joint market intervention.
†† *ORP* refers to the outright purchase of government/corporate bonds introduced by the Bank of Japan.

Note: The estimated parameters are generated from Eq.4 over the pre-crisis period. The "*Cons*" represents the constant of the conditional mean equation; the "*Coeff*" represents the estimated coefficients; the "*t-Stat*" represents the t-statistics generated based on Bollerslev-Wooldridge standard errors; the "*A*" and "*B*" represent the ARCH and GARCH effect of the conditional variance equation in the diagonal BEKK model. The 10%/5%/1% significance level is marked as */**/***.

From Panel A Table 3.9, one can see that the *market* effect (84.4%) of the large U.S. industrial firms has decreased during the crisis period compared to its pre-crisis level (94.5%, Panel A Table 3.8). The reduced *market* effect indicates that the return of large industrial firms is less related to the equity market during the crisis period. Bartram and Bodnar (2009) support our finding as they show the return movement of the U.S. non-financial sector has deviated from the equity market since early 2007.

The magnitude of the interest related risk factors has decreased (increased) for the large (small) U.S. industrial firms during the crisis period. For instance, the *level* effect of large (small) firms has gone up (down) by 1.8% (1.1%) points from 9.3% (9.6%) during the pre-crisis period to 7.5% (11.7%) over the crisis period. We argue that the potential explanation behind this phenomenon is twofold. First, the reduced (increased) long-term interest rate (*i.e. level* and *curvature*) risk factors for large (small) industrial firms are due to their relative performances during the crisis period. The large U.S. industrial firms perform better compared to their smaller counterparts during the crisis period (Panel A Table 3.2). Investors, therefore, would prefer large firms compared to smaller ones due to "flight to quality". As aforementioned, the relationship between equity return and changes in long-term interest rates is able to reflect the potential "flight to quality" phenomenon, as stronger (*i.e.* more positive/less negative) relationship indicates "fly away" while weaker (*i.e.* less positive/more negative) relationship indicates "fly in". Second, the reduced magnitude for large industrial firms could attribute to the fact that banks are reluctant to offer funding to the economy. This argument is supported by Ivashina and Scharfstein (2010) and Santos (2011). The former study shows new loans to borrowers have dropped substantially since the third quarter of 2007, while the latter finds the U.S. banks charge higher loan spread during the crisis period than before and only lend to large industrial firms. Since only large firms are able to access to banks loans during the crisis period (Santos, 2011), the decrease in interest rate risk factors is only observed for large industrial firms.

The collapse of Lehman significantly increases the systemic risk of the U.S. industrial sector, as the incremental value of *market* effect for both large (6.2% points) and small (25.2% points) industrial firms is positive and significant. The empirical evidence suggests that the Lehman bankruptcy has a significant impact on the economic condition of the U.S. market, which indicates that the influence of the recent financial crisis has already gone beyond the financial market and penetrated into the real economy. The interest rate related risk factors are less influenced by the Lehman event. The only noticeable changes come from the small industrial firms, where the *level* (-3.4% points) and *slope* (-1.5% points) effect has decreased followed the Lehman bankruptcy.

By investigating the impact of market intervention on the U.S. industrial portfolios, one can see that rate cuts (*DUM1*), joint market intervention (*DUM4*), TARP (*DUM6*) and stimulus (*DUM7*) related announcements all have strong and positive impacts on the equity return of the large and small U.S. industrial firms. The TARP and stimulus announcements have the most significant influence among the various market interventions. The finding is reasonable given the former enables financial institutions to offload most of their troubled assets to increase their lending ability, while the latter improve the short-term prospect of the economic condition. Both of these two special measures (*i.e.* TARP and stimulus), therefore, benefit the industrial firms as they provide a better operating environment for the latter. Similar to financial institutions in the U.S. market, the liquidity related announcement s has a negative impact on the U.S. industrial firms.

The return sensitivity of the UK industrial sector is presented in Panel B. The empirical evidence from the UK market is similar to the one observed from the U.S. market. For instance, the *market* effect of the large UK industrial portfolio has reduced from 96.8% over the pre-crisis period (Panel B Table 3.8) to 93.0% during the crisis, while its *level* effect has also dropped slightly from 7.5% to 7.2%. The equity value of the small UK industrial firms seems not sensitive to changes in term structure during the crisis period, as none of the interest rate related risk factors are statistically significant. The collapse of Lehman reduces the *market* effect of the large UK industrial firms further by an additional 7.4% points. Given the dominate position of the financial sector in the UK economy (Haldane, 2010), the decrease in market effect for large industrial firms indicates the former performs relatively better compared to the financial institutions especially followed the collapse of Lehman. The average daily return of the two sectors during the crisis period supports our argument. From Table 3.2, one can see that the performance of the UK banking portfolio has worsened during the crisis period as the average daily return over *Sub-Period 3* (-24.3 bps) is much lower than the one over *Sub-Period 2* (-19.4 bps). For large industrial firms, however, the opposite is true.

The market interventions carried out by the UK government/central bank have different impact on the large and small industrial firms during the crisis period. To be specific, the rate cuts (DUM1) have a negative/positive (-2.2%/0.4%) relationship with the large/small industrial firms, while the influence of government bailout is positive/negative (2.0%/-0.6%) for the equity return of large/small firms. This finding is contrary to the result observed by Giannetti and Simonov (2009), who claim that bailouts benefit industrial firms through more loan and increasing investments.[177] We argue the size effect of the bailout announcement is mainly due to the structure of the UK banking

[177] However, Giannetti and Simonov (2009) also claim that the bailout will not necessarily create more jobs.

system. As discussed in the data section, the UK banking industry is dominated by large banking corporations. Previous studies show that large banks are more likely to offer loans to large corporations than small ones (*e.g.* Berger et al, 1998; Strahan and Weston, 1998; Berger and Udell, 2002). Therefore, it is reasonable that the large UK industrial firms benefit more from financial institution bailouts than the small ones. Interestingly, the QE program carried out by the Bank of England only benefits the banking portfolio (Panel B Table 3.5) but not industrial firms (insignificant parameters for *DUM5*). That means the QE program has only provided benefits to banks but not to the real economy yet (Miles, 2009).

From Panel C, one can see that the *market* effect of industrial sector portfolios in the Japanese market has increased during the crisis period. For instance, the coefficient of *market* risk factor for large Japanese industrial firms has enhanced by 11.0% points from 83.0% over the pre-crisis period (Panel C Table 3.8) to 94.0% during the crisis. This finding is contrary to what we observed from the U.S. and UK markets, where the *market* effect of industrial and financial institutions moves in the different directions during the crisis period. We believe the difference is attributed to the different financial system adopted by the two markets. The U.S. and Japanese financial market is commonly regarded as the classic example of a market- and bank-oriented system, respectively.[178] Since firms in bank-oriented system mainly seek external financing through banks, their linkage with the financial institutions is therefore tighter (*e.g.* Weinstein and Yafeh, 1998). The *Flow of Funds* data from Bank of Japan indicates that financial investment and fund raised by the non-financial corporation through shares and other securities is only 41.8% and 1.8% of the amount raised by banks or depository corporations through deposits and

[178] For further discussion on the types of financial systems, and the classifications across major economies, please refer to Thakor (1996), Beck and Levine (2002), and Wang and Ma (2009) among others.

securities in 2009 and 2010, respectively.[179] As non-financial institutions in Japanese market are more relied on funding through banks instead of other sources (*e.g.* equities and bonds), their relationship with banks should be closer than those in the U.S.[180] Therefore, the changes in *market* effect of the banking and industrial portfolio in Japanese market move in the same direction during the crisis period. The interest rate risk of the industrial firms in Japanese market seems remain constant during the crisis period. The only notable change comes from the *level* effect of large industrial portfolio, which has decreased by 1.8% points from -2.7% over the pre-crisis period (Panel C Table 3.8) to -4.5% over the crisis.

This finding suggests that equities of large Japanese industrial firms suffer are treated as safe haven assets similar to long-term government bonds. Given the "flight to quality" hypothesis discussed in the previous section, changes in long-term interest rate can reflect investors' preference during the crisis period. As investors prefer safe haven assets (*i.e.* long-term government bond) during the crisis period, the price of these assets will increase while their yields (*i.e.* long-term interest rate) drop. The enhanced negative relationship between the long-term interest rate changes (*i.e.* level effect) and equity return of large industrial firms, therefore, signalling the similar characteristic of the large industrial firms and long-term government bonds (*i.e.* safe haven assets) during the recent financial turmoil. Finally, the collapse of Lehman does significantly alter the systemic risk (*i.e. market* effect) of the Japanese non-financial institutions, but not their interest rate risks.

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[179] The data is collected from the *Flow of Funds* report issued by Bank of Japan on the 20 September 2011, see: http://www.boj.or.jp/en/statistics/sj/sjlong.zip.

[180] The unconditional correlation between the value of banking and industrial portfolio is 94.7% for Japan over the entire sample period compared to 77.1% and 60.7% for the U.S. and UK market, respectively. The information on unconditional correlations among the sector portfolios within a market is available upon request.

To be specific, the Lehman event reduces the *market* effect of both large and small Japanese industrial firms by 9.9% and 19.8% points, respectively.

All the five types of market interventions have a significant impact on the equity return of Japanese industrial sector during the financial turmoil. Apart from rate cut (*DUM1*) related announcements, which have a negative (-2.5% and -2.1%) relationship with the performances of (large and small) industrial sector portfolios, all other announcements have a positive and statistically significant influence. For instance, the liquidity injection (*DUM2*)/joint market intervention (*DUM3*) announcements are related to the equity return of large (1.1%/1.0%) and small (1.8%/1.6%) industrial firms in a positive manner. It is worth noting that the outright purchase (*DUM4*) program carried out by the Bank of Japan only influences the performances of large industrial firms (0.7%) but not the small ones (insignificant coefficient). We argue that this size effect is attributed to the fact that the outright purchase program only covers the financial instruments issued by the large corporation but not the small ones. Based on the statement issued by the Bank of Japan in early 2009[181], the program only purchases commercial papers issued by the corporations. Given the fact commercial papers are usually used by large corporation with high credit rating as an alternative for bank loans (Hahn, 1993; McKenzie, 1996), it is reasonable that only large firms are influenced by the program but not the small ones. Similarly, the stimulus package announcements (*DUM5*) also have stronger impacts on large (2.9%) industrial firms compared to the small ones (1.7%). The different reaction between the two size portfolios may due to their different systemic risk characteristics. The stimulus package is aiming to improve the overall performances of the whole economy (or market). The firms with higher *market* effect, therefore, will benefit more

[181] The statement issued by the Bank of Japan is *Outright Purchases of Corporate Financing Instruments* (2009), see: http://www.boj.or.jp/en/announcements/release_2009/un0901b.pdf.

from the program as they are more sensitive to the market movements. From Panel C, one can see that large industrial firms do have larger systemic risk (*i.e.* higher *market* effect) than small ones during the crisis period.

3.6. CONCLUSION

The current study uses a modified VAR-BEKK framework to evaluate the return sensitivity of financial and non-financial institutions from the U.S., the UK and Japanese market on changes in the term structure of interest rates before and during the recent financial turmoil. Apart from employing bond indies or yields with a given maturity, we use the *level*, *slope* and *curvature* factor from NS model as interest rate risk factors.

For the U.S. market, the result indicates that increase/decrease in long-/short-term interest rates have a positive/negative impact on the equity value of financial institutions. In other words, a steeper yield curve (*e.g.* higher *level* and *curvature* factor and lower *slope* factor) will increase the equity return of financial institutions. In addition, we find the characteristics of interest rate risk exposure for industrial firms are similar to those for financial institutions. The recent financial crisis had a significant impact on the *level* effect of banks indicating a potential "flight to quality" from banking stocks to safe-haven assets (*e.g.* long-term government bonds). The result also suggests that banks were less willing to "pass on" favourable lending terms to industrial firms during the financial turmoil. Finally, the joint market intervention on funding liquidity in late 2007 temporarily relief the funding pressure on the banking sector SIFIs in the U.S. market until the collapse of Lehman in 2008.

Similar to findings observed in the U.S. market, financial and non-financial institutions in the UK and Japanese market also benefit from a steeper yield curve over the entire sample period. However, the equity value of financial institutions from the UK (Japanese) market is not sensitive to changes in *slope* (*level*) effect, which may attribute to the low level and variance in the short-term (long-term) interest rates during the sample period. Besides, the recent financial turmoil has similar impact on the *market* effect of industrial firms and banks in Japanese market, which indicates that non-financial institutions in a bank-oriented financial system have stronger bond with banks. Furthermore, the joint market interventions on funding liquidity have a much less impact on the interest rate risk exposure of banks in the UK and Japanese markets compared to those in the U.S.

Finally, the market interventions carried out by central bank/government/Treasury have a significant impact on the financial and non-financial firms across the three markets. In general, the interest rate reduction actions have a positive influence in the U.S. market but a negative one in the UK and Japanese markets. Joint market interventions led by the global major central banks seem to have a positive impact across the three markets. Among the various intervention programs, the special measures taken by the respective governments during the crisis period have the strongest influence on both financial and non-financial firms across the three markets. For instance, the TARP program related announcements in the U.S. dramatically increase the equity value of U.S. sector portfolios, while the QE program related announcements in the UK have a similar effect. However, due to the structure of financial system is different across each market, the impact of these market interventions does exhibit size effects for large and small corporations.

CHAPTER 4

THE INFLUENCE OF CURRENCY VALUE FLUCTUATIONS ON FINANCIAL INTERMEDIARIES

4.1. INTRODUCTION

The influence of the currency value fluctuation on the global economy was largely ignored before 1970s because of the Bretton Woods system, which fixed the relative value of all major currencies. Established by the world major economies towards the end of World War II, the Bretton Woods system was designed to help the reconstruction of the broken international economy in the post-war era. The fixed global exchange rate regime helped the economies around the world to balance their foreign payments without worrying the relative appreciation or depreciation of their own currencies against other foreign currencies, which also encouraged the import/export trading across the countries. This unique system also established the dominance position of the US Dollar as a global currency, with its value linked to gold as a benchmark (the Gold Standard).

However, the growing trading deficit of the US economy in the 1960s has put enormous pressure for its currency value to remain stable, and the Gold Standard was under severe pressure. Eventually, the US government was forced to give up the Gold Standard in 1971, which marked the end of the Bretton Woods system. The collapse of the Bretton Woods system not only enabled the US Dollar to float freely against the gold, but also enabled other currencies to float freely against the US Dollar and among each other. Since 1973, most of the world major developed economies had their currencies floated freely on the foreign exchange market, and the value of these currencies is mainly determined by supply and demand.

On the one hand, the post-Bretton Woods era introduced flexibility to the foreign exchange market. On the other hand, the floating currency value created uncertainties within the global financial market. Before the termination of the Bretton Woods system, the currency traders did not concern about the future value of their foreign currency-dominated assets, as their value is relatively stable given the fixed exchange rate regime. However, after the regime had collapsed, traders were exposed to the free floating currency value, which made the future value of their foreign assets or liabilities uncertain. In addition, the oil crisis in 1973, the stock market collapse in the world major financial markets in 1973 and 1974, and the Pound Sterling crisis in the 1976 magnified the impact of this uncertainty among the global financial markets. The recent financial crisis originated from the US market also has a significant impact on the foreign exchange market. Melvin and Taylor (2009) show that the recent financial crisis caused a major unwinding of the currency carry trade, which severely increased the volatility of the foreign exchange market.[182]

Since 1970s, the relationship between the changes in home currency value and the performances of multinational firms started to draw attention from various researchers.[183] For firms based in a particular national market, the home currency refers to the currency that is issued by and widely used in this national market.[184] The currency value is often represented as a bilateral exchange rate or a multivariate currency price index.[185] The

[182] The currency carry trade is a popular investment strategy for investors in the foreign currency market. The carry trade refers to borrowing in low interest rate currencies and investing in high interest rate ones to arbitrage the interest rate differences.

[183] We provide a brief summary of the recent studies on currency exposure of multinational firms in Section 2.

[184] For example, Choi and Prasad (1995) evaluate the relationship between the changes in US Doller value and the return performance of the US firms. Besides, alternative terms have been used by other studies to represent the home currency. For instance, Shapiro (1975 and 1977) uses "local" currency, while De Santis and Gerard (1998) refers the home currency as "domestic" currency.

[185] The bilateral exchange rate is the conversation ratio between one currency and any other foreign currencies, while the multilateral currency price index is the relative value of one currency against a basket

impact of home currency value fluctuation on a firm's equity value is also referred as the currency exposure or currency risk factor.[186]

Recent studies have put more emphasis on the currency exposure of financial institutions, especially banks.[187] As discussed in Saunders and Cornett (2010), financial institutions play an important role in the foreign exchange market. Banks and insurers contribute most of the trading volume in the foreign exchange market, as they buy and sell foreign currency-dominated assets for their clients and themselves. Therefore, it is likely for financial institutions to be exposed to currency risk. Previous studies reveal that the changes in home currency value may influence the equity value of financial institutions in two ways. First, the changes in home currency value have an impact on the value of foreign currency-dominated assets or liabilities in home currency terms. For financial institutions have net long or short foreign position, the changes in home currency value relative to foreign currencies will influence their operating cash flows (Dufey, 1972; Shapiro, 1975 and 1977). Second, the fluctuation in home currency value can influence the profitability of financial institutions through its impact on the market condition. Chamberlain et al. (1997) argue that the extent of foreign competition, the demand for loans in the home country can be influenced by the changes in home currency value.[188]

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of other foreign currencies. In the present study, we refer the currency value as a multilateral currency price index.

[186] For instance, Adler and Dumas (1984) use "currency risk" to describe the influence of home currency value fluctuations on domestic firms, while Choi et al (1992) use "exchange rate risks" to describe the same phenomenon. The phase "currency exposure" is employed by researchers such as Doukas et al (1999), and the "exchange (rate) exposure" is used by studies like Choi (1986), and Bodnar and Wong (2003). However, Adler and Dumas (1984) argue that the definition of "risk" may be different from "exposure", as "risk" refers to whether the fluctuation matters to a firm's value and "exposure" is the amount of this risk. However, in the current study, we assume all the alternative phases contain the same meaning.

[187] The introduction of Basel I by Basel Committee of Banking Supervision (BCBS) in 1988 specifies currency risk as one of the important aspects of the bank's risk management practise. We provide a brief summary of recent studies on the currency exposure of financial institutions in section 4.2.

[188] Chamberlain et al (1997) argue that the changes in home currency value will affect the profitability of exporters. If the exporters in the home country suffer from home currency value appreciation, the default probability of their borrowing will increase, which will affect the value of the loan and the profitability of the banks who lend the money to these exporters.

Therefore, a financial institution without any foreign activities can also be affected by the home currency value fluctuation.

The contribution of the current study is threefold. First, we examine the currency sensitivity of financial institutions across major geographical regions (UK, Japan and U.S.) and types of institutions (banks and insurers). Doukas et al. (1999) and Grant and Marshall (1997) among others, have focused on either different types of institutions within a country or the same type of institutions across countries, although (to our knowledge) no study to date does both.[189] Second, we use an alternative estimation framework, namely the VAR-BEKK model, aiming to capture the time-varying conditional variance-covariance among asset returns, while increasing estimation efficiency (simultaneous estimation of return and variance-covariance). Finally, unlike previous studies focusing on home currency fluctuations, this paper looks at both home and foreign currency sensitivity of bank/insurance equity portfolio returns. With regard to the latter, we test for both home and foreign currency effects.[190] Changes in currency values across markets mirror investors' preferences towards different currencies. Financial assets are usually traded in home currency terms and thus the need to obtain that currency is apparent.[191] In addition, according to the "flight to quality" hypothesis (Lang and Nakamura, 1995; Eichengreen et al., 2001; Vayanos, 2004) investors are likely to reallocate their investments

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[189] See Doukas et al (1999) and Grant and Marshall (1997) using Japanese and U.K. institutions; Chamberlain et al. (1997) for banking firms in the U.S. and Japan; Martin (2000) for major banks in Japan, Switzerland, the U.S. and the U.K.; and Elyasiani and Mansur (2003) using banks from Japan, Germany and the U.S.

[190] Home (foreign) currency effect is defined as the relationship between the equity returns of a financial institution and its home (the foreign) currency value fluctuations measured as the return of a trade weighted currency price index. The latter is a basket of currencies from 21 industrial countries constructed by the BoE.

[191] This is based on the "asset approach" hypothesis first introduced by Branson (1983) and Frankel (1983). Empirically, the studies by Kanas (2000) and Froot and Ramadorai (2005) support this argument. Froot and Ramadorai (2005) refer to the relationship between supply/demand of a currency and the currency value as the "flow-centric" view. The "flow" refers to the order flow for a currency from major currency traders. The empirical evidence show the order flow information is significantly related to currency value.

from risky to safer ones.[192] Therefore, changes in currency values can mirror investors' preference across countries. However, investor's preferences represented by home currency effects may be difficult to detect. Chow et al. (1997a) argue that due to effective hedging activity, the impact of home currency variations on firm's equity value is weak or even undetectable, especially in the short-run. Reichert and Shyu (2003) also argue that the currency swaps generally reduce the currency risk for the U.S., European and Japanese banks. Thus, a model using only home currency fluctuations may fail to detect the existence of the "flight to quality" effect.

A multivariate VAR-BEKK model comprising a VAR system of conditional mean equations for sector portfolio returns and a conditional variance-covariance estimation framework with a BEKK parameterization is employed. The sample period is 2003-11 (1st quarter) and focuses on the U.S., U.K. and Japanese banking and insurance industries. Equally weighted portfolios are constructed for the banking and insurance firms. The conditional mean equation of portfolio returns is specified as a function of market, interest rate, home and foreign currency-related risk factors. The latter includes both the changes and variability of currency values. A structural break is introduced into the VAR-BEKK model in order to investigate the effects of the recent financial crisis on the relationship between fluctuating currency values and the returns of banks and insurance firms.

The empirical analysis suggests that the impact of foreign currency on banking portfolios has changed after the recent financial turmoil. Changes in the value of the U.S. Dollar (Japanese Yen) have a negative influence on large Japanese (U.S.) bank returns providing support for the "flight to quality" hypothesis. Equity returns for U.K. and U.S.

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[192] Oetzel et al. (2001) show that the stability of a country's currency value is related to the country's economic risk level, which is represented by four different measures in their study: *Institutional Investor Index*, country risk rating from *Euromoney*, data from *International Country Risk Guide (ICRG)*, and risk level from *Political Risk Services (PRS)*. Naes et al. (2011) test and support the flight to quality hypothesis across countries.

insurance firms are negatively related to changes in the Japanese Yen. This relationship is accentuated during the recent financial crisis. The returns of the insurance portfolios are unaffected by home currency exposure, but foreign currency exposure has a significant impact on U.K. and U.S. insurers.

The empirical findings indicate that financial institutions are rewarded by bearing currency exposures, which is important from an asset pricing perspective. More specifically, it provides insight into the structure of financial markets. Our findings shed light on the explanatory role of domestic and foreign currency value in equity returns, the function of currency value fluctuation as a vehicle of conveying information. More importantly, the current chapter shows the importance of including such variable in pricing financial institutions equity and the extent to which the price of risk is significant in modern capital markets.

The reminder of the chapter is organized as follow. The following section provides a brief summary of the recent literature on currency exposure. Section 4.3 illustrates the estimation framework of the empirical study, which contains detail information about the proposed VAR-BEKK model and the joint-hypotheses tests used in this chapter. Section 4.4 describes the data set used in the current study. Section 4.5 presents the empirical evidence of the current study. Finally, Section 4.6 concludes the study.

4.2. LITERATURE REVIEW

In this section, we present a brief summary of recent studies on the relationship between home currency value fluctuations and the equity value of the firms. We categorize the literature into four groups according to their common frameworks. In the first group, we discuss the studies focus on the currency exposure of multinational companies (MNCs).

The second group contains papers that examine the currency exposure of financial institutions. Empirical studies which investigate the size effect in currency exposures categorized in group three. The final group collects the papers which inspire us to propose the VAR-BEKK model.

4.2.1. Currency Exposure of Multinational Companies

Early studies mainly focus on how the fluctuations in home currency value influence the performances of the multinational companies (MNCs). The theoretical linkage between the home currency fluctuation and the performances of MNCs is first introduced by Shapiro (1975). Shapiro suggests that the home currency value fluctuations influence MNCs due to competitive effect. The depreciation in home currency value reduces a product's price in foreign currency terms. Therefore, export-oriented MNCs benefit from the decrease in home currency value against foreign currencies, because a weak home currency strengthens their competitive advantage in the foreign markets. He also argues that the appreciation of home currency value will benefit pure domestic MNCs. The pure domestic MNCs purchase materials from oversea markets and sale products domestically. Therefore, the increase in home currency value will reduce the production cost of pure domestic MNCs and increase their profit margin. The idea is supported by Flood and Lessard (1986), who also suggest the competitive effect is the main reason behind the relationship between home currency value changes and the performances of MNCs. In addition, they argue that since for different MNCs the competitive structure of the market is different from one to another, the relationship might not be straightforward. The study by Choi (1986) yields similar conclusion, but is based on a different theoretical framework. He argues that a MNC's home currency exposure can be positive, negative or zero. He rests his argument on the fact that a firm exposes to foreign currency value fluctuation also benefits from international diversification, which can offset the uncertainty associated with the foreign exchange rate market. In addition, he argues that the currency exposure of a firm can be offset by hedging activities. Therefore, the impact of a MNC's home currency exposure on its return performance is uncertain.

The first empirical framework for evaluating the relationship between home currency value fluctuation and the return performance of MNCs is proposed by Adler and Dumas (1984). They suggest that currency exposure has a similar effect on the domestic firm as the market risk represented by the market portfolio. The market risk exposure is usually evaluated through a regression coefficient (market beta) which represents the influence of the market risk. Therefore, one should be able to evaluate the currency exposure by using the regression coefficient of the currency risk (currency beta).[193] The framework enables researchers to investigate the currency exposure of the MNCs on an empirical basis.

Empirical research on currency exposure yields mix results. Jorion (1990) finds no significant relationship between the return of 287 US MNCs and the changes in the trade weighted USD price index from 1971 to 1978. Similar result has been found by Jorion (1991) and Bodnar and Gentry (1993) based on US industry sector portfolios. Jorion (1991) evaluates the impact of changes in trade weighted USD price index on the return of 20 US industry sector portfolios in the 1970s, while Bodnar and Gentry (1993) extends the sample set to 39 US industry sector portfolios in the 1980s. However, only a small proportion of the examined industry sectors are influenced by the home currency value fluctuation. In

[193] Adler et al (1986) improve the model specification by using the changes in currency value as independent variable instead of the level of currency value. The changes in (returns of) currency value ensure the variable representing the currency risk is stationary. The model has been later extended by Jorion (1990) to incorporate the market risk factor into the regression model as well.

contrast, Choi and Prasad (1995) find around sixty percent of the 409 US MNCs are significantly exposed to currency risk from 1978 to 1989. They also show that the proportion of foreign sales is the most important factor for a MNC's currency exposure. In other words, the MNCs with high foreign sales figure are more likely to expose to currency risk.

Bartov and Bodnar (1994) argue that the mixed empirical evidence on currency exposure is mainly due to the problematic sample selection process used in the previous studies. They suggest the sample should only focuses on MNCs with sizable economic exposure to currency risk.[194] In addition, due to the mispricing of currency exposure on firm's value, they argue that market takes time to adjust the firm's value upon the changes of currency value.[195] Therefore, one should use the lagged currency value information instead of the contemporaneous one to evaluate a firm's currency exposure. By controlling the sample set, they show significant negative relationship between the returns of 38 US industry sector portfolios and the lagged changes in the trade weighted USD price index during 1978 to 1989. The result is supported by Doukas et al (1999), who employ a similar empirical framework to investigate the currency exposure in the Japanese market from 1975 to 1995. By controlling the sample according to firm's export level, they show high-exporting Japanese MNCs benefit from the depreciation of the home

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[194] In their study, the economic exposure to currency risk refers to pre-tax income in foreign currency terms. Sizable economic exposure to currency risk means more than 5% pre-tax income is in foreign currency terms in three or more of the past five years. They also control the sample by selecting firms with at least 75% of the foreign currency position is negatively related to the relative value changes in home currency (trade weighted USD price index).

[195] They argue that investors are unable to precisely evaluate the relationship between the changes in home currency value and firm value on a contemporaneous basis, which might introduce systematic mispricing of the currency exposure. The systematic mispricing suggests that investors react to changes in home currency value with a time lag. Therefore, there should be a relationship between the lagged changes in currency value and firm value.

currency value[196], which is in line with the Shapiro's (1975) theory. However, contradicting results have been provided by He and Ng (1998) and Krishnamoorthy (2001). He and Ng (1998) investigate the currency exposure of 171 MNCs in the Japanese market from 1979 to 1993 with lagged currency value information, and found only around four percent of the firms significantly exposed to changes in the trade weighted JPY price index. Krishnamoorthy (2001) evaluates the currency exposure of 20 US industry sector indices from 1995 to 1997, and he also rejects the hypothesis that the currency exposure based on lagged currency value information is more significant than the contemporaneous ones.

Other studies try to solve the puzzle of currency exposure by extending the estimation horizon. Chow et al (1997a) claim that short term currency exposures are mainly transaction exposure, they are difficult to detect as firms can hedge them easily and effectively.[197] However, as the horizon increases, the uncertainty about the currency exposure increases and makes effective hedging more difficult. Therefore, they argue that the currency exposure is more likely to be detected with a long estimation horizon.[198] They investigate the currency exposure of 65 US industry sector portfolios from 1977 to 1989 with a flexible estimation horizon. The empirical evidence shows that the influence of changes in trade weighted USD price index on sector portfolio return is only significant for long estimation horizon (more than 6-month) but not the short ones. Similar findings have been documented by Chow et al (1997b) and Bodnar and Wong (2003) with extended sample sets. Chow et al (1997b) collect 213 US MNCs from 1977 to 1991, while Bodnar and Wong (2003) have a sample of 908 US MNCs from 1977 to 1996. Both papers find the

[196] The high-exporting MNCs refer to the firms with reported foreign sales to total sales in excess of 20%. The home currency value is represented by a bilateral exchange rate between JPY and USD, and a trade weighted JPY price index. Both currency value measures yield similar result.
[197] Transaction exposure refers to the uncertainty when transfer a cash flow with fixed amount in foreign currency terms into home currency due to the uncertainty in exchange rate. This kind of exposure is usually short term in nature, and can be easily hedged with currency derivatives.
[198] The argument made by the authors is not based on empirical evidence but rational speculation.

relationship between changes in trade weighted USD price index and the equity return of MNCs is only significant over long estimation horizons. Consistent with Doukas et al (1999), Bodnar and Wong (2003) also show that the proportion of foreign sales is an important factor for the currency exposure of MNC. The MNCs with high foreign sales are negatively related to changes in home currency value, which means they benefit from home currency depreciation. The finding is in line with Shapiro's (1975) competitive effect. However, Griffin and Stulz (2001) argue that competitive effect is not the main driving force of the currency exposure for MNCs. By examining the relationship among the returns of sector indices from six world major economies from 1975 to 1997, they claim that industry effect dominates competitive effect.[199] The empirical evidence also suggests that industry effect has a common rather than competitive effect across countries.

Apart from estimation horizon, some researchers argue that the mixed result on currency exposure may due to the non-linear relationship between the firm's equity value and the changes in currency value. This argument is based on the fact that the payoff of hedging practice is usually non-linear. In other words, positive shocks in currency value may have a different impact on firm's value than negative ones. For instance, based on industry sector indices from four major countries from 1992 to 1998, Koutmos and Martin (2003a) find that around forty percent of the industry sector indices have a non-linear relationship with the changes in currency value.[200] They argue the reason behind this non-linear currency exposure is three behaviors: asymmetric price-to-market behavior,[201]

[199] The industry effect for an industry sector in country A is represented by the regression coefficient on excess return of the same industry in a competition country B.

[200] The four countries are Germany, Japan, UK and US.

[201] The asymmetric price-to-market (PTM) behaviour refers to the phenomenon that firms do not adjust export price based on changes in relative currency value to the full extent. For further discussion on condition of market competition and its influence on asymmetric PTM behaviour, please refer to Knetter (1994).

hysteretic behavior,[202] and asymmetric hedging behavior.[203] However, Krishnamoorthy (2001) shows that the non-linear feature of currency exposure is not statistically significant for US industry sector indices from 1995 to 1997.

4.2.2. *Currency Exposure of Financial Institutions*

The first empirical study on currency exposure of financial institutions is by Grammatikos et al (1986). They suggest the linkage between home currency value fluctuations and the equity return of financial institutions is due to the mismatch of foreign currency-dominated assets and liabilities. Based on the net position of foreign currency-dominated[204] assets and liabilities of the US banks during 1976 to 1981, the empirical evidence suggests that banks are highly exposed to individual foreign currency exposure but not on an aggregated level.[205] They argue the low aggregated currency exposure of US banks is due to the diversification effect, as the correlations between individual foreign currencies are low or even negative during the sample period.[206] Instead of using USD against individual foreign currencies, Choi et al (1992) investigate how US banks react to changes in the trade weighted USD price index. They only focus on the largest 48 banks over the period from 1975 to 1987. They find that the currency exposure of these largest

[202] Hysteretic behaviour refers the phenomenon that home currency depreciation encourages exporters enter the competition, but home currency appreciation will not drive them away from the market but reduce the overall profit margin of the whole sector.
[203] Asymmetric hedging occurs when firms take one-sided hedge (e.g. options). Therefore, the payoff of the hedging practice is non-linear.
[204] Information on assets and liabilities dominated in five foreign currencies are collected. The five foreign currencies are Canada Dollar, GBP, German Mark, Swiss France, and JPY.
[205] The study investigates the bank's exposure towards 5 different foreign currencies, namely the Canadian Dollar, German Mark, French Franc, GBP and JPY. The currency exposure is measured as the relationship between the bank wealth and the changes in net position for each of the five foreign currencies. Individual currency exposure refers to the changes in bilateral exchange rates of USD against a single foreign currency. The aggregated currency exposure refers to the relative value changes of USD against all the five foreign currencies.
[206] Grammatikos et al (1986) find that the largest correlation is between the value of Canadian Dollar and German Mark which is around 30%, while the value of GBP and German Mark is negatively related at -29%.

US banks changed dramatically from negative to positive during this period[207], especially after the introduction of International Bank Act in 1979. They further prove that the finding is coincide with the accounting evidence that large banks have altered their position in foreign currency-dominated assets from net long to net short during the sample period.

It seems that large banks have attracted more attention than the small ones, as most of the subsequent studies also focus on the currency exposure of large banks across global financial markets.[208] Wetmore and Brick (1994 and 1998) have extended the sample size of the Choi et al (1992). Their 1994 paper investigates the currency exposure of the 79 largest US banks from 1986 to 1991, while the 1998 paper extends the sample period further to 1995. Both empirical studies find significant relationship between the changes in trade weighted USD price index and the equity return of large US banks, and argue that currency exposure is mainly coming from unhedged foreign loan activities. Their argument is supported by the Chamberlain et al (1997). By evaluating the currency exposure of the 30 largest US banks and the 89 largest Japanese banks from 1986 to 1993, they also show that currency exposure is negatively related to the volume of hedging activities.[209] However, this argument is dismissed by Choi and Elyasiani (1997) with empirical evidence based on the 59 largest US banks from 1975 to 1992. They show that the hedging activities represent by the off-balance sheet items could increase the systemic risk of the banks instead of reducing it, especially when the hedging activity is for currency exposure through derivatives. Martin (2000) produces the first empirical study

[207] The negative/positive currency exposure means a positive shock in the relative value of domestic currency decrease/increase bank's value.

[208] Chamberlain et al (1997) suggest that researchers should focus on large size banks for three reasons: 1) the large size banks are more likely to involve in the international activities; 2) large banks are closer to being comparable in size across the national markets; and 3) large banks are the most important contributors to systemic risk.

[209] The hedging activity is represented by off-balance sheet items (interest rate and foreign exchange rate derivates) in Wetmore and Brick (1994 and 1998) and Chamberlain et al (1997).

to cover the large banks across the global financial markets.[210] He evaluates the currency exposure of the 30 world largest banks from 1994 to 1996. The empirical evidence suggests that over forty percent of the sample significantly expose to changes in their home currency value. However, the currency exposure of US banks is not significant during the sample period, which indicates that US banks are more risk averse.[211] That means they are hedging their currency exposures with more care.

In contrast to the enormous attention attracted by the banks, few studies examine the currency exposure of the insurance companies. Mange (2000) is the first one to demonstrate how fluctuation in home currency value will influence the equity value of insurance companies in a theoretical framework.[212] He shows that both life and non-life insurance companies may expose to currency risk through issuing insurance products into foreign markets, especially the long-term ones. For firms which issue long-term insurance products in foreign currency terms, the appreciation of home currency value against foreign currencies may reduce the expected value of the payables in foreign currency terms. In other words, the insurers should benefit from home currency appreciation. Elyasiani et al (2007) provide the first empirical study on currency exposure of US insurance firms from 1991 to 2001.[213] The empirical evidence suggests that there is indeed a significant and positive relationship between the changes in trade weighted USD price index and the returns of US insurance portfolio.

[210] The banks examined in his study come from 10 major developed countries/regions, which are US, UK, Japan, Germany, France, Switzerland, Sweden, Canada, Australia and Hong Kong.
[211] Martin (2000) suggests that US financial institutions have more restrictive regulatory and supervisory requirements.
[212] In this theoretical framework, the insurance premiums are paid in home currency terms and benefits are payable in foreign currency terms.
[213] The study is mainly focused on return linkage among the US financial sector portfolios. However, since they controlled for the changes in the broader stock market, interest rate and foreign exchange rate changes in the model specification, the exchange rate exposure of the financial sector portfolio is also been examined.

4.2.3. *Size Effect in Currency Exposure*

The currency exposure of a firm seems relate to its own size. Given that large size firms are more likely to involve in the global market, they should have a higher probability to expose to currency risk (Jorion, 1990). Therefore, large size firms should have higher currency exposure compares to small ones in theory at least. However, the theory of economies of scale of hedging activity provides a different opinion. Nance et al (1993) argues that financial instruments used for hedging shows economies of scale due to the transaction cost involved. They claim that it is not cost efficient for US firms to hedge a risk exposure which is less than five to ten million USD in market value. Therefore, large firms have more economic incentive to hedge their exposures than small ones as they usually have larger risk exposures. Based on the usage of financial instruments for hedging purpose of 169 of the Fortune 500 firms in 1986, they found that firms which use more hedging instruments are usually larger in terms of market size. The finding is reinforced by Mian (1996). Based on disclosed information of more than three thousand US firms for 1992, he also claims that firms which hedge their financial exposures are much larger than the non-hedgers.[214] In addition, Crabb (2002) shows that the firms which hedge against currency risk should have a lower currency exposure.[215] In other words, large size firms should have a smaller currency exposure instead of a bigger one compares to small firms.

The empirical studies on the size effect of the currency exposure also show mixed results. Chow et al (1997b) run a regression test with the magnitude of a firm's currency exposure on the firm's market capitalization.[216] The result based on a sample of 213 US

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[214] The financial exposures include interest rate exposure and currency exposure. The result is consistent for both financial exposures.
[215] Crabb's (2002) finding is based on data of financial hedging activities of 276 US MNCs.
[216] The magnitude of a firm's currency exposure is represented by the firm's currency risk beta.

MNCs indicates that currency exposure has a negative relationship with the firm size regardless of the direction of the exposure. In contrast, He and Ng (1998) indicates that currency exposure increases with firm size for Japanese MNCs. They access the relationship between changes in trade weighted JPY price index and the equity return of 171 Japanese MNCs from 1979 to 1993, and show that the return of firms with higher market value are more sensitive to changes in home currency value, which is opposite to Chow et al's (1997b) finding.

Chow and Chen (1998) argue that the relationship between the currency exposure and firm size is sensitive to the estimation horizon. They argue that since the short term transaction exposure is comparatively easy to hedge than the long term currency risk (Chow et al, 1997a), the large firms should have higher incentive to hedge the long term currency risk compare to the small firms due to the economies of scale of hedging activity. They investigate the currency exposure of more than one thousand Japanese firms from 1975 to 1992 with different estimation horizons. The empirical evidence suggests that small firms are less exposed to currency risk with a one-month estimation horizon compares to large firms, while large firms have less currency exposure with a estimation horizon above twelve-month.

Bodnar and Wong (2003) suggest that the size effect in currency exposure is mainly due to the difference in characteristic between the large and small firms. Based on empirical evidence from 910 US MNCs from 1977 to 1996, they claim that large firms are more likely to benefit from the depreciation of USD since they are more internationally oriented, while the opposite is true for small firms. The finding is in line with the hypothesis by Shapiro (1975). Shapiro suggests that export-oriented MNCs will benefit from home currency depreciation as it increases their competitive edge in the foreign markets. Small firms are more likely to operate pure domestically, therefore, they will benefit from home currency appreciation as it reduces the foreign product's price in home currency terms.

The size effect in currency exposure among financial institutions has not been extensively explored. Tai (2000) evaluates the potential size effect among commercial banks in the US market from 1987 to 1998. He divides the sample of 31 US banks into three size portfolios, and shows that the currency exposure is only significant for banks with the highest market values. The finding supports the Chamberlain et al's (1997) argument that large banks should have higher currency exposure as they are more likely to have international activities. However, the argument is dismissed by Choi and Jiang (2009) who claim that currency exposure is actually smaller for internationally oriented firms than pure domestic firm. They investigate the currency exposure of MNCs and non-MNCs in the US market from 1983 to 2006, and show that the currency exposure of non-MNCs is significantly higher than MNCs. They argue that the main reason behind this phenomenon is that MNCs are more likely to hedge their foreign exposures compare to non-MNCs, which is consistent with the finding by Crabb (2002).

4.2.4. *Estimation Framework for Currency Exposure*

Early studies on currency exposure usually use simple linear models. Inspired by Adler and Dumas (1984), most researchers use the regression coefficient from an ordinary least square (OLS) model to represent the currency exposure. In Adler and Dumas (1984), the regression coefficient is generated by running a linear regression of a firm's equity price on the level of currency value. However, they ignore the fact that the time series data of the firm's equity price and the level of currency value are non-stationary, which is not suitable for linear regression model without adjustment. The empirical framework has been improved by Adler et al (1986), who suggest the use of equity return of the firm and changes in currency value in the OLS model.

Jorion (1990) argues that market risk factor should also be included into the model as it is commonly regarded as the most important risk factor for equity value.[217] Prasad and Rajan (1995) further suggest that the changes in interest rate should also be included into the estimation framework, as previous empirical studies showed strong connection between interest rate fluctuation and firm value.[218] In addition, they argue that the changes in currency value may be highly correlated with market and interest rate risk factors through common external shocks. Therefore, the one should orthogonalize the changes in currency value with respect to market and interest rate risk factors before put them into the regression model to avoid multicolinearity. On the other hand, Doukas et al (1999) suggest one could also orthogonalize the market and interest rate risk factors on currency risk factor instead of another way round.

Other studies suggest that the value of a firm only reacts to the unexpected changes in currency value (Chow et al, 1997a and 1997b). Therefore, one should use the unexpected changes in currency value in the regression model.[219] Tai (2000) and Koutmos and Martin (2003b) suggest the use of estimated residual from an auto-regression model to represent the unexpected changes in the risk factor. Kolari et al (2008) and Choi and Jiang (2009) use an alternative model specification to evaluate the currency exposure. Instead of

[217] For further discussion on the role of market risk factor, please refer to Sharpe (1964) on the introduction of capital asset pricing model (CAPM) among others.

[218] For further discussion on the role of interest rate risk factor, please refer to Flannery and James (1984), and Sweeney and Warga (1986) among others. Staikouras (2003 and 2006) also provide an extensive review for theoretical and empirical studies on interest rate risk factor.

[219] However, Jorion (1990) argues that the actual changes in currency value are largely unpredictable. Therefore, one could use the actual changes in currency value to represent its unexpected changes. This argument is supported by other empirical studies such as Chamberlain et al (1997).

using market and interest risk factors, they use the three risk factors from Fama-French model for the regression model.[220]

However, OLS model can only evaluate the currency exposure in a univariate framework, which means it can only examine the relationship between the currency value fluctuation and the equity return of a single firm. The model efficiency may be low when apply the estimation framework to a sample with large number of firms, as one needs to run an OLS estimation for each individual firm. In order to resolve this issue, researchers start to employ models with a multivariate framework. Ferson and Harvey (1994) propose the first multivariate estimation framework. They investigate the currency exposure of eighteen national stock market indices based on a seemingly unrelated regression (SUR) model. The subsequent study by Choi and Prasad (1995) and Doukas et al (1999) also evaluate the currency exposure of MNCs in the US and Japanese market with a SUR model, respectively. Choi and Elyasiani (1997) employ the SUR model to evaluate the currency exposure of financial institutions. They examine the relationship between changes in home currency value and the largest US banks. Their paper is followed by Martin (2000) who evaluates the currency exposure of the top banks across the global markets based on similar estimation framework.

The SUR model overcomes the problem of evaluating the currency exposure for multiple assets simultaneously, but it only takes the conditional mean of the involved securities into account. The conditional variances of these securities and the linkages among them have not been considered by the SUR model. The empirical studies on conditional variance and correlation suggest that the variance-covariance matrices among

[220] For further discussion of the Fama-French model, please refer to Fama and French (1993).

securities have a time-varying nature.[221] Therefore, the estimation model should take this time-varying nature into account to avoid potential biasness and inefficiency.

The number of empirical studies who incorporate the time-varying nature of conditional variance-covariance among financial asset returns is limited. De Santis and Gerard (1998) propose the first empirical framework to investigate the currency exposure of firms by estimating the conditional mean and variance-covariance matrix of the firm returns simultaneously. The model used in their study is a parsimonious diagonal multivariate GARCH process. Their empirical framework has been extended by Tai (2000) by including the conditional variance of the risk factor into the mean equation.[222]

Recently, Elyasiani et al (2007) propose another parsimonious multivariate GARCH estimation framework to estimate the currency exposure of financial sector portfolios in the US market. However, their model poses a restriction on conditional variance-covariance matrix among the portfolio returns, which assumes the correlations among financial sector portfolio returns are constant over the estimation period.

4.3. ESTIMATION FRAMEWORK

4.3.1. VAR-BEKK Estimation Model

In the current study, we propose a multivariate VAR-BEKK model to evaluate the relationship between the home and foreign currency value fluctuation and the changes in equity value of different financial sector portfolios across national markets. The changes in equity value are represented by the lognormal returns of the financial sector portfolios.

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[221] Engle (1982) and Bollerslev (1986) show that the conditional variance of the financial asset return is time-varying, while Bollerslev et al (1988) and Cappiello et al (2006) indicate the conditional covariance and correlation among the financial asset return is also time-varying.

[222] In Tai (2000), the main purpose for the introduction of conditional volatility of the currency value is to investigate whether the risk factors remain constant over the estimation period.

The proposed VAR-BEKK model has two components. The first part is a VAR model, which contains a system of equations representing the conditional mean of the financial sector portfolio return. The second part is a conditional variance-covariance estimation framework with a BEKK parameterization.

The conditional mean of financial sector portfolio return is represented by an extended multifactor model. We construct the model based on the conventional multifactor model used by previous empirical studies (Wetmore and Brick, 1994 and 1998; Prasad and Rajan, 1995; Chamberlain et al, 1997; Elyasiani et al, 2007). Instead of using only the market, interest rate, and home currency risk factors as explanatory variables, we also incorporate the changes in foreign currency value into the estimation framework. As discussed in the previous section, the changes in foreign currency value can be served as an alternative measure of shift in investors' preference towards the global financial markets. Therefore, by investigating the impact of foreign currency value fluctuation, we shed light on whether the shift in investors' preference will have a significant impact on the return performances of financial sector portfolios across national markets. In addition, the conditional variances of the currency value fluctuation are also included in the mean equation as explanatory variables. Tai (2000) and Koutmos and Martin (2003b) show that the conditional variance of the home currency value fluctuation seems able to explain the firm's return performances. By including these conditional variances into the estimation framework helps us to eliminate the potential issue of inconsistency and biasness due to omitted variables.

In the current chapter, the value of currency is represented by a trade weighted multilateral currency price index. We prefer multilateral currency index over bilateral exchange rate for two reasons. First, the multilateral currency index provides a more general picture of a currency's relative value compares to the bilateral exchange rate. The bilateral exchange rate only refers to the conversation ratio of one currency against another currency, while the multilateral currency index represents the relative value of a currency against a basket of other currencies. Second, the multilateral currency index helps us to introduce the relative value changes of all the three currencies into the conditional mean equation, which is not achievable by using the bilateral exchange rate. For instance, the three bilateral exchange rates, USD against GBP (USD/GBP), the JPY against USD (JPY/USD) and the JPY against GBP (JPY/GBP), can represent the relative values among these three currencies without introducing linear dependence among the variables.[223] For financial institutions in the Japanese market, however, both JPY/USD and JPY/GBP are actually representing the relative value of the home currency (JPY).[224] Therefore, we have to use multilateral currency price index to introduce the value fluctuations of all the three currencies.

The conditional variance-covariance of the financial sector portfolio returns is estimated based on a BEKK model. We prefer the BEKK model as it provides a more flexible estimation framework with a parsimonious parameter setting. As discussed in previous empirical studies (Kroner and Ng, 1998; Cappiello et al, 2006), the conditional correlation among financial asset returns is not constant over time. Unlike the constant correlation assumption used in Elyasiani et al (2007), there is no restriction on the conditional correlations among financial sector portfolio returns in our model. Therefore, our model is more flexible, and should provide higher estimation accuracy. In addition,

[223] For three currencies, we can only use a set of three bilateral exchange rates to represent the relative values among them. If we use any four bilateral exchange rates among three currencies, we will introduce linear dependence into the system.

[224] Chamberlain et al (1997) suggest that the changes in home currency value can be represented by either a multilateral currency price index, or bilateral exchange rates between the home currency and other major currencies.

we employ the diagonal BEKK parameterization for the proposed VAR-BEKK model to increase the estimation efficiency by reducing the number of estimated coefficients.[225]

However, the issue of nonsynchronous trading arises due to the fact that the equity markets in these countries operate in different time zones. In order to better access the influence of foreign currency value fluctuation on the equity return of financial institutions, we need to first adjust for this nonsynchronous trading issue. According to Greenwich Mean Time (GMT), the Japanese market opens the earliest among the three national markets. The Tokyo Stock Exchange opens at GMT 0:00 and closes at GMT 6:00. It is followed by the UK market, which opens at GMT 8:00 and finishes at 16:30. The New York Stock Exchange operates from GMT 14:30 till GMT 21:00. Therefore, it is reasonable for us to assume that the information generated from the Japanese and UK market is likely to influence the performance of the US market on the same trading day. However, for the US market, its daily price information can only affect the performance of Japanese and UK market for the following trading day. For the UK market, we assume its daily price movement can affect the Japanese market on the following day.

The foreign exchange market crumbled in the recent financial crisis (Melvin and Taylor, 2009). In order to investigate the potential influence of the crisis on the relationship between currency value fluctuation and the equity return of financial sector portfolios, we introduce a structural break into the proposed VAR-BEKK model. Failed to capture this potential variability of the currency exposure can be costly, as Levi (1994) argues that the estimated coefficient may be biased. Previous empirical studies show that the currency exposure of financial institutions does change over time, especially when systemic important event happened. For instance, Choi et al (1992) show that the currency

[225] The number of estimated parameters is negatively related to the degree of freedom of the estimation model. For technical detail of the diagonal BEKK parameterization, please refers to Appendix A.4 in the appendix section.

exposure of US banks changed dramatically after the establishment of the 1979 International Bank Act.[226] Similar to Choi et al's (1992) approach, we also introduce a dummy variable into the model to capture the potential change in the currency exposure during the recent financial crisis.[227]

According to Melvin and Taylor (2009), the bankruptcy announcement made by Lehman Brothers on the *September 15, 2008* has a significant impact on the foreign exchange market. In order to illustrate the influence of this event on the value and variation of currency price indices for the JPY, GBP and USD, we create two diagrams (Figure 4.1 and 4.2) to demonstrate the level and conditional variance of the three currency price indices over the sample period. Figure 4.1 represents the time series of the three trade weighted currency price indices, while Figure 4.2 demonstrates the conditional variance of the three currency price indices over the sample period.

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[226] Choi et al (1992) show that the currency exposure of US banks had changed from negative before the introduction of International Bank Act in October 1979 to positive afterwards.

[227] The dummy variable is only introduced into the conditional mean equation but not the conditional variance-covariance equation. The conditional variance-covariance equation of the proposed model is based on a BEKK parameterization, which contains a component representing the unconditional variance-covariance matrix of the financial sector portfolio returns. However, the unconditional variance-covariance matrix may not change in a linear way before and after the structural break. Therefore, the introduction of a dummy variable may not be suitable for representing a structural break in the BEKK model. In order to solve the issue, we separate the estimation for conditional variance-covariance equations into two sub-periods, namely the pre- and post-crisis periods.

Figure 4.1 Time Series of the Trade Weighted Currency Price Index

The following graph demonstrates the time series of the trade weighted currency price indices for Japanese Yen (JPY), British Pound (GBP), and US Dollar (USD) from the start of 2003 to the end of March 2011. The value of the currencies has been recaled at the level of 100 at the beginning of the sample period.

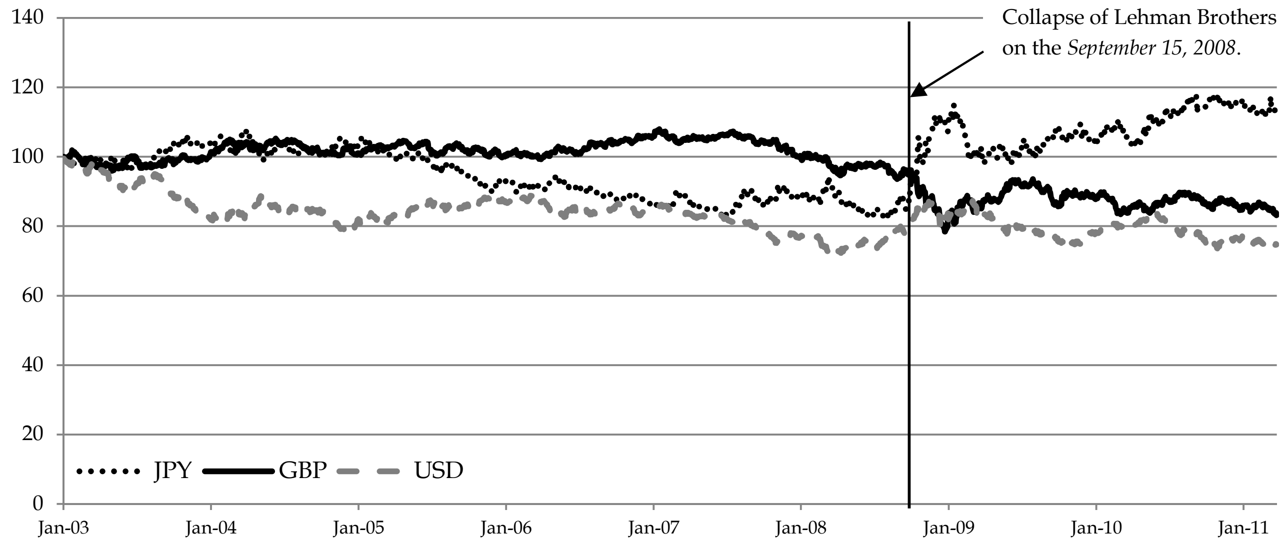
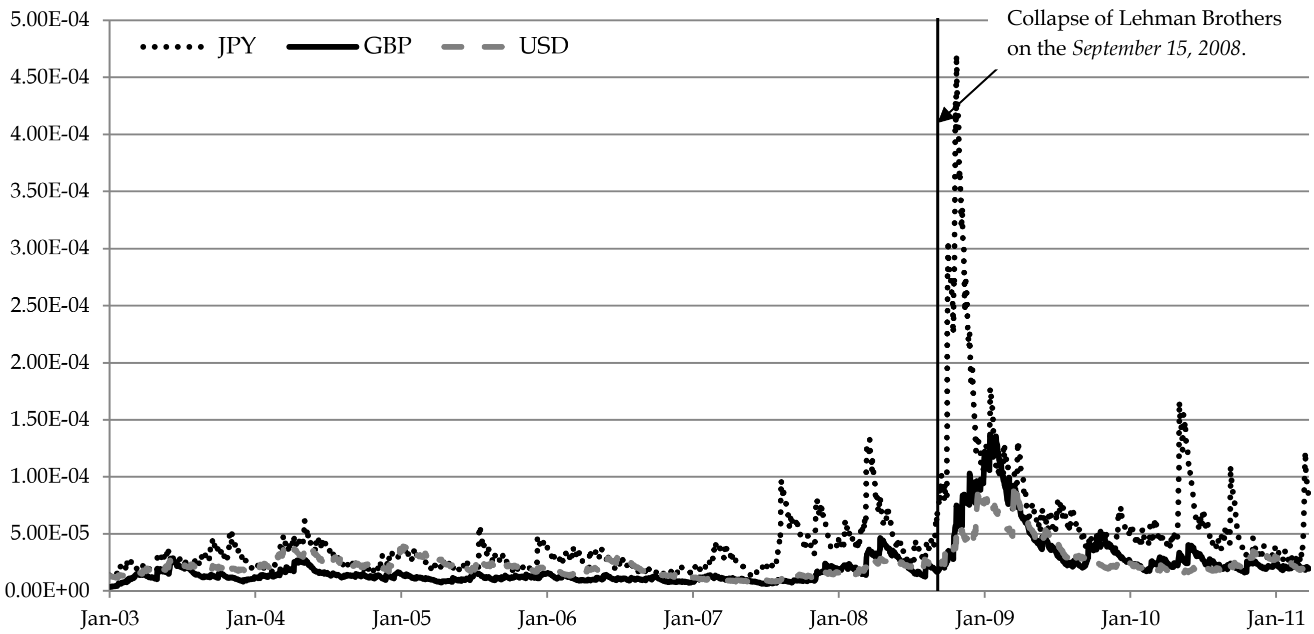


Figure 4.2 Conditional Variance of the Trade Weighted Currency Price Index

The following graph demonstrates the changes in conditional variance of the trade weighted currency price indices for Japanese Yen (JPY), British Pound (GBP), and US Dollar (USD) from the start of 2003 to the end of March 2011.



From the two diagrams, one can see that the relative value of both GBP and USD dropped since the collapse of the Lehman Brother. In contrast, the JPY appreciated dramatically. Furthermore, the conditional variances of all the three currency price indices increased dramatically following the collapse of the Lehman Brother, and remained at a higher level since the event. The empirical evidence suggests that the collapse of Lehman brother is indeed a significant and systemic important event for the foreign exchange market. Therefore, we set the *September 15, 2008* as the start of the recent financial crisis.

The proposed VAR-BEKK model can be illustrated in matrix form as follow:[228]

$$R_t = \beta \circ MF_t \cdot 1 + G \cdot {FX_t}^T + Z \cdot {FX\_Var_t}^T + DUM \cdot \Gamma \cdot {FX_t}^T + DUM \cdot \Theta \cdot {FX\_Var_t}^T + \varepsilon_t \tag{1}$$

$$H_t = C_{pre} \cdot {C_{pre}}^T + A_{pre}\varepsilon_{t-1}{\varepsilon_{t-1}}^T {A_{pre}}^T + B_{pre}H_{t-1}{B_{pre}}^T, \qquad \text{with } t \in [0, \tau]$$

$$H_t = C_{post} \cdot {C_{post}}^T + A_{post}\varepsilon_{t-1}{\varepsilon_{t-1}}^T {A_{post}}^T + B_{post}H_{t-1}{B_{post}}^T, \qquad \text{with } t \in [\tau + 1, T]$$

with ° is the Hadamard product,[229] 1 is a vertical vector of ones which matches the vertical dimension of β, superscript T is the transpose operator for the underlying matrix, and τ represents the date of *September 15, 2008*.

where,

R_t = a [n x 1] matrix represents the return of financial sector portfolios over day t. n depends on how many portfolios within the estimation framework.

β = a [n x 3] parameter matrix where the first column represents the constants, the second and third column represent market and interest rate betas for the corresponding financial sector portfolios, respectively.

[228] For detail explanation of the parameter matrices and the scalar form of the conditional mean equation, please refer to the Appendix C.1.

[229] The Hadamard product is a special operator for matrix multiplication. It refers to the element-by-element multiplication of two matrices with the same dimension.

MF_t = a [n x 3] matrix contains ones for the first column which represent the constants for conditional mean equations. The second and third column of the matrix contains the market and interest rate risk factors for the corresponding financial sector portfolios over day t. The market risk factor is represented by the return of national stock market index, and the interest rate risk factor is represented by the unexpected changes in long-term benchmark bond yields.[230]

FX_t = a [3 x 1] matrix contains the unexpected changes[231] in the trade weighted currency price indices of the JPY, GBP and USD over day t. The unexpected change is the estimated residual from a fitted ARMA-GARCH model for the corresponding currency price index.[232]

FX_Var_t = a [3 x 1] matrix contains the conditional variances for the trade weighted currency price indices of the JPY, GBP and USD over day t. The conditional variance is generated from a fitted ARMA-GARCH model for the corresponding currency price index.

G = a [n x 3] parameter matrix representing the equity return sensitivity given changes in *FX* risk factors over the whole sample period. The elements within G are g_{ij} which refer to the *FX* effect from currency in country j to portfolio in country i. Home *FX* effect is represented by g_i (i=j).

Z = a [n x 3] parameter matrix representing the equity return sensitivity given changes in *FXV* risk factors over the whole sample period. The elements

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230 Follows the previous empirical studies on the effects of interest rate, the interest rate index employed in the current study is the yield relative –[$(Y_t$-$Y_{t-1})/Y_{t-1}$], Y_t is the yield of long-term benchmark bond of the corresponding markets over day t. For further detail please refers to Flannery and James (1984).

231 Chamberlain et al (1997) argues that only the unexpected changes in the currency value can influence the performances of the financial institutions.

232 We first fit the raw changes in the trade weighted currency price index into an ARMA-GARCH(1,1) model, then use the estimated residuals and conditional variances derived from the model as the unexpected changes in the currency value (i.e. *FX*) and conditional variance of the currency (i.e. *FX_Var*), respectively.

within Z are z_{ij} which refer to the *FXV* effect from currency in country j to portfolio in country i. Home *FXV* effect is represented by z_i (i=j).

Γ = a [n x 3] parameter matrix representing the potential changes in equity return sensitivity given changes in *FX* risk factors over the crisis period. The elements within Γ are γ_{ij} which refer to the changes in *FX* effect from currency in country j to portfolio in country i. Changes in home *FX* effect is represented by γ_i (i=j).

Θ = a [n x 3] parameter matrix representing the potential changes in equity return sensitivity given changes in *FXV* risk factors over the crisis period. The elements within Θ are θ_{ij} which refer to the changes in *FXV* effect from currency in country j to portfolio in country i. Changes in home *FX* effect is represented by θ_i (i=j).

DUM = a dummy variable represents the potential structural break in the crisis period. *DUM* = *0* before the *September 15, 2008*, and *DUM* = *1* afterwards.

H_t = a [n x n] three dimensional matrices represent the conditional variance-covariance matrix among the returns of the financial sector portfolios over day t.

ε_t = a [n x 1] matrix represents the estimated residual vector from the conditional mean equations for the returns of the financial sector portfolios over day t.

$C_{pre/post}$ = a [n x n] upper triangle parameter matrix represents the unconditional part of the variance-covariance matrix over the pre- and post-crisis period.

$A_{pre/post}$ = a [n x n] diagonal parameter matrix represents the ARCH effect of the conditional variance-covariance matrix over the pre- and post-crisis period.

$B_{pre/post}$ = a [n x n] diagonal parameter matrix represents the GARCH effect of the conditional variance-covariance matrix over the pre- and post-crisis period.

The unexpected changes in long-term benchmark bond yields are generated from a set of fitted ARMA model for each bond yield series. A modified ARMA model with a GARCH(1,1) conditional variance process has been estimated for each of the three currency price indices. The model enables us to generate the unexpected changes in the currency price index together with its conditional variances, which provides higher estimation efficiency then generate the two series with two separate models.

In order to increase the estimation efficiency, the model is estimated simultaneously for both the conditional mean and variance-covariance equations for all the financial sector portfolios in the system (Elyasiani and Mansur, 2003). We adopt the estimation approach developed by Bollerslev and Wooldridge (1992), which optimize the parameter estimation by maximizing the sum of the quasi-conditional log-likelihood ratio l_t.

$$l_t = -\frac{1}{2}[n\ln(2\pi) + \ln|H_t| + \varepsilon_t{}^T H_t \varepsilon_t]$$

where,

n = the number of conditional mean equations in the model, which depends on how many portfolios within the estimation framework.

H_t = a [n x n] matrices represent the conditional variance-covariance matrix among the returns of the financial sector portfolios over day t.

ε_t = a [n x 1] matrix represents the estimated residual vector from the conditional mean equations for the returns of the financial sector portfolios over day t.

Since we estimate the conditional mean equations simultaneously with the conditional variance-covariance equations, the models are no longer linear. The non-linear nature of the estimation framework poses a big challenge for the parameter optimization process. The initial value of the parameter needs to be properly specified to ensure the sum of l_t achieving a global maximum instead of a local one. Therefore, a proper initial setting of the parameter value is crucial for the success of our estimation. In the current study, we develop a two-step approach to generate the initial values for the parameters. In the first step, the conditional mean equations in the model will be estimated separately with a simple OLS approach. The estimated coefficients will be used as the initial values for the parameters in these mean equations. In the second step, the residual series generated from these individual OLS estimations, $\varepsilon_{i,t}$, will be fitted with a diagonal BEKK model. The estimated coefficients from the diagonal BEKK model will be employed as the initial values for the parameter in the variance equation.

4.3.2. Joint-Hypotheses Test

Six joint-hypotheses tests have been developed for the current study. The purpose of these joint-hypotheses tests is to evaluate the overall significance of the relationship between currency value fluctuations on the return of the financial sector portfolios. The hypothesis tests are designed to focus on the impact of currency value fluctuations over two different periods, namely the whole sample period and the crisis period. The first set of hypotheses (H1 and H2) investigates the potential influence of currency value fluctuations on financial sector portfolios over the whole sample period, while the second set of hypotheses (H3 to

H6) evaluates whether the influence of currency value fluctuations has changed during the recent financial crisis through a set of interactive dummy variables (*DUM*).

In order to save space, we refer the relative value changes in home (foreign) currency as home (foreign) *FX*, and the conditional variance of the relative changes in home (foreign) currency as home (foreign) *FX_Var*. The six joint-hypotheses tests are presented as follow:

H1: No influence of the foreign *FX* and *FX_Var* on the return performances of financial sector portfolios over the whole sample period.

H2: No influence of the home and foreign *FX_Var* on the return performances of financial sector portfolios over the whole sample period.

H3: No changes in the influence of the home *FX* on the return performances of financial sector portfolios during the financial crisis.

H4: No changes in the influence of the home *FX* and *FX_Var* on the return performances of financial sector portfolios during the financial crisis.

H5: No changes in the influence of the home and foreign *FX* on the return performances of financial sector portfolios during the financial crisis.

H6: No changes in the influence of the home and foreign *FX* and *FX_Var* on the return performances of financial sector portfolios during the financial crisis.

We evaluate the above six joint-hypotheses via log-likelihood (LLF) ratio test[233], which examines whether the LLFs of the unrestricted and the restricted models are significantly different. For each hypothesis test, the restricted model assumes the parameters attached to the corresponding *FX* and *FX_Var* variables are equal to zero. For instance, the restricted model for H1 assumes the parameter for the foreign *FX* (Γ) and *FX_Var* (Θ) are

[233] For detail explanation of the LLF ratio test, please refer to Appendix A.5.

all equal to zero. One the other hand, the unrestricted model does not pose any restriction on these parameters.

In order to perform these joint-hypotheses tests, we introduce seven alternative model specifications for conditional mean equation of the proposed VAR-BEKK estimation framework. Since these alternative specifications only affect the parameter setting in the conditional mean equation, we only demonstrate the first part of the VAR-BEKK model to save space. The seven alternative model specifications are illustrated as follow[234]:

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t_i} + \sum z_{i,j} FX\_Var_{j,t} + \varepsilon_{i,t} \quad (2)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{i,t} + z_i FX\_Var_{i,t} + DUM \cdot \gamma_i FX_{i,t} + DUM \cdot \theta_i FX\_Var_{i,t} + \varepsilon_{i,t} \quad (3)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{i,t} + z_i FX\_Var_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t_i} + DUM \cdot \sum \gamma_{i,j} FX_{j,t} + \varepsilon_{i,t} \quad (5)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t_i} + \varepsilon_{i,t} \quad (6)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{i,t} + DUM \cdot \gamma_i FX_{i,t} + \varepsilon_{i,t} \quad (7)$$

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{i,t} + \varepsilon_{i,t} \quad (8)$$

with i and $j \in$ [*Japan, UK, US*].

where,

c_i = the constant of the conditional mean equation for financial sector portfolio i.

$\beta_{i,x}$ = the parameter for each of the two macroeconomic factors (*Market* and *IR*) for regional market i over day t, with $x \in [Market, IR]$.

[234] The model specification for conditional mean equation in *Eq.1* will be referred as specification 1 (*Spec.1*), and the *Eq.2* to *Eq.8* will be referred as *Spec.2* to *Spec.8* for the rest of the paper, respectively.

$MF(X)_{i,t}$ = represents the two macroeconomic factors: 1) the market risk factor represents by the return of domestic stock market index (*Market*), and 2) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio *i* over day *t*, with $X \in [\ Market, IR]$.

$FX_{j,t}$ = the unexpected changes of trade weighted currency price index for currency in country *j* over day *t*, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{j,t}$ = the conditional variance of the trade weighted currency price index for country *j* over day *t*, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* over the whole sample period. g_i represents the *FX* effect of the home currency over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* over the whole sample period. z_i represents the *FX_Var* effect of the home currency over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* during the crisis period. γ_i represents changes in the *FX* effect of the home currency during the crisis period.

$\theta_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* during the crisis period. θ_i represents changes in the *FX_Var* effect of the home currency during the crisis period.

DUM = a dummy variable represents the potential structural break in the crisis period. *DUM = 0* before the *September 15, 2008*, and *DUM = 1* afterwards.

The unrestricted and restricted model specifications for each of the six joint-hypotheses tests are presented as follow:

H1: The unrestricted model is *Spec.1* and the restricted model is *Spec.3*.

To investigate the overall significance for the estimated parameters of z_{ij} *and* θ_{ij} *in Spec.1.*$(i \neq j)$

H2: The unrestricted model is *Spec.1* and the restricted model is *Spec.5*.

To investigate the overall significance for the estimated parameters of z_{ij} *and* θ_{ij} *in Spec.1.*

H3: The unrestricted model is *Spec.7* and the restricted model is *Spec.8*.

To investigate the overall significance for the estimated parameters of γ_i *in Spec.7.*

H4: The unrestricted model is *Spec.3* and the restricted model is *Spec.4*.

To investigate the overall significance for the estimated parameters of γ_i *and* θ_i *in Spec.3.*

H5: The unrestricted model is *Spec.5* and the restricted model is *Spec.6*.

To investigate the overall significance for the estimated parameters of $\theta_{i,j}$ *and* θ_i *in Spec.5.*

H6: The unrestricted model is *Spec.1* and the restricted model is *Spec.2*.

To investigate the overall significance for the estimated parameters of $\gamma_{i,j}$, γ_i, $\theta_{i,j}$ *and* θ_i *in Spec.1.*

4.4. DATA

The portfolios used in the current chapter are composed of financial institutions from three national markets, namely the Japanese, UK and US markets. Our sample includes the daily price information of banks, life insurers and non-life insurers from each of the national markets. We only select companies which are listed on the major equity exchanges to eliminate the issue such as illiquidity and infrequent trading.[235] The Tokyo Stock Exchange, London Stock Exchange and New York Stock Exchange have been chosen for the Japanese, UK and US market, respectively.

From each national market, we only select the financial institutions that are based in this market.[236] This approach eliminates the potential bias when evaluating the impact of foreign currency value fluctuation on the return of financial sector portfolios. Assume that the US portfolio contains UK-based institutions with a strong relationship between the changes in GBP value and the returns of US portfolio. In this case, it is hard to determine the cause of this strong linkage. It could due to the fact that changes in GBP value have a significant impact on the return of US-based institutions, or it may simply because the UK-based institutions within the US portfolio expose to home currency value fluctuation.

For each market, the daily information of the equity market index and long-term benchmark bond yield has been collected.[237] The trade weighted currency price indices have also been collected for the JPY, GBP and USD. The trade weighted currency price indices used in the current study is constructed by Bank of England (BoE). We employ the

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[235] The illiquid stocks usually have a higher expected return and volatility due to the additional illiquidity risk premium attached. For further discussion on the illiquidity and its influence on stock return, please refer to Brennan and Subrahmanyam (1996) and Amihud (2002). On the other hand, the infrequent trading activity will introduce spurious autocorrelations in stock return. For further discussion on the infrequent trading and its influence on stock return, please refer to Roll (1981) and Lo and MacKinlay (1988).

[236] According to the Generally Accepted Accounting Principles (GAAP), the value of foreign currency-dominated assets and liabilities of a firm needs to be converted into value represents in home currency terms. The home currency depends on where the firm is based.

[237] We choose long-term interest rates instead of short-terms ones as they have a stronger influence on insurance companies and banks (Elyasiani and Mansur, 2003; and Elyasiani et al, 2007).

trade weighted currency price index because it is a multilateral currency index, which measures the relative value of a currency against a basket of other currencies. It is calculated as a weighted geometric average of the bilateral exchange rates between the currency and other currencies, which presented in an index form.[238] The trade weighted currency index constructed by BoE uses a basket of currencies from 21 industrial countries.[239] All the price information is provided by DataStream International.

We focus our attention on the recent financial crisis in the 2007/8, and its influence on the relationship between currency value fluctuation and the return of financial sector portfolios. In order to eliminate the potential contamination effect from the previous stock market turmoil of 2000 - 2002, we start our sample period at the beginning of 2003 (*i.e. January 1, 2003*).[240] To ensure equally number of daily observations across all the national markets, we eliminate the dates when any one of the three equity exchanges is closed. The sample period finishes at the *March 31, 2011*, which covers a total of 1924 daily observations.

The current study evaluates the impact of home and foreign currency value fluctuations on the return of different financial sector portfolios.[241] Therefore, we

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[238] The geometric average framework is proposed by IMF. The geometric average is better than the arithmetic one for two reasons. First, the arithmetic average will be influenced by way the bilateral exchange rate is constructed. The magnitude of changes in the arithmetic average based on bilateral rates represented as units of home currency per foreign currency is different from the one based on bilateral rates constructed other way around. Second, the arithmetic average will be distorted when the base period is changed. However, the geometric average overcomes these problematic issues (Brodsky, 1982; Rosenweig, 1987). The weights are derived from the Multilateral Exchange Rate Model (MERM). Please refer to McGuirk (1987) on how the weights are derived for the trade weighted currency index.

[239] For detail information on the 21 industrial countries and the methodology for generating the trade weighted currency price index, please refer to Appendix C.2.

[240] The US stock market crashed in March 2000 due to the collapse of the Internet Bubble. The NASDAQ Composite index, which represents the technology and growth companies in the US market, dropped from 5048.62 in March 2000 to 1229.05 in July 2002. Please find the time series of NASDAQ Composite Index in the Appendix C.3.

[241] The size weighted portfolio will represent the performance of the large institutions, while the equally weighted portfolio will provide a more general performance measure across all institutions involved. We focus on the return performance of a financial sector rather than a group of individual institutions. Therefore, we employ equally weighted portfolios in this chapter.

construct equally-weighted portfolios for each financial sector and across the three markets. In order to eliminate the influence of firm-specific risk, the equally-weighted financial sector portfolios need to be well diversified. Several previous studies on portfolio construction have showed that the portfolio size has a significant impact on the diversification effectiveness.[242] Empirical evidence suggests that a portfolio with more than 20 assets can obtain most of the diversification benefits. We summarize the number of institutions in each financial sector in Table 4.1 to illustrate the diversification effectiveness of the financial sector portfolios used in the current study.

Table 4.1 Number of Financial Institutions across Markets.

	Bank			Life Insurance		Non-Life Insurance		
	Japan	UK	US	UK	US	Japan	UK	US
Date	All	All	All	All	All	All	All	All
2003	79	6	86	5	17	3	14	44
2004	80	7	98	6	19	3	16	47
2005	81	7	101	6	19	3	20	48
2006	83	8	105	7	19	3	20	50
2007	84	8	111	7	21	3	26	52
2008	84	8	111	8	21	3	26	54
2009	86	8	112	8	21	3	26	54
2010	87	8	113	8	23	4	26	56
2011	87	8	114	8	23	4	26	56

From Table 4.1, one can see that the life and non-life insurance sectors within the three markets, as well as the banking sector in the UK market all have small number of institutions during the sample period. Therefore, in order to achieve the highest possible diversification effectiveness, we only construct one portfolio for each of the two insurance

[242] Please refer to Evans and Archer (1968), Elton and Gruber (1977), and Shawky and Smith (2005) for further discussion on the issue of diversification effectiveness.

sectors (life and non-life) across the three markets, and the banking sector in the UK market. In other words, we have six insurance portfolios, and one UK banking portfolio.

In contrast, the Japanese and the US banking sectors have around 80 to 90 institutions during the sample period. The large number of institutions enables us to split the institutions in these two sectors further without sacrificing much on the diversification effectiveness. Previous empirical studies spilt the institutions in a financial sector further into size portfolios to investigate the potential size effect.[243] Therefore, in the current study, we construct two additional equally weighted portfolios for large and small banks in the Japanese and US markets.

For these size portfolios, the large and small banks are selected according to their market capitalizations. To ensure the market capitalization of institutions in the large size portfolio consistently higher than the ones in the small size portfolio, we rebalance our size portfolios on an annually basis. For each calendar year, the banks within these two national markets will be ranked according to their average market capitalization over the year. The institutions within the top 25% region will be picked as the large banks, while the remaining ones will be categorized as small banks.

Table 4.2 illustrates the number of institutions within these size portfolios over the sample period, while the distributional statistics of these equally weighted sector portfolios are represented in Table 4.3.

[243] Please refer to Wetmore and Brick (1994 and 1998), Elyasiani et al (2007), and Carson et al (2008) among others.

Table 4.2 Number of Institutions for the Large and Small Size Portfolios within the Japanese and US Banking Sectors.

	Japan		US	
Date	Small	Large	Small	Large
2003	59	20	65	21
2004	60	20	74	24
2005	61	20	76	25
2006	62	21	79	26
2007	63	21	83	28
2008	63	21	83	28
2009	65	21	84	28
2010	65	22	85	28
2011	65	22	86	28

Note: the size portfolio will be rebalanced at the beginning of each calendar year according to the average market capitalization of the company during that year. For each calendar year, we rank all the company from large to small according to their average market capitalization over the calendar year. The company which is above the 25% percentile will be categorized as Large Size portfolio, while the remaining will be the Small Size portfolio.

Table 4.3 Summary Statistics of the Financial Sector Portfolio Returns.

The following table represents the distributional statistics of the financial sector portfolios. The sample period is from the beginning of 2003 till the end of March 2011.

Panel A: Daily Returns of the Banking Portfolios.

	Japan						UK		US					
Raw Return (%)	All		Large		Small		All		All		Large		Small	
Mean	-0.023		-0.022		-0.031		-0.051		-0.035		-0.027		-0.050	
Maximum	13.467		13.207		15.026		15.174		13.294		13.056		15.337	
Minimum	-10.306		-10.547		-12.262		-15.341		-13.951		-12.675		-18.092	
Std. Dev.	1.546		1.491		1.899		1.847		1.445		1.266		2.289	
Distribution Property														
Skewness	-0.081		-0.094		0.006		-0.207		-0.529		-0.821		-1.031	
Kurtosis	10.019		10.630		9.089		14.881		27.178		35.090		16.976	
Normality Test	3958	***	4677	***	2977	***	11348	***	47028	***	82898	***	16024	***
ADF Test	-44.617	***	-44.894	***	-43.812	***	-43.180	***	-22.343	***	-22.414	***	-22.835	***

Panel B: Daily Returns of the Insurance Portfolios.

	Life Insurance Portfolios				Non-Life Insurance Portfolios					
	UK		US		Japan		UK		US	
Raw Return (%)	All		All		All		All		All	
Mean	-0.007		-0.027		-0.006		0.006		-0.011	
Maximum	14.674		16.784		12.328		4.221		7.898	
Minimum	-16.423		-23.488		-17.581		-3.103		-13.871	
Std. Dev.	1.955		2.478		2.435		0.653		1.533	
Distribution Property										
Skewness	0.069		-1.031		-0.223		-0.207		-0.529	
Kurtosis	5.894		16.976		9.301		14.881		27.178	
Normality Test	674	***	16024	***	3204	***	11348	***	47028	***
ADF Test	-40.587	***	-50.016	***	-43.559	***	-43.18	***	-22.343	***

Note: The normality Test is conducted following the Jarque-Bera test. The ADF Test refers to the Augmented Dickey-Fuller Unit Root test. The test statistics under the serial correlation test is conducted from the Ljung-Box serial correlation test. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

From Table 4.2, one can see that the number of financial institutions in these size portfolios is consistently higher than 20 over the entire sample period. In other words, the size portfolios for the Japanese and US banking sectors are well diversified in terms of firm-specific risk. By examining the statistical property of these sector portfolios in Table 4.3, one can see that the ADF (Augmented Dickey-Fuller Unit Root) test result indicates that all the sector portfolio returns are stationary series, which will help us to avoid the estimation issues due to non-stationary associated with the empirical study by Adler and Dumas (1984). In general, the mean returns are negative for all the banking portfolios across the global markets, including the two size portfolios from the Japanese and US markets. Comparatively, the Japanese banks suffer less than the banks in the UK and US markets. The average daily return of the Japanese banking sector is -0.023% over the sample period, compares to -0.051% and -0.035% for the UK and US banking sector, respectively. This phenomenon is mainly due to the fact that banking sectors suffer significant loss during the 2007/8 financial crisis.[244]

However, even though the insurance sectors in the Japanese and US markets have also been damaged by the recent financial crisis, the magnitude of its impact is smaller compare to the banking sector.[245] The daily average returns are -0.027% and -0.011% for the US life and non-life insurance sector, respectively. Meanwhile, the average return of the Japanese non-life insurance sector is only marginally below zero at -0.006%. This asymmetric impact of the recent financial crisis on different financial sectors is mainly due

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[244] The time series of banking sector portfolio value from different markets are presented in Appendix C.4. All the banking sector portfolios had positive cumulative returns before the financial crisis. However, the gain had been offset by the huge value drop during the crisis period.

[245] The time series of life and non-life insurance sector portfolio value from different national markets are presented in Appendix C.5.

the different characteristics of these financial institutions, and their risk exposures to the credit and liquidity risk.[246]

As discussed in the methodology section, the conditional mean of the sector portfolio return is represented by a multifactor model. Therefore, it is important to ensure the multicolinearity issue does not exist among the risk factors. In order to investigate the potential issue of multicolinearity, we calculate the unconditional correlations of the involved risk factors. Table 4.4 presents the unconditional correlations among the risk factors over the sample period. In general, the correlations among the risk factors are low. The correlation between the conditional variance of the GBP and USD is the highest among all the related risk factors, which is 81.8% over the sample period. However, the highest variance inflation factor (VIF) test statistic based on the three currencies' conditional variances is 3.704, which is less the critical value.[247] Therefore, the empirical evidence indicates that our model is free from multicolinearity.

[246] For discussion on the difference in credit and liquidity risk for banks and insurers, please refer to the report by The Geneva Association under the title of *Systemic Risk in Insurance, An analysis of insurance and financial stability*. The article is available to general public via its website: www.genevaassociation.org.

[247] The VIF is a measure of multicolinearity among related explanatory variables. The critical value of VIF test statistic is 5. If the highest VIF test statistic based on the related explanatory variables is higher than 5, then the variables are highly correlated. One should not include all these variables into the regression model as they will cause multicolinearity issue. For technical detail of the VIF test, please refer to Appendix C.6.

Table 4.4 Unconditional Correlations of the Risk Factors.

The following table represents the unconditional correlation among all the risk factors in the proposed VAR-BEKK model.
The sample period is from the beginning of 2003 till the end of March 2011.

	MKT(Japan)	*MKT(UK)*	*MKT(US)*	*IR(Japan)*	*IR(UK)*	*IR(US)*	*FX(Japan)*	*FX(UK)*	*FX(US)*	*FX_Var(Japan)*	*FX_Var(UK)*
MKT(UK)	0.351										
MKT(US)	0.119	0.534									
IR(Japan)	-0.337	-0.091	-0.030								
IR(UK)	-0.175	-0.339	-0.229	0.147							
IR(US)	-0.081	-0.305	-0.324	0.102	0.516						
FX(Japan)	-0.298	-0.448	-0.282	0.088	0.372	0.292					
FX(UK)	0.157	0.088	0.092	-0.026	-0.197	-0.089	-0.227				
FX(US)	-0.079	-0.091	-0.046	-0.053	-0.131	-0.115	-0.205	-0.119			
FX_Var(Japan)	-0.026	-0.038	-0.069	-0.004	0.036	0.014	0.033	-0.053	0.035		
FX_Var(UK)	-0.009	-0.023	-0.022	-0.008	-0.006	-0.012	-0.013	0.016	0.016	0.632	
FX_Var(US)	0.012	-0.018	-0.024	-0.018	-0.032	-0.036	-0.007	0.021	0.038	0.503	0.818

Note: the *MKT(i)* is the market portfolio return of the national stock market for country *i*; the *IR(i)* is the unexpected changes in the long-term benchmark bond yield for country *i*; the *FX(i)* is the unexpected changes in the trade weighted currency price index for country *i*; the *FX_Var(i)* is the conditional variance of the trade weighted currency price index for country *i*.

There are two interesting findings from Table 4.4 worth further discussions. First, the pair-wised correlations among the three *FX* risk factors are all negative. The unconditional correlations between the JPY and the GBP (USD) is -22.7% (-20.5%), while the correlation between the GBP and USD is -11.9%. The result indicates that an unexpected increase in one *FX* risk factor will have a negative impact on the other two *FX* risk factors. In other words, the unexpected appreciation of one currency is at the expense of depreciation for the other two currencies. The finding is in line with our shift of funding hypothesis. When investors reallocate their investments from other markets into one market, the shift of funding pushes the currency value in the latter to a higher level compares to the former ones.

In addition, one can see that the returns of the three national market indices are all positively correlated.[248] The US and the UK market have the highest unconditional correlation among the three national markets, which is 53.4% during the sample period. The correlation between the Japanese market and the other two national markets are comparatively lower, which is 35.1% and 11.9% for the UK and US markets, respectively. Chen and Zhang (1997) argue that the correlation between two national markets tend to be influenced by their bilateral trading activities. Therefore, the positive correlation among the Japanese, UK and US market indices may due to the heavy bilateral trades across the three national markets. The argument is supported by information from the national statistical bureau of the three markets.[249] The data of annual external trade provided by the national statistical bureaus shows that US is the largest trading partner for both the

[248] The time series of the three national market indices are presented in Appendix C.7.
[249] The external trade information is collected from the *Statistical Hand Book of Japan 2010* by the Statistical Bureau, Japan; the *Statistical Bulletin UK Trade 2011* by Office for National Statistics, UK; and the *U.S. International Trade in Goods and Services January 2011* by the U.S. Bureau of Economic Analysis, US.

Japanese and UK markets, while the Japan and UK is the fourth and sixth largest trading partner for US market in 2010.

4.5. ESTIMATION RESULT

In the following section, we present and discuss the estimation result generated from the proposed VAR-BEKK model. We divide this section into three parts. In the first part, we discuss the result of the six joint-hypotheses tests. In the second part, the impact of home and foreign currency value fluctuation on the return performances of different financial sector portfolios will be analysed. The final part investigates the potential size effect of the currency exposure based on the estimation result for the large and small size banking portfolios in the Japanese and US markets.

4.5.1. Joint-Hypotheses Test Result

Table 4.5 summarizes the result of the six joint-hypotheses tests. As discussed in Section 4.3.2, the first two hypotheses (H1 and H2) investigate the relationship between home and/or foreign currency value fluctuation and the return performances of financial sector portfolios over the entire sample period. The remaining four hypotheses (H3 to H6) examine on the potential change in this relationship during the recent financial crisis.

Table 4.5 Joint-Hypotheses Test Result for FX and FX_Var Risk Factors across Financial Sector Portfolios.

The following table summarizes the test statistics of the log-likelihood restriction test for the VAR-BEKK model. The VAR-BEKK model used in the current study has eight different specifications for the mean equation:

Mean Equation Spec.1: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.2: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.3: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + DUM \cdot \gamma_i FX_{j,t} + DUM \cdot \theta_i FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.4: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.5: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.6: $r_{i,t} = \alpha_{i_i} + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.7: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + DUM \cdot \gamma_i FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.8: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + \varepsilon_{j,t}$

Variance Equation: $h_{i,j,t} = c_{i,j,pre} + a_{i,pre} \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_{j,pre} + b_{i,pre} h_{i,j,t-1} b_{j,pre}$, with $t \in [0, \tau]$

$h_{i,j,t} = c_{i,j,post} + a_{i,post} \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_{j,post} + b_{i,post} h_{i,j,t-1} b_{j,post}$, with $t \in [\tau + 1, T]$

with i and $j \in$ [*Japan, UK, US*], and τ represents the *September 15, 2008*.

where,

$r_{i,t}$ = the return for financial sector portfolio from country i over day t.

α_i = represents the constant of the conditional mean equation for financial sector portfolio from country i.

$MF(X)_{j,t}$ = represents the two macroeconomic factors: i) the market risk factor represents by the stock market index return (*Market*), and ii) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio i over day t, with $X \in [\,Market, IR]$.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for financial sector portfolio from country i over day t, with $x \in [\,Market, IR]$.

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\varepsilon_{i,t}$ = the estimated residual for financial sector portfolio return in country i over day t.

$h_{i,j,t}$ = the conditional covariance between the returns of financial sector portfolios in country i and country j over day t, while $h_{i,i,t}$ represents the conditional variance of the financial sector portfolio return in country i over day t.

$a_{ii,pre/post}$ = the parameter represents the ARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country i over day t.

$b_{ii,pre/post}$ = the parameter represents the GARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country i over day t.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

		ALL			Large			Small		
		DF	Test Stat.		DF	Test Stat.		DF	Test Stat.	
H1. No Foreign *FX* and *FX_Var* effect	**Bank**	**24**	**64.00**	***	**16**	**36.00**	***	**16**	**70.00**	***
Difference between Spec.1 and Spec.3	**Life**	**16**	**54.00**	***						
	Non-Life	**24**	**42.00**	**						
H2. No Home and Foreign *FX_Var* effect	**Bank**	**18**	**0.00**		**12**	**0.00**		**12**	**0.00**	
Difference between Spec.1 and Spec.5	**Life**	**12**	**8.00**							
	Non-Life	**18**	**0.00**							
H3. No Changes in Home *FX* effect factor during the financial crisis	**Bank**	**3**	**8.00**	**	**2**	**6.00**	**	**2**	**4.00**	
Difference between Spec.7 and Spec.8	**Life**	**2**	**4.00**							

	Non-Life	**3**	**0.00**							
H4. No Changes in Home *FX* and *FX_Var* effect during the financial crisis	**Bank**	**6**	**2.00**		**4**	**6.00**		**4**	**4.00**	
Difference between Spec.3 and Spec.4	**Life**	**4**	**6.00**							
	Non-Life	**6**	**10.00**							
H5. No Changes in Home and Foreign *FX* effect during the financial crisis	**Bank**	**9**	**40.00**	***	**6**	**24.00**	***	**6**	**48.00**	***
Difference between Spec.5and Spec.6	**Life**	**6**	**36.00**	***						
	Non-Life	**9**	**24.00**	**						
H6. No Changes in Home and Foreign *FX* and *FX_Var* effect during the financial crisis	**Bank**	**18**	**44.00**	***	**12**	**26.00**	***	**12**	**52.00**	***
Difference between Spec.1 and Spec.2	**Life**	**12**	**72.00**	***						
	Non-Life	**18**	**64.00**	***						

Note: the DF is the degree of freedom of the long-likelihood test, and the Test Stats represents the test statistics of the log-likelihood ratio test. ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

From the test result, one can see that the null hypothesis for H1 is rejected for all the financial sector portfolios. That means the parameters for foreign *FX* (Γ) and *FX_Var* (Θ) are statistically significant. In other words, the changes in foreign *FX* and *FX_Var* do influence the return performances of financial sector portfolios across the national markets. The test result for H2 cannot reject the null hypothesis, which means that both the home and foreign *FX_Var* do not influence the return performance of these financial sector portfolios. Therefore, the financial sector portfolios can only be influenced by the home and foreign *FX*, but not the home or foreign *FX_Var*.

Our finding is in contrast to the empirical study by Koutmos and Martin (2003b), who found strong and positive relationship between the home *FX_Var* and the performances of US financial institutions from 1992 to 1998. They argued that the positive relationship is due to the fact that higher variation in currency value induces greater volume of hedging. Therefore, financial institutions can earn more revenues through sales of currency derivative to the hedgers. We argue that there are two potential reasons why our finding is not consistent with the previous one. First, the currency value in Koutmos and Martin (2003b) is represented by bilateral exchange rates, instead of multilateral currency price indices. The significant impact of a bilateral exchange rate is likely to be smoothed out during the aggregation process to produce multilateral currency price index. By analyzing the information of banks' balance sheet position, Grammatikos et al (1986) show that return of US banks is significantly related to the value changes in five different foreign currencies.[250] However, the banks' return is not influenced by the aggregated foreign currency exposure which contains the net position of all the five foreign currencies.

[250] The authors find that the return of US banks have a positive relationship with value changes in German Mark, French Franc and JPY, while a negative relationship with Canada Dollar and GBP. The value changes in a foreign currency are represented by the changes in a bilateral exchanges rate between the USD and the corresponding foreign currency.

The authors argue that the reason behind that low significance of the aggregated exposure is mainly due to the low correlation among these bilateral exchange rates.

Second, the sample period of the two studies covers different time periods. The sample period of Koutmos and Martin (2003b) is from 1992 to 1998, while ours is from 2003 to 2011. We argue that even though higher variation of currency value will increase the sales of currency derivative, its impact on the profitability of the financial sector could be weak during our sample period. We believe the main concern for investors is credit risk instead of currency risk during our sample period, especially during the recent financial crisis.[251] Therefore, the trading volume of currency derivative should only represent a small proportion of the overall derivative market compares to the credit related instruments. Our argument is supported by the report from the World Federation of Exchanges (WFE).[252] During the 8-year period from 1998 to 2006, the trading volume of the currency derivative is almost unchanged. However, the trading volume of credit related instruments has increased dramatically during the same period.[253] As a result, the proportion of currency derivatives dropped from around a quarter of the world total derivative trading volume in 1998 to 8% at the end of 2008.

The joint result of H3 – H6 suggests that only the impact of foreign *FX* on the return performances of financial sector portfolios has changed during the recent financial crisis. The test result for both H3 and H4 shows that the null hypothesis cannot be rejected, which means the impact of home *FX* and *FX_Var* on the return of financial sector portfolios has not been affected by the recent financial crisis. However, the result for H5

[251] The recent financial crisis is also referred as a "credit crunch" around the global financial market (Brunnermeier, 2009). Therefore, the global investors should more concern about the credit related risk. The credit default swap (CDS) is one of the most popular hedging instrument for credit risk, as its volume has grew rapidly during the turn of the new century and picked at the end of 2007 (Vause, 2010).

[252] The report by WFE is under the title *Derivative Trading: Trends since 1998*, see: http://www.world-exchanges.org.

[253] The credit risk related instrument is represented by the derivatives for equity indices, individual stocks, credit default swap (CDS) and interest rate.

and H6 argue that the impact of home and foreign *FX* and *FX_Var* has changed in the financial crisis. Therefore, although no further hypothesis test is performed, it is reasonable to argue that the significant change in the impact of *FX* and *FX_Var* in H5 and H6 can only come from the ones in foreign currency terms. In addition, the result from H1 and H2 shows that the influence of home and foreign *FX_Var* on the return of financial sector portfolio is not significant over the whole estimation period, which reinforces the argument.

In general, both the home and foreign *FX_Var* risk factors have no significant influence on the returns of the financial sector portfolios. However, the estimated parameters for both the home and foreign *FX* are statistically significant in the proposed model. In addition, the result suggests the impact of foreign *FX* has changed significantly for all the financial sector portfolios during the recent financial crisis. We will present and discuss the impact of the home and foreign *FX* on the returns of the financial sector portfolios in the following sections.

4.5.2. *Currency Value Fluctuations and Return of Financial Sector Portfolios*

The estimation result of the proposed VAR-BEKK model for different financial sector portfolios across the three markets is presented in the following tables. Table 4.6 summarizes the estimated parameters for the banking portfolios, and the Table 4.7 and 4.8 illustrate the output of the VAR-BEKK model for the life and non-life insurance portfolios, respectively. In order to save space, we only report the estimation result for the VAR-BEKK model with the first model specification (*Spec.1*) in this empirical chapter.[254] We choose *Spec.1* instead of the other seven alternative specifications (*Spec.2 – 8*) because the

[254] The estimation result for the rest of the conditional mean equation specification (*Spec.2 - 8*) is available from the author upon request.

conditional mean equation of *Spec.1* poses no restrictions on any of the risk factors.[255] Therefore, the output of *Spec.1* provides the most general picture on how different risk factors will influence the returns of the financial sector portfolios, and the potential changes in the impact of the currency related risk factors (*FX* and *FX_Var*) during the crisis period.

[255] The other model specifications put restrictions on either the *FX* and/or *FX_Var* related parameters (*Spec.3, 5, 7*), or the dummy related variables (*Spec.2, 4, 6, 8*).

Table 4.6 Estimation Output of the VAR-BEKK Model for Banking Portfolios.

Mean Equation: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Variance Equation: $h_{i,j,t} = c_{i,j,pre} + a_{i,pre}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,pre} + b_{i,pre}h_{i,j,t-1}b_{j,pre}$, with $t \in [0, \tau]$

$h_{i,j,t} = c_{i,j,post} + a_{i,post}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,post} + b_{i,post}h_{i,j,t-1}b_{j,post}$, with $t \in [\tau + 1, T]$

with i and $j \in$ [*Japan, UK, US*], and τ represents the *September 15, 2008*.

where,

$r_{i,t}$ = the return for financial sector portfolio from country *i* over day *t*.

α_i = represents the constant of the conditional mean equation for financial sector portfolio from country *i*.

$MF(X)_{j,t}$ = represents the two macroeconomic factors: i) the market risk factor represents by the stock market index return (*Market*), and ii) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio *i* over day *t*, with $X \in [Market, IR]$.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for financial sector portfolio from country *i* over day *t*, with $x \in [Market, IR]$.

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country *j* over day *t*, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country *j* over day *t*, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\varepsilon_{i,t}$ = the estimated residual for financial sector portfolio return in country *i* over day *t*.

$h_{i,j,t}$ = the conditional covariance between the returns of financial sector portfolios in country *i* and country *j* over day *t*, while $h_{i,i,t}$ represents the conditional variance of the financial sector portfolio return in country *i* over day *t*.

$a_{ii,pre/post}$ = the parameter represents the ARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

$b_{ii,pre/post}$ = the parameter represents the GARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	Japan			UK			U.S.		
	Coeff.	Z-stat.		Coeff.	Z-Stat.		Coeff.	Z-stat.	
Mean Equation									
Constant	0.000	-0.733		0.000	-0.430		0.000	-2.113	**
Market ($\beta_{i,Market}$)	0.780	38.671	***	0.931	19.733	***	0.480	36.941	***
IR ($\beta_{i,IR}$)	0.014	1.548		-0.026	-0.610		0.035	4.412	***
FX ($g_{i,Japan}$)	-0.013	-0.283		0.031	0.712		-0.021	-0.914	
FX ($g_{i,UK}$)	-0.009	-0.139		0.047	0.683		-0.005	-0.182	
FX ($g_{i,US}$)	-0.097	-1.782	*	0.111	1.688	*	-0.041	-1.853	*
FX-Var ($z_{i,Japan}$)	0.002	0.038		-0.008	-0.020		0.001	0.031	
FX-Var($z_{i,UK}$)	-0.002	-0.055		0.001	0.028		0.001	0.023	
FX-Var ($z_{i,US}$)	0.001	0.025		0.001	0.005		0.003	0.045	
DUM*FX ($\gamma_{i,Japan}$)	0.130	1.643	†	-0.172	-0.766		-0.200	-4.055	***
DUM*FX ($\gamma_{i,UK}$)	0.044	0.466		-0.002	-0.007		-0.044	-0.808	
DUM*FX ($\gamma_{i,US}$)	0.025	0.256		-0.221	-0.786		-0.029	-0.470	
DUM*FX-Var($\theta_{i,Japan}$)	-0.002	-0.015		-0.007	-0.023		0.003	0.038	
DUM*FX-Var ($\theta_{i,UK}$)	-0.003	-0.006		-0.001	-0.022		0.001	0.031	
DUM*FX-Var ($\theta_{i,US}$)	-0.003	-0.014		-0.001	-0.034		0.001	0.017	

Variance Equation									
ARCH (a_{ii}^2, Pre-Crisis)	**0.000**	**0.190**		**0.315**	**5.402**	***	**0.004**	**0.855**	
GARCH (b_{ii}^2, Pre-Crisis)	**1.000**	**429.910**	***	**0.747**	**20.432**	***	**0.994**	**197.680**	***
ARCH (a_{ii}^2, Post-Crisis)	**0.046**	**4.193**	***	**0.040**	**2.702**	***	**0.146**	**8.396**	***
GARCH (b_{ii}^2, Post-Crisis)	**0.958**	**105.610**	***	**0.969**	**92.074**	***	**0.874**	**72.998**	***
Persistence (Pre-Crisis)	**1.000**			**1.063**			**0.998**		
Persistence (Post-Crisis)	**1.004**			**1.009**			**1.020**		
Log-Likelihood	**20264.0**								

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. † represents the test statistic is marginally insignificant at 10% level (critical value equals to 1.645). In order to avoid Type-II error, in the current study, we define † is significant at 10% level.

Table 4.7 Estimation Output of the VAR-BEKK Model for Life Insurance Portfolios.

Mean Equation: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Variance Equation: $h_{i,j,t} = c_{i,j,pre} + a_{i,pre} \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_{j,pre} + b_{i,pre} h_{i,j,t-1} b_{j,pre}$, with $t \in [0, \tau]$

$h_{i,j,t} = c_{i,j,post} + a_{i,post} \varepsilon_{i,t-1} \varepsilon_{j,t-1} a_{j,post} + b_{i,post} h_{i,j,t-1} b_{j,post}$, with $t \in [\tau + 1, T]$

with i and $j \in$ [*Japan, UK, US*], and τ represents the *September 15, 2008*.

where,

$r_{i,t}$ = the return for financial sector portfolio from country *i* over day *t*.

α_i = represents the constant of the conditional mean equation for financial sector portfolio from country *i*.

$MF(X)_{j,t}$ = represents the two macroeconomic factors: i) the market risk factor represents by the stock market index return (*Market*), and ii) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio *i* over day *t*, with $X \in [Market, IR]$.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for financial sector portfolio from country *i* over day *t*, with $x \in [Market, IR]$.

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country *j* over day *t*, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country *j* over day *t*, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\varepsilon_{i,t}$ = the estimated residual for financial sector portfolio return in country *i* over day *t*.

$h_{i,j,t}$ = the conditional covariance between the returns of financial sector portfolios in country *i* and country *j* over day *t*, while $h_{i,i,t}$ represents the conditional variance of the financial sector portfolio return in country *i* over day *t*.

$a_{ii,pre/post}$ = the parameter represents the ARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

$b_{ii,pre/post}$ = the parameter represents the GARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	UK			U.S.		
	Coeff.	Z-stat.		Coeff.	Z-stat.	
Mean Equation						
Constant	0.000	0.347		0.000	0.127	
Market ($\beta_{i,Market}$)	1.156	45.131	***	1.088	36.973	***
IR ($\beta_{i,IR}$)	-0.033	-1.482		-0.011	-1.002	
FX ($g_{i,Japan}$)	-0.121	-2.834	***	0.020	0.492	
FX ($g_{i,UK}$)	0.159	2.539	***	0.042	0.805	
FX ($g_{i,US}$)	0.016	0.309		0.027	0.628	
FX-Var ($z_{i,Japan}$)	-0.003	-0.026		0.003	0.016	
FX-Var($z_{i,UK}$)	0.001	0.033		-0.001	-0.020	
FX-Var ($z_{i,US}$)	0.002	0.011		0.001	0.013	
DUM*FX ($\gamma_{i,Japan}$)	0.105	1.457		-0.346	-4.481	***
DUM*FX ($\gamma_{i,UK}$)	0.168	1.464		-0.102	-0.976	
DUM*FX ($\gamma_{i,US}$)	-0.155	-1.457		-0.121	-1.296	
DUM*FX-Var($\theta_{i,Japan}$)	0.002	0.089		-0.002	-0.047	
DUM*FX-Var ($\theta_{i,UK}$)	0.001	0.009		-0.001	-0.037	

DUM*FX-Var ($\theta_{i,US}$)	**0.000**	**0.025**		**0.001**	**0.225**	
Variance Equation						
ARCH (a_{ii}^2, Pre-Crisis)	**0.000**	**0.941**		**0.000**	**0.110**	
GARCH (b_{ii}^2, Pre-Crisis)	**0.998**	**352.640**	***	**0.997**	**230.340**	***
ARCH (a_{ii}^2, Post-Crisis)	**0.041**	**7.250**	***	**0.082**	**7.781**	***
GARCH (b_{ii}^2, Post-Crisis)	**0.960**	**203.900**	***	**0.925**	**111.420**	***
Persistence (Pre-Crisis)	**0.998**			**0.997**		
Persistence (Post-Crisis)	**1.001**			**1.007**		
Log-Likelihood	**12973.0**					

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 4.8 Estimation Output of the VAR-BEKK Model for Non-Life Insurance Portfolios.

Mean Equation: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Variance Equation: $h_{i,j,t} = c_{i,j,pre} + a_{i,pre}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,pre} + b_{i,pre}h_{i,j,t-1}b_{j,pre}$, with $t \in [0, \tau]$

$h_{i,j,t} = c_{i,j,post} + a_{i,post}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,post} + b_{i,post}h_{i,j,t-1}b_{j,post}$, with $t \in [\tau + 1, T]$

with i and $j \in$ [*Japan, UK, US*], and τ represents the *September 15, 2008*.

where,

$r_{i,t}$ = the return for financial sector portfolio from country i over day t.
α_i = represents the constant of the conditional mean equation for financial sector portfolio from country i.
$MF(X)_{j,t}$ = represents the two macroeconomic factors: i) the market risk factor represents by the stock market index return (*Market*), and ii) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio i over day t, with $X \in [Market, IR]$.
$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for financial sector portfolio from country i over day t, with $x \in [Market, IR]$.
$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.
$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.
$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.
$z_{i,j}$ = the parameter represents the impact of the FX_Var effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.
$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.
$\theta_{i,j}$ = the parameter represents the changes in the impact of the FX_Var effect from currency in country j towards the financial sector portfolio in country i during the crisis period.
$\varepsilon_{i,t}$ = the estimated residual for financial sector portfolio return in country i over day t.
$h_{i,j,t}$ = the conditional covariance between the returns of financial sector portfolios in country i and country j over day t, while $h_{i,i,t}$ represents the conditional variance of the financial sector portfolio return in country i over day t.
$a_{ii,pre/post}$ = the parameter represents the ARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country i over day t.
$b_{ii,pre/post}$ = the parameter represents the GARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country i over day t.
DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	Japan			UK			US		
All Size Portfolio	**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**		**Coeff.**	**Z-stat.**	
Mean Equation									
Constant	0.000	0.448		0.000	0.713		0.000	-0.465	
Market ($\beta_{i,Market}$)	0.989	23.264	***	0.288	17.172	***	0.837	40.816	***
IR ($\beta_{i,IR}$)	-0.018	-0.927		0.007	0.604		-0.014	-1.391	
FX ($g_{i,Japan}$)	0.069	0.766		-0.106	-3.649	***	0.011	0.348	
FX ($g_{i,UK}$)	-0.036	-0.268		0.053	1.314		0.110	2.680	***
FX ($g_{i,US}$)	-0.194	-1.744	*	0.007	0.193		0.011	0.312	
FX-Var ($z_{i,Japan}$)	-0.001	-0.046		0.001	0.016		0.000	-0.123	
FX-Var($z_{i,UK}$)	-0.001	-0.023		0.000	-0.034		-0.001	-0.054	
FX-Var ($z_{i,US}$)	0.000	-0.008		0.001	0.187		0.000	-0.007	
DUM*FX ($\gamma_{i,Japan}$)	0.064	0.449		0.112	2.579	***	-0.083	-1.648	*
DUM*FX ($\gamma_{i,UK}$)	0.012	0.065		0.018	0.339		-0.161	-2.561	***
DUM*FX ($\gamma_{i,US}$)	-0.066	-0.341		0.005	0.099		0.035	0.564	
DUM*FX-Var($\theta_{i,Japan}$)	-0.002	-0.014		0.005	0.013		-0.001	-0.020	
DUM*FX-Var ($\theta_{i,UK}$)	-0.001	-0.009		0.001	0.006		-0.001	-0.028	

DUM*FX-Var ($\theta_{i,US}$)	**-0.001**	**-0.042**		**0.001**	**0.083**		**-0.001**	**-0.008**	
Variance Equation									
ARCH (a_{ii}^2, Pre-Crisis)	**0.025**	**0.629**		**0.000**	**0.305**		**0.002**	**0.431**	
GARCH (b_{ii}^2, Pre-Crisis)	**0.975**	**25.079**	***	**0.995**	**395.790**	***	**1.000**	**198.560**	***
ARCH (a_{ii}^2, Post-Crisis)	**0.038**	**3.182**	***	**0.007**	**0.754**		**0.083**	**6.012**	***
GARCH (b_{ii}^2, Post-Crisis)	**0.965**	**93.770**	***	**0.991**	**114.400**	***	**0.926**	**81.733**	***
Persistence (Pre-Crisis)	**1.000**			**0.995**			**1.002**		
Persistence (Post-Crisis)	**1.004**			**0.998**			**1.009**		
Log-Likelihood	**19902.0**								

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively.

As discussed in the methodology section, we include the market and interest rate risk factors because pervious empirical studies show that they have the potential to influence the returns of the financial institutions. Therefore, a model without these risk factors may suffer from inefficiency and biasness due to omitted variables. However, in the current study, our main focus is on the relationship between the currency value fluctuation and the return performances of financial sector portfolios. Therefore, we only discuss the estimated coefficients for the currency related risk factors in this chapter.[256] However, it is worth noting that the estimated volatility persistence is higher than unity for most financial sector portfolios, especially during the post-crisis period (i.e. 1.020 for the U.S. banking portfolio). The high persistence is mainly caused by the higher ARCH effect observed during the post-crisis period compared to its pre-crisis level. This finding might due to the fact that the conditional volatility is more sensitive to current shocks when financial market is volatile. The finding suggests that the impact of current shocks on volatility will not decline geometrically over time but enhanced instead (i.e. non-stationary GARCH process). One possible explanation could be that the simple GARCH-type models can no-longer accurately evaluate the behavior of financial assets' conditional volatility during the recent financial crisis as the distribution of returns might have fat tails (Carnero et al., 2004).[257]

The currency related risk factors refer to the home and foreign *FX* and *FX_Var*. In order to present these estimated coefficients in a clear fashion, we create another set of summary tables.[258] Table 4.9 contains the estimated coefficient of the significant currency

[256] For discussion on the market risk factor of the financial institutions and potential size effects please see Demsetz and Strahan (1997), De Nicoló et al (2004), and Elyasiani et al (2007) among others. For discussion on the interest rate risk factors, please see Staikouras (2003 and 2006).
[257] For instance, Exponential GARCH or Glosten-Jagannathan-Runkle GARCH model might be good alternatives.
[258] In these summary tables, we only report the estimated coefficients from *Spec.1, 3, 5,* and *7* as they all have the structural break feature in their model specifications.

related risk factors for the banking portfolios, while Table 4.10 and 4.11 summarize the estimated coefficients of the significant currency related risk factors for the life and non-life insurance portfolios, respectively.

Table 4.9 Significant Currency Related Risk Factors for the Banking Portfolios.

The table below summarizes the estimated coefficients for significant *FX* and *FX_Var* effects from the proposed VAR-BEKK model. For foreign *FX* and *FX_Var* effect, the origin country of the foreign currency will be specified. In order to illustrate the potential change in *FX* and *FX_Var* effect during the recent financial crisis, only the model specifications with the *DUM* variable (Spec.1, 3, 5, and 7) are reported in the following table. The currency related parameters for Spec.1 are selected from Table 4.6. The four model specifications are demonstrated as follow:

Mean Equation Spec.1: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.3: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + DUM \cdot \gamma_i FX_{j,t} + DUM \cdot \theta_i FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.5: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.7: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + DUM \cdot \gamma_i FX_{j,t} + \varepsilon_{j,t}$

with i and $j \in$ [*Japan, UK, US*].

where,

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	**Japan**				**UK**				**US**			
Model Specification	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**
Home FX									**-0.041**	**-0.034**	**-0.040**	**-0.032**
z-stat.									***(-1.853)***	***(-1.864)***	***(-1.813)***	***(-1.751)***
Home FX_Var												
z-stat.												
DUM*Home FX	**0.130**		**0.127**									
z-stat.	***(1.643)***		***(1.685)***									
DUM*Home FX_Var												
z-stat.												

Foreign FX	**USD: -0.097**		**USD: -0.099**	**USD: 0.111**		**USD: 0.109**			
z-stat.	***(-1.782)***		***(-1.816)***	***(1.688)***		***(1.673)***			
Foreign FX_Var									
z-stat.									
DUM*Foreign FX							**JPY: -0.200**		**JPY: -0.200**
z-stat.							***(-4.055)***		***(-4.057)***
DUM*Foreign FX_Var									
z-stat.									

Note: The estimated coefficient for *Home FX / FX_Var* effects indicate the fluctuation of currency value in country *i* have an significant impact on financial sector portfolio in the same country, while the *Foreign FX/FX_Var* effects indicate the fluctuation of currency *j* have an significant impact on financial sector portfolio from country *i*. For *Foreign FX/FX_Var* effects the name of currency *j* is specified before the estimated coefficient. The JPY, GBP and USD refer to Japanese Yen, British Pound, and US Dollar, respectively. For instance, for financial sector portfolio from *US*, the *JPY: -0.050* for the *Foreign FX* effect represents that for *1%* appreciation in *JPY* the return will cause *0.05%* decrease for financial sector portfolio from *US*. The shadings in the above table means the corresponding *FX* and/or *FX_Var* effects are not available for the model specification.

From Table 4.9, one can see that the home and foreign *FX_Var* do not have a significant impact on the return performances of the banking portfolios. In addition, the result shows that the relationship between changes in home currency value and the return performances of Japanese and UK banking portfolio is not significant over the estimation period. Previous studies argue that the lack of significance of home currency exposure may due to the effective hedging practice carried out by the firms (Levi, 1994; Bartov et al, 1996; Chow et al, 1997a). Also, empirical studies by Cummins et al (1996) and Grant and Marshall (1997) both confirm the use of derivatives can be an effective way to hedge currency exposures. The data provided by BoE suggests that foreign currency derivative was indeed one of the heavily used hedging instruments by UK banks over the last decade, especially during the crisis period.[259] On average, the outstanding volume of foreign currency related derivatives occupied around 25 percent of the total volume of financial derivatives used by the UK banking industry.[260] Therefore, we argue that the lack of home currency exposure for the UK banks is mainly due to the effective hedging activities.

The only exception is the banks from the US market. Empirical evidence shows that the home currency exposure of the US banking portfolio is significantly negative over the whole estimation period. The estimated coefficients for home *FX* is varied from -0.041 in *Spec.1* to -0.032 in *Spec.7* for the US banking portfolio. We believe the significant currency exposure of the US banking sector is mainly coming from the small banks, as they have less incentive to hedge their currency exposures due to the economics of scale for hedging

[259] The data on outstanding volume of financial derivative is collected from the *Financial Derivative Position of Banks at Market Values* (F1.1) table provided by BoE, see: http://www.bankofengland.co.uk/statistics/bankstats/current/tabf1.1.xls

[260] The most heavily used financial derivative was the interest rate related derivatives, which represents more than 50 percent of the total derivative usage in terms of market value. The commodity and credit related derivatives only represented around 13 and 7 percent of the total derivative volume used by the UK banking industry, respectively.

activities. We will discuss the phenomenon based on the estimation result of large and small size banking portfolios in the next section.

The coefficient of foreign *FX* risk factor is significant for most banking portfolios during the pre-crisis period, and all banking portfolios are sensitive to foreign *FX* fluctuations during the post-crisis period. The result indicates that the returns of all the banking portfolios are influenced by the changes in foreign currency value. The estimated coefficient of foreign (USD) *FX* risk factor is -0.097 for the Japanese banking portfolio over the entire estimation period.[261] Similarly, the estimated coefficient of foreign (JPY) *DUM*FX* risk factor is -0.200 for the US banking portfolio during the crisis period.[262] In other words, the empirical evidence suggests that the changes in JPY (USD) value have a negative impact on the return of US (Japanese) banking portfolio.

In order to explain the meaning of the foreign *FX* risk factors and their influence on financial sector portfolios, we need to first examine the interactions among the three currencies. According to our "shift of funding" hypothesis, the changes in currency value can be treated as an alternative measure of investors' preference towards the global financial markets. Since a country's currency value is related to the willingness of holding financial asset in this country (Branson, 1983; and Frankel, 1983), as investors shift their investments from one market to another the currency value of these countries should change accordingly. Melvin and Taylor (2009) support our hypothesis by showing the value of JPY is steadily increasing during the recent financial crisis because Japanese financial market did not suffer from the recent financial crisis as much as the European

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[261] The sign and value of the estimated coefficients for *FX* and *FX_Var* are similar across different model specifications, which reinforce the fact that there is no multicolinearity among these variables. The consistence across these model specifications also indicates that the estimation process is unbiased. In order to save space, we only present the estimation result from Spec.1 for the rest of the paper unless specified.

[262] The estimation coefficient of a currency risk factor during the crisis period is equal to the estimated coefficient over the entire estimation period (*FX* or *FX_Var*) plus the estimated dummy variable during the crisis period (*DUM*FX* or *DUM*FX_Var*). [-0.200 = 0 (*FX*) – 0.200 (*DUM*FX*)]

countries and the US. In contrast, the value of GBP and USD is in a downward channel since the start of the crisis.[263] Under our "shift of funding" hypothesis, the GBP and USD depreciated because the economic risk level in the UK and US markets increased dramatically during the crisis period. Therefore, investors would "fly" away from these two markets, and "fly" into the Japanese market which was not been as severally damaged as the other two. This "shift of funding" will increase the demand for JPY and drive up the JPY value, while reduce the value of the currencies as well as the financial assets in the other two markets. Therefore, the return of financial sectors in the UK and US markets should have an inverse relationship with the value of JPY. In contrast, the Japanese financial market benefits from the depreciation of the GBP and USD. As one can see from Table 4.9, the relationship between the changes in JPY (USD) and the return of US (Japanese) banking portfolio is indeed negative. Therefore, the empirical evidence supports our "shift of funding" hypothesis between the two national markets.

The equity value of the UK banking industry is positively related to the changes in the USD value, with the estimated coefficient of foreign (USD) *FX* risk factor is 0.111 over the whole estimation period. This finding reinforces our "shift of funding" hypothesis. The UK and the US financial markets were highly connected over the sample period.[264] The empirical study by Chiang and Zheng (2010) also shows the UK and US financial markets are highly linked through herding effect.[265] In other words, the investors who invest in the UK market are closely following the behavior of the investors who invest in the US market. Therefore, when investors move away from the US financial market, the

[263] We also illustrate the time series of the three currency price indices over the sample period in Figure 4.1.
[264] From Table 4, one can see the unconditional correlation between the UK and US markets is 53.4% over the entire sample period, which is the highest among the three.
[265] In their study, the herding effect is defined as the phenomenon that a group of investors trading in the same direction. Their sample period is from 1989 till 2009 which covers most of the sample period used in the present study.

UK financial market is likely to suffer as well. Since the value of USD will decrease when investors shift their investments away from the US financial market, the USD value should have a positive relationship with the performance of UK financial market. In addition, the UK banking sector is highly exposed to the market risk. The estimation result from Table 4.6 shows the market beta of UK banking portfolio is 0.931 over the sample period. That means the changes in USD value should be positively related to the return of UK banking sector.

Another interesting finding from Table 4.9 is that the impact of home *FX* risk factor on Japanese banking portfolio has changed during the crisis period. The estimated coefficient of home *DUM**FX* risk factor is 0.130 based on model *Spec.1*. That means the changes in JPY value has a positive and significant impact on the return of Japanese banks over the crisis period.[266] We argue the reason behind this change in home currency exposure is mainly due to the large amount of foreign losses for the Japanese banks over the crisis period. Since foreign losses are recorded in foreign currency value, an increase in home currency value will reduce the amount of foreign losses in home currency terms. Therefore, banks with large amount of foreign losses should benefit from the appreciation of home currency. Our argument is supported by the accounting data from Japanese Bankers Association (JBA).[267] The annual amount of written-off of loans for the Japanese banking sector has ballooned from JPY 452,273 million in 2007 to JPY 1,409,363 million in 2009, with the largest annual increase of JPY 750,036 million from 2008 to 2009.

[266] The estimated coefficient 0.130 (from Table 6) is marginally insignificant (Z-stat.=1.643) at the 10% level (critical value 1.645). In order to prevent Type II error, we treat this parameter is significant at the 10% level in the current study.

[267] The information of accounting data is collected from the aggregate annual banking sector financial statements (2006 – 2010) issued by the JBA. The financial statements are available from JBA's website, www.zenginkyo.org.jp.

Table 4.10 Significant Currency Related Risk Factors for the Life Insurance Portfolios.

The table below summarizes the estimated coefficients for significant *FX* and *FX_Var* effects from the proposed VAR-BEKK model. For foreign *FX* and *FX_Var* effect, the origin country of the foreign currency will be specified. In order to illustrate the potential change in *FX* and *FX_Var* effect during the recent financial crisis, only the model specifications with the *DUM* variable (Spec.1, 3, 5, and 7) are reported in the following table. The currency related parameters for Spec.1 are selected from Table 4.7. The four model specifications are demonstrated as follow:

Mean Equation Spec.1: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$
Mean Equation Spec.3: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + DUM \cdot \gamma_i FX_{j,t} + DUM \cdot \theta_i FX\_Var_{j,t} + \varepsilon_{j,t}$
Mean Equation Spec.5: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + \varepsilon_{j,t}$
Mean Equation Spec.7: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + DUM \cdot \gamma_i FX_{j,t} + \varepsilon_{j,t}$
with i and $j \in$ [*Japan, UK, US*].

where,

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	**UK**				**U.S.**			
Model Specification	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**
Home FX	**0.159**	**0.163**	**0.167**	**0.163**				
z-stat.	***(2.539)***	***(2.570)***	***(2.669)***	***(2.572)***				
Home FX_Var								
z-stat.								
DUM*Home FX								
z-stat.								
DUM*Home FX_Var								
z-stat.								

Foreign FX	**JPY: -0.121**		**JPY: -0.100**			
z-stat.	***(-2.834)***		***(-2.334)***			
Foreign FX_Var						
z-stat.						
DUM*Foreign FX				**JPY: -0.346**		**JPY: -0.327**
z-stat.				***(-4.481)***		***(-4.251)***
DUM*Foreign FX_Var						
z-stat.						

Note: The estimated coefficient for *Home FX* / *FX_Var* effects indicate the fluctuation of currency value in country *i* have an significant impact on financial sector portfolio in the same country, while the *Foreign FX* / *FX_Var* effects indicate the fluctuation of currency *j* have an significant impact on financial sector portfolio from country *i*. For *Foreign FX* / *FX_Var* effects the name of currency *j* is specified before the estimated coefficient. The JPY, GBP and USD refer to Japanese Yen, British Pound, and US Dollar, respectively. For instance, for financial sector portfolio from *US*, the *JPY: -0.050* for the *Foreign FX* effect represents that for *1%* appreciation in *JPY* the return will cause *0.05%* decrease for financial sector portfolio from *US*. The shadings in the above table means the corresponding *FX* and/or *FX_Var* effects are not available for the model specification.

Table 4.10 contains the estimated coefficient of the significant currency risk factors for the life insurance portfolios. Similar to the findings from banking portfolios, the estimated coefficients of the home and foreign *FX_Var* are also not significant over the entire estimation period. The reason behind the insignificant *FX_Var* is mainly because the insurers are not the main dealers for currency derivatives. As discussed in the previous section, the conditional volatility of the currency value fluctuation influences the return of financial institutions through its impact on the sales volume of currency related derivatives (Koutmos and Martin, 2003b). The main dealer of derivative is banks instead of insurers. That means the changes in the sales volume of derivative should not have an impact on the profitability of the insurance companies. Therefore, the return of insurance companies should not be affected by the home and foreign *FX_Var*.

From Table 4.10, one can see that the life insurance sector in the UK market is exposure to the changes in home currency value. The estimated coefficient of home *FX* risk factor is *0.159* for UK life insurance portfolio based on model *Spec.1*. Mange (2000) argues that the return of the life insurers can be positively linked with the home currency value through issuing insurance products into oversea markets. He shows that as the home currency value increases, the amount of payables in foreign currency terms will be reduced. Therefore, the life insurance companies will benefit from the appreciation of the home currency. Based on a theoretical framework, he further argues that the positive impact of home currency value fluctuation on the return of life insurers can be very strong if the products they issued are long-term ones.

The data from the Association of British Insurers (ABI) confirms this argument.[268] According to the information provided by ABI, around twenty percent of the net premium

[268] The information is collected from several documents issued by ABI. The relevant documents include the *UK Insurance – Key Facts*, the *Annual Invested Assets Overview Statistics*, the *Long-term Insurance Net Premium*

income of UK insurance sector is coming from oversea, and more than seventy percent of that is coming from sales of long-term products. Therefore, it is reasonable that the return of the UK life insurance portfolio will be influenced by the fluctuation of GBP value in a positive way.

Based on the estimation result of foreign *FX*, one can see that the returns of both the UK and US life insurance portfolios are negatively related to the changes in JPY value. The estimated coefficient of foreign (JPY) *FX* risk factor for the UK life insurance portfolio is -0.121 over the entire estimation period, while the foreign (JPY) *DUM*FX* risk factor is negative and significant (-0.346) for the US life insurance portfolio over the crisis period. Once again, we show that the increase in JPY value is an indication that investors prefer the Japanese market over the other two national markets. As investors shift their investments from the UK and US markets into the Japanese market, they drive up the JPY value and reduce the value of the other two financial markets. Therefore, the changes in JPY value have a negative impact on the return of both the US life insurance sectors, especially during the crisis period.

Income Statistics, and the *Annual General Insurance Overview Statistics,* which are available on the ABI website, www.abi.org.uk.

Table 4.11 Significant Currency Related Risk Factors for the Non-Life Insurance Portfolios.

The table below summarizes the estimated coefficients for significant *FX* and *FX_Var* effects from the proposed VAR-BEKK model. For foreign *FX* and *FX_Var* effect, the origin country of the foreign currency will be specified. In order to illustrate the potential change in *FX* and *FX_Var* effect during the recent financial crisis, only the model specifications with the *DUM* variable (Spec.1, 3, 5, and 7) are reported in the following table. The currency related parameters for Spec.1 are selected from Table 4.8. The four model specifications are demonstrated as follow:

Mean Equation Spec.1: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.3: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + DUM \cdot \gamma_i FX_{j,t} + DUM \cdot \theta_i FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.5: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.7: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + DUM \cdot \gamma_i FX_{j,t} + \varepsilon_{j,t}$

with i and $j \in$ [*Japan, UK, US*].

where,

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Country	**Japan**				**UK**				**US**			
Model Specification	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**
Home FX												
z-stat.												
Home FX_Var												
z-stat.												
DUM*Home FX												
z-stat.												
DUM*Home FX_Var												
z-stat.												
Foreign FX	**USD: -0.194**		**USD: -0.190**		**JPY: -0.106**		**JPY: -0.108**		**GBP: 0.110**		**GBP: 0.099**	
z-stat.	***(-1.744)***		***(-1.747)***		***(-3.649)***		***(-3.731)***		***(2.680)***		***(2.418)***	

Foreign FX_Var *z-stat.*									
DUM*Foreign FX *z-stat.*				**JPY: 0.112** *(2.579)*		**JPY: 0.129** *(2.966)*	**JPY: -0.083 / GBP: -0.161** *(-1.648)/(-2.561)*		**JPY: -0.092/GBP: -0.173** *(-1.814)/(-2.778)*
DUM*Foreign FX_Var *z-stat.*									

Note: The estimated coefficient for *Home FX* / *FX_Var* effects indicate the fluctuation of currency value in country *i* have an significant impact on financial sector portfolio in the same country, while the *Foreign FX* / *FX_Var* effects indicate the fluctuation of currency *j* have an significant impact on financial sector portfolio from country *i*. For *Foreign FX* / *FX_Var* effects the name of currency *j* is specified before the estimated coefficient. The JPY, GBP and USD refer to Japanese Yen, British Pound, and US Dollar, respectively. For instance, for financial sector portfolio from *US*, the *JPY: -0.050* for the *Foreign FX* effect represents that for *1%* appreciation in *JPY* the return will cause *0.05%* decrease for financial sector portfolio from *US*. The shadings in the above table means the corresponding *FX* and/or *FX_Var* effects are not available for the model specification.

The significant currency risk factors for non-life insurance portfolios are presented in Table 4.11. Consistent with the findings from banking and life insurance portfolios, the estimated coefficients of the home and foreign *FX_Var* risk factors are not significant over the sample period. Furthermore, the non-life insurance portfolios are all free from home currency exposure, as none of the estimated coefficient of home *FX* is significant over the estimation period.

By investigating the impact of foreign *FX* value fluctuations on the return of non-life insurance portfolios, we find the result is similar to the one for the banking sectors. For the Japanese market, the changes in USD value have a negative and significant impact on the return of non-life insurance portfolios. The estimated coefficient of foreign (USD) *FX* risk factor is -0.194 over the estimation period. For US non-life insurance portfolio, estimated coefficient of foreign (JPY) *DUM*FX* risk factor is -0.083 during the crisis period.[269] The empirical evidence is once again in line with our "shift of funding" hypothesis as foreign *FX* has a negative impact on the return of home institutions. As investors shift their investments from one market to another, the currency value and the performances of the national financial markets move in opposite direction.

The changes in GBP value are positively related with the return of the US non-life insurance portfolio before the financial crisis. The estimated coefficient of foreign (GBP) *FX* risk factor is 0.110 for the US non-life insurers. The finding is similar to the positive linkage between the USD value fluctuation and the return of the UK banks over the whole sample period. The positive relationship between the currency value of one market and financial sector return of another market indicates that the two markets are highly connected. However, this relationship has changed dramatically during the financial

[269] It is worth noting that the t-statistics of the estimated coefficient is only marginally above the 10% significance level (1.645). Therefore, the economic value of the JPY effect on US non-life insurance portfolios could be minimal if not negligible.

crisis. The estimated coefficient of foreign (GBP) *DUM*FX* risk factor is -0.161 for the US non-life insurers. That means the relationship between the changes in GBP value and the return of the US non-life insurance portfolio has dropped from 0.110 to -0.051 over the crisis period.[270] One possible explanation for this could be that investors no longer treat the equities of non-life insurance sectors in these two markets as financial assets with similar characteristics. Therefore, the currency value changes in one market can no long served as the indicator of investors' preference for the financial assets in the other market. We believe the change is mainly due to the differences between the asset compositions of the two non-life insurance sectors. The asset composition of a firm provides important information about the firm's risk composition, and therefore, is a good indicator of its risk characteristic. The data provided by Swiss Re indicates that during the financial crisis, the asset compositions of the two non-life insurance sectors are distinctively different.[271] The UK non-life insurers invest more than fifteen percent of their asset into real estate and property-secured loans, while the non-life insurers in the US market have not property related assets in 2008.

The empirical evidence on the relationship between changes in JPY value and the return performances of UK non-life insurance portfolio also provides some interesting result. The estimated coefficient of foreign (JPY) *FX* risk factor is -0.106 for UK non-life insurance portfolio. In order words, the changes in JPY value have a negative impact on the equity value of UK non-life insurers. The finding is consistent with our "shift of funding" hypothesis, as investors move away from the UK financial market into Japanese

[270] The influence of foreign (GBP) *FX* risk factor on the performances of US non-life insurance sector portfolio is -0.051 over the crisis period. The value -0.051 is generated by summing up the estimated coefficients of both the foreign (GBP) *FX* risk factor and the foreign (GBP) *DUM*FX* risk factor. The FX risk factor represents the impact of the changes in currency value over the entire sample period, while the DUM*FX risk factor represents the changes in the magnitude of the risk factor during the crisis period. [-0.051 = 0.110 (*FX*) - 0.161 (*DUM*FX*)]

[271] The information is collected from the report by the Swiss Re under the title: *SIGMA – Insurance Investment in a Challenging Global Environment* (2010), which is available from Swiss Re's website, www.swissre.com.

market, the value of the UK financial assets will drop while the JPY value will rise. However, the relationship has changed during the crisis period. The estimated coefficient of foreign (JPY) *DUM*FX* risk factor is 0.112 for the UK non-life insurance portfolio, which means the relationship between the JPY value fluctuation and the return performances of UK non-life insurers has changed from negative (-0.106) to positive (0.006) during the recent financial crisis.[272]

4.5.3. Currency Value and Size Effect

The size effect in currency exposure has been documented in the previous empirical studies. The relationship between the currency value fluctuation and the returns of firms with different market size may be different due to their incentive to hedge (Mian, 1996), or the risk characteristics associate with their size (He and Ng, 1998). In the present study, we also investigate the potential size effect of the currency exposure for the large and small size banking portfolios from the Japanese and US market. The estimation result of the proposed VAR-BEKK model for these size portfolios is represented in Table 4.12. In order to present the estimated coefficients of the currency related risk factors in a clear fashion, we also create a summary table (Table 4.13) for the currency related risk factors which are statistically significant.

[272] The value 0.006 is generated by summing up the estimated coefficients of both the foreign (JPY) *FX* risk factor and the foreign (JPY) *DUM*FX* risk factor. The FX risk factor represents the impact of the changes in currency value over the entire sample period, while the DUM*FX risk factor represents the changes in the magnitude of the risk factor during the crisis period. [0.006 = -0.106 (*FX*) + 0.112 (*DUM*FX*)]

Table 4.12 Estimation Output of the VAR-BEKK Model for Large and Small Size Banking Portfolios.

Mean Equation: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j} FX\_Var_{j,t} + \varepsilon_{j,t}$

Variance Equation: $h_{i,j,t} = c_{i,j,pre} + a_{i,pre}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,pre} + b_{i,pre}h_{i,j,t-1}b_{j,pre}$, with $t \in [0, \tau]$

$h_{i,j,t} = c_{i,j,post} + a_{i,post}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{j,post} + b_{i,post}h_{i,j,t-1}b_{j,post}$, with $t \in [\tau + 1, T]$

with i and $j \in$ [*Japan, US*], and τ represents the *September 15, 2008*.

where,

$r_{i,t}$ = the return for financial sector portfolio from country *i* over day *t*.

α_i = represents the constant of the conditional mean equation for financial sector portfolio from country *i*.

$MF(X)_{j,t}$ = represents the two macroeconomic factors: i) the market risk factor represents by the stock market index return (*Market*), and ii) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (*IR*) for financial sector portfolio *i* over day *t*, with $X \in [Market, IR]$.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for financial sector portfolio from country *i* over day *t*, with $x \in [Market, IR]$.

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country *j* over day *t*, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country *j* over day *t*, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country *j* towards the financial sector portfolio in country *i* during the crisis period.

$\varepsilon_{i,t}$ = the estimated residual for financial sector portfolio return in country *i* over day *t*.

$h_{i,j,t}$ = the conditional covariance between the returns of financial sector portfolios in country *i* and country *j* over day *t*, while $h_{i,i,t}$ represents the conditional variance of the financial sector portfolio return in country *i* over day *t*.

$a_{ii,pre/post}$ = the parameter represents the ARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

$b_{ii,pre/post}$ = the parameter represents the GARCH effect before the crisis period (*pre*) / during the crisis period (*post*) for country *i* over day *t*.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Panel A: Large Size Banking Sector Portfolios

Country	Japan			US		
	Coeff.	Z-stat.		Coeff.	Z-stat.	
Mean Equation						
Constant	0.000	-0.860		0.000	-2.582	***
Market ($\beta_{i,Market}$)	0.944	46.104	***	0.980	47.184	***
IR ($\beta_{i,IR}$)	0.004	0.311		0.035	2.731	***
FX ($g_{i,Japan}$)	0.012	0.218		-0.035	-0.930	
FX ($g_{i,UK}$)	0.033	0.393		0.013	0.317	
FX ($g_{i,US}$)	-0.159	-2.413	***	-0.054	-1.367	
FX-Var ($z_{i,Japan}$)	-0.003	-0.012		-0.005	-0.032	
FX-Var($z_{i,UK}$)	-0.003	-0.029		-0.001	-0.030	
FX-Var ($z_{i,US}$)	0.000	-0.032		0.000	0.060	
DUM*FX ($\gamma_{i,Japan}$)	0.130	1.640	†	-0.270	-3.686	***
DUM*FX ($\gamma_{i,UK}$)	0.009	0.075		-0.171	-1.775	*
DUM*FX ($\gamma_{i,US}$)	0.045	0.431		0.066	0.600	
DUM*FX-Var($\theta_{i,Japan}$)	-0.009	-0.015		-0.003	-0.031	
DUM*FX-Var ($\theta_{i,UK}$)	-0.004	-0.009		-0.001	-0.020	
DUM*FX-Var ($\theta_{i,US}$)	-0.004	-0.016		0.000	-0.022	

Variance Equation						
ARCH (a_{ii}^2, Pre-Crisis)	0.000	0.068		0.099	0.689	
GARCH (b_{ii}^2, Pre-Crisis)	1.004	234.180	***	0.912	7.121	***
ARCH (a_{ii}^2, Post-Crisis)	0.069	6.792	***	0.065	6.720	***
GARCH (b_{ii}^2, Post-Crisis)	0.936	114.730	***	0.937	114.970	***
Persistence (Pre-Crisis)	1.004			1.011		
Persistence (Post-Crisis)	1.006			1.002		
Log-Likelihood	12791.0					

Panel B: Small Size Banking Sector Portfolios

Country	Japan			US		
	Coeff.	Z-stat.		Coeff.	Z-stat.	
Mean Equation						
Constant	0.000	-0.862		0.000	-1.235	
Market ($\beta_{i,Market}$)	0.732	35.366	***	0.309	31.239	***
IR ($\beta_{i,IR}$)	0.019	1.859	*	0.031	5.172	***
FX ($g_{i,Japan}$)	-0.018	-0.383		-0.018	-1.061	
FX ($g_{i,UK}$)	-0.028	-0.417		0.004	0.211	
FX ($g_{i,US}$)	-0.072	-1.104		-0.044	-2.333	***
FX-Var ($z_{i,Japan}$)	0.003	0.026		0.005	0.029	
FX-Var($z_{i,UK}$)	-0.002	-0.062		0.004	0.042	
FX-Var ($z_{i,US}$)	0.001	0.032		0.007	0.027	
DUM*FX ($\gamma_{i,Japan}$)	0.119	1.455		-0.195	-3.973	***
DUM*FX ($\gamma_{i,UK}$)	0.047	0.497		-0.026	-0.469	
DUM*FX ($\gamma_{i,US}$)	-0.017	-0.167		-0.057	-0.931	
DUM*FX-Var($\theta_{i,Japan}$)	0.001	0.044		0.004	0.067	
DUM*FX-Var ($\theta_{i,UK}$)	-0.002	-0.040		0.001	0.050	
DUM*FX-Var ($\theta_{i,US}$)	-0.002	-0.038		0.000	0.028	
Variance Equation						
ARCH (a_{ii}^2, Pre-Crisis)	0.004	-0.803		0.089	1.249	
GARCH (b_{ii}^2, Pre-Crisis)	0.999	211.970	***	0.950	16.609	***
ARCH (a_{ii}^2, Post-Crisis)	0.053	4.873	***	0.194	8.736	***
GARCH (b_{ii}^2, Post-Crisis)	0.952	110.880	***	0.831	58.155	***
Persistence (Pre-Crisis)	1.004			1.040		
Persistence (Post-Crisis)	1.004			1.025		
Log-Likelihood	14394.0					

Note: ***,** and * represent significance at the 1%, 5% and 10% levels, respectively. † represents the test statistic is marginally insignificant at 10% level (critical value equals to 1.645). In order to avoid Type-II error, in the current study, we define † is significant at 10% level.

Table 4.13 Significant Currency Related Risk Factors for the Large and Small Banking Portfolios.

The table below summarizes the estimated coefficients for significant FX and FX_Var effects from the proposed VAR-BEKK model. For foreign FX and FX_Var effect, the origin country of the foreign currency will be specified. In order to illustrate the potential change in FX and FX_Var effect during the recent financial crisis, only the model specifications with the *DUM* variable (Spec.1, 3, 5, and 7) are reported in the following table. The currency related parameters for Spec.1 are selected from Table 4.12. The four model specifications are demonstrated as follow:

Mean Equation Spec.1: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.3: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + z_i FX\_Var_{j,t} + DUM \cdot \gamma_i FX_{j,t} + DUM \cdot \theta_i FX\_Var_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.5: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + \varepsilon_{j,t}$

Mean Equation Spec.7: $r_{i,t} = \alpha_i + \sum \beta_{i,x} MF(X)_{i,t} + g_i FX_{j,t} + DUM \cdot \gamma_i FX_{j,t} + \varepsilon_{j,t}$

with i and $j \in$ [*Japan, UK, US*].

where,

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the changes in the impact of the *FX* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

$\theta_{i,j}$ = the parameter represents the changes in the impact of the *FX_Var* effect from currency in country j towards the financial sector portfolio in country i during the crisis period.

DUM = the dummy variable represents the current financial crisis. *DUM = 0* before *September 15, 2008*, and *DUM = 1* afterwards.

Panel A: Large Size Banking Sector Portfolios.

Country	Japan				US			
Model Specification	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**
Home FX								
z-stat.								
Home FX_Var								
z-stat.								
DUM*Home FX	**0.130**		**0.136**					
z-stat.	***(1.640)***		***(1.711)***					
DUM*Home FX_Var								
z-stat.								

Foreign FX ***z-stat.***	**USD: -0.159** ***(-2.413)***		**USD: -0.154** ***(-2.342)***					
Foreign FX_Var ***z-stat.***								
DUM*Foreign FX ***z-stat.***					**JPY: -0.270 / UK: -0.171** ***(-3.686) / (-1.775)***		**JPY: -0.265 / UK: -0.167** ***(-3.632) / (-1.734)***	
DUM*Foreign FX_Var ***z-stat.***								

Panel B: Small Size Banking Sector Portfolios.

Country	**Japan**				**US**			
Model Specification	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**	**Spec. 1**	**Spec. 3**	**Spec. 5**	**Spec. 7**
Home FX ***z-stat.***					**-0.044** ***(-2.333)***	**-0.039** ***(-2.452)***	**-0.044** ***(-2.304)***	**-0.039** ***(-2.464)***
Home FX_Var ***z-stat.***								
DUM*Home FX ***z-stat.***								
DUM*Home FX_Var ***z-stat.***								
Foreign FX ***z-stat.***								
Foreign FX_Var ***z-stat.***								
DUM*Foreign FX ***z-stat.***					**JPY: -0.195** ***(-3.973)***		**JPY: -0.194** ***(-3.980)***	
DUM*Foreign FX_Var ***z-stat.***								

Note: The estimated coefficient for *Home FX* / *FX_Var* effects indicate the fluctuation of currency value in country *i* have an significant impact on financial sector portfolio in the same country, while the *Foreign FX / FX_Var* effects indicate the fluctuation of currency *j* have an significant impact on financial sector portfolio from country *i*. For *Foreign FX* / *FX_Var* effects the name of currency *j* is specified before the estimated coefficient. The JPY, GBP and USD refer to Japanese Yen, British Pound, and US Dollar, respectively. For instance, for financial sector portfolio from *US*, the *JPY: -0.050* for the *Foreign FX* effect represents that for *1%* appreciation in *JPY* the return will cause *0.05%* decrease for financial sector portfolio from *US*. The shadings in the above table means the corresponding *FX* and/or *FX_Var* effects are not available for the model specification.

From Table 4.13, one can see that only the small size US banking portfolio expose to home currency value fluctuation over the entire sample period. The estimated coefficient of home *FX* for the US small banks is -0.044 based on model *Spec.1*. In contrast, the large banks in the US market are free from the home currency exposure. One potential explanation behind this size effect is the economics of scale for hedging activities. As showed in Mian (1996), large size firms are more likely to involve into hedging activities compares to the smaller ones because the economic incentive for hedging is higher.[273]

Opposite result has been found for Japanese banks over the crisis period. The estimated coefficient of home *DUM*FX* risk factor (0.130) for large Japanese banks is significant.[274] For small Japanese banks, however, no home *FX* risk factor is statistically significant. In order words, the changes in JPY value is positively related with the equity value of large banks in the Japanese market over the crisis period, but not the small one. The reason behind the positive relationship between the JPY value fluctuation and the return of large size Japanese banking portfolio may due to that large banks have large amount of foreign losses during the recent financial crisis.

Banks with large amount of write-offs should benefit more from the home currency appreciation than the one with less foreign losses, since the appreciation of home currency will reduce the value of foreign losses in home currency terms. Chamberlain et al (1997) suggest that large size financial institutions are more likely to involve in the international activities. Therefore, large banks are more likely to expose to foreign losses during the recent financial crisis than the small ones. As a result, the large banks should enjoy more benefits as the home value appreciates. The information provided by JBA supports our

[273] Nance et al (1993) suggest that it is not cost efficient to hedge a risk exposure with a market value less than 5 to 10 million in USD.

[274] The estimated coefficient 0.130 (from Table 4.12) is marginally insignificant (Z-stat.=1.640) at the 10% level (critical value 1.645). In order to prevent Type II error, we treat this parameter is significant at the 10% level in the current study.

arguments.[275] The large banks indeed entitled to more foreign related write-offs during the crisis period. The value of written-off loans for large Japanese banks is more than twice the amount for the rest of the Japanese banks in 2008 and 2009.[276]

The estimated coefficient of foreign (JPY) *DUM*FX* risk factor is -0.270 and -0.195 based on model *Spec.1* for the large and small size US banking portfolio, respectively. In order words, the changes in JPY value have a negative and significant impact on the equity value of the large and small size US banking portfolios over the crisis period. The changes in USD value also have a negative and significant impact on the Japanese banks, but only the large ones. The estimated coefficient of foreign (USD) *FX* risk factor for large size Japanese banking portfolio is -0.159 over the entire sample period. This finding is consistent with the empirical evidence based on the all size banking portfolios in Table 4.9. In order words, the empirical evidence supports our "shift of funding" hypothesis. Therefore, the financial assets in the Japanese market benefit from the depreciation of USD, while the US financial market suffers from the JPY value appreciation.

However, there is no significant foreign (USD) *FX* risk factor for small size Japanese banking portfolio, even during the crisis period. That means the small size Japanese banking portfolio does not benefit from the depreciation of USD, which seems not consistent with our "shift of funding" hypothesis. We argue that the reason behind this violation is mainly due to the low liquidity of the small firm. As mentioned in the previous section, investors prefer assets with low risk and high liquidity, which is known as "flight-to-quality/liquidity". Hameed et al (2010) suggest that the market liquidity

[275] The information of accounting data is collected from the aggregate annual banking sector financial statements (2006 – 2010) issued by the JBA. The financial statements are available from JBA's website, www.zenginkyo.org.jp.

[276] The JBA refers large size bank as "city bank". The number of city banks is only 5% of the total number of banks in the Japanese market (6 out of 120 in 2010), but occupies more than one-fifth of the market share in terms of funding-raising and loan-making. The value of written-off loans is JPY 470,445 million and JPY 1,002,194 million for city banks in 2008 and 2009, respectively. The value of written-off loans for the rest of the banks is JPY 188,882 million and JPY 407,169 million in 2008 and 2009, respectively.

tends to decline during market downturn, which makes the investors even more concern about the liquidity of the asset during the crisis period. Therefore, when investors reallocate their investments from the US market into the Japanese market during the crisis period, they would prefer the financial assets with higher liquidity over the lower ones. Previous empirical studies on liquidity premium suggest that small firms usually have lower liquidity compare to the large ones (Brennan and Subrahmanyam, 1996; Amihud, 2002). Therefore, small Japanese banks are less likely to benefit from the depreciation of USD compares to the big size banks, especially during the crisis period.

4.6. CONCLUSION

This empirical chapter uses the VAR-BEKK methodology to examine the relationship between the returns and currency exposure for a sample of U.S., U.K. and Japanese bank and insurance firms between January 2003 and March 2011. We find little evidence that the portfolio returns of banks and insurance firms are related to the conditional variance of home or foreign currencies.

Looking at the banking portfolios, we find that both home and foreign currency changes affect returns and the latter are more pervasive. We also find that the impact of foreign currency on banking portfolios generally change after the recent financial crisis. Typically, the home currency effects on bank returns are found to be more important in the U.S. than in the U.K. or Japan – this is put down to the activities of relatively small banks who have less incentive to hedge or are otherwise limited in their currency hedging activities.

Considering the results for insurance firms, we find that the portfolio returns of both U.K. and U.S. insurers are negatively related to changes in the JPY. However, the impact of the JPY on the U.K. insurers has changed from negative to positive during the crisis period. For the Japanese insurers, changes in the USD have also a negative impact on their equity return over the entire sample period. Furthermore, insurance portfolios are generally free from home currency exposure - apart from the U.K. insurers who have extensive operations in foreign markets.

Finally, when size is taken into account, we find that only small U.S. banks are exposed to home currency value fluctuation over the entire sample period. Furthermore, changes in the value of the USD (JPY) have a negative influence on large Japanese (U.S.) banks.

We argue the negative relationship between the currency value of JPY (USD) and equity value of institutions in the U.S./UK (Japan) market is due to the "shift of funding" phenomenon base on the "flight to quality" or "flight to liquidity" behaviour of investors. Investors shift their investments from sectors/countries with high uncertainty or low liquidity (i.e. the finaing sector in US/UK) into sectors/countries with high credit quality (i.e. the financial sector in Japan). Therefore, the "flight to quality" or "flight to liquidity" behaviour will push the currency value of JPY (USD) and the equity value of US/UK (Japan) financial sector portfolio in an opposite direction. Therefore, the "shift of funding" phenomenon will create an inverse relationship between the JPY and equity value of the US/UK financial sector portfolio. Our results further indicate that there is a competitive effects exist between Japan and the U.K./U.S. in the sense of attracting investor's funds, at least during our sample period.

As a final point, the latest developments in financial markets (although credit-related) have cast doubt on the risk management attitude of financial institutions. Governments and regulators across the world are currently working towards a safer financial system.

Future research should seek to investigate whether sector-specific features and/or regulatory frameworks of the markets under examination influence currency exposure relationships. Appropriate modelling/methodologies attenuating the nature of market data could be of vital importance. One should be very broad minded, however, when analysing both risk factors and regulatory/economic environments where financial institutions operate. Any framework developed should bear in mind the dynamic market condition embracing financial intermediaries' diverse activities and risk taking nature.

CHAPTER 5

ON THE DYNAMIC OF ASSET CORRELATIONS: WHAT MATTERS TO PORTFOLIO MANAGERS?

5.1. INTRODUCTION

Apart from banks and insurers, non-banking financial service firms (e.g. mutual funds, pension funds and hedge funds) also play an increasingly important role in the modern financial market. For instance, mutual funds are one of the fastest growing institution in the US since 1980 (Chen et al., 2004; Khorana et al., 2005), and now have become one of the primary investment vehicles for households with more than $21.4 trillion in assets under management worldwide (Cremers et al., 2011). Similarly, the hedge fund industry has also has experienced a recent surge in popularity, with the number of funds and assets under management increasing at a much faster rate than in the mutual fund industry (Bollen and Pool, 2006).[277] As a requirement for employers in most developed countries, pension fund is one of the biggest regulated financial service institutions in the world. The study conducted by Towers Watson shows that pension funds hold more than $27 trillion assets in the world's largest 13 developed countries/regions in 2011, which accounts for more than 72% of the GDP of these markets.[278]

The main functionality of these abovementioned non-banking financial institutions is to invest money for their clients. According to recent study, different choices of asset allocation strategy account for above 90% of the difference in return for pension funds

[277] The growth has generated a corresponding increase in aggregate managerial income. Incentive contracts are highly lucrative, usually including a guaranteed management fee between 1% and 2% of fund assets and a performance fee between 15% and 20% of fund profits.
[278] The report by Towers Watson is under the title "*Global Pension Assets Study 2012*". The largest 13 developed countries/regions are Australia, Brazil, Canada, France, Germany, Hong Kong, Ireland, Japan, Netherland, South Africa, Switzerland, UK and US.

(Bogle, 1994). In other words, how to construct a portfolio with optimal combination of assets is the key to the success of any fund managers. Besides, stability is also vital for fund management business from managers and regulators point of view. Therefore, reduce risk while maintain a desirable level of return becomes increasingly important for the asset management industry, which could be achieved with the help of modern portfolio theory through diversification.

Volatility and correlation among asset returns are central inputs of modern portfolio theory. Over the last few decades, there has been a voluminous literature on time series models for the estimation of asset return volatility and their application in financial economics is abundant. More recently, research focus has shifted to the estimation of the remainder of the covariance structure of asset returns, and many different multivariate models have been proposed for this purpose (Engle and Kroner, 1995; Engle, 2002; Engle and Sheppard, 2001). As time-variation, asymmetry and structural breaks are fast becoming stylized facts of returns' second moment (Cappiello et al, 2006), the evidence in favour of conditional correlation models for characterizing dynamics is quite compelling. Most extant studies on the evaluation of conditional correlation estimators largely focus on statistical metrics. Engle and Sheppard (2001) are the first to show that the dynamic conditional correlation (DCC) model outperforms the industry standard RiskMetrics exponential smoother on the basis of *iid* normal standardized residuals and more accurate portfolio standard deviations, while Engle and Colacito (2006) rank different multivariate conditional correlation minimum variance portfolios.

Continuous advances in correlation modelling could potentially facilitate profitable investment or better risk management. Several recent contributions have documented the economic value of conditional volatility forecasts for market timing (Fuertes et al, 2009;

Chong, 2005; Noh et al, 1994) or asset allocation (Fleming et al, 2001), but less attention has been paid to the value of explicitly modelling correlation dynamics. This is an important issue with direct implications for investors and portfolio managers entertaining the use of conditional correlation models, such as the popular DCC (Engle, 2002), for correlation timing. The well-documented statistical merits of multivariate volatility models are of little use if they do not translate into economic value. The typically low association between statistical accuracy and profitability (Satchell and Timmermann, 1995) renders the question of whether there are incentives for investors to opt for dynamic asset allocation based on conditional correlation models even more pertinent.

The contribution of this chapter to the literature is threefold. First, the benefits of correlation timing vis-à-vis static allocation are assessed and the impact of transaction costs on the strategy performance is scrutinized. Second, the role of asset-specific dynamics, correlation asymmetries and structural breaks in sector portfolio management is statistically and economically evaluated. Finally, we investigate the effect of rebalancing frequency on the performance of the correlation timing strategies.

The empirical analysis is based on daily prices from ten sector indices in three markets (Japan, UK, US) over July 1, 1996 to May 31, 2007. The evaluation framework is designed to appraise the differences arising from rival correlation forecasting approaches, and for this reason the sample is divided into an in-sample estimation period (July 1, 1996 to May 31, 2005) and a holdout evaluation period (June 1, 2005 to May 31, 2007). A dynamic mean-variance framework is deployed to construct portfolios based on different daily covariance matrix forecasts obtained using DCC models, which allow for time variation in both volatility and correlation. Variants of the DCC estimator are used to facilitate the modelling of asymmetries in the conditional correlations as well as structural breaks in the long-run mean and in the dynamics of correlations. We adopt as industry benchmark the RiskMetrics exponential smoother which is a simple and viable way of estimating large dimensional covariance matrices. The evaluation framework draws upon the seminal work of Fleming et al. (2001), where the relative economic value of dynamic strategies is gauged by their ability to generate incremental utility to investors relative to static allocation as well as statistically significant increases in the Sharpe Ratio. The feasibility of correlation timing is judged on the basis of breakeven transaction costs, which account for the economic value and the turnover rate of the strategies, and the issue of optimal rebalancing frequency is explored.

The findings suggest that timing correlation is fruitful to sector investors. Correlation timing strategies provide superior performance than the static constant covariance strategy and generally outperform the volatility-only timing strategy. Incorporating DCC-type models in asset allocation can enhance risk-adjusted returns and investor utility and even more so if correlation asymmetries and breaks are allowed for. The latter are found to be more beneficial than the nonparametric RiskMetrics approach whose incremental value dissipates in the presence of transaction costs. Different portfolio construction strategies perform differently across the three equity markets under examination. For instance, return oriented strategy performs better in the Japanese equity market compared to risk oriented strategy, and vice versa for the UK and UK markets. Furthermore, reducing the rebalancing frequency is proved to be beneficial.[279] For instance, monthly rebalancing investors adopting a non-overlapping approach are willing to pay performance fees in the range of 700-1100 bps per annual compared to 550-1010 bps

[279] For further interpretation on the return and risk oriented portfolio strategy, please refers to Section 5.4.2.

paid by investors with a daily rebalancing frequency.[280] Finally and most importantly, the incremental gains from conditional correlation models over and above static strategies are robust to reasonable levels of transaction costs and are more pronounced for monthly than daily rebalancing.

The empirical findings have three potential implications for managers in the fund management industry. First, fund managers should focus more on correlation timing instead of volatility timing in order to generate higher economic value for risk adverse clients. Second, fund managers invested in different markets should first investigate which portfolio construction strategy is best suited to the corresponding equity market in order to achieve the highest possible risk adjusted return. Third, managers should reduce the rebalancing frequency of their portfolios to cut trading costs. Besides, in order to achieve a nice balance between low turnover rate and high flexibility, a non-overlapping approach might be the optimal choice for fund managers.

The remainder of this chapter is organized as follows. Section 5.2 reviews the relevant literature. Section 5.3 describes the data, while section 5.4 illustrates the correlation forecasting models, the portfolio construction strategies and performance assessment criterions. Section 5.5 reports the empirical results and section 5.6 concludes.

5.2. BACKGROUND LITERATURE

5.2.1. Stylized Facts of Volatility and Correlation

A burgeoning literature in financial economics has focused on the volatility of asset returns and their comovement. As a result several features of volatility and covariance dynamics have by now become stylized facts. The prolific literature on the relationship

[280] For further interpretation on the non-overlapping approach for low rebalancing frequency (e.g. weekly/monthly rebalancing), please refers to Section 5.5.4.

between stock returns and their volatility has established that volatility is not only time varying but also asymmetric, which implies that negative shocks have a greater impact on future volatility than positive shocks of equal-size. Black (1976) was the first empirical study on the return-risk relation and found that the future conditional stock volatility is negatively linked with the current stock return. He attributed the phenomenon to the increased leverage surfacing when the market value of a firm declines, which is in turn reflected in an increase in the volatility of the firm's equity.[281] Christie (1982) empirically corroborates the "leverage hypothesis" by finding a positive relation between the firm's debt-to-equity ratio and volatility. On the other hand Campbell and Hentschel (1992), the proponents of the "volatility feedback" hypothesis behind volatility asymmetry, argue that negative unlike positive shocks increase volatility which has to be compensated for by a sufficiently high expected return, thereby causing more volatility. Many econometric specifications have been developed to capture asymmetric effects in volatility (EGARCH by Nelson, 1991; GJR by Glosten et al, 1993; APARCH by Ding et al, 1993).[282]

A second strand of this literature focuses on the dynamics of asset correlations. The consensus view is that correlation is time varying (Bollerslev et al, 1988) and correlations between international equity markets increased over time (Longin and Solnik, 1995). Erb et al (1994) link correlation dynamics to cyclicality and show that correlations are higher in recessions relative to expansions and low when business cycles are out of phase. Conditional correlation asymmetry is another regularity that has been found in the second moment of equity returns, although less attention has been paid in empirically capturing it.

[281] Black (1976) argues that even for pure equity firms the leverage (in the form of "operating leverage") of the firm will increase as the value of the company fall. The increased operating leverage is caused by the relatively constant cost the firm facing over the short-term.

[282] The "leverage" and "volatility feedback" interpretations of asymmetric volatility differ in regards to causalities: leverage hypothesis rests on the conjecture that return shocks lead to changes in conditional volatility; whereas the volatility feedback theory contends that return shocks are caused by changes in conditional volatility. Bekaert and Wu (2000) show that the two arguments are complementary and confirm that peaks in portfolio volatility typically correspond to large market declines.

Ang and Bekaert (2002) document the presence of a high volatility-high correlation regime in the US, UK and Germany, which tends to coincide with a bear market but does not negate the long-term benefits of international diversification. Longin and Solnik (2001) corroborate that correlations rise in bear markets, but not in bull markets. Cappiello et al (2006) exploit an asymmetric DCC model and find strong evidence of asymmetry in conditional correlations of international equity and bond returns. Although the economic rationale behind asymmetric effects is a relatively less researched terrain, a few studies have put forth some potential explanations. Bekaert and Wu (2000) attribute covariance asymmetry among financial assets to volatility feedback and postulate using a conditional CAPM – GARCH - M model that volatility increases dramatically upon a large price decline but does not react to price increase, therefore, negative shocks among financial assets generate higher conditional covariance than positive shocks. Bekaert et al (2005) rationalize sudden jumps in correlation between equity market indices during crises as a result of dependence on a common factor and not of volatility spillovers.

More recently, researchers have also documented structural breaks in correlations. Billio and Pelizzon (2003) find an increase in the levels of conditional correlation of European equity markets in the aftermath of the EMU introduction and note that the effect was not only regional but had a fundamental impact on global markets. Goetzmann et al (2005) suggest that the structure of global correlations shifted considerably over time, while Cappiello et al (2006) find significant correlation increase post-EMU not mirrored in conditional volatility. Hyde et al (2007) corroborate correlation asymmetry and an Asian crisis structural break in the Asian-Pacific, European and US equity returns, and also show that correlations rise over time suggesting greater market integration.

5.2.2. Performance of Volatility and Correlation Timing

The upshot of the extant literature is that although, under extreme conditions, investors cannot gain extra protection from global or domestic diversification, the long-term benefits are still attainable (De Santis and Gerard, 1997; Xia and Phylaktis, 2009). Since asset allocation is still an attractive investment route, the efficient construction of such a diversified portfolio comes to the forefront. One key input is the asset covariance matrix but the question emanating is whether it pays off to accurately capture all the stylized facts of covariance structure of asset returns. Balasubramanyan (2004) compares the performance of portfolios constructed on the basis of different covariance matrix estimators and finds value in incorporating time-varying correlation, asymmetric volatility and spillovers. Engle and Colacito (2006) investigate the variance minimization problem subject to a required return and find that the efficiency loss of the portfolio is minimized when the estimated correlation equals the true value. They further argue that assuming constant correlation during volatile correlation phases can be very costly and as much as 40% of return can be dismissed, if the wrong conditional correlation model were employed. In a simple stock and bond portfolio exercise, Engle and Colacito (2006) show that the asymmetric DCC was the best performer among the range of multivariate GARCH models examined.

An alternative way to assess the potential gain from accurately modelling the stylized facts of the conditional covariance of the asset returns is to compare dynamic and static strategies. Fleming et al (2001) deploy a utility criterion to examine the economic value of volatility timing for short-horizon investors and find that the predictability of conditional volatility models with rolling nonparametric correlations is economically significant and robust to transaction costs. In a similar vein, Della Corte et al (2009) document economic gains from the short-horizon predictive ability of economic fundamentals and forward premia on the volatility of monthly exchange rate returns. Della Corte et al (2010) find that accounting for correlation dynamics in exchange rate returns is fruitful for daily portfolio rebalancing even after transaction costs.

5.3. DATA

The empirical analysis is based on daily prices for sector indices from the Nikkei 225, FTSE-All and S&P500 obtained from Thomson DataStream International. The industry data pertain to ten broad sectors: Energy (ENG), Basic Material (BML), Industrial (IND), Consumer Goods (CGS), Health Care (HCR), Consumer Service (CSV), Telecommunication (TEL), Utility (UTL), Financial (FIN) and Technology (TEC). The sample spans the period from *July 1, 1996* to *May 31, 2007*, which results in a total of 2681, 2758, 2747 logarithmic local currency daily returns, respectively, for the Japanese, UK, US sector portfolios. The three-month Japanese interbank loan, the LIBOR, and the Treasury bill middle rates are employed as risk free assets for Japan, UK and US, respectively. The summary statistics in Table 5.1 suggest positive mean daily returns over the period for most sectors.

Table 5.1 Unconditional Daily Stock Return Distribution

	Sector Indices									
	ENG	BML	IND	CGS	HCR	CSV	TEL	UTL	FIN	TEC
Japan										
Mean	0.000	0.006	0.015	0.022	0.019	-0.011	0.006	0.011	-0.017	0.008
Maximum	11.926	8.488	5.622	7.189	7.775	6.567	10.343	5.699	11.267	8.861
Minimum	-11.220	-7.251	-7.459	-8.622	-5.386	-5.583	-11.602	-5.264	-8.317	-9.428
StDev	1.891	1.452	1.428	1.447	1.084	1.195	1.893	0.978	1.848	1.900
Skewness	0.09*	0.05	-0.11***	-0.14***	0.13***	0.09*	0.04	0.09*	0.29***	0.01
Kurtosis	5.11***	5.40***	4.29***	5.21***	5.13***	4.87***	5.93***	5.77***	5.72***	4.52***
JB test	503.11***	645.52***	191.95***	552.42***	514.04***	395.98***	958.36***	863.49***	866.14***	256.67***
ADF test	-51.95***	-47.64***	-37.68***	-38.89***	-56.99***	-51.81***	-37.73***	-52.53***	-36.26***	-44.68***
LB(5)	13.83**	27.38***	19.75***	22.33***	46.60***	22.36***	25.96***	18.36***	82.22***	63.86***
$LB^2(5)$	348.16***	334.68***	242.71***	364.85***	209.30***	247.56***	501.20***	373.33***	300.51***	469.62***
UK										
Mean	0.031	0.027	0.01	0.011	0.021	0.009	0.02	0.046	0.033	-0.058
Maximum	8.867	7.312	8.266	13.856	7.286	5.48	8.044	4.818	6.791	14.47
Minimum	-7.618	-6.213	-15.639	-10.878	-6.323	-7.755	-8.006	-5.707	-9.969	-23.194
StDev	1.484	1.289	1.503	1.887	1.22	1.117	1.788	0.994	1.406	2.747
Skewness	-0.02	-0.13***	-0.71***	0.09*	-0.12***	-0.09**	0.15**	-0.01	-0.06	-0.58***
Kurtosis	5.27***	5.49***	11.17***	7.30***	5.95***	6.18***	4.96***	5.19***	6.38***	10.34***
JB test	590.95	718.86	7906.18	2131.31	1007.83	1166.96	450.01	550.77	1316.93	6351.73
ADF test	-33.66***	-33.82***	-47.08***	-53.10***	-38.89***	-49.19***	-34.11***	-53.89***	-49.43***	-49.87***
LB(5)	31.11***	31.91***	36.66***	13.52**	21.23***	16.28***	29.18***	4.83	30.66***	10.49**
$LB^2(5)$	448.73***	579.30***	132.92***	427.96***	357.96***	657.65***	643.39***	386.66***	692.24***	126.62***
US										
Mean	0.048	0.029	0.035	0.011	0.029	0.029	0.015	0.021	0.043	0.032
Maximum	8.679	7.292	8.281	6.475	6.84	8.619	6.967	8.45	8.139	15.929
Minimum	-7.469	-9.958	-9.616	-12.382	-7.71	-10.628	-8.177	-9.023	-7.681	-10.103
StDev	1.441	1.394	1.302	1.292	1.07	1.28	1.35	1.128	1.378	2.054
Skewness	-0.03	0.08*	-0.14***	-0.25***	-0.16***	-0.18***	-0.12***	-0.40***	0.11***	0.22***
Kurtosis	4.69***	6.11***	7.16***	8.68***	8.05***	8.25***	5.83***	9.92***	6.22***	6.59***
JB test	327.77***	1107.81***	1991.10***	3722.58***	2936.51***	3173.80***	924.59***	5558.63***	1190.30***	1499.44***
ADF test	-39.46***	-51.38***	-51.77***	-53.98***	-33.91***	-38.06***	-53.15***	-49.88***	-50.93***	-52.46***
LB(5)	21.78***	11.31**	13.39**	14.11**	32.65***	25.99***	8.02	9.69*	6.35	10.10*
$LB^2(5)$	193.79***	327.58***	504.95***	295.23***	370.18***	284.22***	288.24***	1011.4***	643.51***	459.28***

Note: Returns and StDev are in percentage terms. JB denotes the Jarque-Bera test statistic for the null hypothesis of normality. ADF is the Augmented Dickey-Fuller test for the null of a unit root with 5% and 1% critical values -2.862 and -3.433, respectively. The trunaction lag is chosen based on a max lag of ½ √ T = 27, and a downward selection procedure based on the SIC so as no serial correlation is present. LB(p) and $LB^2(p)$ are the Ljung-Box Q-statistics for the null of no serial correlation up to a maximum lag of p days in the residuals and squared residuals, respectively. *, **, *** denote significance at the 10%, 5% and 1% level, respectively.

All daily returns are non-normally distributed, particularly in the form of leptokurtosis. The extent and direction of skewness differs across sectors and equity markets. Most of the sector returns in the UK and US markets are significantly negatively skewed, whereas in Japan sector returns are positively skewed.[283] The ADF test strongly rejects the hypothesis of a unit root for all returns series. The Ljung-Box Q test on daily and squared daily returns portrays serial dependence and volatility persistence in virtually all sector returns and supports the stylized fact that there is far more predictability in conditional volatility than in mean returns with strong volatility clustering in all sectors.

Table 5.2 reports the unconditional sector correlations over the sample period. Sector correlations are significantly positive in all markets. The mean unconditional sector correlation for Japan, UK and US is 54.9%, 44.3% and 52.5%, respectively.[284] Overall, CSV and IND exhibit the highest correlations with other sectors 61.6% and 58.3%, respectively, averaged across sectors and markets, while the UTL sector is the least correlated at 36.4%.[285]

[283] The lack of symmetry in the return distribution is consistent with previous findings (Bekaert and Wu, 2000; Glosten et al, 1993).

[284] The three mean correlations are significant with t-statistics at 38.8, 35.3 and 27.26, respectively. The t-statistic is computed as $\rho\sqrt{(t-2)/(1-\rho^2)}$ and follows a Student-t distribution with *(t-2)* degrees of freedom. The critical value at the *95%* significance level is 0.01253.

[285] The mean correlation across sectors within a market and the average correlation of one sector against other sectors are not reported in Table 2 to save space. All the aforementioned information is available from the author upon request.

Table 5.2 Unconditional Daily Return Correlations

	Sector Indices									
	ENG	BML	IND	CGS	HCR	CSV	TEL	UTL	FIN	TEC
Japan										
ENG	1									
BML	0.61	1								
IND	0.44	0.78	1							
CGS	0.38	0.65	0.80	1						
HCR	0.46	0.66	0.59	0.58	1					
CSV	0.54	0.82	0.79	0.72	0.71	1				
TEL	0.29	0.51	0.65	0.57	0.44	0.61	1			
UTL	0.35	0.42	0.30	0.31	0.48	0.46	0.22	1		
FIN	0.50	0.77	0.70	0.61	0.56	0.76	0.54	0.32	1	
TEC	0.27	0.58	0.83	0.68	0.42	0.64	0.67	0.14	0.58	1
UK										
ENG	1									
BML	0.48	1								
IND	0.41	0.59	1							
CGS	0.33	0.45	0.49	1						
HCR	0.43	0.39	0.37	0.35	1					
CSV	0.44	0.60	0.58	0.48	0.49	1				
TEL	0.35	0.39	0.41	0.30	0.39	0.64	1			
UTL	0.38	0.37	0.33	0.28	0.46	0.47	0.35	1		
FIN	0.52	0.57	0.56	0.48	0.60	0.72	0.57	0.49	1	
TEC	0.26	0.39	0.41	0.30	0.24	0.60	0.51	0.22	0.47	1
US										
ENG	1									
BML	0.47	1								
IND	0.41	0.72	1							
CGS	0.35	0.69	0.72	1						
HCR	0.40	0.52	0.63	0.53	1					
CSV	0.35	0.65	0.79	0.73	0.59	1				
TEL	0.32	0.47	0.59	0.52	0.51	0.63	1			
UTL	0.45	0.39	0.42	0.37	0.42	0.37	0.37	1		
FIN	0.37	0.64	0.77	0.69	0.63	0.76	0.60	0.45	1	
TEC	0.23	0.43	0.65	0.55	0.39	0.68	0.55	0.24	0.58	1

An economic evaluation framework is designed to gauge the value of correlation timing and appraise the economic differences materializing from rival correlation forecasting approaches. To this end, the sample is divided into an in-sample estimation period *July 1, 1996* to *May 31, 2005* (T= 2274, 2266, 2209 days, respectively, for the UK, US and JPN sector portfolios) and a holdout evaluation period *June 1, 2005* to *May 31, 2007* (T*= 484, 481, 472 days, respectively, for the UK, US and Japanese sector portfolios) over which we generate one-step-ahead rolling covariance forecasts on the basis of the fixed length-T window.

5.4. METHODOLOGY

The ensuing analysis builds upon the recursive construction of optimal mean-variance sector portfolios in the Japanese, UK and US equity markets and their performance evaluation on the basis of utility metrics and risk-adjusted returns. First, daily sector correlation and volatility forecasts, the main inputs alongside expected returns for dynamic asset allocation, are generated. The covariance forecasting approaches deployed range from the simplest constant covariance model (static strategy) and the constant correlation (volatility timing strategy) to dynamic specifications where various stylized facts of correlations such as time variation, asymmetry, and structural breaks are accounted for (correlation timing strategy).

5.4.1. The Conditional Covariance Structure

Let r_t denote the day t logarithmic close-to-close return vector on n risky assets and ξ_{t-1} be the information set available at the end of day t-1. The [n x 1] conditional expected return vector of r_t is defined as $\mu_t \equiv \mu_{t|t-1} = E[r_t \mid \xi_{t-1}]$ and $H_t \equiv H_{t|t-1} = E[(r_t - \mu_t)(r_t - \mu_t)' \mid \xi_{t-1}]$ is the symmetric [n x n] asset conditional covariance matrix. At the open of day t, the investor formulates a target return/volatility quadratic optimization problem and different forecasts for the covariance matrix H_t are considered as inputs.

The most basic estimator for H_t is the unconditional covariance matrix $H_t = r_t r_t'$, which is kept constant throughout the out-of-sample period. We make the covariance matrix dynamic by adopting in a multivariate setting the RiskMetrics estimator widely used in the industry.[286] The RiskMetrics EWMA conditional covariance estimator is as follows

$$H_t = \lambda r_{t-1} r_{t-1}' + (1-\lambda) H_{t-1} \tag{1}$$

where the decay factor ($0 < \lambda < 1$) is λ=0.94 for daily data and the sample covariance matrix can be taken as H_0. The RiskMetrics model is computationally very simple given its nonparametric nature, however, its disadvantage is that it imposes identical dynamics to all assets represented by the constant decay factor λ = 0.94.

Allowing for more flexibility while at the same time preserving parsimony we consider the conditional correlation models and extend their basic versions to account for correlation asymmetries and structural breaks in the data. Correlation models rely on decomposing the conditional covariance into conditional standard deviations and correlations. The simplest is the Constant Conditional Correlation (CCC) GARCH model introduced by Bollerslev (1990) which imposes time invariant correlation and covariance that changes over time proportionally as dictated by the time-varying volatilities. The CCC model is estimated in two steps. First, a univariate GARCH (p,q) model is fitted to each return series to generate the conditional variance h_{it}, $i = 1,\ldots, n$. Then, the covariance is specified as

$$H_t = D_t R D_t \tag{2}$$

[286] RiskMetrics was originally proposed by JP Morgan as part of their market VaR methodology. It has by now become a standard model for portfolio risk assessment.

where $D_t = diag\left(\sqrt{h_{1t}},...,\sqrt{h_{nt}}\right)$ and R is a positive definite [n x n] correlation matrix typically estimated by the unconditional correlation matrix.

The constant correlation assumption has been found to be too restrictive in several empirical studies (Korner and Ng, 1998; Ang and Bekaert, 2002; Tse and Tsui, 2002), and so the covariance decomposition in (2) has been extended to allow for dynamics in the correlation matrix. Among the many specifications proposed for the evolution of R_t the Generalized Dynamic Conditional Correlation (G-DCC) GARCH model of Engle (2002) is the most popular. The G-DCC estimator has the same first step as the CCC approach, but for each series the standardized errors, $\varepsilon_{it} = u_{it}/\sqrt{h_{it}}$ where u_{it} are the whitened returns, are also generated alongside the conditional variance. In the second step, the time-varying correlation matrix is formalized via the following process

$$R_t = (Q_t^*)^{-1}\, Q_t\, (Q_t^*)^{-1} \tag{3}$$

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B) + A'\varepsilon_{t-1}\,\varepsilon'_{t-1}A + B'Q_{t-1}B$$

where $\bar{Q} = E[\varepsilon_t\varepsilon_t']$ is the unconditional covariance matrix of standardized innovations, A and B are [n x n] diagonal parameter matrices, $Q_t^* = \text{diag}(\sqrt{q_{i,t}},\ldots, \sqrt{q_{n,t}})$ and ensures that R_t has the structure of a correlation matrix as long as the conditional covariance matrix Q_t is positive definite.[287] The diagonal formulation in (3) poses asset-specific correlation dynamics but permits no transmission of shocks between assets. The DCC is obtained as a special case of the G-DCC where the parameter matrices are replaced by scalars, A= [a] and B= [b], and implies identical correlation dynamics for all assets.[288]

The Asymmetric Generalized DCC (AG-DCC) of Sheppard (2002), extends (3) by allowing for asymmetries in the conditional covariance as follows

$$Q_t = C + A'\varepsilon_{t-1}\,\varepsilon'_{t-1}A + B'Q_{t-1}B + G'\eta_{t-1}\,\eta'_{t-1}G \tag{4}$$

[287] Q_t will be positive definite with probability one if $(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B)$ is positive definite.
[288] Appendix D.1 sets out the details of the DCC in the two-asset case.

where $\eta_t = I[\varepsilon_t<0] \otimes \varepsilon_t$ and $\otimes$ indicates the element-by-element Hadamard product, G is [n x n] diagonal parameter matrix, $C = \overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G$ and $\overline{N} = E[\eta_t \eta'_t]$ where expectation is replaced by its sample analogue. Model (4) allows joint negative shocks to have a stronger impact on the future variances and correlations than positive shocks of the same magnitude. When G= **0** (no asymmetry) the model collapses to the G-DCC. The Asymmetric DCC (A-DCC) is the restricted scalar version of (4), where A= [a], B= [b], C= [c] and G= [g].[289]

We consider also an extension of (4) which accommodates the presence of structural breaks both in the long-run mean and in the dynamics of correlations (AG-DCC-break) as in Cappiello et al (2006). The AG-DCC-break model accounts for two regimes as follows

$$Q_t = d\, Q_t^1 + (1-d)\, Q_t^2$$

$$Q_t^j = C_j + A_j'\varepsilon_{t-1}\, \varepsilon'_{t-1}A_j + B_j'Q_{t-1}B_j + G_j'\eta_{t-1}\, \eta'_{t-1}G_j \qquad j = 1, 2 \qquad (5)$$

where d is a break indicator defined as d = 1 for $t < \tau$, and 0 else. When $G_1 = G_2 =$ **0** the model collapses to G-DCC-break, while the corresponding scalar model is the A-DCC-break.

The News Impact Surface (NIS) for MGARCH, the analogue to a news impact curve for univariate GARCH models, portrays how the conditional correlation of two assets reacts to their joint past shocks (Kroner and Ng, 1998). The NIS correlation function $f(\varepsilon_1,\varepsilon_2)$ for the ADCC model is given by[290]

$$f(\varepsilon_i, \varepsilon_j) = c_{ij} + (a_i a_j \varepsilon_i \varepsilon_j + g_i g_j \eta_i \eta_j) \qquad (6)$$

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[289] Appendix D.2 gives details of the A-DCC in the two asset case.
[290] This is a simplified form of the NIS function under the assumption of linearity. Appendix D.7 gives the exact form.

where c_{ij} is the ij^{th} element of the constant matrix in (4). In the presence of asymmetry g is significant and it is expected that joint bad news ($\varepsilon_i < 0$, $\varepsilon_j < 0$) has a greater impact on future correlation than joint good news or a combination of good and bad news, *ceteris paribus*.

Model estimation is by quasi maximum likelihood (QML).[291] Inferences are based on Bollerslev-Wooldridge non-normality robust standard errors (Bollerslev and Wooldridge, 1992). Individual significance and joint hypothesis tests are based on *t*-statistics.

5.4.2. *Dynamic Asset Allocation using Correlation Timing Strategies*

A dynamic mean-variance framework is deployed to construct portfolios based on the daily covariance matrix forecasts from the different models. We consider an investor with a short or medium term investment horizon who allocates funds across n risky assets plus a riskless security according to two different objectives. The investor solves the following constrained optimization problems at time t,

A. Maximize the conditional expected portfolio return subject to a target conditional volatility σ_p* (Max-R, hereafter).

$$\begin{cases} \max \quad \mu_p = w'_t\mu_t + (1 - w'_t\mathbf{I})r_f \\ \quad \text{s.t.} \quad \sigma_p^* = \sqrt{w'_tH_tw_t} \end{cases} \tag{7}$$

B. Minimize the conditional portfolio variance subject to a target conditional expected return μ_p* (Min-V, hereafter).

$$\begin{cases} \min \quad w'_tH_tw_t \\ \text{s.t.} \quad \mu_p^* = w'_t\mu_t + (1 - w'_t\mathbf{I})r_f \end{cases} \tag{8}$$

[291] Detail information about the QML is provided in Appendix D.3.

where w_t is an [n x 1] vector of portfolio weights on the risky assets, r_f is the return on the risk free asset, $\mathbf{I}$ is an [n x 1] vector of *1s*. In order to guarantee a feasible solution, no short selling constraints are imposed. The optimal risky asset weight vectors are as follows

$$w_t = \frac{\sigma_p^* H_t^{-1}(\mu_t - r_f\mathbf{I})}{\sqrt{(\mu_t - r_f\mathbf{I})' H_t^{-1}(\mu_t - r_f\mathbf{I})}}, \text{ for the Max- R strategy,}$$

$$w_t = \frac{(\mu_p^* - r_f\mathbf{I}) H_t^{-1}(\mu_t - r_f\mathbf{I})}{(\mu_t - r_f\mathbf{I})' H_t^{-1}(\mu_t - r_f\mathbf{I})}, \text{ for the Min-V strategy,}$$

and the weight on the risk free asset is ($1 - w_t'\mathbf{I}$).

When the conditional expected return μ_t and/or covariance H_t are perceived to be time-varying, the investors will rebalance their portfolio weights accordingly following the dynamic strategies outlined above. In order to purely focus on the quality of the covariance forecast the expected return is treated as constant and equal to the ex-post unconditional mean return ($r = \Sigma r_t/n$).[292] The target return and variance levels (μ_p^* , σ_p^*) are proxied by the out-of-sample mean values for an equally weighted portfolio. The portfolios are rebalanced daily, weekly or monthly using the alternative covariance forecasts to produce a sequence of optimal mean-variance portfolios spanning the out-of-sample period. The benchmark static strategy is that adopted by an investor who believes that the conditional expected return and covariance are constant, and thus the optimal portfolio weights will be constant over time. The static optimal weights are based on the in-sample unconditional covariance matrix and are rebalanced every period back to their initial (first iteration) values.

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[292] Our purpose is to isolate the effect on asset allocation of different correlation forecasting approaches, and so attempting to model return dynamics goes beyond the scope of this study. The r refers to the ex-post mean return vector of the sector indices over the out-of-sample period; r_t refers to the daily return vector for sector indices over day t; and n refers to number of days over the out-of-sample period.

5.4.3. *Evaluation Framework and Transaction Costs*

The adequacy of the correlation timing strategies based on alternative covariance forecasts is judged on the basis of the incremental utility vis-a-vis the benchmark static strategy. We follow the utility-based evaluation framework of Fleming et al (2001) drawing upon the presumption that at a given point in time, one estimate of conditional covariance is better than another if it leads to higher average utility.

The quadratic utility function introduced by West et al (1993) as a second-order approximation to the investor's true utility in period *t+1* is

$$\bar{U}(W_{t+1}) = W_t R_{p,t+1} - \frac{\alpha W_t^2}{2} R_{p,t+1}^2 \tag{9}$$

$$R_{p,t+1} = (1 - w'_t \mathrm{I}) r_f + w'_t r_{t+1}$$

where W_{t+1} is the wealth in period *t+1*, a is the absolute risk aversion and $R_{p,t+1}$ is the portfolio return at *t+1*. The expected end-of-period utility for a given level of initial wealth W_0 is estimated as

$$\bar{U}(W_{t+1}) = W_0 \cdot \left(R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R_{p,t+1}^2 \right) \tag{10}$$

We follow Fleming et al (2001) and assume a constant relative risk aversion $\gamma_t = \alpha W_t / (1 - \alpha W_t)$ equal to γ= 1, 10 to represent reasonably low and high risk-aversions. Han (2006) focus only on a moderate risk aversion level implied by γ= 6. The incremental value of correlation timing vis-a-vis the static allocation is assessed by the return that would render an investor indifferent between the two strategies as follows

$$\sum_{t=0}^{T^*-1} \left[(R_{d,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{d,t+1} - \Delta)^2 \right] = \sum_{t=0}^{T^*-1} \left[R_{s,t+1} - \frac{\gamma}{2(1+\gamma)} R_{s,t+1}^2 \right] \tag{11}$$

where $R_{d,t+1}$ and $R_{s,t+1}$ denote the returns for the dynamic and static strategies, respectively. The equality in (11) implies that the investor would incur a daily expense Δ for the dynamic strategy, and so we interpret Δ as the maximum performance fee (*PF*) in annualized basis points the investor would be willing to pay to switch from the static to the dynamic strategy.

Transaction costs play an important role when assessing the profitability of active trading strategies. Accurate estimation of the size of transaction costs is challenging since it requires information on the type of investor, the value of transaction, and the nature of the broker (Della Corte et al, 2009). In order to sidestep these issues we compute break-even transaction costs (*BTC*) per trade as proposed by Han (2006). The *BTC* is a fixed proportion (τ) of the value traded in each transaction, which makes an investor with the quadratic utility function in (9) indifferent between the two strategies (*i.e.* dynamic and static) considered. Thus, the total cost of a transaction in period *t* can be represented as follows

$$\tau \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-1} \frac{1+r_{i,t}}{1+R_{p,t}} \right| \tag{12}$$

where $w_{i,t-1} \frac{1+r_{i,t}}{1+R_{p,t}}$ is the weight of asset *i* in the portfolio just before rebalancing in period *t*. In comparing a dynamic strategy with a static one, an investor who pays transaction costs lower than the *BTC* would prefer the dynamic strategy and in selecting between two equally performing dynamic strategies the one with higher *BTC* is preferable. *BTC* is proportional to the value of each trade, and so we report it at the relevant trading frequency. Finally, we compute the average daily turnover rate (*TO*), defined as the proportion of the portfolio value rebalanced each day $TO = {}^{1}/_{T^*} \sum_{t=1}^{T^*} \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-1} \frac{1+r_{i,t}}{1+R_{p,t}} \right|$, reported monthly.

The turnover rate directly affects the post-transaction cost strategy performance to the extent that realistic levels of transaction costs can negate the advantages of incorporating daily correlation fluctuations in the determination of the optimal asset allocation weights. We account for transaction costs by taking a generic approach that avoids assuming investor-specific levels of transaction costs. For each strategy we compute break-even transaction costs per trade (*BTC*, reported in Table 5.5 and 5.6 in daily bp) as the minimum cost that renders the investor indifferent between the dynamic strategy at hand and the static strategy, *i.e.* the transaction cost beyond which the benefits of the dynamic strategy over the static strategy disappear. As the daily correlation timing strategies trigger rather extensive rebalancing, *BTCs* would be an indication of the viability of the strategies.

Sector index trading can be effectively replicated with Exchange Traded Funds (ETFs) at a relatively low cost.[293] The total cost of investing in ETFs comprises the total expense ratio (TER), bid-ask spread, commission, and cost of market impact. TER refers to the annual management fee charged for operating expenses and is comparatively lower for ETFs than mutual funds or other actively traded equity funds. The average level of TER for a US investor trading sector SPDR ETFs listed on the NYSE is 20 bp.[294] Sector ETFs traded on the Tokyo Stock Exchange incur a TER of 22-28 bp.[295] Despite the fact that no UK sector ETFs have been launched as yet, the TER associated with the SPDR MSCI Europe Sector ETFs, 30 bp, can be used as a reasonable proxy for UK sector index-linked trading. For a daily trader the TER seems negligible (Jares and Lavin, 2004), however, for monthly traders TER can play a role in the total trading cost. Assuming investors will pay

[293] Since the first ETF introduced by State Street Global Advisor which tracks the performance of S&P 500 (SPDR S&P 500 listed on NYSE) in 1993, the number of actively traded ETFs has ballooned due to their popularity among investors. In 2008, the number of actively traded ETFs has reached 797 in the US and 350 in Europe. The cost of investing in ETFs has been brought down significantly in recent years as the turnover volume soared.

[294] SPDR is the division of State Street Global Advisor responsible for running and managing ETF products. Their Select Sector SPDR Index Funds split the S&P 500 into nine sectors traded individually on the NYSE.

[295] Daiwa Asset Management provides 19 different sector ETFs for TOPIX constituent companies (see, for instance, Daiwa ETF-TOPIX Energy Resources, Daiwa ETF-TOPIX Banks).

a fraction of the TER proportional to the length of the holding period a sector ETF trader who adjusts her position monthly should bear a TER around 2 bp per trade.

For frequent traders of ETFs the trading cost depends primarily on the bid-ask spread. Previous studies on ETFs tend to use the close bid-ask price on a trading day to calculate the bid-ask spread (Engle and Sarkar, 2002; Jares and Lavin, 2004). However, bid-ask spreads tend to be wider at the end of the trading day compared to the ones during the trading hours since traders face a higher risk that their order might not be executed (Foucault, 1999; McInish and Wood, 1992). The higher bid-ask spread of the last trade(s) can also be attributed to the introduction of the closing auction on most of the exchanges.[296] This implies that using the end-of-day bid-ask spread would inflate the actual trading cost. To circumvent this problem we use intraday price quotations and compute the bid-ask spread on day t as $\text{Bid-Ask}_t = \min(\Delta P_{jt}) / \text{Low } P_t$ for $j = 1,\ldots M$ intraday intervals, where ΔP_{jt} is the smallest intraday bid and ask spread that can be observed.[297] Using intraday data on Japanese, US and European sector ETFs we corroborate that bid-ask spreads during the trading hours are considerably smaller than at the last trade. The average Bid-Ask_t over the last 200 trading days based on the lowest price level is 3 bp for SPDR US Industrial Sector ETF and ranges from 1.8 to 4.5 bp for other US sectors, with the exception of the Financial Sector which is at 7 bp. For Daiwa

[296] Admati and Pfleiderer (1988) argue that the bid-ask spread or terms of trade is determined by the number of informed traders in the market. If the number of informed traders increases, the terms of trade will worsen especially when the opinions of these informed traders are diversified. The closing auction will attract more informed traders into the price discovery process as they possess more information about the underlying asset and could form a better strategy in the auction. Therefore, the terms of trade will worsen.

[297] The bid and ask spread is derived as the difference between the bid and ask price. In order to translate the spread into percentage measures in a conservative manner, we further divide the spread over the bid price (as the bid price is relatively lower, therefore, the Bid-Ask will be relatively higher compared to the one use ask price as denominator). When using intraday price information, once again, we measure the Bid-Ask spread in a conservative manner by using the lowest observed price as denominator.

JPN ETF-TOPIX Construction & Material the average bid-ask spread is 28.5 bp, whereas for the SPDR MSCI Europe Sector ETF it is typically at 48 bp.[298]

Similar to trading other securities, investors who buy ETFs need to pay commissions to their brokers. However, since the commission fee is charged on the number of trades, the percentage cost of commission can be very small when the volume of transactions per trade is very high. Dellva (2001) shows that the commission for SPDR ETFs is only $20 per trade, which means the cost of commission is only 2 bp if one invests $100,000 at once. For institutional or large individual investors the percentage cost of commission can be even lower. Furthermore, in order to reduce the trading cost and attract more investors, some of the ETF providers have introduced commission-free ETFs in recent years.[299]

Finally, transaction costs are affected by the cost of market impact, that is, the influence of an investor's decision on the market price of the underlying asset. The cost of market impact tends to be lower for highly liquid assets, which implies the behaviour of one trader does not have a big influence on the price. Given that the trading volume of popular ETFs exceeds tens of millions per day, the market impact of a single institutional or individual investor is almost negligible.[300] Jares and Lavin (2004) do not take the cost of market impact into account when considering the trading cost of ETFs, however, practitioners still count it as one of the trading cost components.[301] We take a conservative approach and use a cost of market impact of 2 bp as suggested for large cap index ETFs.

In general, the total trading cost of ETFs for a daily trader can be represented as the sum of bid-ask spread and the cost of market impact as both the commission and TER are

[298] The average close bid-ask spread is found to be 45 bp for the SPDR US Industrial Sector ETF and 54 bp for the DAIWA JPN ETF-TOPIX Construction & Material.

[299] For instance, Fidelity and Vanguard Asset Management have recently waived the commission for some of their widely traded ETFs, see: www.fidelity.com and www.vanguard.com.

[300] For instance, the average daily trading volume of SPDR US Industrial ETF and SPDR US Financial ETF is 30.15 and 120.5 million over the last three months of 2011, respectively.

[301] See Frontier Investment Management report at: http://www.frontierim.com/uploads/frontierinvestmentmanagement -whenisaternotater.pdf.

negligible. In the context of sector-linked ETFs this amounts to approximately 7 bp per day for US investors, 30 bp per day for Japanese investors and 50 bp per day for European sector investors. For monthly traders we follow the industry practice and assume an additional TER proportional to the holding period that is equal to of 2 bp. The total trading cost in each case will be used as a benchmark to assess the practical feasibility of the correlation timing strategies. If the *BTC* of the dynamic strategy exceeds the realistic benchmark level, the strategy can generate economic value not wiped out by transaction costs. In our asset allocation framework, all inputs but the covariance matrix are constant across strategies, and so differences in *BTC* would reflect the variability in the forecasted covariance.

5.4.4. Significance of Sharpe Ratio Differentials

We statistically evaluate the risk-adjusted performance of correlation timing by assessing the significance of the observed differences between the Sharpe Ratios (SR) of the dynamic allocation strategy and the static benchmark denoted by d and s, respectively. In order to test the null hypothesis H_0: $(SR_d - SR_s) = 0$ we follow the framework developed by Christie (2005) and Opdyke (2007) for deriving the asymptotic variance of the SR differential $Var(\widehat{SR}_{diff}) = \widehat{SR}_d - \widehat{SR}_s$ under very general conditions as follows

$$Var(\widehat{SR}_{diff}) = 1 + \frac{SR_d^2}{4}\left[\frac{\mu_{4d}}{\sigma_d^4} - 1\right] - SR_d\frac{\mu_{3d}}{\sigma_d^3} + 1 + \frac{SR_s^2}{4}\left[\frac{\mu_{4s}}{\sigma_s^4} - 1\right] - SR_s\frac{\mu_{3s}}{\sigma_s^3}$$

$$-2\left[\rho_{ds} + \frac{SR_d SR_s}{4}\left(\frac{\mu_{2d,2s}}{\sigma_d^2\sigma_s^2} - 1\right) - \frac{1}{2}SR_d\frac{\mu_{1s,2d}}{\sigma_s\sigma_d^2} - \frac{1}{2}SR_s\frac{\mu_{1d,2s}}{\sigma_d\sigma_s^2}\right] \tag{13}$$

where $\mu_{nd,ms}$=E[$(r_d$-E$(r_d)^n(r_s$-E$(r_s))^m$] is the joint central (n,m) moment of the joint distribution of the two portfolio returns r_d and r_s. Unlike Lo (2002) where *iid* returns are required, the asymptotic distribution in (13) requires only stationarity and ergodicity of returns and is therefore valid under the more realistic conditions of time-varying volatilities, serial correlation and otherwise non-*iid* returns. A minimum variance unbiased estimator for this joint moment is provided by the *h*-statistic of Rose and Smith (2002). Since the SR statistic is asymptotically unbiased and normally distributed via the Central Limit Theorem

$$\sqrt{T}\left(\widehat{SR}_{diff}\right) \overset{a}{\sim} N\left(0, Var\left(\widehat{SR}_{diff}\right)\right) \tag{14}$$

Thus, the test statistic for SR equality of the competing strategies is $z = \frac{\sqrt{T}(\widehat{SR}_d - \widehat{SR}_s)}{\sqrt{Var(\widehat{SR}_{diff})}}$.

5.5. Empirical Result

5.5.1. The Dynamics of Asset Correlations

We start by examining the estimation results of the different multivariate correlation estimators. The correlation matrices are estimated over the entire sample period (*July 1, 1996* to *May 31, 2007*) for the three domestic sector portfolios (Japan, UK and US sectors). The first-step in the estimation of conditional correlation models is to specify the univariate conditional variance. Thus, for each daily return series we fit a GARCH (1,1) and an EGARCH (1,1,1) to account for potential asymmetry in the impact of news on conditional volatility. The Akaike (AIC) and Schwarz (SIC) information criteria are deployed to select the most appropriate model. We find no evidence of volatility asymmetry and the GARCH specification is favored for all sector index returns.[302]

Given the conditional volatilities, the conditional correlations are estimated using equations (2) to (5) for each of the three portfolios. Following the pertinent literature (Baele, 2005; Billio and Pelizzon, 2003 *inter alios*), we introduce a structural break at the

[302] Appendix D.4 reports the estimated parameters of the GARCH and EGARCH models alongside the log-likelihood values and the AIC and SIC.

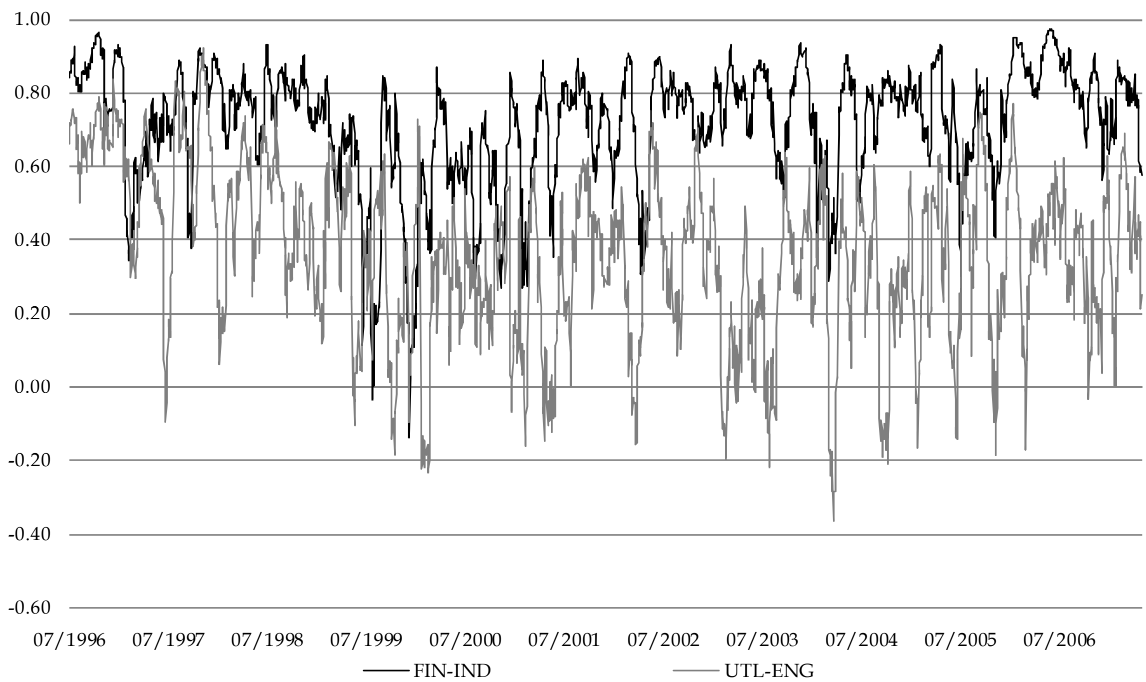
onset of the European Monetary Union (EMU) on *January 1, 1999*, when all the EMU members irrevocably fix their exchange rate and the Euro is introduced to replace the national currency. The radical transform of the European money market influenced the interdependence of the EMU member economies and that of the closely integrated UK, US and Japanese markets.[303]

Figure 5.1 shows the rolling daily unconditional correlations between financial-industrial and energy-utility sectors over the sample period.

Figure 5.1 Unconditional Daily Correlation Dynamics

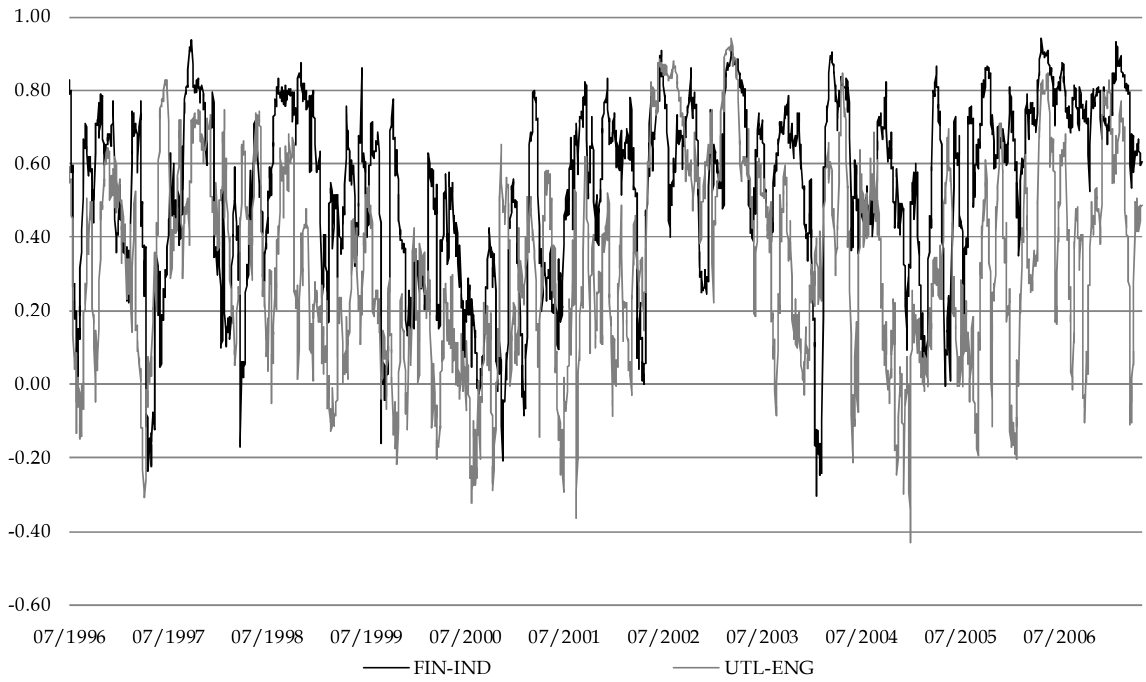
Time series graphs of daily correlation among selected sector indices and the three national market indices. The correlations are estimated using a rolling window of one month. "ENG", "IND", "CGS", "CSV", "UTL", "FIN", and "TEC" refer to the Engineering, Industrial, Consumer Goods, Consumer Service, Utility, Financial and Technology sector, respectively.

Panel A: Unconditional correlation between Japanese FIN-IND and UTL-ENG.

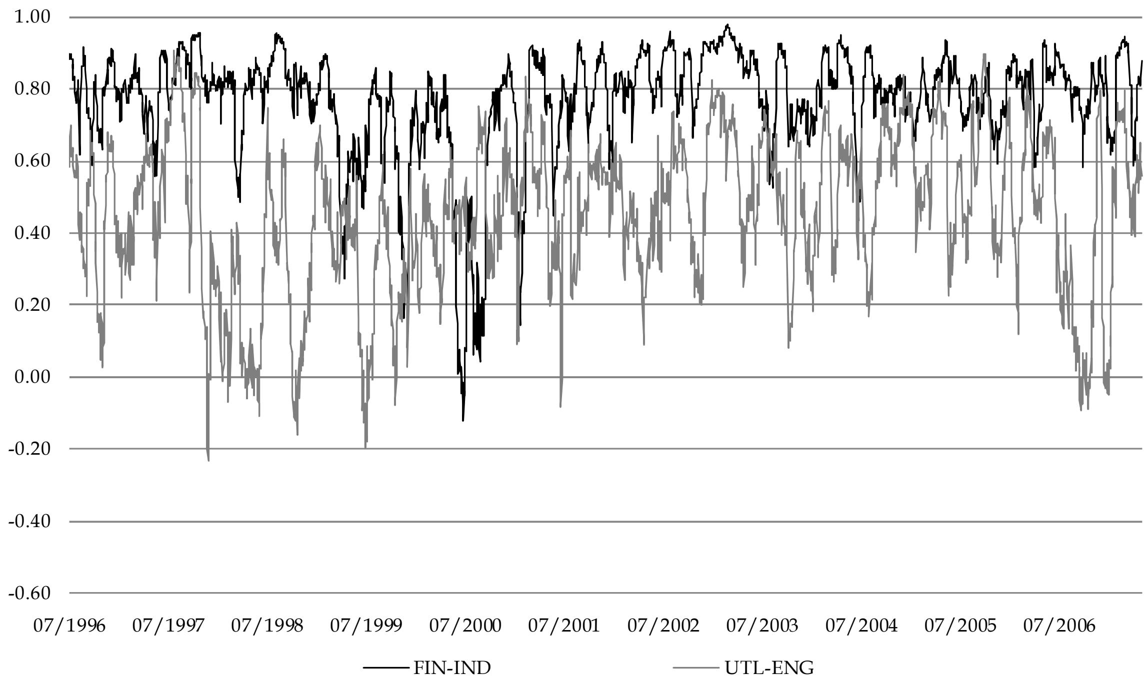


[303] The transformation of the European money market also affected the US dollar cash flows, through its impact on Euro-dollar interest rates. The change in the term structure influenced the value of the US dollar and consequently impacted the US economy. The fundamental changes in the European and US money markets affected the domestic equity markets, and further transmitted to the Japanese market due to the strong degree of globalization (Hamao, Masulis and Ng, 1990; Koutmos and Booth, 1995). Nonetheless, the time taken for the effects of the money market transformation in Europe to transmit to the US and then further influence Japan is less clear.

Panel B: Unconditional correlation between the UK FIN-IND and UTL-ENG.



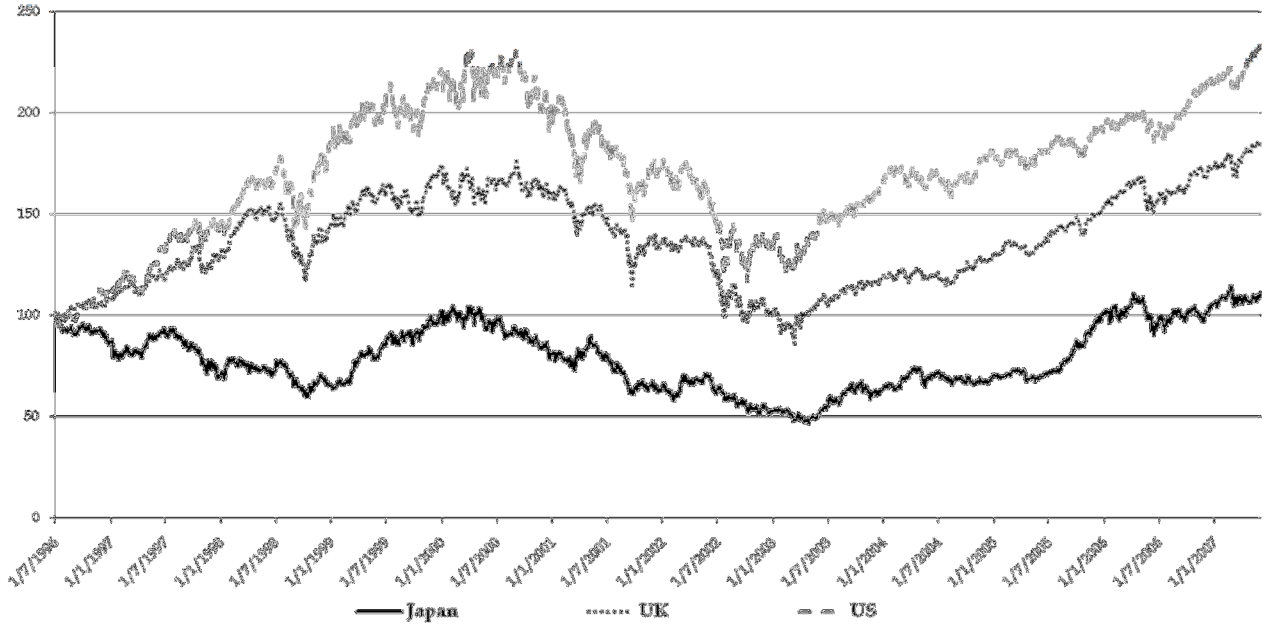
Panel C: Unconditional correlation between the US FIN-IND and UTL-ENG.



The graphs confirm the extensive time variation in sector correlations and provide support for a regime change after 1999. Correlations tend to bottom out in 1999 and gradually recover over the next few years. Figure 5.2 illustrates the daily price dynamics of the three national market indices rescaled to 100 at the beginning of the sample period.

Figure 5.2 Daily Price Dynamics of the National Market Indices

The graph shows the evolution of the Nikkei, FTSE-All and S&P 500 over the sample period, rescaled to 100 at the beginning of the period.



The figure shows that the very low correlations observed in 1999 coincide with the upward trend in the three national markets, while the subsequent correlation rise relates to the bear market observed globally over 2000-2002. This is in line with previous studies on correlation dynamics which support the conjecture that correlations among financial assets tend to increase during bear markets and decrease during bull markets (see, *inter alios*, Longin and Solnik, 1995; Ang and Bekaert, 2002). Default risk plays an important role in explaining the increase in sector correlations during bear markets. As a common risk factor for all sectors, default risk tends to be higher in economic downturns which will increase the sector exposure to this common risk factor, and therefore result in higher sector correlations. Düllmann et al (2007) provides evidence in this regard by finding a positive link between asset correlations and borrowing size, which tends to increase during recessions.

Empirical likelihood ratio (LR) tests reported in Table 5.3 give strong evidence for the existence of a regime switch in sector correlation dynamics.

Table 5.3 Empirical Likelihood Ratio Test

Model	Log-likelihood	Number of parameters	AIC	SIC	LR test	p-value	Model under H_0	Inference on correlation
				Japanese Sectors				
CCC	87722	75	127.24	569.28				
Scalar DCC	88526	32	**41.22**	**229.82**				
Scalar ADCC	88528	33	43.22	237.72	4	0.046	Scalar DCC	Asymmetry
Scalar DCC-Break	88651	34	45.22	245.61	250	0.000	Scalar DCC	Break
Scalar ADCC-Break	88659	36	49.21	261.40	262	0.000	Scalar ADCC	Break
Diagonal DCC	88587	50	77.22	371.91	122	0.000	Scalar DCC	Different asset dynamics
Diagonal ADCC	88765	60	97.21	450.85	356	0.000	Diagonal DCC	Asymmetry
Diagonal DCC-Break	88734	70	117.21	529.79	294	0.000	Diagonal DCC	Break
Diagonal ADCC-Break	88935	90	157.21	1002.82	402	0.000	Diagonal DCC-Break	Asymmetry
				UK Sectors				
CCC	86218	75	127.27	571.44				
Scalar DCC	86623	32	**41.26**	**230.77**				
Scalar ADCC	86632	33	43.26	238.70	18	0.000	Scalar DCC	Asymmetry
Scalar DCC-Break	86737	34	45.26	246.62	228	0.000	Scalar DCC	Break
Scalar ADCC-Break	86745	36	49.26	262.46	226	0.000	Scalar ADCC	Break
Diagonal DCC	86676	50	77.26	373.37	106	0.000	Scalar DCC	Different asset dynamics
Diagonal ADCC	86834	60	97.26	452.59	316	0.000	Diagonal DCC	Asymmetry
Diagonal DCC-Break	86927	70	117.25	531.81	502	0.000	Diagonal DCC	Break
Diagonal ADCC-Break	86949	90	157.25	690.26	44	0.002	Diagonal DCC-Break	Asymmetry
				US Sectors				
CCC	92008	75	127.14	571.01				
Scalar DCC	92603	32	**41.13**	**230.51**				
Scalar ADCC	92603	33	43.13	238.43	0	1.000	Scalar DCC	No Asymmetry
Scalar DCC-Break	92684	34	45.13	246.35	162	0.000	Scalar DCC	Break
Scalar ADCC-Break	92687	36	49.13	262.18	168	0.000	Scalar ADCC	Break
Diagonal DCC	92603	50	77.13	373.04	0	1.000	Scalar DCC	Identical asset dynamics
Diagonal ADCC	92887	60	97.12	452.22	568	0.000	Diagonal DCC	Asymmetry
Diagonal DCC-Break	92639	70	117.13	531.41	72	0.000	Diagonal DCC	Break
Diagonal ADCC-Break	92992	90	157.12	689.76	706	0.000	Diagonal DCC-Break	Asymmetry

Note: AIC is the Akaike Information Criterion $AIC = 2 \times k - 2 \times ln(LLF)$ where k is the number of parameters and LLF is the log-likelihood value, SIC is the Schwarz Information Criterion $SIC = k \times ln(LLF) - 2 \times ln(LLF)$. Bold indicates the selected model under each criterion. Reported for each model is the Likelihood Ratio (LR) test for the hypothesis that correlation dynamics is sufficiently characterized by the model under the null.

Moreover, the diagonal G-DCC outperforms its scalar counterpart for all three sector portfolios - LR tests reject the null hypothesis of restricting correlation dynamics to be the same across assets. Asymmetry in sector correlations is also borne out by a significant increase in the value of the log-likelihood function. On the other hand, the AIC and SIC information criteria that trade-off fit and parsimony provide evidence towards the more parsimonious DCC model.

The parameter estimates for the dynamic conditional correlation models are set out in Table 5.4. Most parameters are statistically significant at the conventional levels.

Table 5.4 Estimation Output of Dynamic Conditional Correlation Models

	Period 1			Period 2		
Scalar Models	*a*	*b*	*g*	*a*	*b*	*g*
			Japanese Sectors			
DCC-Break	0.023 ***	0.878 ***		0.014 ***	0.980 ***	
A-DCC-Break	0.023 ***	0.878 ***	0.000	0.011	0.980 ***	0.004 ***
			UK Sectors			
DCC-Break	0.015 ***	0.910 ***		0.014 ***	0.975 ***	
A-DCC-Break	0.010 ***	0.914 ***	0.013 ***	0.011 ***	0.974 ***	0.005 ***
			US Sectors			
DCC-Break	0.023 ***	0.897 ***		0.011 ***	0.987 ***	
A-DCC-Break	0.015 ***	0.908 ***	0.012 ***	0.010 ***	0.987 ***	0.001

Diagonal Models	a_i^2	b_i^2		a_i^2	b_i^2	
G-DCC-Break						
			Japanese Sectors			
ENG	0.011	0.894 ***		0.009 ***	0.961 ***	
BML	0.031 **	0.874 ***		0.021 ***	0.970 ***	
IND	0.013 ***	0.973 ***		0.019 ***	0.978 ***	
CGS	0.009 *	0.947 ***		0.014 ***	0.986 ***	
HCR	0.007 *	0.898 ***		0.012 ***	0.977 ***	
CSV	0.011	0.952 ***		0.021 ***	0.962 ***	
TEL	0.009	0.958 ***		0.020 ***	0.951 ***	
UTL	0.012 *	0.833 ***		0.003 ***	0.997 ***	
FIN	0.056 *	0.890 ***		0.037 ***	0.933 ***	
TEC	0.023 ***	0.940 ***		0.023 ***	0.968 ***	
			UK Sectors			
ENG	0.011 ***	0.893		0.011 ***	0.982 ***	
BML	0.008	0.989 ***		0.013 ***	0.979 ***	
IND	0.020	0.897 ***		0.016 ***	0.976 ***	
CGS	0.035	0.732 ***		0.007	0.993 ***	
HCR	0.035 ***	0.894 ***		0.022 ***	0.966 ***	
CSV	0.047	0.773 ***		0.016 ***	0.975 ***	
TEL	0.022	0.917 ***		0.017 ***	0.970 ***	
UTL	0.002	0.884 ***		0.008 ***	0.978 ***	
FIN	0.021 ***	0.933 ***		0.019 ***	0.971 ***	
TEC	0.000	0.950 ***		0.010 ***	0.981 ***	
			US Sectors			
ENG	0.008	0.963 ***		0.009 ***	0.982 ***	
BML	0.009 ***	0.989 ***		0.009 ***	0.990 ***	
IND	0.020 ***	0.945 ***		0.009 ***	0.986 ***	
CGS	0.015 ***	0.953 ***		0.006 ***	0.993 ***	
HCR	0.017 ***	0.941 ***		0.068 ***	0.922 ***	
CSV	0.013 ***	0.947 ***		0.002 ***	0.997 ***	
TEL	0.020 **	0.866 ***		0.005 ***	0.991 ***	
UTL	0.061	0.732 ***		0.008 ***	0.981 ***	
FIN	0.015 ***	0.958 ***		0.008 ***	0.988 ***	
TEC	0.020 **	0.932 ***		0.006 ***	0.991 ***	

AG-DCC-Break	Period 1 a_i^2		b_i^2		g_i^2		Period 2 a_i^2		b_i^2		g_i^2	
Japanese Sectors												
ENG	0.009		0.905	***	0.009		0.008	***	0.969	***	0.003	**
BML	0.032	***	0.820	***	0.034	**	0.019	***	0.972	***	0.005	***
IND	0.019	***	0.774	***	0.010		0.016	***	0.977	***	0.007	***
CGS	0.010		0.741	***	0.019		0.009	***	0.985	***	0.017	***
HCR	0.003	***	0.999	***	0.002	***	0.012	***	0.970	***	0.002	**
CSV	0.023	***	0.786	***	0.006	***	0.018	***	0.961	***	0.009	***
TEL	0.012		0.849	***	0.002		0.013	***	0.970	***	0.004	***
UTL	0.018	***	0.989	***	0.000		0.004	***	0.997	***	0.000	
FIN	0.073	***	0.789	***	0.029	*	0.029	***	0.948	***	0.012	***
TEC	0.038	**	0.672	***	0.023		0.017	***	0.973	***	0.006	***
UK Sectors												
ENG	0.000		0.771		0.072		0.010	***	0.978	***	0.010	*
BML	0.003		0.995	***	0.006		0.014	***	0.977	***	0.001	
IND	0.006		0.925	***	0.033	*	0.018	***	0.973	***	0.000	
CGS	0.016		0.768	***	0.025	*	0.007	***	0.995	***	0.001	
HCR	0.018		0.882	***	0.024	*	0.019	***	0.962	***	0.014	***
CSV	0.011		0.710	***	0.091	***	0.016	***	0.974	***	0.002	
TEL	0.055		0.896	***	0.012	**	0.015	***	0.970	***	0.004	**
UTL	0.003		0.094		0.000		0.006	***	0.979	***	0.009	**
FIN	0.020		0.923	***	0.015	**	0.018	***	0.970	***	0.004	**
TEC	0.002		0.926	***	0.000		0.011	***	0.980	***	0.000	
US Sectors												
ENG	0.009	***	0.995	***	0.000		0.008	***	0.988	***	0.000	
BML	0.003		0.988	***	0.012	***	0.019	***	0.975	***	0.004	***
IND	0.009		0.948	***	0.019	***	0.018	***	0.973	***	0.006	***
CGS	0.006		0.950	***	0.022	***	0.015	***	0.979	***	0.007	***
HCR	0.013	***	0.941	***	0.012	***	0.011	***	0.986	***	0.002	
CSV	0.005		0.953	***	0.014	***	0.015	***	0.978	***	0.007	***
TEL	0.019		0.876	***	0.013	***	0.010	***	0.980	***	0.000	
UTL	0.073	**	0.735	***	0.000		0.006	***	0.988	***	0.000	
FIN	0.004		0.941	***	0.048	***	0.014	***	0.981	***	0.002	***
TEC	0.010	**	0.926	***	0.040	***	0.014	***	0.976	***	0.005	***

Note: The table presents parameter estimates for the AG-DCC-Break model for daily stock returns and for its special cases G-DCC-Break, **G**=[0], A-DCC-Break, **A**=[*a*], **B**=[*b*], **G**=[*g*] and DCC-Break, **A**=[*a*], **B**=[*b*], **G**=[*g*]=0 . The sample period is July 1, 1996 to May 31, 2007. Period 1 and 2 represents the two sub-periods before and after the introduction of EMU on January 1, 1999, respectively.
ENG, BML, IND, CGS, HCR, CSV, TEL, UTL, FIN, TEC are Engineering, Basic Material, Industrial, Consumer Goods, Health Care, Consumer Service, Telecommunication, Utility, Financial and Technology sectors, respectively. JPN is the Nikkei 225, UK is the FTSE-All and US is the S&P500.
*, **, *** indicate parameters significant at the 10%, 5% and 1% levels, respectively.

We find evidence of correlation asymmetry in most of the U.S. and UK sector correlations indicated by the significance of the asymmetry parameter over the entire sample period. For the Japanese sector indices, however, the correlation asymmetry is only observed over the post-EMU sub-period. The findings also indicate a change in the dynamic structure of conditional correlations following the introduction of the EMU. Asymmetric effects in correlations tend to dampen significantly in magnitude post-EMU. In addition, the dynamic of the time varying correlation (*i.e.* parameter a and b in the scalar model and a^2 and b^2 in the diagonal model) among the sector index returns has also changed significantly over the post-EMU period.[304] The degree of persistence in conditional correlation, measured by $a + b + g$ in the scalar models and $a^2 + b^2 + g^2$ in the diagonal models, also undergoes a structural break. Conditional correlations become more persistent after the introduction of the EMU. For instance, the persistence in conditional correlation for the US sectors is 0.920 (DCC-break) and 0.935 (A-DCC-break) in the pre-break period, and rises to 0.998 and 0.997, respectively, in the post-break period.

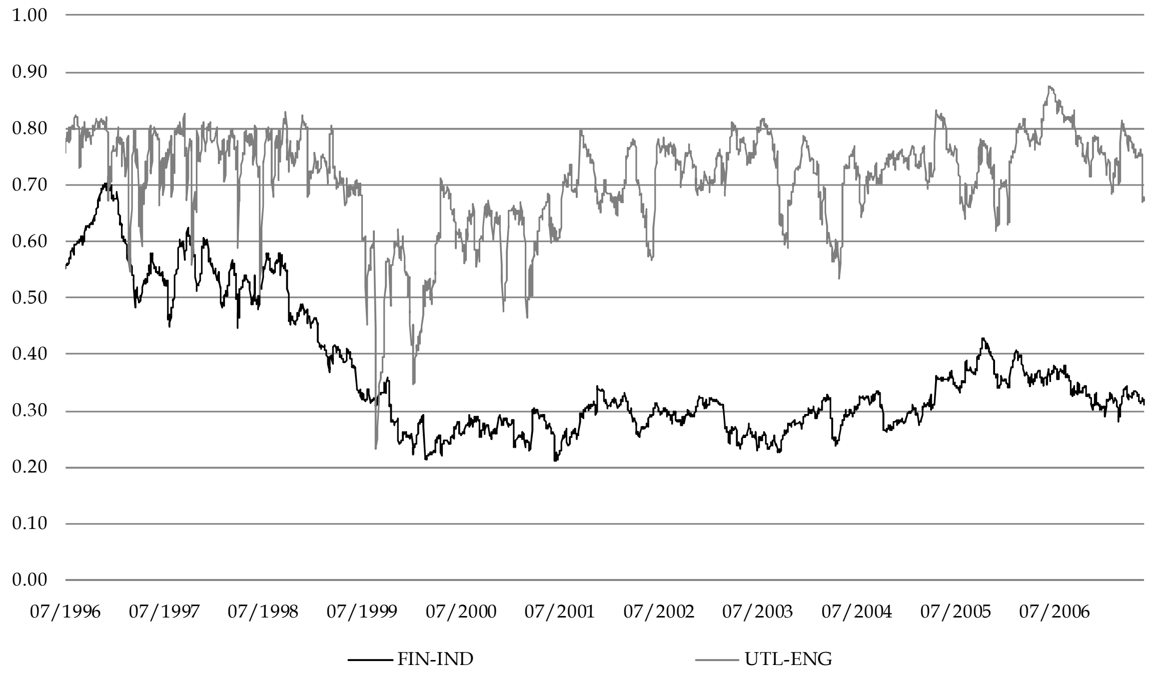
Time series graphs of the conditional sector correlations obtained from the AG-DCC-Break model are presented in Figure 5.3.

[304] Appendix D.5 presents the Welch's Student's t-test to assess the difference between the parameters in the two periods. Appendix D.6 reports the test results.

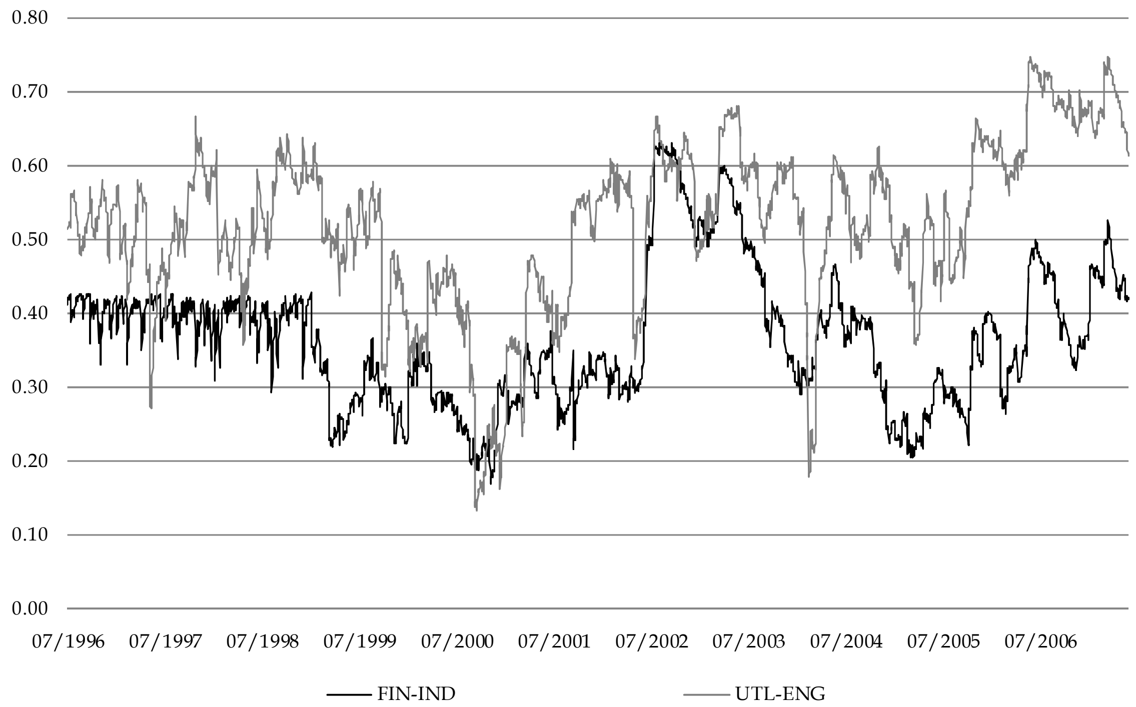
Figure 5.3 Conditional Daily Correlation Dynamics

Time series graphs of daily conditional correlations among selected sector indices obtained using the AG-DCC-Break model with a structural break on 1 Jan 1999 (DCC-Break). "ENG", "IND", "CGS", "CSV", "UTL", "FIN", and "TEC" refer to the Engineering, Industrial, Consumer Goods, Consumer Service, Utility, Financial and Technology sector, respectively.

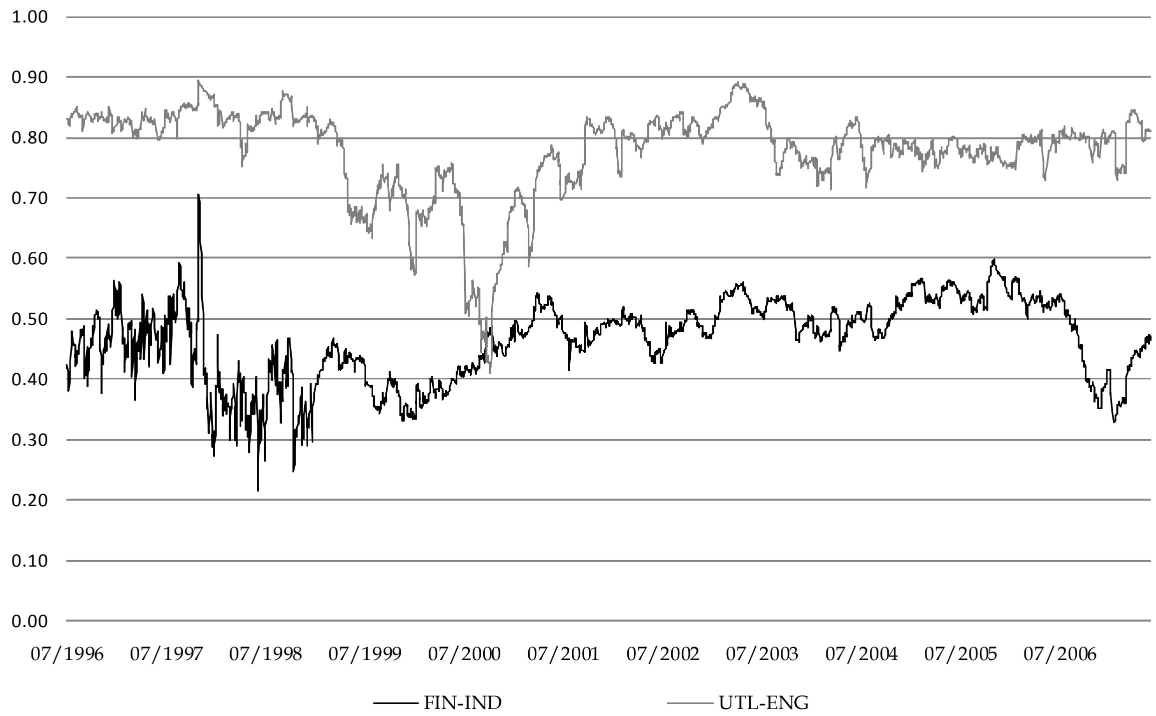
Panel A: Conditional correlation from AG-DCC-Break model between Japanese FIN-IND and UTL-ENG.



Panel B: Conditional correlation from AG-DCC-Break model between the UK FIN-IND and UTL-ENG.



Panel C: Conditional correlation from AG-DCC-Break model between the US FIN-IND and UTL-ENG.

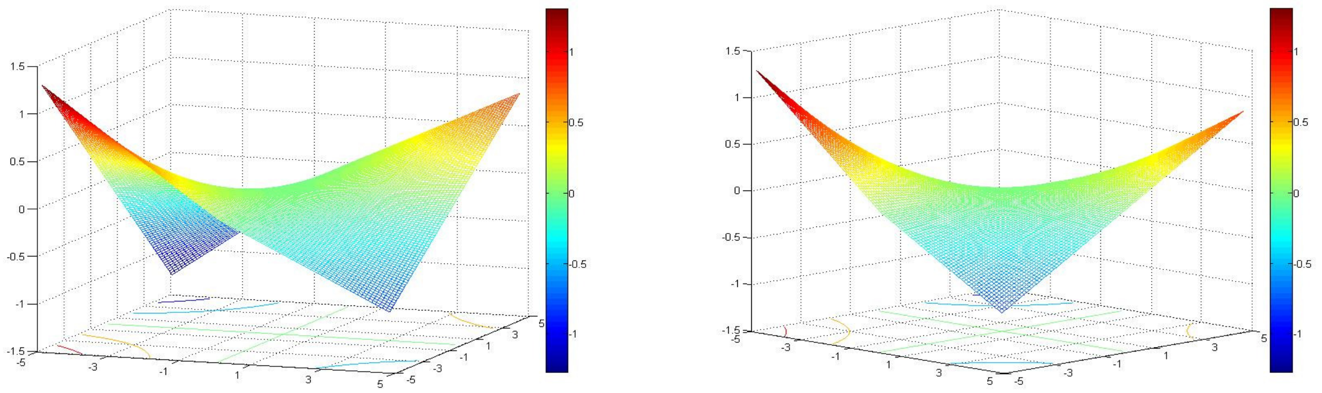


In all three markets sectors correlations decrease sharply at the end of 1998 and recover to their pre-EMU level by the end of 2002. To gain more insight into the effect of the structural break and asymmetries on correlation dynamics, in Figure 5.4 we plot the correlation news impact surface (NIS) derived from the AG-DCC-Break.

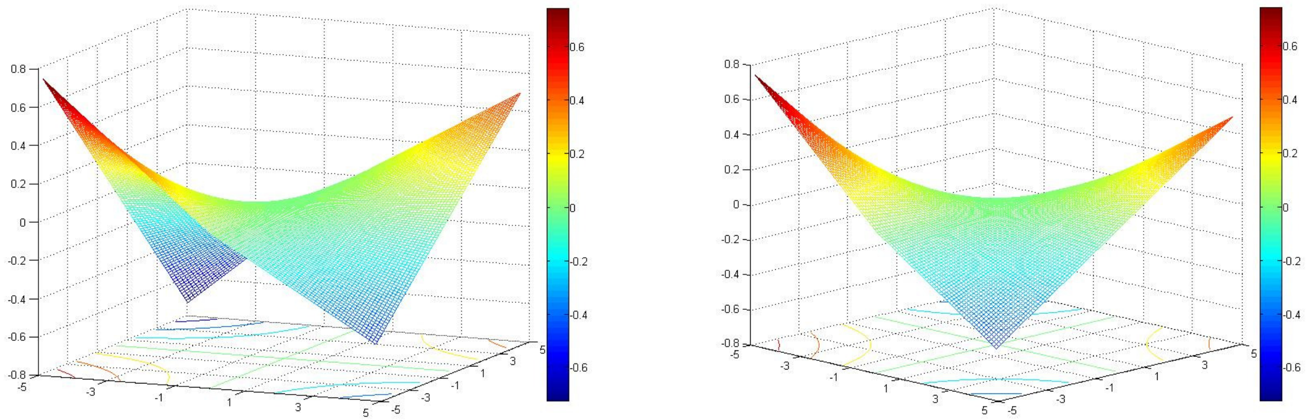
Figure 5.4 Correlation News Impact Surfaces for Pre- and Post-Event Periods

The graphs below show the conditional correlation News Impact Surface (NIS) between industrials and financials derived from the Diagonal ADCC model with structural break on January 1, 1999 (AG-DCC-Break). The horizontal axis represents the shocks originated from the IND and FIN sector indices in terms of units of standard deviation, while the vertical axis represents the changes in conditional correlation between the two sector indices.

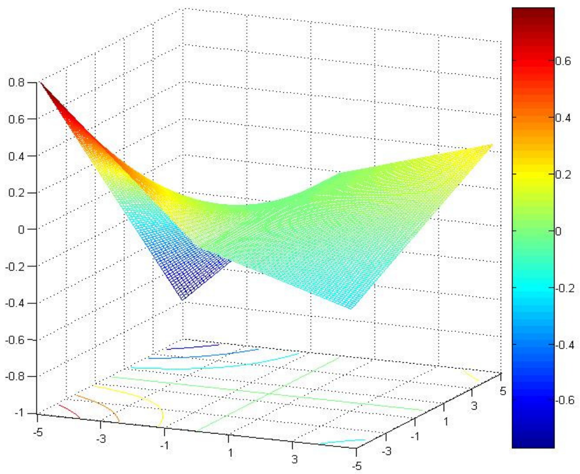
Panel A1: The correlation NIS for Japanese IND-FIN during the pre-event period

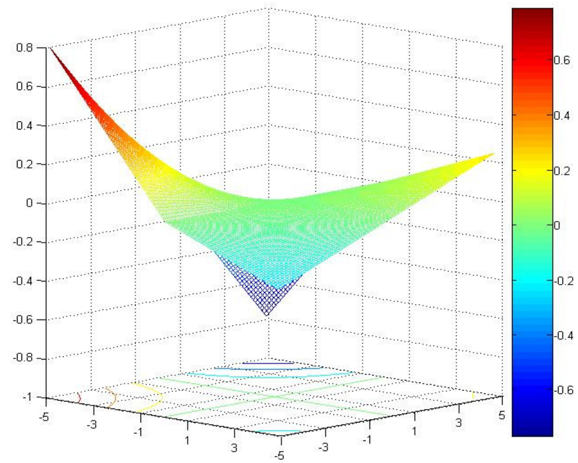


Panel A2: The correlation NIS for Japanese IND-FIN during the post-event period

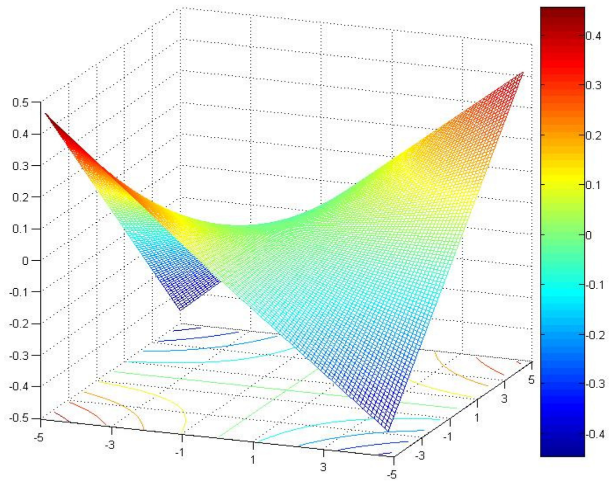


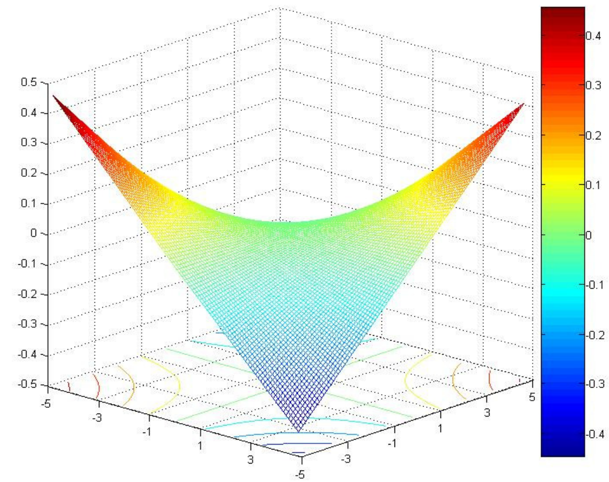
Panel B1: The correlation NIS for the UK IND-FIN during the pre-event period



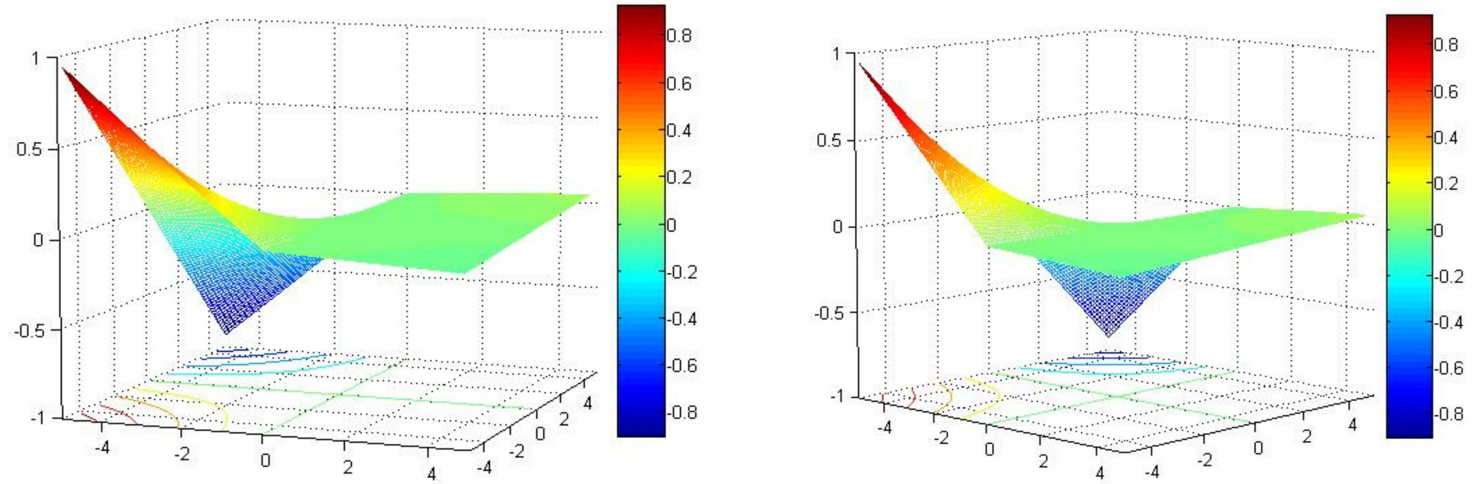


Panel B2: The correlation NIS for the UK IND-FIN during the post-event period





Panel C1: The correlation NIS for the US IND-FIN during the pre-event period



Panel C2: The correlation NIS for the US IND-FIN during the post-event period

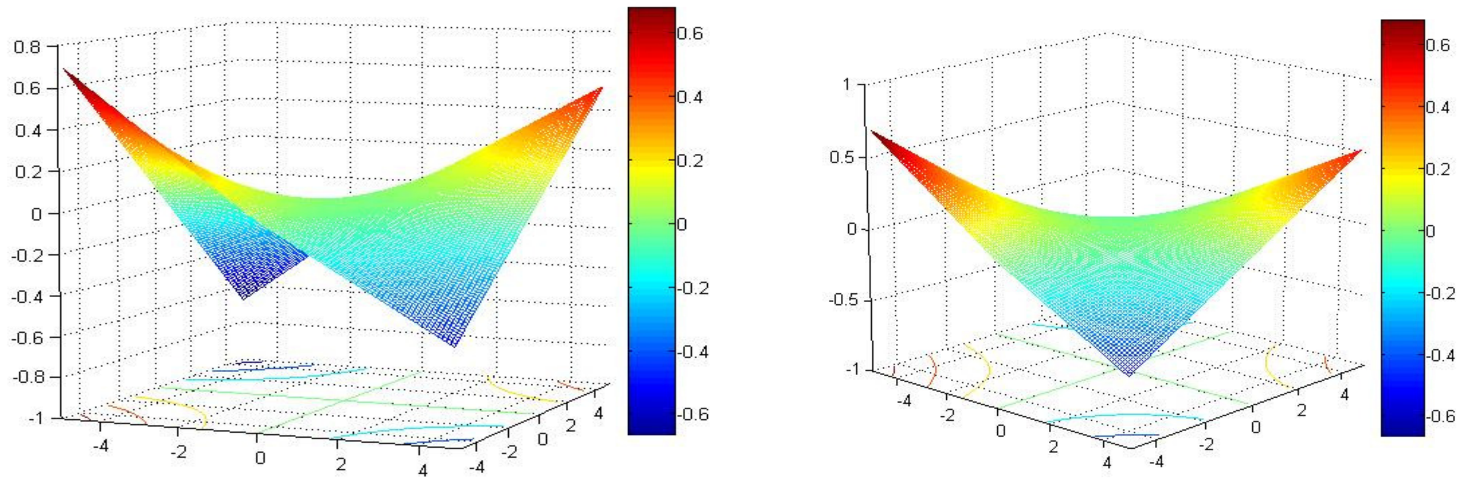


Figure 5.4 shows the NIS for industrial and financial sectors across the three markets during the pre- and post-1999 periods. The NIS corroborates the evidence obtained from the parameter estimates in Table 5.4 regarding the presence of sector asymmetric effects and structural break. Pre-1999 the correlation between industrials and financials increases dramatically when both sectors suffer negative returns, while the impact of joint positive returns is relatively lower. However, asymmetry in correlation dynamics is largely eliminated post-1999.

In summary, the results suggest that there is significant asymmetry in domestic sector correlation dynamics. Moreover, accounting for a structural break is important, particularly for the US and UK sectors, as asymmetric effects in correlations dampen post-1999 and correlations tend to become more sluggish.

5.5.2. Timing the Correlation Signals

We now turn to investigate whether accounting for correlation dynamics as vindicated by the statistical evidence in Section 5.5.1 would be fruitful for fund managers. To this end, we assess the performance of the correlation timing strategies against static sector allocation. The alternative covariance estimators are contrasted within the economic framework outlined in Section 5.4.3 that gauges their ability to generate excess risk-adjusted returns and incremental utility. The mean-variance portfolios are recursively constructed based on one-step-ahead covariance forecasts, while the static portfolio is based on the constant unconditional covariance matrix over the in-sample period.

Table 5.5 presents the out-of-sample evaluation of the correlation timing strategies for the conditional covariance estimators against the static benchmark under the Max-R scheme.

Table 5.5 Portfolio performance for maximum return strategy (daily rebalancing)

Strategy	*μ*	*σ*	*SR*	*ΔSR*	*p*-value	*TO*	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static										
Constant Weights	36.63	18.35	2.00			0.71				
Dynamic										
EWMA	55.53	25.80	2.15	0.156	(0.377)	25.00	**1890.88**	6.43	**1892.18**	6.38
CCC	43.17	18.23	2.37	0.371	(0.198)	8.68	680.97	7.12	704.19	7.34
DCC	42.47	17.44	2.44	0.439	(0.177)	9.30	613.83	5.50	640.16	5.36
A-DCC	42.08	17.46	2.41	0.413	(0.191)	9.79	573.38	4.85	598.54	4.72
DCC-Break	43.38	17.67	2.46	0.459	(0.175)	8.87	706.62	6.73	733.81	6.57
A-DCC-Break	43.36	17.69	2.45	0.454	(0.177)	8.96	704.34	6.63	731.36	6.48
G-DCC	43.43	18.00	2.42	0.420	(0.199)	14.55	708.64	4.25	733.70	4.37
AG-DCC	44.77	17.83	2.51	0.514	(0.147)	14.13	847.79	4.95	877.33	4.86
G-DCC-Break	42.73	18.11	2.36	0.363	(0.231)	12.21	635.91	4.59	658.60	4.73
AG-DCC-Break	46.16	18.14	2.54	**0.548**	(0.134)	13.32	989.11	6.19	1019.84	6.10
				UK Sectors						
Static										
Constant Weights	31.44	16.54	1.90			0.28				
Dynamic										
EWMA	44.50	20.10	2.21	0.313	(0.239)	17.24	**1282.24**	5.97	**1293.43**	5.98
CCC	36.54	12.28	2.98	1.075	(0.041)	5.12	554.29	9.08	591.57	9.66
DCC	39.33	12.14	3.24	**1.340**	(0.018)	5.49	838.53	12.45	879.88	12.79
A-DCC	39.44	12.19	3.24	1.334	(0.018)	5.52	849.50	12.56	890.79	12.89
DCC-Break	38.14	12.25	3.11	1.212	(0.031)	5.53	717.03	10.56	756.66	10.89
A-DCC-Break	38.31	12.31	3.11	1.210	(0.032)	5.56	733.79	10.75	773.42	11.08
G-DCC	38.83	12.37	3.14	1.239	(0.025)	6.19	786.45	11.08	826.44	11.58
AG-DCC	39.75	12.48	3.19	1.285	(0.021)	5.92	879.74	12.78	920.38	13.13
G-DCC-Break	38.61	12.57	3.07	1.171	(0.035)	6.20	763.16	10.76	802.22	11.26
AG-DCC-Break	38.33	12.60	3.04	1.143	(0.039)	6.14	735.16	10.26	773.80	10.60
				US Sectors						
Static										
Constant Weights	16.94	8.97	1.89			0.20				
Dynamic										
EWMA	33.13	16.46	2.01	0.125	(0.490)	21.31	**1596.96**	6.26	**1584.20**	6.17
CCC	26.41	10.21	2.59	**0.698**	(0.063)	4.75	950.84	17.34	953.51	17.32
DCC	26.54	10.50	2.53	0.640	(0.117)	5.27	945.27	15.48	932.71	15.22
A-DCC	26.55	10.50	2.53	0.640	(0.117)	5.27	946.17	15.49	933.58	15.23
DCC-Break	26.86	10.70	2.51	0.622	(0.130)	5.07	975.75	16.65	961.31	16.33
A-DCC-Break	26.83	10.71	2.51	0.618	(0.132)	5.10	972.04	16.49	957.52	16.17
G-DCC	25.29	10.55	2.40	0.508	(0.173)	9.22	836.27	7.70	836.92	7.68
AG-DCC	23.96	10.59	2.26	0.376	(0.238)	7.34	702.33	8.17	701.88	8.14
G-DCC-Break	25.53	10.76	2.37	0.485	(0.201)	10.25	858.93	7.09	858.93	7.06
AG-DCC-Break	27.01	10.73	2.52	0.629	(0.125)	9.32	1008.78	9.17	1010.16	9.13

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. daily bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

First we appraise the standard portfolio performance measures. Reported for each domestic sector portfolio is the annualized mean portfolio return (μ), annualized returns standard deviation (σ), Sharpe Ratio (*SR*) along with *SR* differentials relative to the static benchmark strategy and the associated *p*-values for Opdyke's (2007) test of equality of *SRs* between the two strategies. A significant test statistic (*i.e.* p-value is less than the 5% or 10% level) indicates rejection of H_0: $SR_d = SR_s$ in favour of the alternative that the dynamic strategy yields a higher *SR* than the static. The results suggest that dynamic sector allocation strategies are generally able to generate higher reward-to-risk ratios than the static constant covariance strategy. In the UK, a dynamic strategy entails significantly (5% level) better *SR* than the static strategy irrespective of the model employed. The best model for the UK sector portfolio turns out to be the DCC which accrues significant incremental gains in risk-adjusted return of ΔSR = 1.340 in excess of the static strategy, while for the US the CCC model that maintains constant correlation achieves a significant (10% level) increase in the *SR* of 0.698 relative to the static sector allocation. In Japan dynamic allocation increases the *SR* albeit not significantly so (top-ranked model is AG-DCC-Break).

We now turn attention to the economic value of the covariance forecasting models on the basis of annualized performance fee (*PF*) of the strategy at hand vis-à-vis the static benchmark. We find large and positive performance fees across all portfolios providing overwhelming evidence that the dynamic strategies outperform the static constant covariance strategy in all three markets. Among the various strategies, the EWMA entails the largest gains for sector investors with *PF*s ranging from a low of 1282 bp to a high of 1892 bp depending on the portfolio and risk-aversion coefficient. That is, a highly risk averse Japanese sector investor would be willing to pay up to a maximum of 1892 bp per annum to reap the benefits of a dynamic covariance strategy, whereas a similar US investor would be willing to pay up to 1584 bp. Focusing on conditional correlation models, it turns out that it pays off to account for correlation asymmetries and possibly breaks as the more flexible models provide the highest performance fee (AG-DCC-Break for Japan and US, and the AG-DCC for the UK).

Table 5.6 reports the performance evaluation of the dynamic versus the static portfolios under the Min-V portfolio construction scheme.

Table 5.6 Portfolio performance for minimum variance strategy (daily rebalancing)

Strategy	μ	σ	SR	ΔSR	p-value	TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static										
Constant Weights	21.91	10.91	2.01			0.37				
Dynamic										
EWMA	19.40	11.02	1.76	-0.247	(0.364)	10.01	-259.11	-	-266.26	-
CCC	20.73	9.58	2.16	0.155	(0.355)	4.11	-114.61	-	-111.17	-
DCC	20.81	9.62	2.16	0.154	(0.367)	4.79	-106.67	-	-103.22	-
A-DCC	20.46	9.58	2.14	0.127	(0.389)	4.96	-142.40	-	-139.54	-
DCC-Break	21.14	9.65	2.19	0.182	(0.349)	4.55	-72.96	-	-68.92	-
A-DCC-Break	21.01	9.60	2.19	0.181	(0.349)	4.59	-85.77	-	-81.77	-
G-DCC	21.12	9.67	2.18	0.176	(0.351)	7.62	-75.06	-	-71.14	-
AG-DCC	21.36	9.59	2.23	0.220	(0.320)	7.74	-49.77	-	-44.98	-
G-DCC-Break	20.43	9.65	2.12	0.108	(0.409)	6.93	-144.94	-	-142.46	-
AG-DCC-Break	21.67	9.65	2.25	0.237	(0.307)	7.20	-18.12	-	-12.92	-
				UK Sectors						
Static										
Constant Weights	16.92	7.53	2.25			0.13				
Dynamic										
EWMA	15.90	5.29	3.00	0.754	(0.095)	4.69	-110.11	-	-105.32	-
CCC	17.53	4.84	3.63	1.378	(0.013)	2.08	69.81	2.99	77.37	3.31
DCC	18.11	4.72	3.84	**1.591**	(0.007)	2.26	**128.25**	4.82	**136.48**	4.95
A-DCC	18.07	4.71	3.84	1.590	(0.007)	2.25	124.03	4.66	132.25	4.80
DCC-Break	17.68	4.73	3.74	1.488	(0.012)	2.22	85.54	3.22	93.42	3.35
A-DCC-Break	17.65	4.72	3.74	1.489	(0.013)	2.21	82.23	3.09	90.10	3.23
G-DCC	17.69	4.72	3.75	1.501	(0.009)	2.36	86.21	3.23	94.13	3.53
AG-DCC	17.93	4.71	3.80	1.556	(0.008)	2.29	110.07	4.06	118.18	4.21
G-DCC-Break	17.53	4.75	3.69	1.443	(0.014)	2.38	69.79	2.59	77.52	2.88
AG-DCC-Break	17.51	4.75	3.69	1.440	(0.015)	2.36	68.00	2.38	75.72	2.52
				US Sectors						
Static										
Constant Weights	14.38	7.15	2.01			0.16				
Dynamic										
EWMA	15.58	6.15	2.53	0.522	(0.279)	7.69	117.21	1.30	118.11	1.31
CCC	16.91	5.60	3.02	**1.007**	(0.014)	2.46	**256.28**	9.26	**259.57**	9.37
DCC	16.31	5.44	3.00	0.990	(0.034)	2.63	191.26	6.44	189.69	6.39
A-DCC	16.31	5.43	3.00	0.989	(0.034)	2.63	190.66	6.42	189.06	6.36
DCC-Break	16.30	5.42	3.01	0.995	(0.036)	2.47	189.36	6.82	187.54	6.75
A-DCC-Break	16.27	5.42	3.00	0.989	(0.037)	2.48	186.28	6.69	184.42	6.62
G-DCC	16.32	5.44	3.00	0.987	(0.034)	4.98	197.26	3.41	200.36	3.46
AG-DCC	15.36	5.49	2.80	0.788	(0.068)	4.15	99.91	2.09	102.10	2.13
G-DCC-Break	16.46	5.50	2.99	0.982	(0.039)	5.92	211.92	3.06	215.01	3.10
AG-DCC-Break	15.93	5.44	2.93	0.920	(0.046)	5.54	158.14	2.45	160.93	2.49

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. daily bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

The results suggest that the dynamic strategies outperform the static benchmark on the basis of lower portfolio volatility and significantly higher risk-adjusted returns of the sector portfolios. There is strong evidence that dynamic strategies significantly enhance the *SR* of the static strategy in the UK sector portfolio with all models and in the US with the CCC and all the diagonal DCC-type models. From the viewpoint of risk-adjusted returns in sector allocation the best performing model for the UK is the DCC and for US it is the CCC, both with significant *SR* differentials of ΔSR = 1.591 (p-value = 0.007) and ΔSR = 1.007 (p-value = 0.014). In Japan dynamic allocation entails *SR* gains but these are not statistically significant.

In terms of utility-based *PF* dynamic strategies outperform the static for strategy for the UK and US sector portfolios. A highly risk-averse UK investor is willing to pay up to 136 bp per annum to switch from the static constant weights strategy to the top-ranked DCC correlation timing strategy. In the US, such an investor is willing to pay up to 259 bp per annum to switch from the static strategy to one where rebalancing is driven by CCC volatility forecasts.

In contrast, the Japanese sector investor does not seem to benefit from correlation or volatility timing consistent with the evidence derived from SRs. One potential explanation could be that the Japanese equity market is comparatively more efficient compared to the UK and US in the sense that market timing strategy cannot yield positive abnormal performances in a systemic way. However, difficult to generate conditional volatility and correlation forecast with sufficiently high accuracy might also attribute to the poor performances of the dynamic strategy in Japan. From the table, one can see that dynamic strategies do manage to achieve a lower volatility compared to the static one (*e.g.* σ = 9.58% A-DCC vs. σ = 10.91% Static), which means the volatility and correlation forecasts are meaningful. However, this is gain from lower portfolio risk is not sufficient to compensate the relatively lower portfolio return generated by the dynamic portfolio compared to the static one (μ = 20.46% A-DCC vs. μ = 21.91% Static).

5.5.3. Turnover Rate and Break-Even Transaction Costs

The empirical results obtained thus far suggest that the dynamic strategies outperform the static constant covariance strategy in terms of reward-to-risk ratio and performance fees for risk-averse investors with a quadratic utility function. However, active trading strategies are prone to high turnovers and are therefore substantially impacted by transaction costs. For each strategy the corresponding monthly turnover volume of the portfolio (*TO*) can also be seen in Table 5.5 and 5.6. The *TO* of the static strategy that builds upon constant covariance and only rebalances in order to maintain constant weights as required by returns fluctuations is as low as 0.20 – 0.71 (Max-R) and 0.13 – 0.37 (Min-V), or equivalently 13% - 37% of total portfolio value. The monthly turnover for the conditional correlation timing strategies is considerable, ranging at 4.75 – 14.55 (Max-R) and 2.08 – 7.74 (Min-V) across models/portfolios. The strategy with the lowest *TO* employs the CCC model that rebalances in response to volatility but not correlation changes. In case the EWMA approach is used for forecasting the covariance matrix, the *TO* increases even further to 17.24 – 25 (Max-R) and 4.69 – 10.01 (Min-V).

The results in Tables 5.5 and 5.6 suggest that among the dynamic strategies the one based on the EWMA covariance forecast has the highest *TO*, around twofold that of conditional correlation models, which in turn materializes in relatively low *BTC*. For instance, a highly risk-averse US sector investor using the Max-R (Min-V) EWMA model faces a *BTC* of 6.17 bp (1.31 bp) per trade, much lower than the actual transaction cost for US Sector ETFs (7 bp), thereby rendering the EWMA strategy unsustainable under realistic trading conditions. On the other hand, a US investor opting for the CCC model faces a higher and economically plausible *BTC* of 17.32 bp (9.37 bp) per trade under Max-R (Min-V). Therefore, portfolio managers opting for the simple EWMA rather than conditional correlation models would face a much higher level of transaction costs which would severely undermine its performance. Nonetheless, for UK and Japanese sector-linked ETFs the *BTC* of conditional correlation models with daily rebalancing is below the indicated average trading costs. Despite the positive *PFs* consideration of transaction costs casts doubt on the practical feasibility of sector correlation timing in these two markets.

5.5.4. The Impact of Rebalancing Frequency on the Performance of Dynamic Strategies

As seen in the previous section, day traders engaging in dynamic correlation strategies face small *BTCs*, implying that realistic levels of transaction costs are bound to wipe out their incremental gains relative to the static strategy. Lower rebalancing frequency will reduce the *TO*, which is negatively related to the revision interval, and result in *BTC*s that are high enough for investors to be able to implement the dynamic strategies. There is, however, a trade-off between rebalancing frequency and portfolio performance. By holding a portfolio with low rebalancing frequency, the investor might have to rely on less accurate long term (weekly or monthly) variance-covariance forecasts which might reduce the economic value of the portfolio (Han, 2006). Furthermore, an investor with low rebalancing frequency cannot react timely to the arrival of new information.

In order to investigate the impact of rebalancing frequency on the performance of dynamic asset allocation, we conduct the same analysis for monthly and weekly investment horizons. To this end, we rebalance the portfolio daily based on the daily covariance matrix forecast and hold the new portfolio for a *m*-day holding period, where m = 21 for a monthly horizon and m = 5 for a weekly horizon. This overlapping approach assumes that, the investor will hold multiple portfolios simultaneously on every trading day, each formed one day apart. The weights for each portfolio are equal at the beginning of the sample period (*i.e.* 20% each for the 5 portfolios hold by an investor with weekly rebalancing frequency). On each trading day, only one of the *m* portfolios will be revised.[305] The return on day *t* is then calculated as the weighted average return of the *m* portfolios held on day *t*. As the time elapses, the weight of each portfolio will change as the value of each portfolios changes on a daily basis. The turnover ratio on each trading day is equal to the turnover ratio of the revised portfolio (one of the *m* portfolios due to rebalance on that trading day) multiplied by its relative weight to the total asset holding on the corresponding day.[306] A non-overlapping approach, which assumes the investor only holds one portfolio and rebalances it at the end of each holding period, is used instead in Fleming et al. (2003). The advantage of the overlapping approach is twofold. First, it enables the use of all available one-day-ahead variance-covariance forecasts in the rebalancing process. Second, it eliminates the potential bias arising from different rebalancing dates, and accounts for uncertainty over the choice of rebalancing day by creating the empirical distribution of portfolio returns across the different rebalancing occurrences.

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[305] This approach is inspired by Jegadeesh and Titman's (1993) and Rouwenhorst's (1998) early work on portfolio trading strategies, which propose an overlapping method to evaluate the performance of stock picking techniques with different rebalancing frequencies.

[306] Our approach differs from De Pooter et al (2008) in that they use static equal weights to calculate the overall day-*t* return and turnover ratio for the *m* portfolios whereas we allow for time-varying weights.

Tables 5.7 to 5.10 set out the impact of lowering the rebalancing frequency on the out-of-sample performance of the dynamic correlation strategies. By using the same benchmark (*i.e.* daily static portfolio) for all dynamic strategies, we are able to directly assess the impact of the different rebalancing frequency on the performance of dynamic portfolios.

Table 5.7 Portfolio performance for maximum return strategy (weekly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static (Daily Rebalancing)	36.63	18.35	2.00			0.71				
Static	38.19	18.38	2.08	0.082	(0.334)	0.31	156.5072	-	156.97	-
Dynamic										
EWMA	61.89	26.06	2.38	0.379	(0.277)	12.16	**2410.27**	17.60	**2321.04**	16.86
CCC	47.19	18.45	2.56	0.562	(0.093)	4.04	1053.34	26.48	1051.00	26.25
DCC	46.85	17.72	2.64	0.648	(0.080)	4.47	1026.19	22.87	1029.33	22.83
A-DCC	46.68	17.75	2.63	0.633	(0.085)	4.52	1008.27	22.18	1011.31	22.14
DCC-Break	48.59	18.01	2.70	**0.702**	(0.074)	4.29	1195.09	27.97	1194.60	27.80
A-DCC-Break	48.57	18.03	2.69	0.698	(0.075)	4.31	1193.16	27.72	1192.59	27.56
G-DCC	47.75	18.02	2.65	0.653	(0.079)	5.19	1111.88	20.76	1112.15	20.65
AG-DCC	45.93	18.09	2.54	0.542	(0.124)	5.24	930.84	17.25	932.01	17.20
G-DCC-Break	49.17	18.45	2.66	0.668	(0.085)	4.75	1248.52	25.85	1244.24	25.63
AG-DCC-Break	49.32	18.47	2.67	0.673	(0.082)	4.93	1263.15	25.11	1258.55	24.90
				UK Sectors						
Static (Daily Rebalancing)	31.44	16.54	1.90			0.28				
Static	32.83	16.51	1.99	0.088	(0.306)	0.16	139.92	-	140.65	-
Dynamic										
EWMA	47.75	19.81	2.41	0.509	(0.236)	8.68	**1590.39**	15.75	**1558.12**	15.37
CCC	38.03	12.45	3.05	1.152	(0.036)	2.60	688.23	24.89	712.17	25.67
DCC	40.47	12.28	3.30	**1.396**	(0.014)	2.81	931.65	30.84	954.81	31.49
A-DCC	40.63	12.34	3.29	1.393	(0.015)	2.82	947.64	31.20	970.37	31.83
DCC-Break	39.79	12.42	3.20	1.302	(0.023)	2.82	863.15	28.45	886.12	29.10
A-DCC-Break	40.01	12.49	3.20	1.303	(0.023)	2.83	884.83	28.99	907.31	29.61
G-DCC	40.24	12.54	3.21	1.309	(0.019)	2.88	907.50	29.19	929.55	29.79
AG-DCC	40.59	12.65	3.21	1.308	(0.020)	2.86	941.16	30.51	962.37	31.06
G-DCC-Break	40.19	12.75	3.15	1.252	(0.027)	2.91	900.96	28.71	922.00	29.27
AG-DCC-Break	39.90	12.76	3.13	1.225	(0.030)	2.90	872.05	27.88	893.22	28.45
				US Sectors						
Static (Daily Rebalancing)	16.94	8.97	1.89			0.20				
Static	17.10	8.96	1.91	0.021	(0.451)	0.10	37.14	-	53.73	-
Dynamic										
EWMA	35.80	16.55	2.16	0.275	(0.329)	10.70	**1871.71**	14.48	**1860.65**	13.99
CCC	26.36	10.23	2.58	**0.688**	(0.063)	2.21	953.33	38.90	962.29	38.45
DCC	26.71	10.49	2.55	0.659	(0.107)	2.44	988.10	36.26	996.52	35.84
A-DCC	26.72	10.49	2.55	0.659	(0.107)	2.44	988.84	36.28	997.25	35.86
DCC-Break	27.04	10.69	2.53	0.641	(0.119)	2.37	1020.09	38.61	1028.00	38.11
A-DCC-Break	27.03	10.70	2.53	0.639	(0.120)	2.37	1019.78	38.49	1027.70	38.00
G-DCC	26.49	10.54	2.51	0.626	(0.117)	2.40	966.58	36.03	975.34	35.56
AG-DCC	25.50	10.56	2.42	0.528	(0.153)	2.58	869.38	29.81	879.57	29.40
G-DCC-Break	26.12	10.75	2.43	0.542	(0.157)	3.03	930.23	26.81	939.53	26.43
AG-DCC-Break	27.28	10.71	2.55	0.659	(0.112)	2.92	1044.38	31.42	1051.89	30.95

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Table 5.8 Portfolio Performance for minimum variance strategy (weekly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static (Daily Rebalancing)	21.91	10.91	2.01			0.37				
Static	22.52	10.92	2.06	0.054	(0.389)	0.18	60.38	-	60.51	-
Dynamic										
EWMA	20.92	10.94	1.91	-0.097	(0.437)	4.89	-100.36	-	-100.90	-
CCC	22.30	9.58	2.33	0.319	(0.212)	1.97	45.82	2.42	51.55	2.71
DCC	22.59	9.66	2.34	0.331	(0.225)	2.33	74.65	3.20	80.14	3.44
A-DCC	22.40	9.61	2.33	0.323	(0.230)	2.34	55.58	2.38	61.23	2.62
DCC-Break	23.15	9.71	2.39	0.377	(0.205)	2.23	130.48	5.90	135.87	6.14
A-DCC-Break	23.06	9.65	2.39	0.381	(0.202)	2.24	121.37	5.47	126.97	5.72
G-DCC	22.86	9.64	2.37	0.362	(0.204)	2.72	101.70	3.64	107.29	3.83
AG-DCC	21.47	9.60	2.24	0.228	(0.305)	2.75	-37.67	-	-32.26	-
G-DCC-Break	22.96	9.71	2.36	0.356	(0.219)	2.56	111.59	4.29	116.93	4.50
AG-DCC-Break	23.32	9.64	2.42	**0.410**	(0.185)	2.57	**147.58**	5.64	**153.25**	5.86
				UK Sectors						
Static (Daily Rebalancing)	16.92	7.53	2.25			0.13				
Static	17.29	7.51	2.30	0.054	(0.396)	0.07	36.76	-	36.89	-
Dynamic										
EWMA	15.99	5.23	3.06	0.807	(0.137)	2.25	-86.85	-	-81.09	-
CCC	17.87	4.86	3.68	1.428	(0.012)	1.02	103.28	9.81	110.23	10.46
DCC	18.36	4.74	3.87	**1.626**	(0.006)	1.11	**152.36**	13.09	**159.57**	13.69
A-DCC	18.33	4.73	3.87	1.626	(0.007)	1.11	149.74	12.89	156.96	13.50
DCC-Break	18.05	4.76	3.79	1.544	(0.010)	1.10	121.61	10.63	128.77	11.25
A-DCC-Break	18.04	4.75	3.79	1.545	(0.011)	1.10	119.85	10.49	127.02	11.11
G-DCC	18.01	4.75	3.79	1.542	(0.008)	1.12	117.50	10.05	124.68	10.66
AG-DCC	18.07	4.75	3.80	1.556	(0.008)	1.11	123.58	10.64	130.76	11.25
G-DCC-Break	17.80	4.78	3.72	1.476	(0.013)	1.11	95.76	8.27	102.86	8.87
AG-DCC-Break	17.79	4.77	3.73	1.480	(0.013)	1.11	94.94	8.17	102.06	8.77
				US Sectors						
Static (Daily Rebalancing)	14.38	7.15	2.01			0.16				
Static	14.46	7.14	2.02	0.014	(0.470)	0.08	7.90	-	7.94	-
Dynamic										
EWMA	16.03	6.14	2.61	0.601	(0.182)	3.78	168.24	3.90	171.16	3.97
CCC	16.80	5.58	3.01	0.998	(0.013)	1.14	**246.54**	21.04	**250.72**	21.37
DCC	16.26	5.41	3.01	0.996	(0.031)	1.22	193.36	15.36	197.98	15.72
A-DCC	16.25	5.41	3.01	0.995	(0.031)	1.22	192.72	15.31	197.35	15.67
DCC-Break	16.20	5.39	3.00	0.993	(0.035)	1.16	187.78	15.78	192.44	16.17
A-DCC-Break	16.19	5.39	3.00	0.991	(0.035)	1.16	186.55	15.66	191.21	16.05
G-DCC	16.27	5.40	3.01	**1.002**	(0.031)	1.52	194.81	12.03	199.45	12.31
AG-DCC	15.69	5.43	2.89	0.882	(0.047)	1.41	136.86	9.17	141.46	9.47
G-DCC-Break	15.51	5.42	2.86	0.849	(0.060)	1.64	118.19	6.73	122.80	6.99
AG-DCC-Break	16.24	5.40	3.01	0.995	(0.031)	1.51	191.36	11.91	195.99	12.18

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Table 5.9 Portfolio performance for maximum return strategy (monthly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
Japanese Sectors										
Static (Daily Rebalancing)	36.63	18.35	2.00			0.71				
Static	37.34	18.61	2.01	0.010	(0.479)	0.15	68.45	-	66.78	-
Dynamic										
EWMA	61.28	26.31	2.33	0.333	(0.292)	5.47	2347.10	42.71	2256.72	40.70
CCC	46.96	19.14	2.45	0.457	(0.128)	1.69	1023.80	92.82	1016.49	90.90
DCC	46.01	18.36	2.51	0.509	(0.121)	1.92	937.12	68.18	936.30	67.38
A-DCC	46.01	18.40	2.50	0.504	(0.123)	1.93	936.33	67.86	935.24	67.06
DCC-Break	47.93	18.71	2.56	0.566	(0.114)	1.89	1123.54	84.03	1118.67	82.58
A-DCC-Break	48.02	18.69	2.57	**0.573**	(0.111)	1.89	**1132.77**	84.31	**1127.92**	82.87
G-DCC	46.09	18.73	2.46	0.465	(0.143)	2.11	941.39	59.34	937.83	58.55
AG-DCC	45.61	18.72	2.44	0.439	(0.160)	2.14	893.49	55.07	890.26	54.35
G-DCC-Break	47.98	19.16	2.50	0.508	(0.141)	1.93	1124.27	80.69	1115.97	79.02
AG-DCC-Break	47.64	19.26	2.47	0.477	(0.155)	2.02	1089.71	73.05	1080.96	71.56
UK Sectors										
Static (Daily Rebalancing)	31.44	16.54	1.90			0.28				
Static	33.05	16.49	2.00	0.103	(0.293)	0.08	162.50	-	163.38	-
Dynamic										
EWMA	51.99	19.57	2.66	0.755	(0.156)	3.99	**2006.46**	47.14	**1968.97**	45.98
CCC	39.67	12.63	3.14	1.241	(0.024)	1.08	850.52	94.98	872.61	96.77
DCC	41.94	12.54	3.34	1.442	(0.010)	1.19	1075.84	105.46	1096.37	106.68
A-DCC	42.14	12.60	3.34	**1.443**	(0.011)	1.19	1095.49	106.96	1115.52	108.10
DCC-Break	42.00	12.72	3.30	1.400	(0.015)	1.21	1080.92	103.57	1100.49	104.66
A-DCC-Break	42.28	12.79	3.31	1.404	(0.015)	1.21	1107.35	105.60	1126.32	106.59
G-DCC	42.26	12.81	3.30	1.398	(0.013)	1.23	1105.34	104.06	1124.23	105.08
AG-DCC	42.56	12.91	3.30	1.395	(0.013)	1.24	1134.78	105.80	1152.84	106.68
G-DCC-Break	42.40	13.03	3.25	1.354	(0.017)	1.25	1118.04	102.29	1135.68	103.15
AG-DCC-Break	42.55	13.08	3.25	1.352	(0.018)	1.26	1132.93	103.23	1150.13	104.03
US Sectors										
Static (Daily Rebalancing)	16.94	8.97	1.89			0.20				
Static	17.16	8.91	1.93	0.039	(0.419)	0.05	22.61	-	22.83	-
Dynamic										
EWMA	31.15	16.21	1.92	0.034	(0.453)	4.97	**1364.84**	24.92	**1320.56**	24.07
CCC	25.99	10.37	2.51	0.619	(0.085)	0.93	894.48	107.49	886.16	105.94
DCC	27.35	10.65	2.57	0.681	(0.103)	1.04	1027.95	106.72	1017.15	105.11
A-DCC	27.36	10.65	2.57	0.682	(0.103)	1.04	1028.86	106.81	1018.04	105.20
DCC-Break	27.88	10.89	2.56	0.671	(0.112)	1.04	1078.79	111.66	1066.39	109.80
A-DCC-Break	27.87	10.90	2.56	0.670	(0.113)	1.04	1078.13	111.42	1065.71	109.57
G-DCC	27.16	10.72	2.53	0.646	(0.111)	1.01	1008.40	108.60	997.49	106.78
AG-DCC	26.70	10.69	2.50	0.609	(0.125)	1.11	963.79	91.99	953.47	90.58
G-DCC-Break	27.58	10.88	2.54	0.648	(0.116)	1.20	1049.26	91.39	1037.26	89.89
AG-DCC-Break	28.43	10.89	2.61	**0.723**	(0.094)	1.17	1133.04	101.98	1120.05	100.21

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Table 5.10 Portfolio Performance for minimum variance strategy (monthly rebalancing)

Strategy	*μ*	*σ*	*SR*	*ΔSR*		*TO*	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static (Daily Rebalancing)	21.91	10.91	2.01			0.37				
Static	21.94	10.99	2.00	-0.011	(0.476)	0.09	2.66	-	2.37	-
Dynamic										
EWMA	20.07	10.52	1.91	-0.100	(0.430)	2.22	-183.18	-	-182.26	-
CCC	22.54	9.59	2.35	0.342	(0.185)	0.81	69.99	14.31	75.75	15.45
DCC	22.49	9.68	2.32	0.316	(0.222)	0.99	64.21	9.19	69.61	9.95
A-DCC	22.39	9.63	2.32	0.315	(0.222)	0.99	54.27	7.76	59.81	8.54
DCC-Break	23.06	9.71	2.38	0.367	(0.200)	0.97	**121.72**	17.95	**127.09**	18.70
A-DCC-Break	23.04	9.65	2.39	**0.379**	(0.193)	0.98	119.37	17.46	124.96	18.24
G-DCC	22.06	9.68	2.28	0.271	(0.252)	1.08	21.39	2.67	26.71	3.33
AG-DCC	21.76	9.64	2.26	0.247	(0.277)	1.11	-9.29	-	-3.94	-
G-DCC-Break	22.55	9.70	2.32	0.316	(0.234)	1.01	70.07	9.76	75.37	10.49
AG-DCC-Break	22.34	9.67	2.31	0.302	(0.242)	1.04	48.75	6.49	54.11	7.19
				UK Sectors						
Static (Daily Rebalancing)	16.92	7.53	2.25			0.13				
Static	17.42	7.49	2.33	0.079	(0.357)	0.03	50.04	-	50.26	-
Dynamic										
EWMA	16.52	5.09	3.25	0.998	(0.099)	1.05	-32.91	-	-26.67	-
CCC	18.00	4.85	3.71	1.462	(0.010)	0.41	116.26	36.75	123.24	38.89
DCC	18.52	4.76	3.89	1.642	(0.005)	0.46	**168.64**	45.82	**175.81**	47.69
A-DCC	18.51	4.75	3.89	**1.645**	(0.005)	0.46	167.52	45.55	174.70	47.43
DCC-Break	18.45	4.78	3.86	1.609	(0.008)	0.46	161.73	44.15	168.86	46.01
A-DCC-Break	18.45	4.78	3.86	1.614	(0.008)	0.46	161.76	44.19	168.90	46.06
G-DCC	18.39	4.78	3.85	1.600	(0.006)	0.46	155.46	41.82	162.59	43.67
AG-DCC	18.43	4.78	3.86	1.609	(0.006)	0.47	159.10	42.35	166.24	44.18
G-DCC-Break	18.33	4.80	3.82	1.574	(0.009)	0.46	149.59	39.95	156.69	41.78
AG-DCC-Break	18.32	4.79	3.82	1.576	(0.009)	0.47	148.60	19.97	155.71	21.37
				US Sectors						
Static (Daily Rebalancing)	14.38	7.15	2.01			0.16				
Static	14.52	7.10	2.05	0.034	(0.432)	0.04	13.97	-	14.11	-
Dynamic										
EWMA	12.96	5.94	2.18	0.172	(0.379)	1.76	-138.56	-	-135.70	-
CCC	16.01	5.62	2.85	0.836	(0.031)	0.47	**168.01**	47.03	**172.16**	48.10
DCC	15.87	5.45	2.91	0.902	(0.047)	0.51	154.68	38.57	159.23	39.65
A-DCC	15.87	5.45	2.91	0.902	(0.047)	0.51	154.19	38.46	158.74	39.54
DCC-Break	15.88	5.44	2.92	**0.907**	(0.051)	0.50	155.20	39.62	159.77	40.72
A-DCC-Break	15.87	5.44	2.92	0.906	(0.051)	0.50	154.06	39.34	158.62	40.44
G-DCC	15.73	5.43	2.90	0.886	(0.050)	0.57	140.64	30.04	145.23	30.97
AG-DCC	15.56	5.46	2.85	0.839	(0.057)	0.57	123.62	26.35	128.14	27.29
G-DCC-Break	15.67	5.45	2.87	0.864	(0.059)	0.62	134.52	25.81	139.06	26.64
AG-DCC-Break	15.71	5.43	2.89	0.883	(0.050)	0.57	138.77	29.57	143.35	30.50

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Reducing the rebalancing frequency increases considerably the mean return of the dynamic portfolios, while the increases in portfolio volatility are negligible. This trade-off leads to enhanced risk-adjusted performance when rebalancing less frequently. Our findings are in line with Fleming et al (2003) and De Pooter et al (2008).[307] Investors are prepared to pay higher *PFs* in favour of the dynamic strategy when rebalancing less often. Correlation timing with weekly or monthly rebalancing generate *PF*s ranging from 688 bp to 2410 bp (Max-R) a notable increase from 554 bp to 1892 bp for daily rebalancing.[308]

Furthermore, the decrease in the *TO* rate when switching from daily rebalancing to weekly or monthly is quite dramatic, thereby substantially benefiting the post-transaction cost performance of the dynamic strategies. The *TO* of weekly dynamic portfolios is less than half the trading volume of the daily portfolios (Tables 5.7 and 5.8), while revising the dynamic portfolios on a monthly basis (Tables 5.9 and 5.10) reduces the *TO* even further to less than a quarter of the turnover of the daily portfolios. For instance, in the US/Japanese sector portfolios, the daily dynamic portfolio based on the CCC model has a *TO* rate of 4.75/8.68 under Max-R whereas the *TO* rate of the corresponding weekly and monthly portfolios is only 2.21/4.04 and 0.93/ 1.69, respectively.

As a result, the *BTC*s per trade with a lower rebalancing frequency are substantially higher, which implies that dynamic portfolios are more likely to maintain post-transaction cost benefits over the static benchmark if they are revised less frequently. Weekly rebalancing correlation timing is only feasible within the US market. However, as borne

[307] De Pooter et al (2008) assess the impact of rebalancing frequency on the performance of dynamic portfolios and find that lower frequencies are preferable in terms of utility-based performance fees investors are willing to pay to switch from daily to weekly or monthly rebalancing. In addition, they find that a lower rebalancing frequency emphasizes more the benefits of using intraday data for covariance matrix estimation.
[308] Della Corte et al (2010) explore monthly and weekly rebalancing in the context of correlation timing. However, the lower rebalancing frequency also means lower sampling frequency. In essence, for monthly rebalancing they re-sample the data at lower frequency and use monthly information to estimate the covariance matrix. They find that dynamic strategies are poor performers at low rebalancing frequencies and attribute this to the diminishing persistence of correlation and volatilities as investors move from daily to monthly or weekly frequencies.

out in Table 5.9 (Max-R) monthly rebalancing generates *BTC*s that are markedly above realistic levels of transaction costs pointing towards the use of dynamic strategies in all markets. Depending on the model and risk-aversion level, the *BTC*s generated by portfolios based on conditional correlation models range from 40 bp to 111 bp per trade. Monthly Min-V correlation timing (Table 5.10) is feasible for US based investors and although not convincingly above the quite high realistic levels of transaction costs for UK and Japan, the improvement is noticeable. In contrast the EWMA fails to beat the static strategy by providing *BTCs* that are higher than the realistic level of transaction costs.

In summary, conditional correlation models outperform the industry standard EWMA model when transaction costs are brought into the picture. The longer holding period not only entails a much higher *BTC* per trade for the dynamic strategies relative to the static, thus making the strategies more feasible but also their outperformance of the dynamic strategies relative to the static benchmark becomes typically more pronounced. In order to more directly evaluate the effect of rebalancing frequency on the dynamic investment strategies we compute for a given model the maximum return an investor is willing to forfeit to switch from daily to weekly and monthly rebalancing. Table 5.11 presents these performance fees for each strategy/model and level of investor risk-aversion.

Table 5.11 Performance of weekly/monthly relative to daily rebalancing frequency

Dynamic Strategy	Weekly Rebalancing Portfolio						Monthly Rebalancing Portfolio					
	Japan		UK		US		Japan		UK		US	
Model	$PF_{\gamma=1}$	$PF_{\gamma=10}$	$PF_{\gamma=1}$	$PF_{\gamma=10}$	$PF_{\gamma=1}$	$PF_{\gamma=10}$	$PF_{\gamma=1}$	$PF_{\gamma=10}$	$PF_{\gamma=1}$	$PF_{\gamma=10}$	$PF_{\gamma=1}$	$PF_{\gamma=10}$
Panel A. Maximum return target variance												
EWMA	636.46	636.17	365.91	368.93	341.09	395.47	571.29	568.31	791.00	795.43	-190.84	-190.46
CCC	401.86	401.74	147.91	147.58	20.84	42.56	371.98	366.47	311.80	310.97	-43.90	-44.84
DCC	438.11	437.56	113.15	112.90	71.57	115.93	348.15	342.71	259.49	258.33	107.17	128.47
A-DCC	459.27	458.62	118.63	118.37	71.47	115.90	386.67	381.17	268.73	267.54	107.23	128.59
DCC-Break	519.24	518.30	164.19	163.96	75.56	123.14	446.87	440.67	384.71	383.36	130.13	153.63
A-DCC-Break	519.63	518.71	169.71	169.46	78.87	126.54	458.51	452.61	395.10	393.71	133.11	156.69
G-DCC	427.81	429.18	139.96	139.64	148.59	171.45	255.28	250.95	340.54	339.31	186.69	186.34
AG-DCC	114.49	113.23	81.91	81.34	181.32	204.17	76.61	70.33	278.53	277.26	273.44	273.37
G-DCC-Break	642.49	641.24	156.77	156.44	88.51	112.51	516.94	510.44	376.75	375.43	204.94	204.90
AG-DCC-Break	314.41	313.39	155.21	154.93	56.52	80.45	138.05	130.24	419.46	417.98	141.34	140.99
Panel B. Minimum variance target return												
EWMA	151.96	152.56	21.98	22.08	48.60	48.66	69.52	71.87	75.91	76.31	-258.84	-259.46
CCC	157.86	158.17	33.99	33.93	-10.98	-11.05	182.03	182.28	46.99	46.98	-89.87	-90.28
DCC	178.89	179.09	25.10	25.02	1.06	6.41	168.52	168.59	41.42	41.33	-37.75	-32.58
A-DCC	194.71	194.93	26.66	26.58	1.02	6.39	193.45	193.51	44.51	44.39	-37.64	-32.46
DCC-Break	201.75	201.88	36.73	36.66	-2.62	3.02	193.02	193.12	76.91	76.87	-35.30	-29.85
A-DCC-Break	205.16	205.30	38.24	38.17	-0.80	4.85	203.18	203.29	80.22	80.18	-33.40	-27.94
G-DCC	175.23	175.66	31.90	31.82	-4.57	-4.56	95.09	95.26	69.92	69.85	-58.94	-59.15
AG-DCC	11.31	11.29	14.26	14.11	34.18	34.31	39.70	39.57	49.90	49.77	20.86	20.94
G-DCC-Break	253.17	253.26	26.44	26.35	-95.89	-96.09	211.77	211.88	80.34	80.31	-79.51	-79.71
AG-DCC-Break	165.43	165.80	27.40	27.32	30.90	30.97	66.63	66.74	81.12	81.11	-21.89	-21.95

Note: The table reports for each model the performance fee, in annualized basis points, an investor is willing to pay to switch from weekly/monthly to daily rebalancing.

The results suggest that dynamic portfolios with lower rebalancing frequency (*i.e.* weekly or monthly) outperform their daily counterparts by generating positive *PFs* regardless the risk-aversion levels. This finding is in line with De Pooter et al (2008). For the Max-R strategy we find that the *PF* for switching from daily to weekly/monthly rebalancing is between 20 bp - 795 bp for sector investors with different risk-aversions, while for the Min-V strategy *PF*s are lower but still largely positive. The only exception come from the US market where the gains of conditional correlation models seem to be more pronounced for daily rebalancing, especially under Min-V. By comparing the risk-return performances of daily and weekly/monthly US sector portfolios under Min-V (Table 5.6 and 5.8/5.10), one can see that the negative *PFs* generated by the weekly/monthly portfolios over their daily counterparts are mainly due to the decrease in portfolio returns when rebalancing less frequently.

However, from Tables 5.7 to 5.10, one can see that static portfolios also benefit from reducing the rebalancing frequency as their dynamic rivals. For instance, the *TO* of Japanese static portfolio under Max-R has decreased from 0.71 (daily rebalancing) to 0.31/0.15 (weekly/monthly rebalancing). Besides, the risk-adjusted reward (*i.e. SR*) of the static portfolio has increased as well when rebalancing less often. For instance, the *SR* of the static portfolio in the UK market under Min-V is 2.25 when rebalancing on a daily basis, while the *SR* of the weekly and monthly static portfolio is 2.30 and 2.33, respectively.

Our findings are in line with Fleming et al (2003), who argue that both static and dynamic portfolios benefit from longer revision interval. Therefore, the relative performance of the dynamic strategies over their static rival with the same rebalancing frequency is unclear. Tables 5.12 to 5.15 summarize the performance evaluation of the dynamic verse the static portfolio with the same weekly/monthly rebalancing frequency under the Max-R/Min-V portfolio construction scheme.

Table 5.12 Portfolio performance for maximum return strategy (weekly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static	38.19	18.38	2.08			0.31				
Dynamic										
EWMA	61.89	26.06	2.38	0.297	(0.321)	12.16	**2259.83**	15.98	**2174.41**	15.31
CCC	47.19	18.45	2.56	0.480	(0.130)	4.04	899.28	20.22	898.51	20.12
DCC	46.85	17.72	2.64	0.566	(0.111)	4.47	872.06	17.59	876.75	17.64
A-DCC	46.68	17.75	2.63	0.551	(0.116)	4.52	854.09	17.02	858.64	17.07
DCC-Break	48.59	18.01	2.70	0.620	(0.102)	4.29	1041.41	21.96	1042.82	21.93
A-DCC-Break	48.57	18.03	2.69	0.616	(0.102)	4.31	1039.52	21.78	1040.79	21.74
G-DCC	47.75	18.02	2.65	0.572	(0.110)	5.19	957.97	16.45	959.96	16.43
AG-DCC	45.93	18.09	2.54	0.460	(0.164)	5.24	776.46	13.24	778.95	13.25
G-DCC-Break	49.17	18.45	2.66	0.587	(0.114)	4.75	1094.98	20.67	1092.69	20.57
AG-DCC-Break	49.32	18.47	2.67	**0.592**	(0.111)	4.93	1109.64	20.18	1107.07	20.09
				UK Sectors						
Static	32.83	16.51	1.99			0.16				
Dynamic										
EWMA	47.75	19.81	2.41	0.421	(0.274)	8.68	**1454.01**	14.17	**1423.69**	13.83
CCC	38.03	12.45	3.05	1.064	(0.049)	2.60	549.68	18.74	574.13	19.54
DCC	40.47	12.28	3.30	**1.308**	(0.020)	2.81	793.66	24.89	817.84	25.59
A-DCC	40.63	12.34	3.29	1.305	(0.021)	2.82	809.69	25.27	833.47	25.95
DCC-Break	39.79	12.42	3.20	1.214	(0.031)	2.82	724.99	22.65	748.85	23.34
A-DCC-Break	40.01	12.49	3.20	1.215	(0.032)	2.83	746.73	23.19	770.13	23.86
G-DCC	40.24	12.54	3.21	1.221	(0.027)	2.88	769.45	23.49	792.47	24.13
AG-DCC	40.59	12.65	3.21	1.220	(0.028)	2.86	803.19	24.70	825.44	25.31
G-DCC-Break	40.19	12.75	3.15	1.164	(0.036)	2.91	762.90	23.08	784.89	23.69
AG-DCC-Break	39.90	12.76	3.13	1.137	(0.041)	2.90	733.91	22.27	755.98	22.89
				US Sectors						
Static	17.10	8.96	1.91			0.10				
Dynamic										
EWMA	35.80	16.55	2.16	0.254	(0.340)	10.70	**1835.88**	14.22	**1810.22**	13.74
CCC	26.36	10.23	2.58	**0.667**	(0.069)	2.21	916.83	36.42	910.27	36.03
DCC	26.71	10.49	2.55	0.637	(0.114)	2.44	951.62	34.13	944.56	33.75
A-DCC	26.72	10.49	2.55	0.637	(0.114)	2.44	952.36	34.15	945.29	33.77
DCC-Break	27.04	10.69	2.53	0.619	(0.127)	2.37	983.63	36.31	976.10	35.87
A-DCC-Break	27.03	10.70	2.53	0.618	(0.128)	2.37	983.32	36.21	975.79	35.77
G-DCC	26.49	10.54	2.51	0.604	(0.125)	2.40	930.10	33.88	923.34	33.46
AG-DCC	25.50	10.56	2.42	0.507	(0.163)	2.58	832.83	28.06	827.39	27.69
G-DCC-Break	26.12	10.75	2.43	0.520	(0.167)	3.03	893.72	25.43	887.47	25.09
AG-DCC-Break	27.28	10.71	2.55	0.638	(0.120)	2.92	1007.99	29.83	1000.03	29.41

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Table 5.13 Portfolio Performance for minimum variance strategy (weekly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static	22.52	10.92	2.06			0.18				
Dynamic										
EWMA	20.92	10.94	1.91	-0.151	(0.403)	4.89	-160.91	-	-161.73	-
CCC	22.30	9.58	2.33	0.266	(0.254)	1.97	-14.61	-	-8.97	-
DCC	22.59	9.66	2.34	0.277	(0.264)	2.33	14.25	0.56	19.67	0.77
A-DCC	22.40	9.61	2.33	0.269	(0.269)	2.34	-4.81	-	0.73	0.03
DCC-Break	23.15	9.71	2.39	0.323	(0.240)	2.23	70.18	2.88	75.51	3.09
A-DCC-Break	23.06	9.65	2.39	0.327	(0.237)	2.24	61.06	2.50	66.60	2.72
G-DCC	22.86	9.64	2.37	0.308	(0.241)	2.72	41.37	1.37	46.88	1.55
AG-DCC	21.47	9.60	2.24	0.175	(0.348)	2.75	-98.15	-	-92.95	-
G-DCC-Break	22.96	9.71	2.36	0.302	(0.256)	2.56	51.27	1.81	56.54	2.00
AG-DCC-Break	23.32	9.64	2.42	**0.356**	(0.219)	2.57	**87.30**	3.07	**92.92**	3.27
				UK Sectors						
Static	17.29	7.51	2.30			0.07				
Dynamic										
EWMA	15.99	5.23	3.06	0.753	(0.153)	2.25	-123.69	-	-118.12	-
CCC	17.87	4.86	3.68	1.374	(0.016)	1.02	66.57	5.90	73.42	6.50
DCC	18.36	4.74	3.87	**1.572**	(0.008)	1.11	**115.68**	9.33	**122.83**	9.90
A-DCC	18.33	4.73	3.87	1.572	(0.008)	1.11	113.05	9.14	120.21	9.71
DCC-Break	18.05	4.76	3.79	1.490	(0.013)	1.10	84.91	6.96	91.99	7.54
A-DCC-Break	18.04	4.75	3.79	1.491	(0.013)	1.10	83.14	6.83	90.23	7.41
G-DCC	18.01	4.75	3.79	1.489	(0.011)	1.12	80.80	6.49	87.89	7.06
AG-DCC	18.07	4.75	3.80	1.502	(0.011)	1.11	86.88	7.03	93.98	7.60
G-DCC-Break	17.80	4.78	3.72	1.422	(0.016)	1.11	59.04	4.79	66.05	5.35
AG-DCC-Break	17.79	4.77	3.73	1.426	(0.017)	1.11	58.22	4.70	65.25	5.27
				US Sectors						
Static	14.46	7.14	2.02			0.08				
Dynamic										
EWMA	16.03	6.14	2.61	0.587	(0.186)	3.78	160.37	3.64	163.26	3.70
CCC	16.80	5.58	3.01	0.984	(0.014)	1.14	**238.64**	18.87	**242.84**	19.19
DCC	16.26	5.41	3.01	0.982	(0.033)	1.22	185.49	13.72	190.09	14.06
A-DCC	16.25	5.41	3.01	0.981	(0.033)	1.22	184.85	13.67	189.45	14.01
DCC-Break	16.20	5.39	3.00	0.979	(0.037)	1.16	179.91	14.03	184.55	14.39
A-DCC-Break	16.19	5.39	3.00	0.977	(0.037)	1.16	178.68	13.92	183.32	14.28
G-DCC	16.27	5.40	3.01	**0.988**	(0.033)	1.52	186.94	10.92	191.56	11.18
AG-DCC	15.69	5.43	2.89	0.868	(0.049)	1.41	128.99	8.14	133.56	8.42
G-DCC-Break	15.51	5.42	2.86	0.835	(0.063)	1.64	110.31	5.96	114.89	6.21
AG-DCC-Break	16.24	5.40	3.01	0.981	(0.033)	1.51	183.49	10.79	188.10	11.06

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion γ = {1, 10} would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

Table 5.14 Portfolio performance for maximum return strategy (monthly rebalancing)

Strategy	μ	σ	SR	ΔSR		TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
				Japanese Sectors						
Static	37.34	18.61	2.01			0.15				
Dynamic										
EWMA	61.28	26.31	2.33	0.322	(0.298)	5.47	**2281.37**	37.16	**2194.39**	35.57
CCC	46.96	19.14	2.45	0.447	(0.133)	1.69	956.51	54.21	951.73	53.73
DCC	46.01	18.36	2.51	0.499	(0.127)	1.92	869.78	42.71	871.38	42.64
A-DCC	46.01	18.40	2.50	0.494	(0.129)	1.93	868.98	42.56	870.32	42.49
DCC-Break	47.93	18.71	2.56	0.556	(0.119)	1.89	1056.40	52.89	1054.12	52.57
A-DCC-Break	48.02	18.69	2.57	**0.562**	(0.115)	1.89	1065.65	53.18	1063.39	52.86
G-DCC	46.09	18.73	2.46	0.454	(0.148)	2.11	874.05	38.89	872.92	38.73
AG-DCC	45.61	18.72	2.44	0.429	(0.166)	2.14	826.09	36.16	825.25	36.01
G-DCC-Break	47.98	19.16	2.50	0.498	(0.146)	1.93	1057.13	51.48	1051.41	50.98
AG-DCC-Break	47.64	19.26	2.47	0.467	(0.160)	2.02	1022.54	47.51	1016.33	47.02
				UK Sectors						
Static	33.05	16.49	2.00			0.08				
Dynamic										
EWMA	51.99	19.57	2.66	0.652	(0.190)	3.99	**1849.17**	40.98	**1814.69**	40.05
CCC	39.67	12.63	3.14	1.138	(0.035)	1.08	690.05	59.55	712.98	61.39
DCC	41.94	12.54	3.34	1.339	(0.016)	1.19	915.94	71.43	937.87	72.96
A-DCC	42.14	12.60	3.34	**1.339**	(0.016)	1.19	935.65	72.74	957.12	74.22
DCC-Break	42.00	12.72	3.30	1.297	(0.022)	1.21	921.04	70.53	942.02	71.95
A-DCC-Break	42.28	12.79	3.31	1.301	(0.022)	1.21	947.55	72.29	967.98	73.65
G-DCC	42.26	12.81	3.30	1.294	(0.019)	1.23	945.53	71.40	965.87	72.76
AG-DCC	42.56	12.91	3.30	1.292	(0.020)	1.24	975.05	73.07	994.62	74.34
G-DCC-Break	42.40	13.03	3.25	1.251	(0.025)	1.25	958.25	70.73	977.38	71.96
AG-DCC-Break	42.55	13.08	3.25	1.248	(0.026)	1.26	973.19	71.59	991.90	72.78
				US Sectors						
Static	17.16	8.91	1.93			0.05				
Dynamic										
EWMA	31.15	16.21	1.92	-0.005	(0.474)	4.97	**1342.78**	23.76	**1298.60**	22.95
CCC	25.99	10.37	2.51	0.580	(0.098)	0.93	872.23	86.47	863.90	85.48
DCC	27.35	10.65	2.57	0.643	(0.115)	1.04	1005.75	88.27	994.98	87.18
A-DCC	27.36	10.65	2.57	0.643	(0.115)	1.04	1006.66	88.35	995.87	87.26
DCC-Break	27.88	10.89	2.56	0.633	(0.125)	1.04	1056.62	92.51	1044.26	91.25
A-DCC-Break	27.87	10.90	2.56	0.631	(0.126)	1.04	1055.96	92.34	1043.58	91.07
G-DCC	27.16	10.72	2.53	0.607	(0.124)	1.01	986.19	89.28	975.31	88.06
AG-DCC	26.70	10.69	2.50	0.571	(0.139)	1.11	941.57	76.93	931.26	75.93
G-DCC-Break	27.58	10.88	2.54	0.609	(0.129)	1.20	1027.08	77.57	1015.10	76.49
AG-DCC-Break	28.43	10.89	2.61	**0.685**	(0.105)	1.17	1110.89	86.34	1097.96	85.08

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position

Table 5.15 Portfolio Performance for minimum variance strategy (monthly rebalancing)

Strategy	μ	σ	SR	ΔSR	TO	$PF_{\gamma=1}$	$BTC_{\gamma=1}$	$PF_{\gamma=10}$	$BTC_{\gamma=10}$
Japanese Sectors									
Static	21.94	10.99	2.00		0.09				
Dynamic									
EWMA	20.07	10.52	1.91	-0.089 (0.438)	2.22	-185.85	-	-184.59	-
CCC	22.54	9.59	2.35	0.354 (0.177)	0.81	67.34	8.17	73.44	8.90
DCC	22.49	9.68	2.32	0.327 (0.214)	0.99	61.55	5.96	67.29	6.50
A-DCC	22.39	9.63	2.32	0.327 (0.214)	0.99	51.61	4.99	57.50	5.55
DCC-Break	23.06	9.71	2.38	0.379 (0.193)	0.97	**119.06**	11.76	**124.78**	12.31
A-DCC-Break	23.04	9.65	2.39	**0.390** (0.186)	0.98	116.71	11.46	122.65	12.03
G-DCC	22.06	9.68	2.28	0.282 (0.243)	1.08	18.73	1.65	24.40	2.14
AG-DCC	21.76	9.64	2.26	0.259 (0.269)	1.11	-11.96	-	-6.26	-
G-DCC-Break	22.55	9.70	2.32	0.327 (0.226)	1.01	67.41	6.40	73.06	6.94
AG-DCC-Break	22.34	9.67	2.31	0.313 (0.234)	1.04	46.09	4.24	51.83	4.76
UK Sectors									
Static	17.42	7.49	2.33		0.03				
Dynamic									
EWMA	16.52	5.09	3.25	0.919 (0.118)	1.05	-83.00	-	-77.05	-
CCC	18.00	4.85	3.71	1.383 (0.014)	0.41	66.30	15.25	73.10	16.80
DCC	18.52	4.76	3.89	1.563 (0.008)	0.46	**118.73**	24.41	**125.76**	25.85
A-DCC	18.51	4.75	3.89	**1.566** (0.008)	0.46	117.60	24.19	124.65	25.63
DCC-Break	18.45	4.78	3.86	1.530 (0.011)	0.46	111.82	23.07	118.80	24.50
A-DCC-Break	18.45	4.78	3.86	1.535 (0.011)	0.46	111.85	23.09	118.85	24.52
G-DCC	18.39	4.78	3.85	1.521 (0.009)	0.46	105.53	21.54	112.53	22.95
AG-DCC	18.43	4.78	3.86	1.530 (0.009)	0.47	109.18	22.11	116.18	23.51
G-DCC-Break	18.33	4.80	3.82	1.495 (0.012)	0.46	99.66	20.23	106.61	21.62
AG-DCC-Break	18.32	4.79	3.82	1.497 (0.012)	0.47	98.67	19.98	105.63	21.37
US Sectors									
Static	14.52	7.10	2.05		0.04				
Dynamic									
EWMA	12.96	5.94	2.18	0.138 (0.397)	1.76	-152.57	-	-149.92	-
CCC	16.01	5.62	2.85	0.802 (0.036)	0.47	**154.07**	30.97	**158.08**	31.76
DCC	15.87	5.45	2.91	0.868 (0.053)	0.51	140.75	26.00	145.15	26.80
A-DCC	15.87	5.45	2.91	0.868 (0.053)	0.51	140.25	25.92	144.65	26.72
DCC-Break	15.88	5.44	2.92	**0.874** (0.056)	0.50	141.27	26.56	145.69	27.37
A-DCC-Break	15.87	5.44	2.92	0.872 (0.057)	0.50	140.12	26.34	144.54	27.16
G-DCC	15.73	5.43	2.90	0.852 (0.056)	0.57	126.70	20.82	131.14	21.54
AG-DCC	15.56	5.46	2.85	0.805 (0.063)	0.57	109.67	18.00	114.04	18.71
G-DCC-Break	15.67	5.45	2.87	0.830 (0.065)	0.62	120.57	18.23	124.96	18.88
AG-DCC-Break	15.71	5.43	2.89	0.849 (0.056)	0.57	124.82	20.48	129.26	21.20

Note: The table reports the annualised mean return (%μ), standard deviation (%σ) and Sharpe Ratio (SR) of portfolios based on static constant covariance matrix and dynamic covariance forecasting models. The Sharpe Ratio differential (ΔSR) and p-value are also reported for the null hypothesis of equality of Sharpe Ratios (SR) between the static strategy and a given dynamic covariance strategy against the alternative that the dynamic strategy has a higher SR. A significantly positive (negative) t-statistic indicates that the SR of the dynamic strategy is higher (lower) than that of the static strategy. Performance Fee (PFγ) is the average annualized fee in basis points (bp) an investor with quadratic utility and constant relative risk-aversion $\gamma = \{1, 10\}$ would be willing to pay to switch from the static to a dynamic covariance strategy. Bold indicates the model that yields the highest metric relative to the static strategy. Break-even Transaction Cost (BTCγ) is the minimum average cost per trade (i.e. monthly bps) that renders the investor is indifferent between the static and the dynamic strategy at hand. TO is the average monthly turnover volume of the portfolio total position.

The results suggest that dynamic portfolios are able to outperform static ones even both are rebalanced at a lower frequency (*i.e.* weekly/monthly) as the former still enjoys positive *PFs* over the latter in most cases regardless the risk aversion level of the investor and portfolio construction strategies. However, due to the enhanced risk-return performances of the static strategy with lower rebalancing frequency, the magnitude of positive *PFs* enjoyed by dynamic portfolios in Tables 5.12 to 5.15 is comparatively lower than the ones in Tables 5.7 to 5.10. For instance, in the UK market, the *PF* earned by the monthly dynamic portfolio based on AG-DCC-Break over daily static portfolio is 1132 bp for investor with lower risk aversion (*i.e.* $\gamma = 1$) under Max-R (Table 5.9), while the *PF* over monthly static portfolio is only 973 bp for the same investor (Table 5.14). Additionally, since the *TO* of the static portfolio also decreased when rebalancing less often, the *BTC* of the dynamic portfolio also decreases in Tables 5.12 to 5.15 compared to the one in Tables 5.7 to 5.10. For instance, the weekly US dynamic portfolio based on CCC under Min-V is able to generate 21 bp *BTC* over the static strategy when the latter is daily rebalanced (Table 5.8), while the figure drops to around 19 bp when the static portfolio is also rebalanced on a weekly basis (Table 5.13).

However, despite the drop in *BTCs* when comparing dynamic portfolios verse static ones with the same rebalancing frequency, the former is still able to bring benefits to investors when realistic level of transaction costs are taking into account. As borne out in Table 5.14, the *BTCs* generated by monthly dynamic strategies under Max-R are noticeably higher than realistic levels of transaction costs in all markets. Besides, weekly dynamic portfolios based on the US sector indices (Table 5.12) can also generate sufficient amount of *BTCs* (ranging from 25 bp to 36 bp), which are reasonably higher than the transaction cost facing by investors under realistic conditions. Similar to findings from Tables 5.7 to

5.10, the EWMA fails to beat the static strategy with the same rebalancing frequency by providing *BTCs* which are higher than the realistic level.

5.5.5. ***Robustness Tests***

In this section, we conduct two robustness checks of the relative performance of dynamic correlation strategies vis-à-vis the static strategy. First, we address whether the value added over the constant covariance strategy is sensitive to portfolio construction strategies (*i.e.* Max-R or Min-V) by comparing the efficient frontier of the dynamic and static strategies over the out-of-sample period. The efficient frontier based on ex-post unconditional variance-covariance matrices is also produced as the optimal frontier the best correlation timing strategy can ever achieve. Second, we investigate whether the superior performance of dynamic portfolios is sensitive to different target return and variance settings by comparing the risk-return efficiency (*i.e. SR*) of the dynamic portfolios under both Max-R and Min-V scheme against the capital market line (CML) based on the static benchmark.

Although both robustness tests involve the efficient frontier of dynamic and static strategies, their motivation and purpose are different.[309] The first test is effectively assessing the variance-covariance forecast accuracy of the dynamic and static strategies. Engle and Colacito (2006) show that portfolio based on more accurate variance-covariance forecast provides lower volatility. That means the portfolio based on more accurate variance-covariance forecasts should have a higher efficient frontier compared to portfolios based on less accurate forecasts, as the former can provide the same expected return with lower portfolio variance. Therefore, one can inspect the forecast accuracy of

[309] One could argue that the second robustness test also involves the efficient frontier of static strategy as the CML is derived based on risk-free rate and efficient frontier.

different correlation timing strategies visually. The second robustness test is focusing on the sensitivity of dynamic and static portfolios' risk-return efficiency under different target return and variance levels. Although it can be seen as another way to investigate the accuracy of the variance-covariance forecast by different strategies, the main emphasis of the two tests is different. The second test concerns the asset allocation implication of the variance-covariance forecast accuracy, but not the accuracy itself. It may be intuitive that asset allocation strategy triggered by more accurate variance-covariance forecast should perform better under Max-R/Min-V regardless the target return/variance settings. However, the conclusion cannot be draw until proper empirical analysis is conducted. Therefore, the two robustness tests are not over-lapped as they focus on different aspects of the various correlation timing strategies.

In order to carry out the first robustness test, we track the efficient frontier of all strategies using the one-day ahead variance-covariance forecasts based on a given strategy and a set of target returns.[310] For each target return, the realized daily portfolio volatility is generated based on the weighting scheme derived from the variance-covariance forecast together with the ex-post return vector and ex-post variance-covariance matrix over the out-of-sample period.[311] The target return setting of these daily efficient frontiers is constant, while the realized daily portfolio volatility for each target return on the frontier may vary as the weighting scheme may vary on a daily basis. Finally, we average the realized daily portfolio volatilities for each target return over the out-of-sample period and plot these pair-wised target returns and average realized daily volatilities into an

[310] We employed 20 target returns in the current study. These target returns are equally distributed between the lower and upper limit of the efficient frontier.

[311] The ex-post return vector is generated by averaging the daily return vector of sector indices over the out-of-sample period ($r = \Sigma r_t/n$; n is number of trading days over the out-of-sample period), while the ex-post variance-covariance matrix is derived from the daily realized variance-covariance matrix over the out-of-sample period ($H_t = \Sigma h_t/n$; $h_t = r_t r_t'$).

aggregated efficient frontier. We also produce the efficient frontier based on weighting scheme derived from the ex-post variance-covariance matrix as an alternative benchmark to evaluate the performance of dynamic correlation timing strategies. The ex-post efficient frontier represents the best possible efficient frontier a correlation timing strategy can achieve.

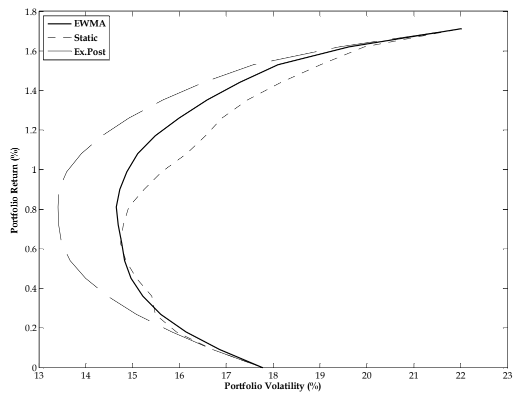
The estimated efficient frontiers of both the static and dynamic strategies are presented in Figure 5.5. In each graph, the ex-post efficient frontier (dashed line) is plotted together with the efficient frontier of the static strategy (dotted line) and the one of the dynamic strategy (solid line). The portfolio returns and volatilities are in annualized percentage figures.

Figure 5.5 Comparison of Efficient frontier based on Dynamic and Static Models

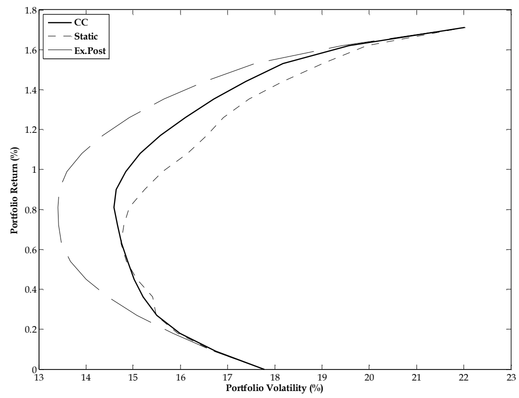
The graphs below illustrate the aggregated efficient frontier of dynamic and static strategies over the out-of-sample period. In each graph, the aggregated efficient frontier of a given dynamic portfolio (solid line) is plotted together with the static (dotted line) and ex-post (dash line) efficient frontier.

Panel A: Aggregated efficient frontier for Japanese sector portfolios

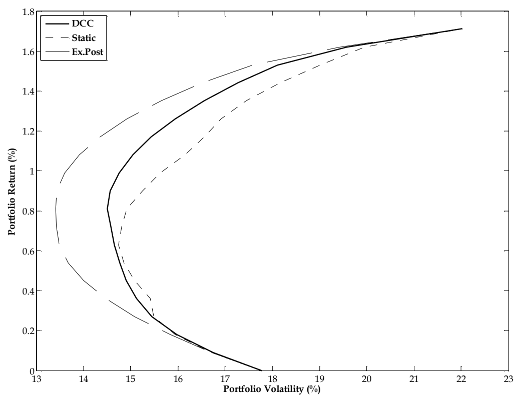
EWMA



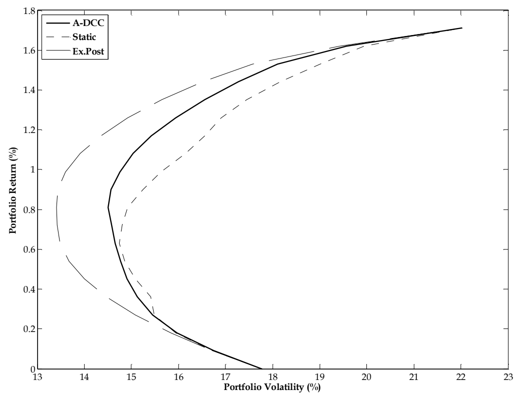
CCC



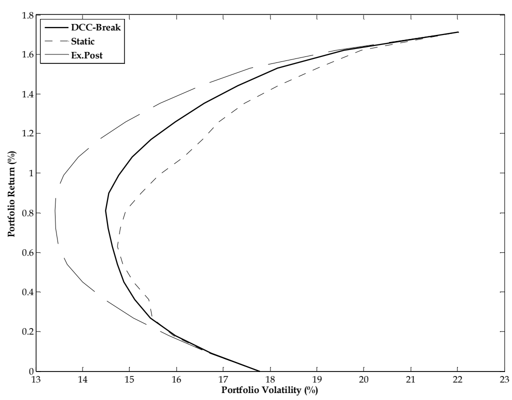
DCC



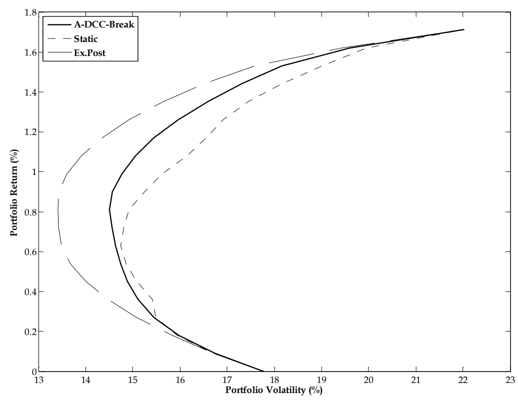
A-DCC



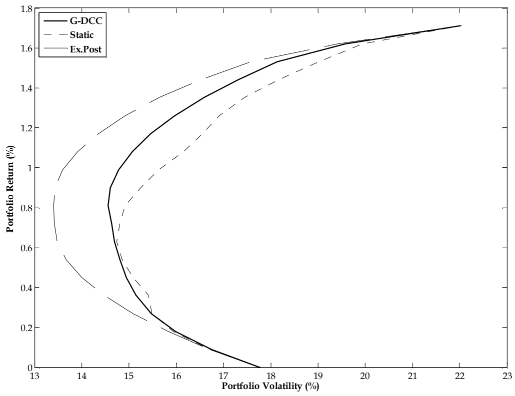
DCC-Break



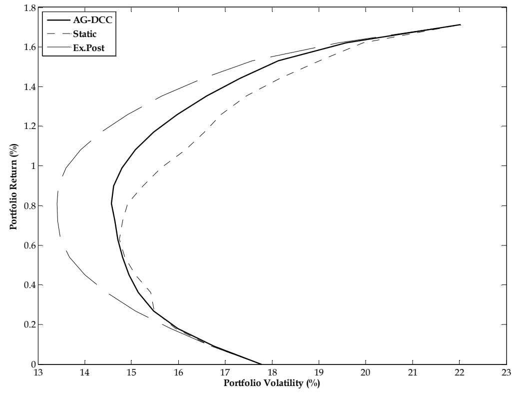
A-DCC-Break



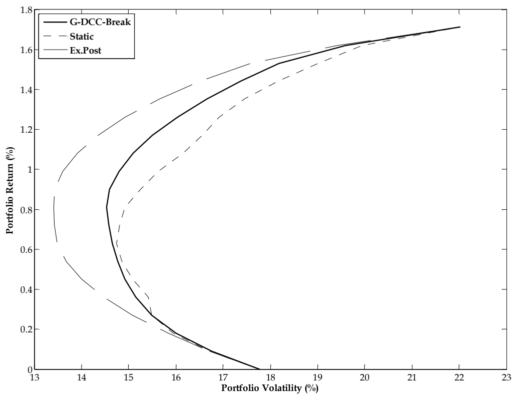
G-DCC



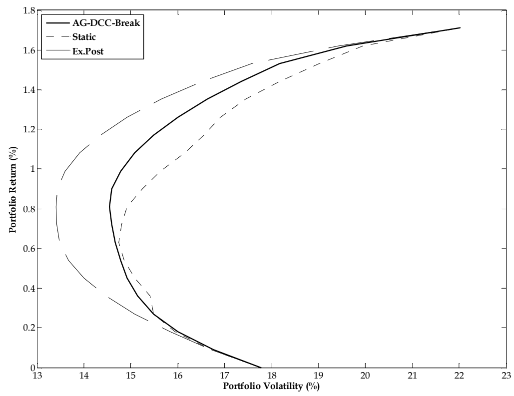
AG-DCC



G-DCC-Break

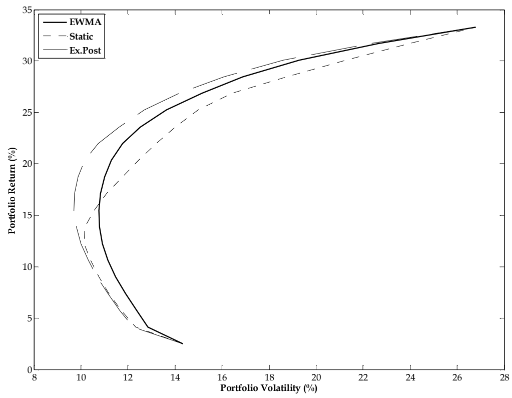


AG-DCC-Break

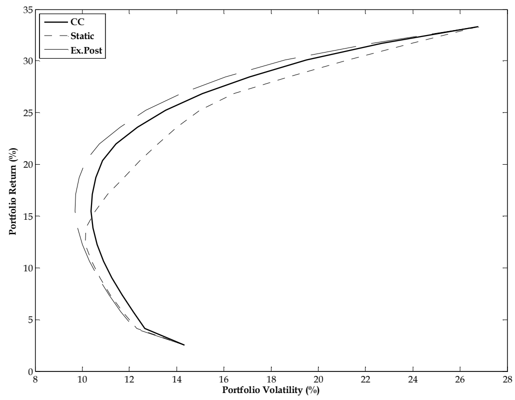


Panel B: Aggregated efficient frontier for the UK sector portfolios

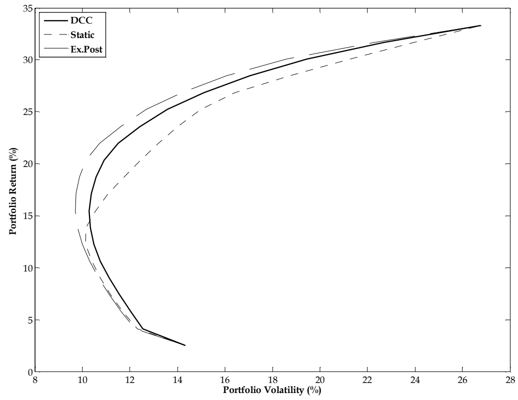
EWMA



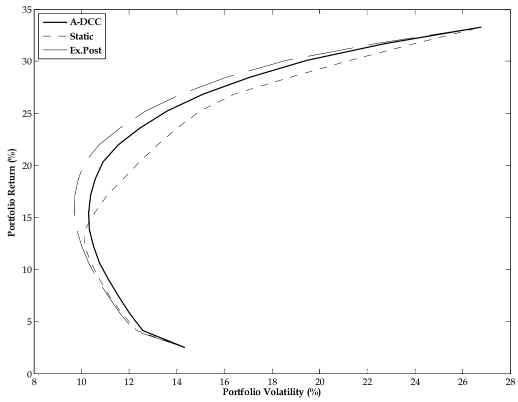
CCC



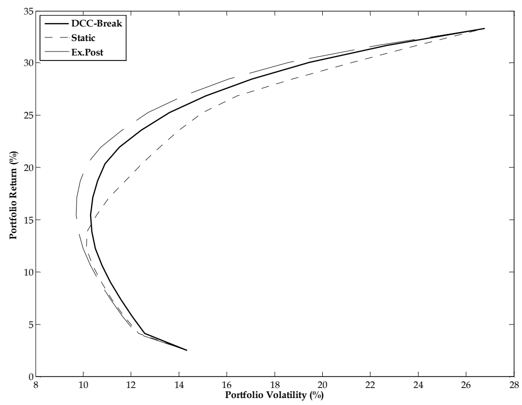
DCC



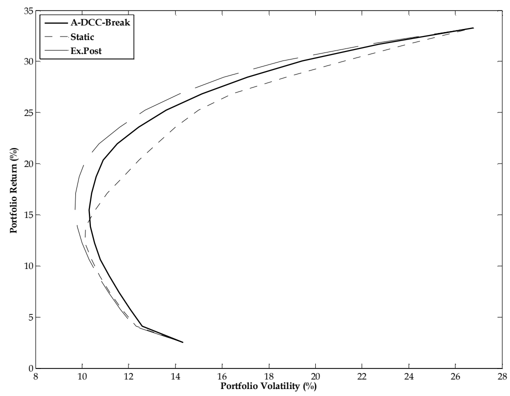
A-DCC



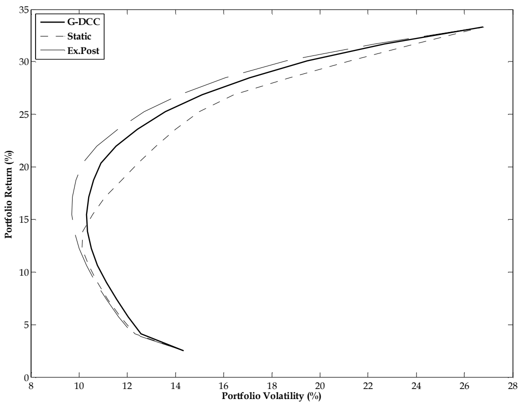
DCC-Break



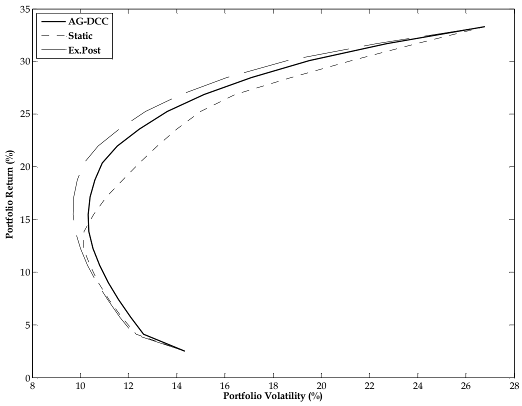
A-DCC-Break



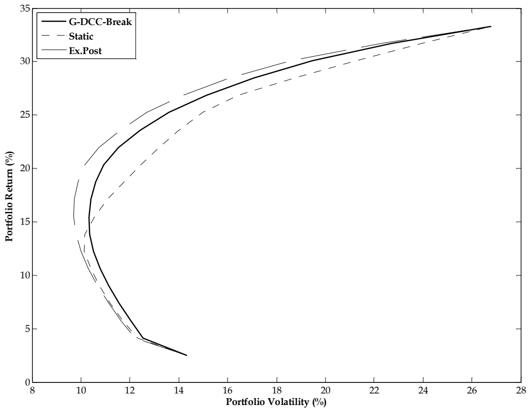
G-DCC



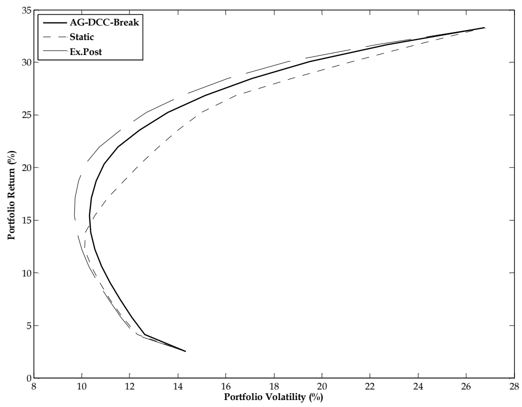
AG-DCC



G-DCC-Break

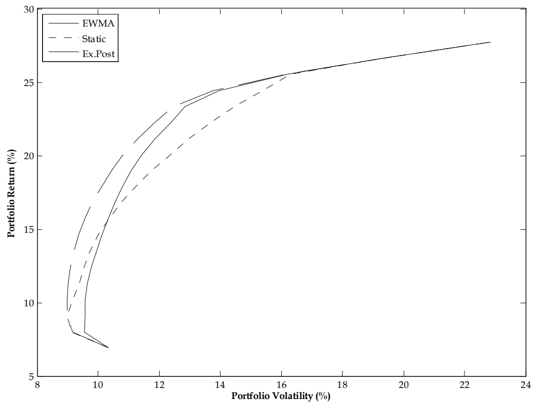


AG-DCC-Break

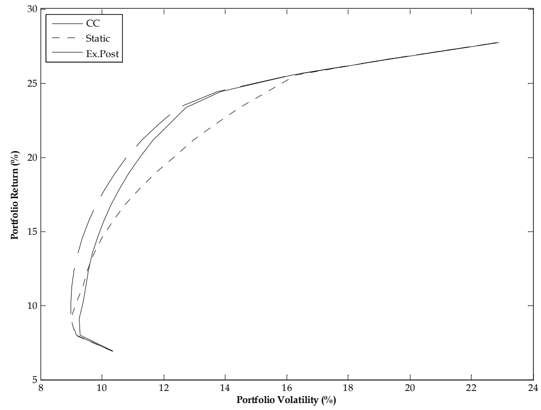


Panel C: Aggregated efficient frontier for the US sector portfolios

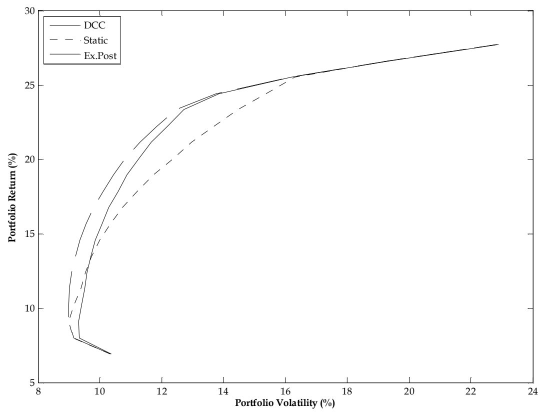
EWMA



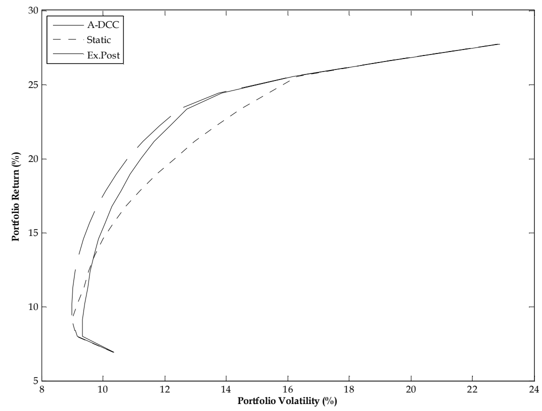
CCC



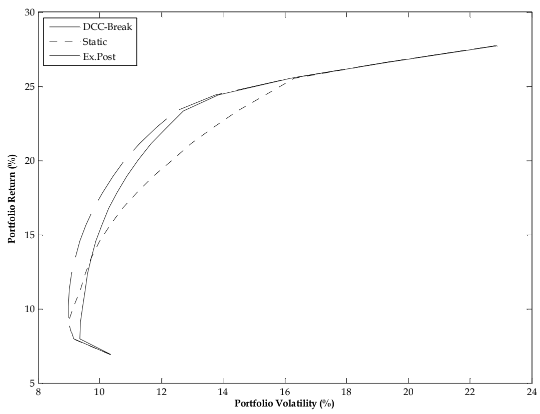
DCC



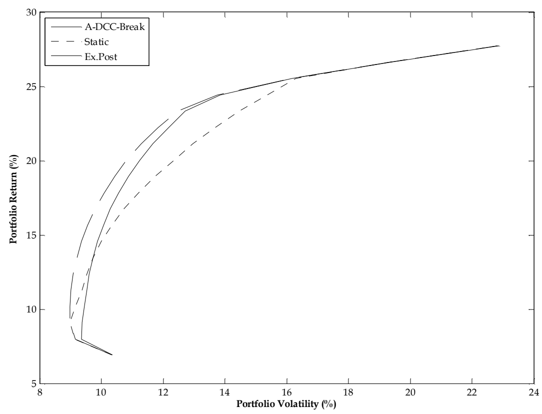
A-DCC



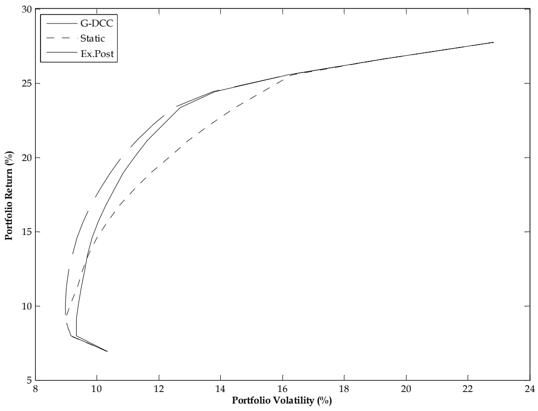
DCC-Break



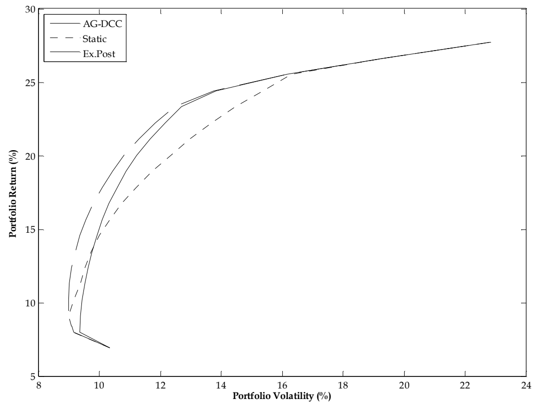
A-DCC-Break



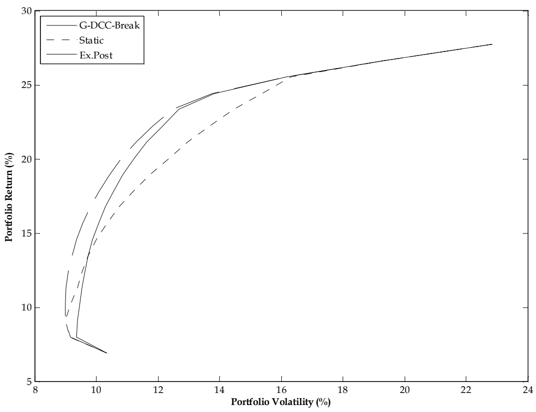
G-DCC



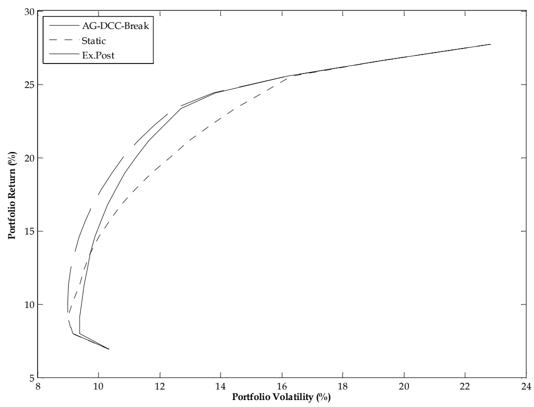
AG-DCC



G-DCC-Break



AG-DCC-Break



In all three markets the efficient frontier of the dynamic strategies (solid line) is always above the static frontier (dotted line), which implies that efficient dynamic portfolios can achieve a better risk return trade-off than the efficient static portfolio. In addition, the efficient dynamic frontier (solid line) is closer to the ex-post efficient frontier (dash line) compared to the static one (dot line) suggesting that the daily conditional covariance matrix forecasts are more accurate than the unconditional covariance matrix benchmark. The results, therefore, confirm that the superior performance of dynamic strategies is due to more accurate variance-covariance forecasts and is robust across all efficient portfolios that can be generated by any given portfolio construction strategy.

The second robustness test is motivated by Fleming et al's (2001) argument that *PF* results based on the Max-R and Min-V portfolio construction strategies may be sensitive to the target return/variance settings. That means dynamic portfolios may outperform the static one because the target return/variance setting is unfavourable to the latter. In order to evaluate the robustness of *PF* results for different target return/variance settings, we construct the CML based on the static model with ex-post return vector over the out-of-sample period. Portfolios on the CML provide the highest possible *SR* for any given target return/ variance. Therefore, if dynamic portfolios under both Max-R and Min-V scheme (Table 5.5 and 5.6) can outperform the CML based on the static model, we can claim that the positive *PF*s enjoyed by the former is robust to different target return/variance settings.

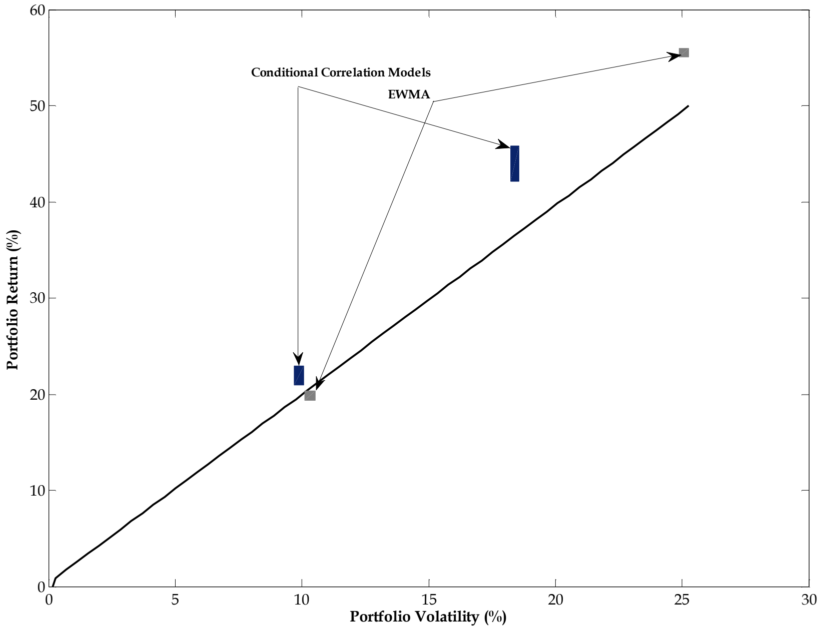
We construct the CML by generating Min-V portfolios for the static strategy with different target return settings. For each market, the highest target return setting equals to the highest realized return achieved by dynamic strategies (Table 5.5 and 5.6), while the lowest target return setting equals to zero.[312] Figure 5.6 illustrates the risk-adjusted performance of dynamic portfolios in Tables 5.5 and 5.6 against the CML of the static model for the three markets.

[312] In this study, we use Min-V portfolios to substitute portfolios on CML as both strategies maximize the Sharpe ratio of the portfolio. In addition, both strategies allow investors to hold risk-free asset in their portfolio and have no restriction on leverage.

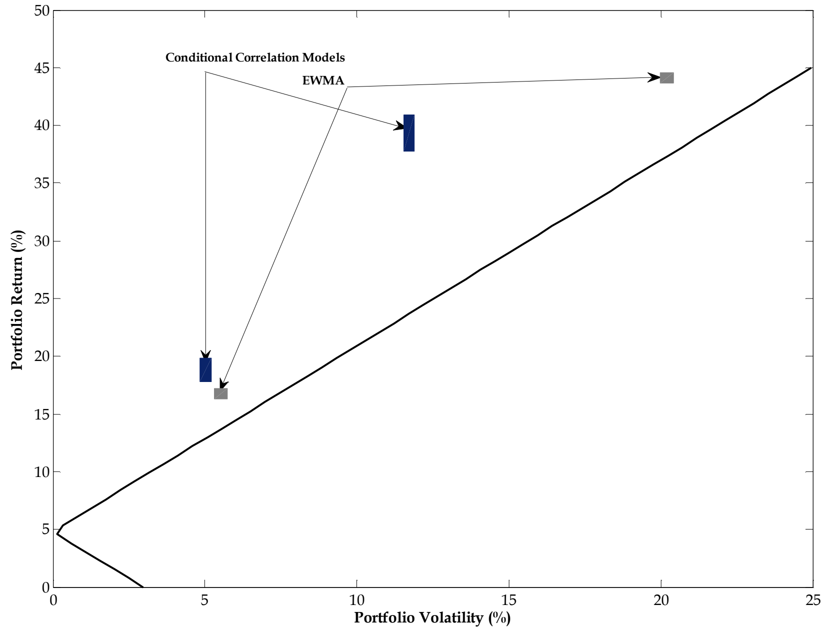
Figure 5.6 Dynamic Strategies versus the Capital Market Line Based on the Static Strategy

The graphs below demonstrate the relative performance of dynamic portfolios under Max-R and Min-V compared to the capital market line (CML) based on static stratgy. The CML is constructed as Min-V static portfolio with different target returns. The upper level of the target return setting equals to the highest realized portfolio return achieved by the dynamic strategy under Max-R over the out-of-sample period. The risk-return performance of dynamic portfolio under Max-R and Min-V is plotted in the graph as rectangles. The blue rectangles represent the risk-return performance of dynamic portfolios based on conditional correlation models, while the gray rectangles represent the performance of dynmaic portfolios based on EWMA. The risk-return performance of dynmaic portfolios under Max-R and Min-V can be found in Table 5.5 and 5.6.

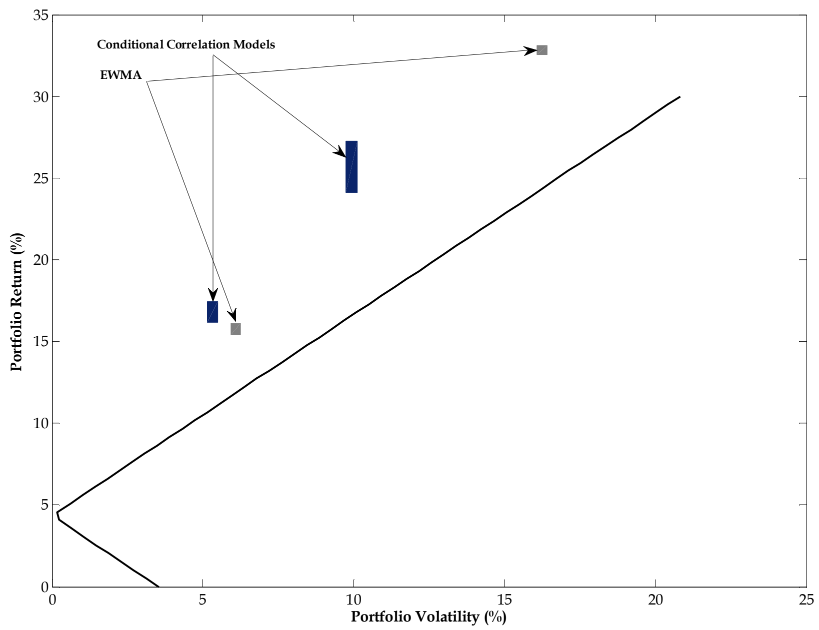
Panel A: Comparison result for Japanese sector portfolios



Panel B: Comparison result for the UK sector portfolios



Panel C: Comparison result for the US sector portfolios



From the above figure, one can see that dynamic portfolios based on dynamic correlation timing strategies outperform the CML of static model by providing higher *SR* for all the three markets. For instance, in the UK market, the *SR* of dynamic portfolios based on conditional correlation models ranges from 2.98/3.63 to 3.24/3.84 under the Max-R/Min-V scheme, while the *SR* of portfolios on the CML with similar volatility is only between 1.90 and 2.25. Therefore, the results validate the robustness of the positive *PFs* enjoyed by dynamic portfolios under different target return/variance settings for all the three markets.

5.6. CONCLUSIONS

Forecasting the covariance of asset returns is crucial for portfolio management and asset pricing. Various covariance estimation techniques have been developed for this purpose. However, a comprehensive evaluation of the different approaches has not been carried out as yet. In the current study, we investigate the economic value of correlation timing relative to static investment strategies using a utility based framework that accounts for the impact of transaction costs. In this vein, we gauge the relative merits of various multivariate conditional correlation estimators by looking at the risk-return profile and incremental utility of the resulting portfolios. For completeness we undertake a statistical evaluation of the competing correlation forecasting approaches using goodness of fit criteria.

The empirical results suggest that additional economic value can be achieved from correlation timing compared to static asset allocation strategy.[313] The findings based on sector portfolios suggest that the dynamic asset allocation strategies based on one-day-

[313] In this empirical study, we only test the significance of the additional economic value obtained by the dynamic strategy in terms of *SR* but not in terms of utility gain or positive *PF*. However, it is worth noting that none of the previous empirical studies (e.g. Fleming et al., 2001; 2003; Della Corte et al., 2009; De Pooter et al., 2008) have performed significant test to verify the difference between the economic value (in terms of *PF*) obtained by the dynamic and static strategy.

ahead covariance forecasts outperform the optimal static portfolios both in terms of risk-adjusted returns and economic value post transaction costs. Risk-averse investors are willing to pay up to 2000 bps per annum to switch from a static target variance strategy to one based on the nonparametric RiskMetrics approach.

Although correlation timing has been found to afford gains to investors over and above the static covariance benchmark, transaction costs have been shown to impinge substantially on the performance of daily rebalancing strategies. Correlation timing conducted monthly can outperform static allocation. The result is robust to trading costs as it generates economically plausible break-even transaction costs. Our findings further suggest that the incremental gains of dynamic strategies relative to the static one are more pronounced when considering monthly holding periods instead of daily. Switching fees imply that exploiting correlation dynamics is more beneficial for longer horizon investors. Overall, we show that the statistical evidence in favour of models that account for the stylized facts of asset correlations such as time-variation, asymmetry and structural breaks is mirrored by substantial economic payoffs in the context of dynamic asset allocation.

CHAPTER 6

CONCLUSION

6.1. CONCLUDING REMARKS

This thesis investigates the risk-related behaviours of financial institutions (banking, insurance, and fund management based financial service firms) across the global financial markets and provides reasonable explanations for the empirical findings. The results of this thesis not only add to the existing body of literature but also have important implication for regulators, risk managers and investors alike both at the firm level and public policy level. Identification of these risk-related behaviours and the precise measure of their magnitudes would help the relevant stakeholders to improvement their management/investment performances. Besides, the empirical results could also be useful for government agencies and international regulatory bodies. The ultimate goal of any regulation/policy for financial sector is to secure the stability and prosperity of the financial market while stimulate the real economy through steady growth in credit supply. Better understanding of financial intermediaries' behaviours upon changes in different risk exposures, therefore, provides valuable information for formulating successful regulation/policy in the future.

The application of modern econometric approaches in applied time series analysis of financial data is another very important issue which has been covered throughout this research. The existing empirical studies, related to our research questions, failed to employ a more comprehensive framework, which provides better estimation efficiency and accuracy through capturing the conditional interactions among the return series. Each procedure is discussed and explained in the light of its application on our data and the research interest concerned.

A number of stylised facts have been drawn from the present study. As a starting point we address the cross-country spillovers among financial markets. To be specific, we investigate the return and risk transmission among banking/insurance sector portfolios across markets in chapter 2. By using a multivariate conditional correlation estimation framework with up-to-date data, the empirical findings provide valuable insights regarding the interdependence among global financial industries during the recent financial turmoil. First, return contagion across the global financial market is strong, especially during the financial turmoil, which is supported by previous studies on the globalization/consolidation trend of the financial industry (*e.g.* De Nicolo et al, 2004) and the contagion effect during economic downturns (*e.g.* Forbes and Rigobon, 2002; Tai, 2007). Second, the return transmission between the U.S. and Japanese banking sector is absent even during the financial turmoil, which could attribute to the structural differences between the two financial markets (*i.e.* market- and bank-oriented financial system). Third, cross-country return and volatility spillovers among insurance sectors show different pattern during the crisis period. The magnitude of return transmissions remains unchanged, while the magnitude of volatility transmissions intensified. Finally, strong interdependence has been recorded between the banking and insurance sector portfolios both on the country and global level during the pre-crisis period, which verifies the increasing integration/convergence between the two financial intermediary types (*e.g.* Staikouras, 2006b). During the crisis, however, insurers enjoyed a competitive edge over banks in the sense that negative shocks for banks have a positive impact on insurers' return. These findings is in line with the industrial and academic reports, which claim that insurers, in general, perform better compared to banks due to their different credit and liquidity risk characteristics (*e.g.* Eling and Schmeiser, 2010).

The two major risk factors - interest rate and foreign exchange rate risk - for financial intermediaries are examined in chapter 2 and 3, respectively. Existing literatures on the interest rate exposure of financial intermediaries often employ changes in interest rate environment with fluctuations in a bond index/spot rate with fixed maturity or the spread between long- and short-term rates as approximation of changes in the interest rate environment. The relationship between the behaviour of financial intermediaries' equity value and the evolution of the whole term structure, however, is rarely examined. The examination of the latter constitutes the empirical work of chapter 3, which measures fluctuations in the entire yield curve using the Nelson-Siegel three-factor model.

Using a more general multivariate estimation framework that takes the non-linear and heteroskedasticity property of the return series into account, we yield five main findings. First, the profitability of banking institutions is sensitive to changes in the term structure of interest rates. Steeper yield curve (*i.e.* decrease/increase in short/long-term rates) seems to enhance the profitability of banks. This finding coincides with the funding and investment mismatch commonly seen in the banking industry, where long-term investments are usually financed by short-term funding (*e.g.* Saunders and Cornett, 2010). Second, the positive relationship between changes in long-term rates and banks' equity value intensified during the recent financial turmoil. We argue the enhancement may attribute, at least partially, to the "flight to quality" hypothesis (Vayanos, 2004). As investors' risk aversion increases during the economic downturn, they switch from risky investments (*i.e.* banks' equity) to more secure securities (*i.e.* long-term government bonds). That means, the long-term interest rate will have a positive relationship with the equity value of banks as they both go down. Third, insurers expose to evolution in the yield curve in a similar fashion as banks, which indicates that the two intermediary types share similar risk factors. This finding reinforces the evidence from chapter 2, which suggests increasing convergence between banks and insurers. Fourth, contrary to the previous empirical findings, industrial firms also have similar interest rate exposure as banks across markets. The empirical evidence seems to support the "pass on" hypothesis (Drehamann et al, 2010; Alessandri and Drehamnn, 2010), which suggests that banks are able to "pass" the changes in interest rate and/or credit risk onto their borrowers. Last but not least, our empirical work shows that market interventions (*e.g.* government bailouts and stimulus packages) play an important role in the equity value of financial intermediaries during the recent financial turmoil.

Having analysed the interest rate risk exposure of financial intermediaries, we turn to evaluate their behaviours upon fluctuations in currency value in chapter 4. The collapse of Bretton Woods system in early 1970s has introduced uncertainties into the foreign exchange market ever since. The recent financial turmoil also plays an important role in the foreign currency market as the world's major currencies (*i.e.* the U.S. Dollar, British Pound and Japanese Yen) fluctuate violently as the crisis intensified (Melvin and Taylor, 2009). In this study, we propose an alternative estimation framework that takes the first and second moment of both the home and foreign currency value fluctuations into account.

Four stylised facts have been identified from the empirical analysis. First, both home and foreign currency value changes can affect the equity value of financial intermediaries across markets, while the latter are more pervasive. The recent crisis significantly alters the return sensitivity of financial intermediaries and changes in foreign currency value, which may due to the "flight to quality" phenomenon observed during the financial turmoil. We argue that investors prefer high quality assets during the economic downturns and have an incentive to switch from countries with poor economic performance to better ones (Naes et al, 2011). This "shift of fund" behaviour has a significant impact on the currency value of the involved markets (*e.g.* Branson, 1983; Frankel, 1983; Kanas, 2000), which further influence the equity value of their financial intermediaries. Second, the volatility of currency value fluctuation has no influence on the equity value of financial intermediaries. This finding is contrary to previous empirical studies (*e.g.* Koutmos and Martin, 2003b), which argue that higher the variability of currency value better the bank's equity performances since the latter benefits from the former by collecting more underwriting premiums through increased hedging demands for currency derivatives. We argue the difference is mainly driven by the different hedging demand in our sample period from the one in theirs. Given that investors are more emphasis on credit risk during the recent decade, the influence of underwriting premium collected from currency derivative is, therefore, relatively small and hard to detect. Finally, the relationship between currency value fluctuation and equity value of financial intermediaries shows size effects. That means small institutions are more likely to expose to changes in home currency value, while large one are more sensitive to foreign currency fluctuations. The incentive to hedge foreign exposure (*e.g.* Nance et al, 1993) and the risk characteristic (*e.g.* Tai, 2000; Chamberlain et al, 1997) associated with the firm size could be the main reason behind this size effect.

Finally, the economic value of dynamic correlation timing strategies is investigated in chapter 5. This is the first study to comprehensively assess the role of introducing equity return correlation dynamics in sector asset allocations and the findings suggest that timing correlation is fruitful to sector investors. The empirical evidence indicates four main stylized facts. First, correlation timing strategies provide superior performance than the static asset allocation by providing economically meaningful performance fees. Additionally, correlation timing strategies generally outperform the volatility-only timing strategies. The empirical study shows that incorporating DCC-type models in asset allocation can enhance risk-adjusted returns and investor utility and even more so if correlation asymmetries and break are allowed for. Second, our results are robust to trading costs as it generates economically plausible break-even transaction costs. Third, transaction costs are positively related to rebalancing frequency. Revise the portfolio at a lower frequency, therefore, can improve the performance by reducing the transaction cost. The empirical evidence shows that monthly rebalancing correlation timing strategies do outperform static asset allocation in a more favorable way than the daily ones. Furthermore, weekly/monthly correlation timing strategies generally perform better than the daily ones indicating that reducing the rebalancing frequency not only increases the transaction cost but also increases their risk-adjusted performance. Finally, our results are robust to different target return/volatility settings, as well as the portfolio construction strategies.

The findings from the thesis pave ways for future researches in, at least, three directions. First, chapter 2 shows that the interdependence among global financial intermediaries increased over the recent decade, especially during the financial turmoil. In this chapter, the financial turmoil refers to the crisis originated from the credit and liquidity risk within the banking sector from 2007 to 2009. The latest episode regarding the sovereign credit issues of the European countries and its influence on the global financial markets is, therefore, not yet been revealed. The impact of the recent European sovereign-debt crisis on the interdependence of financial institutions and its influence on the real economy across the global provides valuable information for international investors seeking for better risk-adjusted performance through international diversification. Besides, it is important from a regulatory perspective as it offers valuable insight about the cause and consequence of the recent events, which is helpful for designing better regulatory frameworks and fiscal policies.

The second direction is pointing toward the better understanding of investor's behavior during market downturns. In chapter 3 and 4, we have shown that investor's sentiment (*i.e.* increased risk aversion) and behavior (*i.e.* "flight to quality") plays an important role in the risk-related behavior of financial intermediaries and their equity values. The understanding about the determinants of investor's sentiment, therefore, is very important for practitioners in risk management and investment, as well as policy makers.

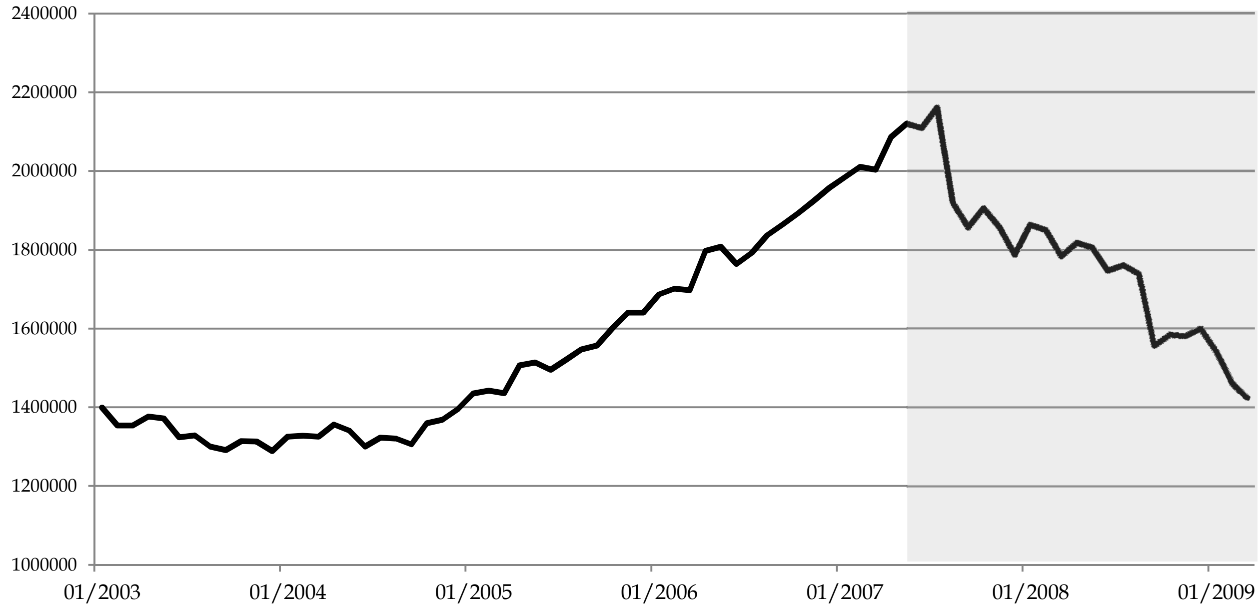
Finally, the rebalancing frequency of dynamic asset allocation strategies is worth further investigation in the future studies. The empirical evidence from chapter 5 shows that the practical feasibility of the correlation timing strategies is sensitive to rebalancing frequency through its impact on transaction costs. Conventional approaches usually use equally distributed revise intervals (*i.e.* daily or monthly) to rebalance the portfolio, which is convenient but failed to capture the stochastic nature of the arrival of new information. For instance, the weighting scheme of weekly/monthly rebalancing portfolios is unable to reflect the influence of the new arrival information (*i.e.* systemic shocks like unexpected jump in inflation) on portfolio's risk-return profile in a timely manner (*i.e.* new information arrives on Monday, but the rebalancing date is on Friday). Correlation timing strategies that incorporate the stochastic nature of the arrival of new information (*i.e.* rebalancing with a "trigger mechanism"), therefore, are urgently needed.

APPENDIX

SECTION A

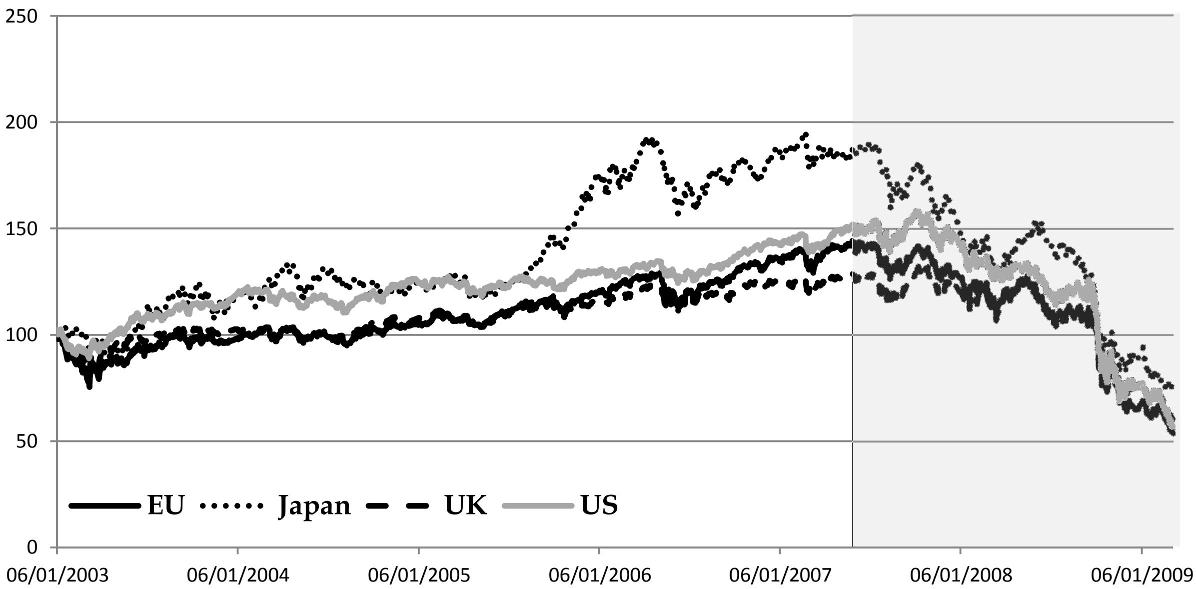
A.1 Monthly Outstanding Volume of the Asset Backed Securities

The following figure represents the monthly movements of the outstanding volume of the asset backed securities. The asset backed security is represented by the commercial paper. The monthly information on the outstanding volume of commercial paper is provided by the *Board of Governors of the Federal Reserve System*. The unit of measurement is million USD on the vertical axis. The gray shading area represents the crisis period from the *April 2007* till the *March 2009*.



A.2 Time Series of Equity Market Indices

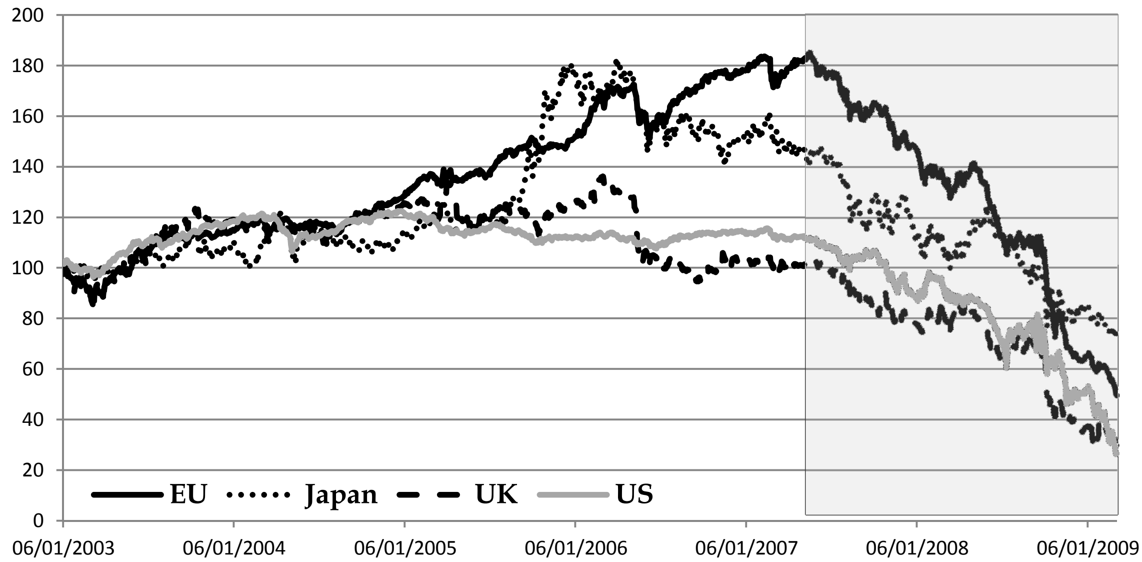
The following figure represents the daily movements of the equity market indices. For EU, Japanese, UK and US market the national equity market indices are represented by *STOXX EUROPE 600*, *NIKKEI 225*, *FTSE 100*, and *S&P 500*, respectively. In order to present the movements of the market indices in a better manner, the level of these market indices are rebased at 100 level at the beginning of the sample period. The gray shading area represents the crisis period from the *April 2, 2007* till the *March 9, 2009*.



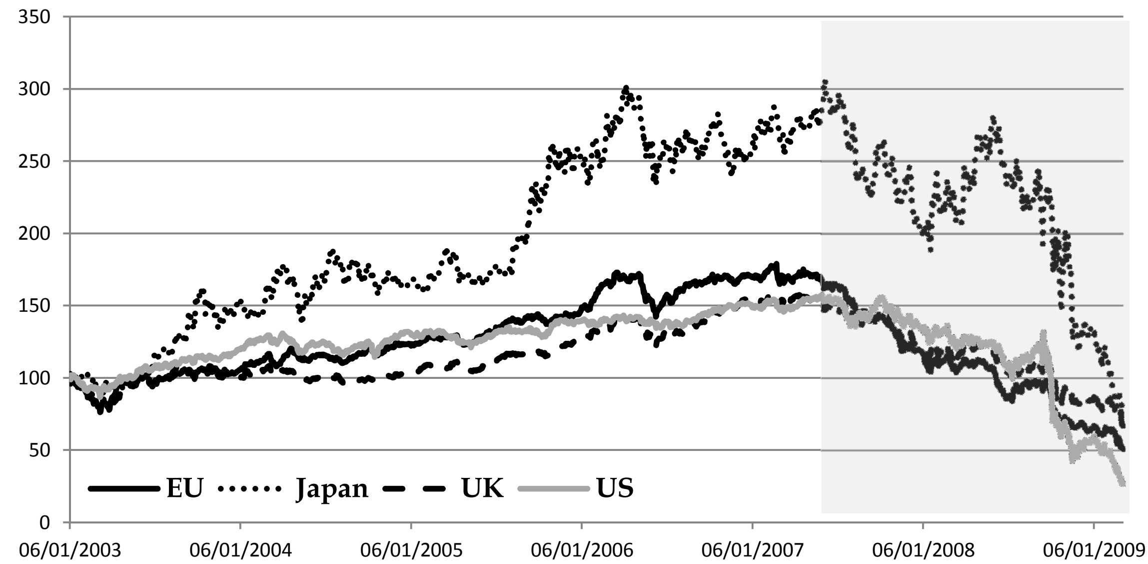
A.3 Time Series of Financial Sector Portfolios' Value

The following figures represent the daily movements of the financial sector equity value. All the financial sector portfolios are equally weighted, and rebalanced on a daily basis. In order to demonstrate the value of the portfolios in a better manner, the values of these portfolios are rebased at 100 level at the beginning of the sample period. The gray shading area represents the crisis period from the *April 2, 2007* till the *March 9, 2009.*

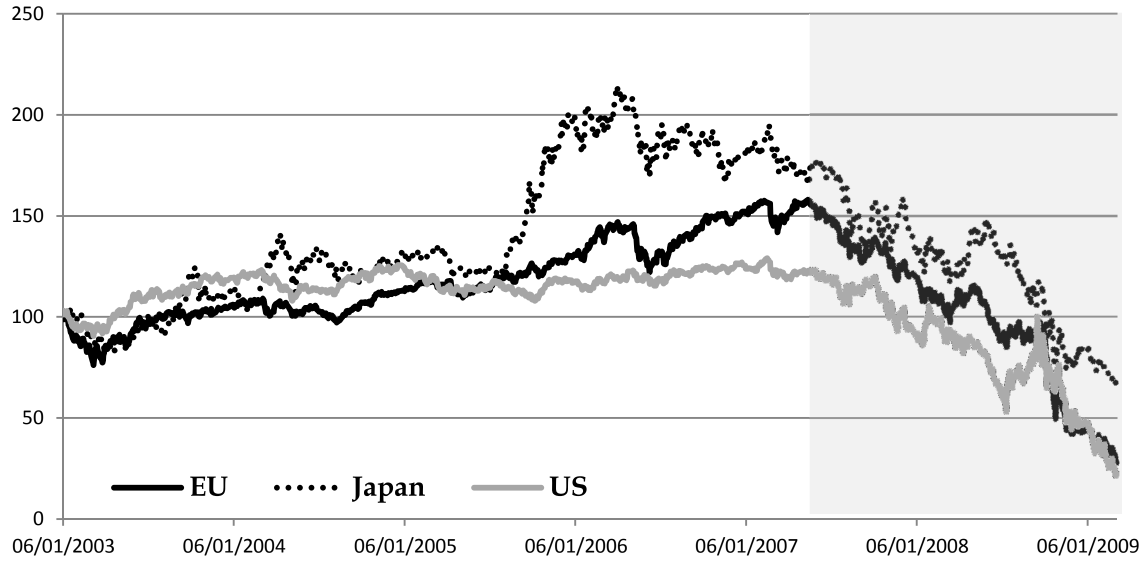
Panel A: Banking Portfolios.



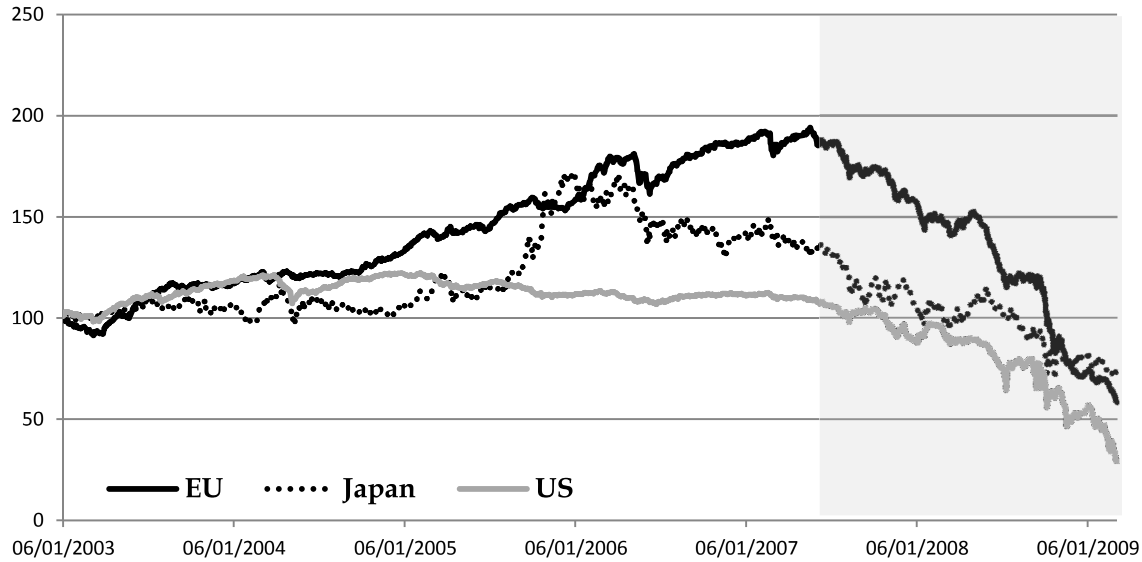
Panel B: Insurance Sector Portfolios.



Panel C: Large Size Banking Portfolios.



Panel D: Small Size Banking Portfolios.



A.4 Technical Detail of the BEKK Model

The BEKK model is named after Baba-Engle-Kraft-Kroner (BEKK) which first introduced by Engle and Kroner (1995). The BEKK specification can be viewed as a restricted version of the VEC model, which developed by Bollerslev et al (1988).

Compare to the VEC model, the BEKK model is preferable as it guarantee the conditional covariance matrices are positive definite by construction. The first order model, which can also be viewed as a multi-dimensional GARCH(1,1), has the following functional form.

$$H_t = C \cdot C' + A' \cdot \varepsilon_t \varepsilon_t' \cdot A + B' \cdot H_{t-1} \cdot B$$

where parameter C is a [k x k] lower triangle matrix, while A and B are [k x k] matrices.

The number of parameters involved in the BEKK model is highly sensitive to the dimension of H_t[314], the total number of parameter is equal to $2k^2+k(k+1)/2$. There is a simplified version of the full BEKK model to significantly reduce the number of estimated parameters. The simple model is named diagonal BEKK, where the parameter A and B are [k x k] diagonal matrices. The following equation demonstrates the diagonal BEKK model with diagonal parameters setting.

$$H_t = \begin{bmatrix} c_{11} & 0 & \dots & 0 \\ c_{21} & c_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ c_{k1} & c_{k2} & \dots & c_{kk} \end{bmatrix} \cdot \begin{bmatrix} c_{11} & 0 & \dots & 0 \\ c_{21} & c_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ c_{k1} & c_{k2} & \dots & c_{kk} \end{bmatrix}^{\mathrm{T}} + \begin{bmatrix} a_{11} & 0 & \dots & 0 \\ 0 & a_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & a_{kk} \end{bmatrix} \cdot \varepsilon_t \varepsilon' \cdot \begin{bmatrix} a_{11} & 0 & \dots & 0 \\ 0 & a_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & a_{kk} \end{bmatrix}^{\mathrm{T}}$$
$$+ \begin{bmatrix} b_{11} & 0 & \dots & 0 \\ 0 & b_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & b_{kk} \end{bmatrix} \cdot H_{t-1} \cdot \begin{bmatrix} b_{11} & 0 & \dots & 0 \\ 0 & b_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & b_{kk} \end{bmatrix}^{\mathrm{T}}$$

314 For a [3 x 3] system, the total number of parameters in a full BEKK model is 24, while for a [5 x 5] system, the total number of parameters in the full BEKK model will increase to 65.

A.5 Technical Detail of the BEKK Model

The LLF ratio test is designed to compare the fit of the two competing models. The two competing models are related, as one of the models is a restricted version of the other one. The restricted model poses restrictions on one or several parameters of the unrestricted model, which makes the restricted model less flexible. The LLF ratio test investigates whether the restrictions posed by the restricted model is suitable by using a Chi-square test.

Assume there are two models A and B, while model A is the restricted version of model B. In other words, model A is the restricted model and model B is the unrestricted one. In order to perform the log-likelihood ratio test, we first estimate the two models, and generate the value of their log-likelihood functions (LLF). Then, we compare the difference between the two LLFs, and assess the significance of the difference based on a Chi-square test. The degree-of-freedom (DoF) of the Chi-square test is equal to the number of restrictions in model A compares to model B. The number of restrictions can be calculated as the difference of the DoFs between the two models. The log-likelihood ratio test can be illustrated as follow:

$$D_{LLF} \sim \chi_k^2$$

where,

$$D_{LLF} = LLF_{Unrestricted} - LLF_{Restricted} = LLF_B - LLF_A$$

$$k = DoF_{Restricted} - DoF_{Unrestricted} = DoF_A - DoF_B$$

SECTION B

B.1 Selected SIFIs across Markets

U.S.	UK	Japan
Bank of America	Barclays	Mitubishi UFJ Financial Group
Bank of New York Mellon	HSBC	Mizuho Financial Group
Citigroup	Lloyds Banking Group	Sumitomo Financial Group
Goldman Sachs	Royal Bank of Scotland	
JP Morgan Chase		
Morgan Stanley		
State Street		
Wells Fargo		

The SIFIs in the banking sector are provided by the Financial Stability Board.
The above institutions are listed according to alphabetic order.

B.2 Selected Large Insurers across Markets

U.S.	UK	Japan
Aflac	Aviva	Dai-Ichi Life Insurance
AIG	Legal and General	Tokio Marine Holdings
AllState	Old Mutual	T&D Holdings
Berkshire Hathaway	Prudential	MS and AD Insurance Group
Genworth Financial	Standard Life	NKSJ Holdings
Hartford Financial	Resolution	
Lincoln National		
MetLife		
Principal Financial		
Prudential Financial		
Travelers		

The large insurers are selected according to their total asset value. The entry level is $100 billion on the *December 31, 2010*. For institutions in the UK and Japanese market, the value of the total asset is first converted into the U.S. dollar terms based on the corresponding bilateral exchange rate on the *December 31, 2010*.
The above institutions are listed according to alphabetic order.

B.3 Selected Large Industrial Firms across Markets

U.S.	UK	Japan
3M	3i Group	Astellas Pharma
Alcoa	BAE System	Canon
AT&T	British Gas	East Japan Railway
Boeing	BP	Honda Motor
Caterpillar	British American Tobacco	Japan Tobacco
Chevron Corporation	BT	Kansai Electric Power
Cisco System	Compass Group	KDDI
Coca-Cola	Diageo	Komatsu
DuPont	GKN	Mistubishi Estate
Exxon Mobile	GlaxoSmithKline	Nintendo
General Electric	IAG*	Nippon Steel
Hewlett-Packard	Invensys	Nippon Telegraph and Telecom
The Home Depot	ITV	Nissan Motor
Intel	Ladbrokes	NTT Docomo Inc
IBM	Land Securities Group	Panasonic
Johnson & Johnson	Logica	Seven and I Holding Group
Kraft Foods	Man Group	Shin-Etsu Chemical
McDonald's	Marks & Spencer	Softbank
Merch	National Grid	Sony
Microsoft	Reckitt Benckiser	Takeda Pharmaceutical
Pfizer	Smiths Group	Tokio Marine Holding
Procter & Gamble	Tate & Lyle	Toshiba
United Technologies Corp.	TESCO	Toyota Motor
Verizon Communication	Vodafone	Yokyo Electric Power
Wal-Mart	Wolseley	
Walt Disney	WPP	

*IAG, International Airlines Group, is the holding company for British Airway (BA) and Iberia after the two merged in January 2011. We use the stock price information from BA for the period before the establishment of IAG.

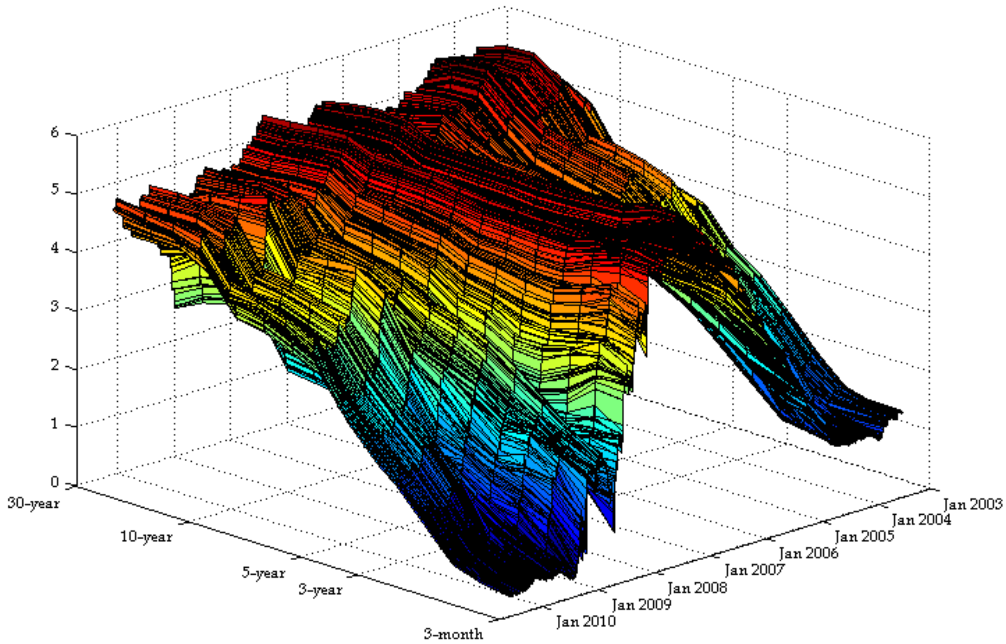
The large industrial firms are the non-financial institutions from the DJIA, FT 30 and TOPIX Core 30 indices for the U.S., the UK and Japanese market, respectively.

The above institutions are listed according to alphabetic order.

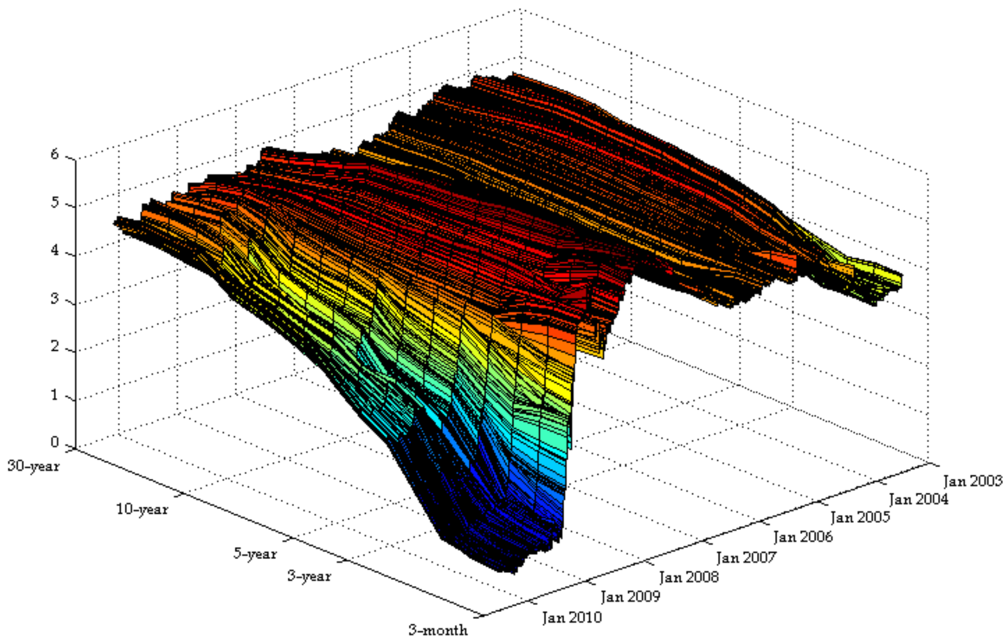
B.4 Daily Term Structure of Interest Rates

The term structure of interest rate is based on the daily interest rate of Treasury security with maturity equals to 3-, 6-, 9-, 12-month, 2-, 3-, 4-, 5-, 7-, 8-, 9-, 10-, 15-, 20-, 25-, and 30-year from *January 31, 2003* till *January 31, 2010*. The yield curve data is collected from Bloomberg®. The vertical axis in the following 3 dimensional graph represents the level of the interest rate (in percentage terms) at different maturity; the horizontal axis on the left hand side refers to the maturity of the interest rate on the yield curve, while the horizontal axis on the right hand side refers to the dates when the yield curve is recorded.

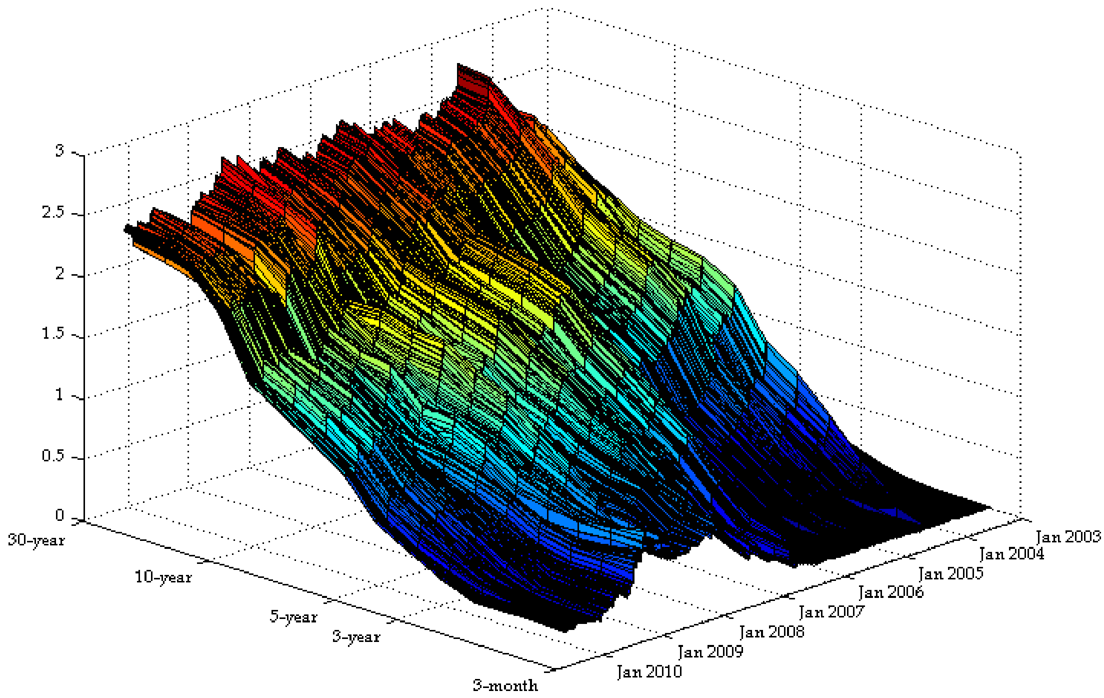
Panel A: Daily term structure of the U.S. interest rates



Panel B: Daily term structure of the UK interest rates



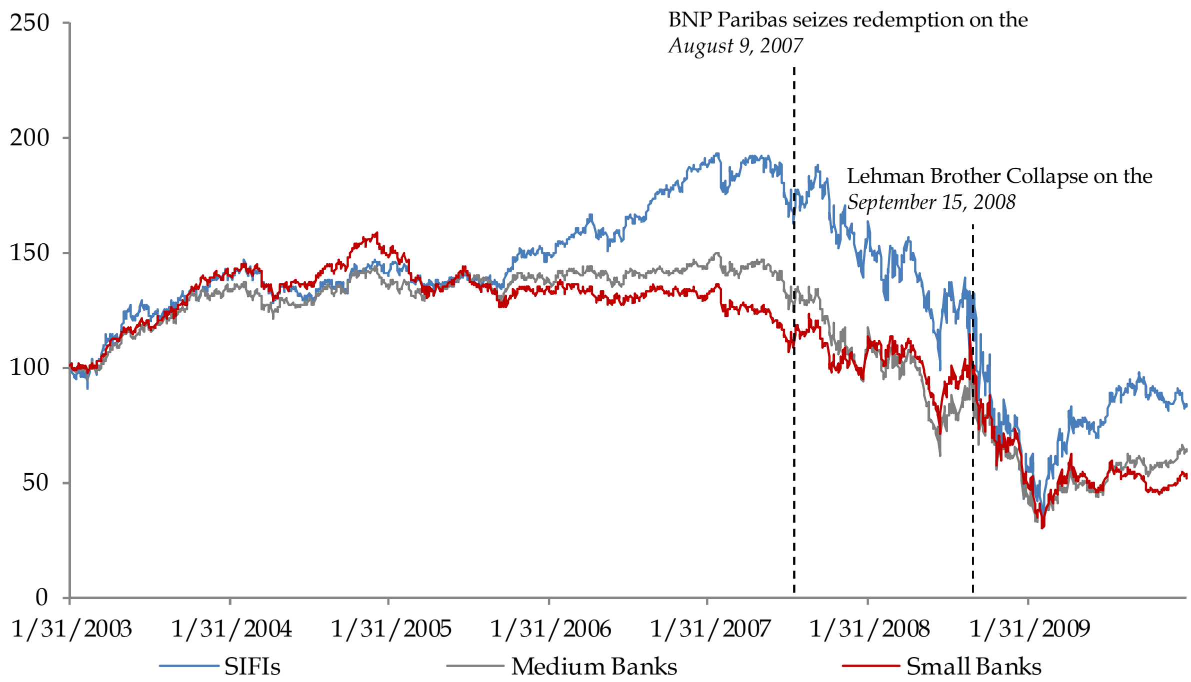
Panel C: Daily term structure of Japanese interest rates



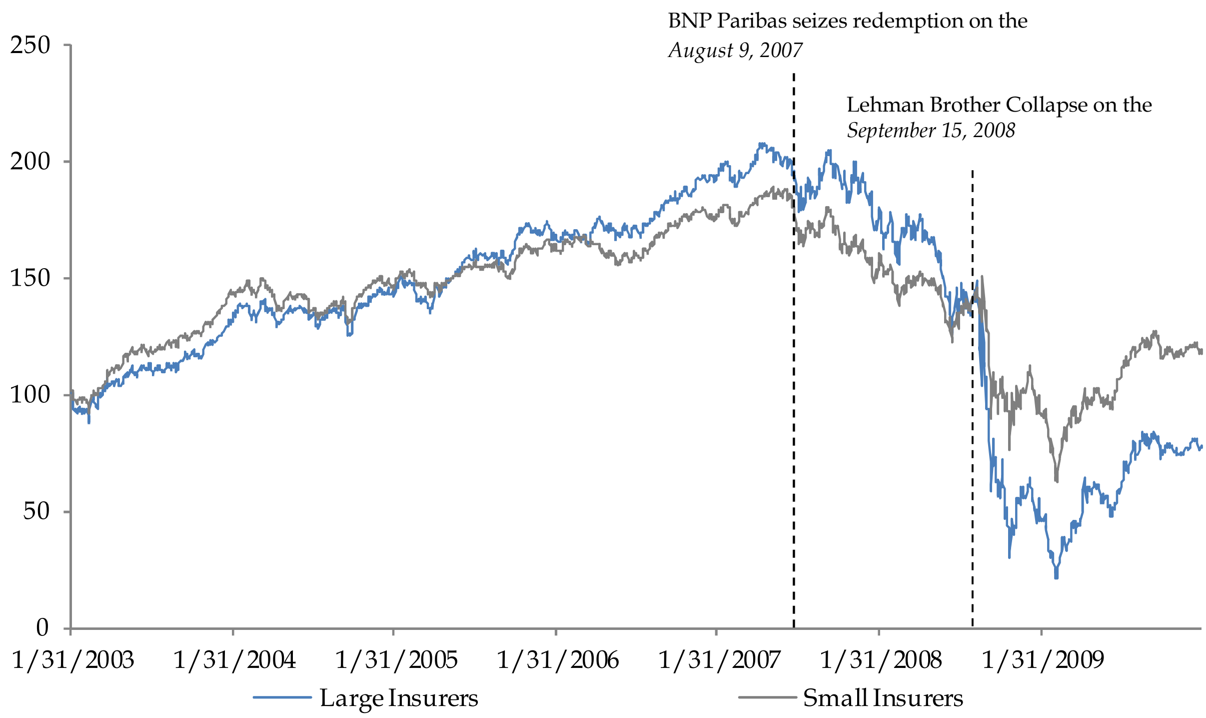
B.5 Time Series of Sector Portfolios' Value

The following figures represent the daily movements of the sector portfolio value. All the sector portfolios are equally weighted, and rebalanced on a daily basis. In order to demonstrate the value of the portfolios in a better manner, the values of these portfolios are rebased at 100 level at the beginning of the sample period. The sample period is from *January 31, 2003* till *January 31, 2010*. The crisis period starts from the *August 9, 2007* when BNP Paribas seized the redemption its investment funds.

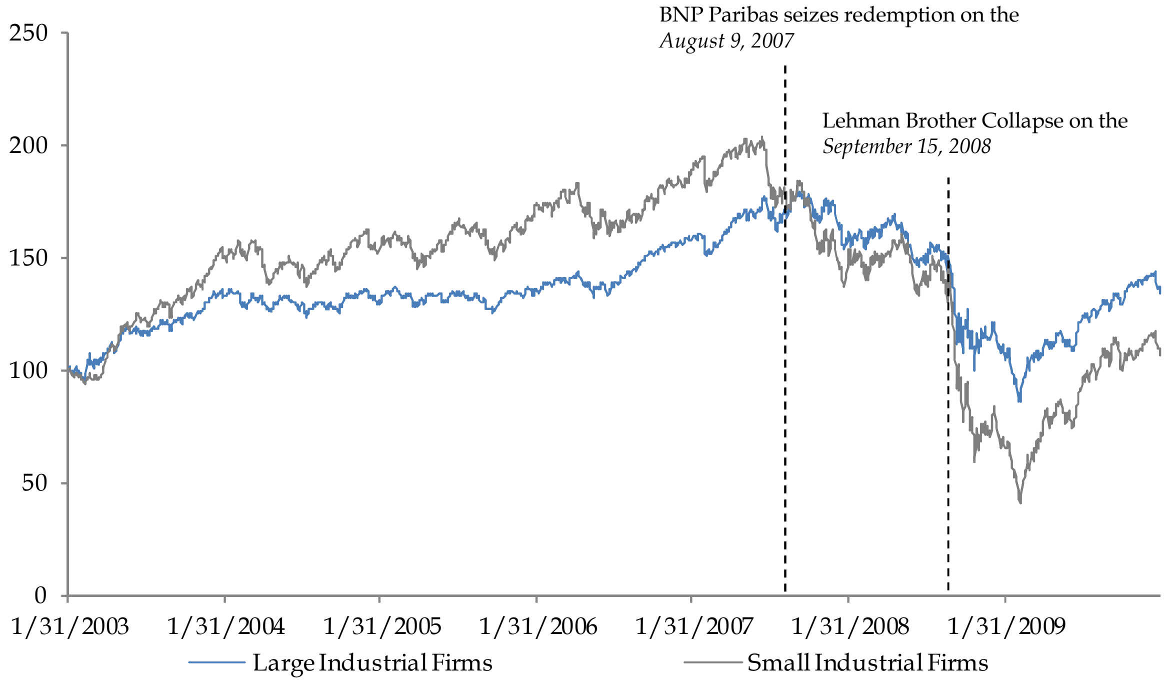
Panel A1: The U.S. Banking Sector Portfolios



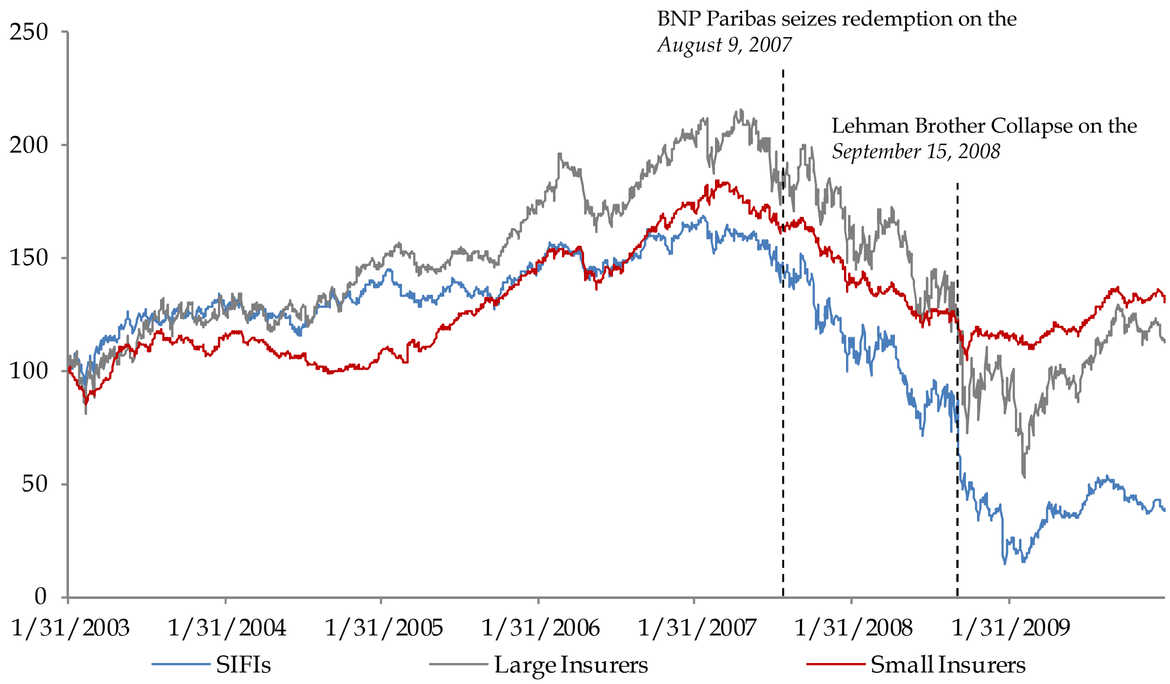
Panel A2: The U.S. Insurance Sector Portfolios



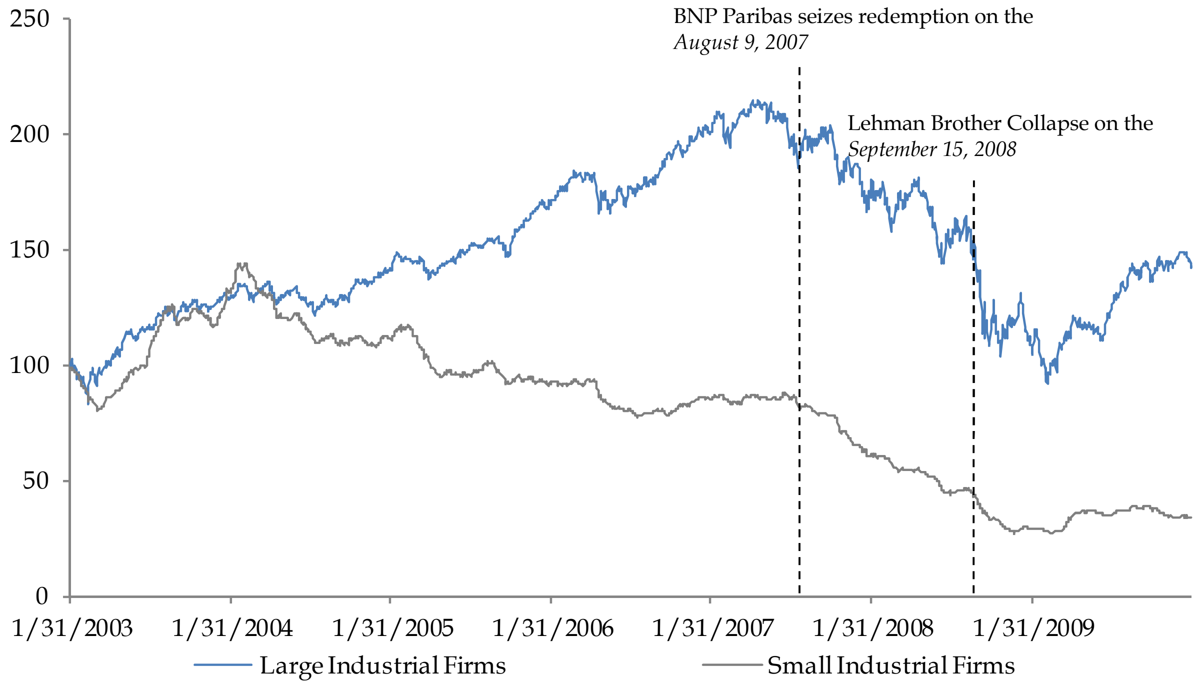
Panel A3: The U.S. Industrial Sector Portfolios



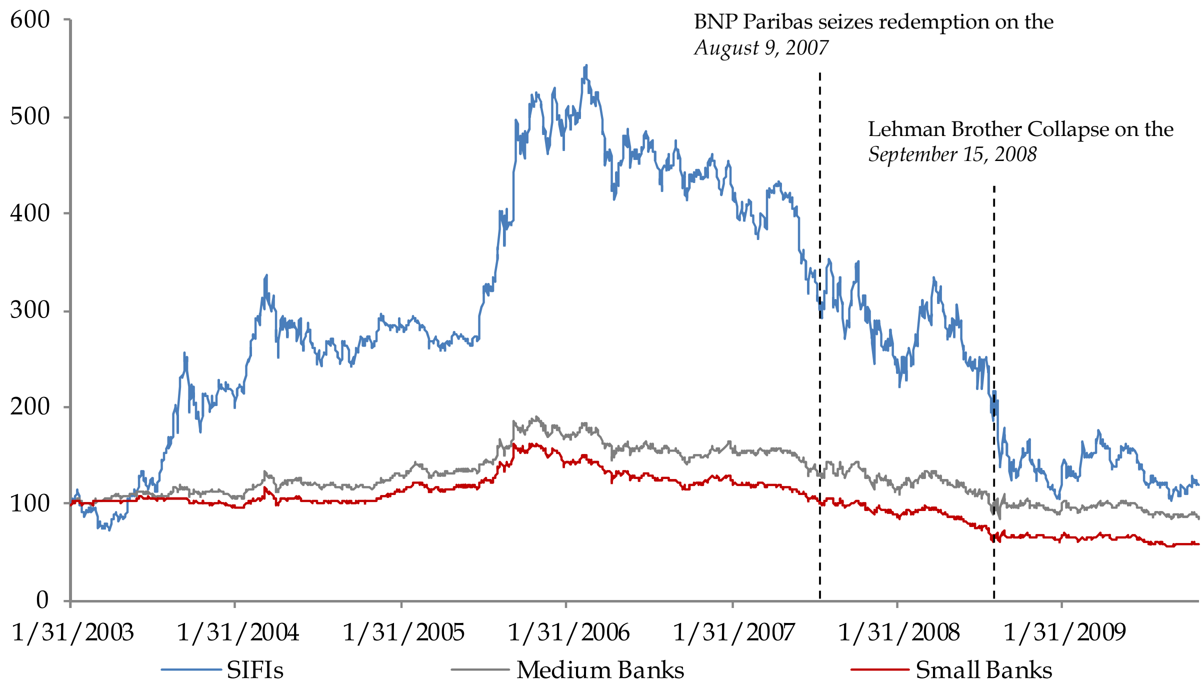
Panel B1: The UK Banking and Insurance Sector Portfolios



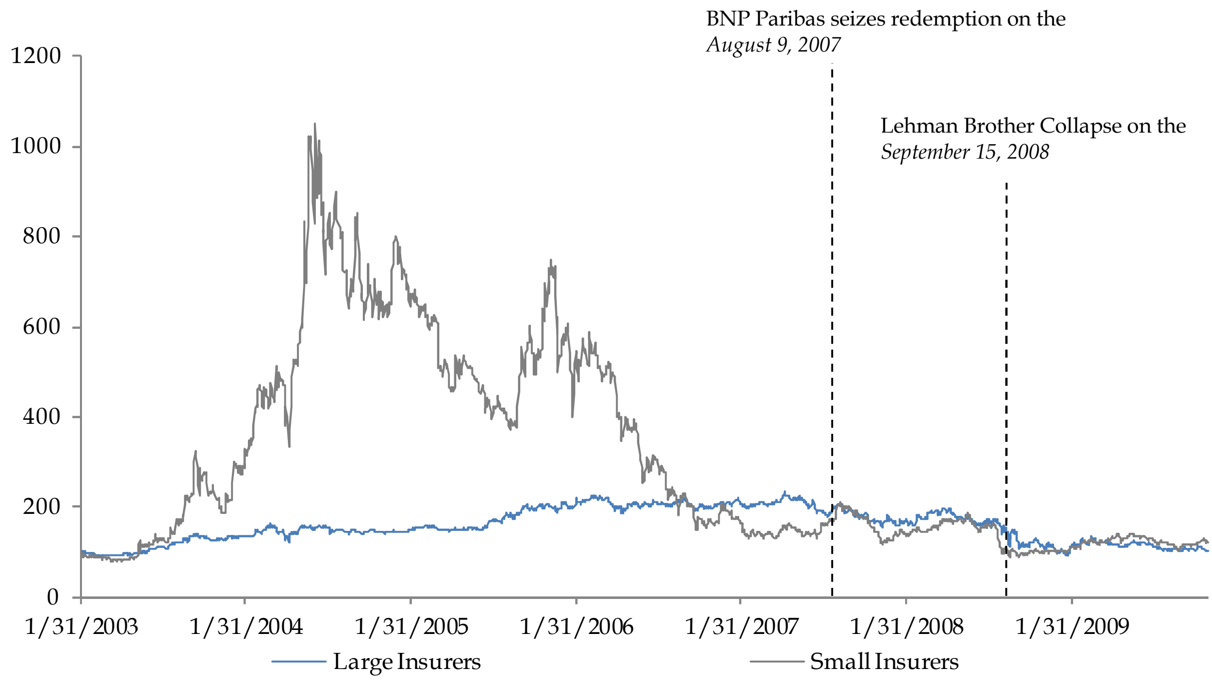
Panel B2: The UK Industrial Sector Portfolios



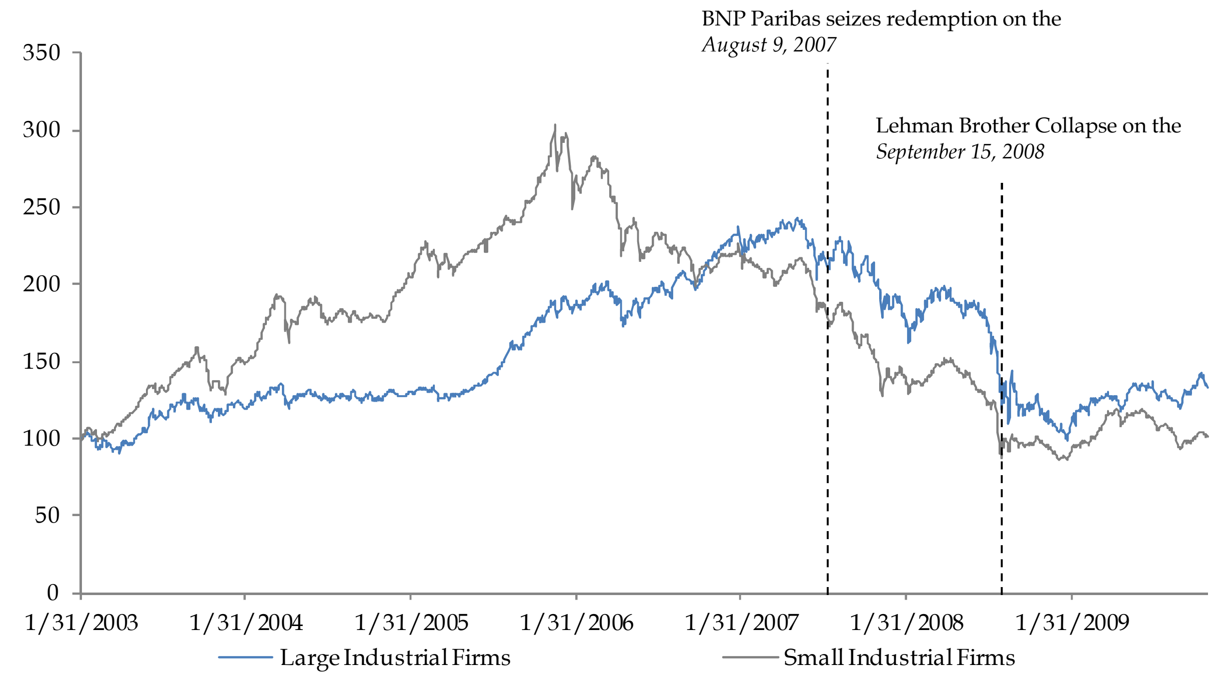
Panel C1: Japanese Banking Sector Portfolios



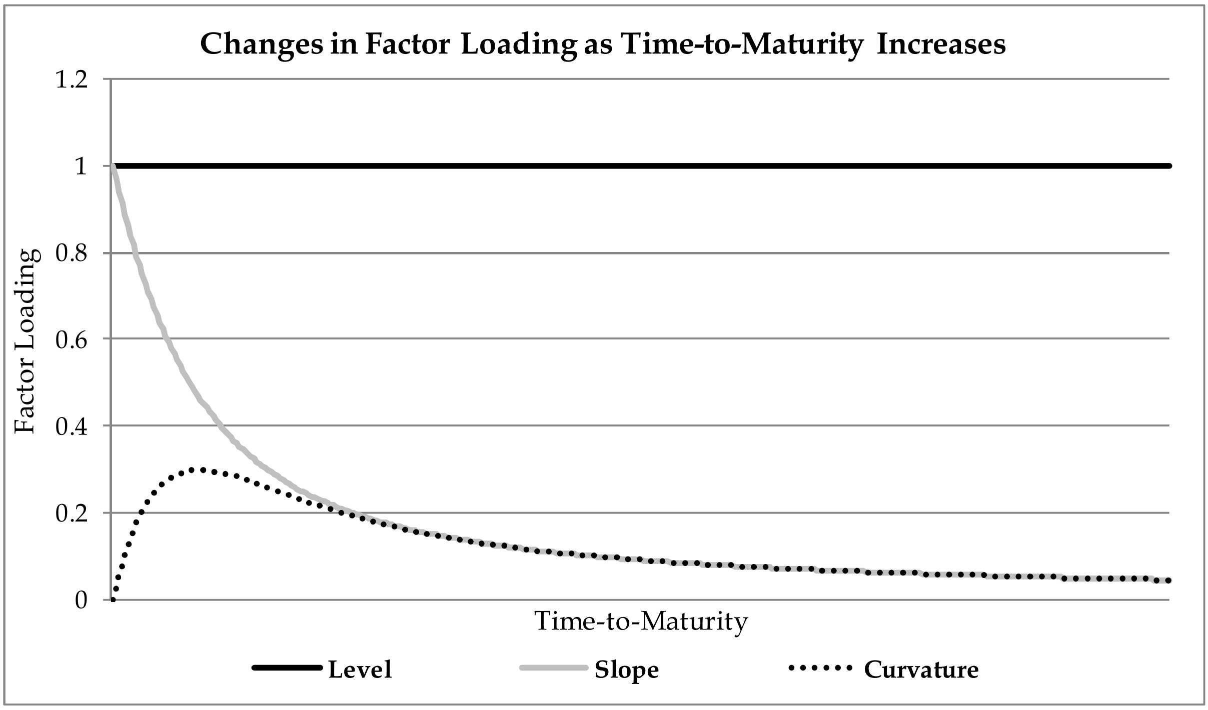
Panel C2: Japanese Insurance Sector Portfolios



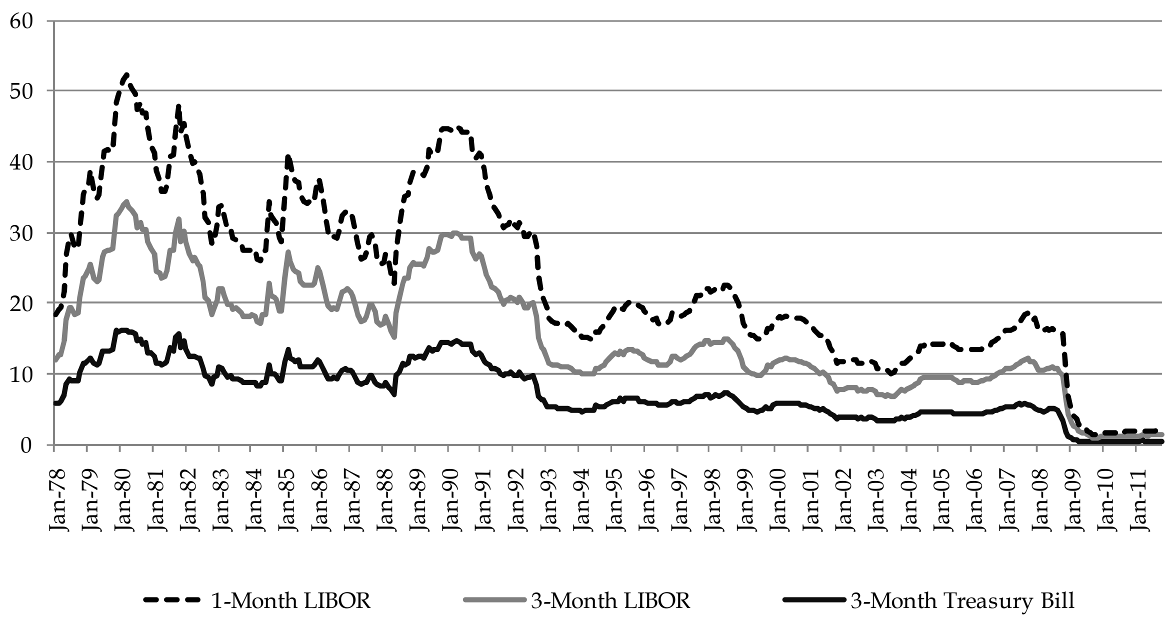
Panel C3: Japanese Industrial Sector Portfolios



B.6 Factor Loadings in Nelson-Siegel Three Factor Model

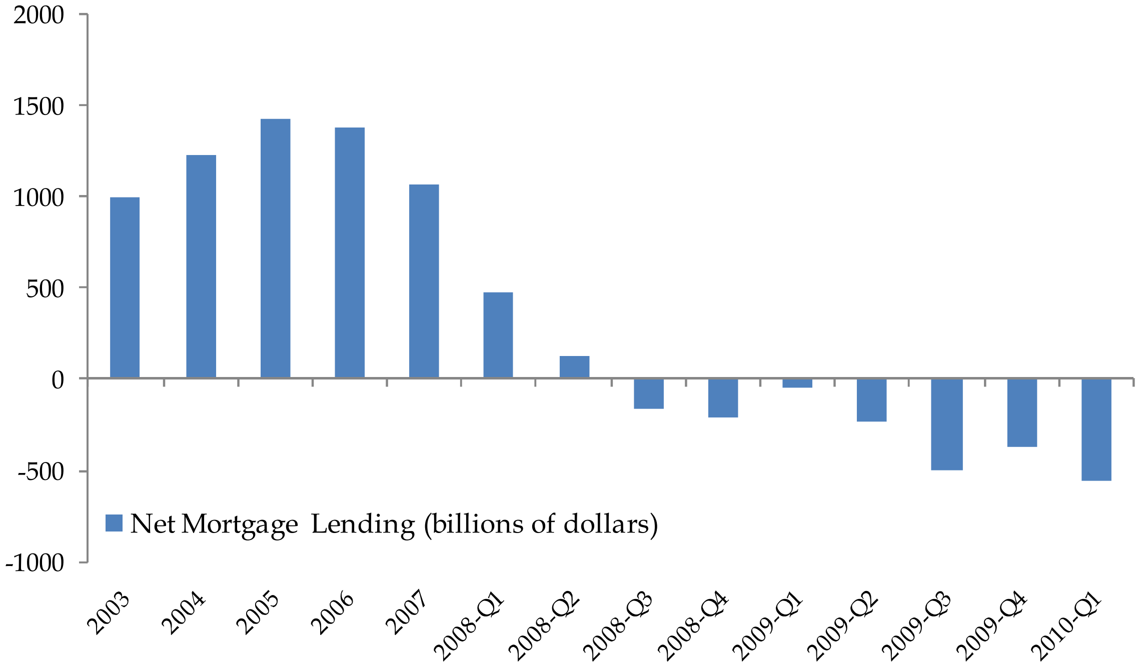


B.7 Short-Term Interest Rates in the UK Financial Market



Note: the short-term interest rates represented in the above figure is collected from the Bank of England, which is available from: http://www.bankofengland.co.uk/statistics/index.htm.

B.8 Net Mortgage Lending in the U.S. Financial Market



Note: the data for net mortgage lending in the above figure is collected from the two *Flow of Fund* reports issued by Federal Reserve on the *June 11, 2009* and *June 10, 2010*.

B.9 Daily Value Changes in the Equity Market Index and Banking portfolio in Japan

Note: the value of banking portfolio and market equity index is on the left-and right-hand side axis, respectively. The equity market index for Japan is presented by the NIKKEI 225. The value of the equity market index and banking portfolio has been rescaled at 100-level at the beginning of the sample period.

SECTION C

C.1 Conditional Mean Equation of VAR-BEKK model

The conditional mean equation of the VAR-BEKK model is an extended multifactor model. In the VAR-BEKK model, there is a system of conditional mean equations, which can be represented in a matrix form. In this section, we provide the detail explanation of the parameters used in the system of equations. We also illustrate the conditional mean equation in a scalar form.

The system of conditional mean equations presented as follow:

$$R_t = \beta \otimes MF_t + G \cdot {FX_t}^T + Z \cdot {FX\_Var_t}^T + DUM \cdot \Gamma \cdot {FX_t}^T + DUM \cdot \Theta \cdot {FX\_Var_t}^T + \varepsilon_t$$

As discussed in the Methodology Section, the parameters used in the above equations are all in matrix forms. The detail structure of these parameter matrices is represented as follow:

$$\beta = \begin{bmatrix} c_{Japan} & \beta_{Japan,Market} & \beta_{Japan,IR} \\ c_{UK} & \beta_{UK,Market} & \beta_{UK,IR} \\ c_{US} & \beta_{US,Market} & \beta_{US,IR} \end{bmatrix}$$

$$G = \begin{bmatrix} g_{Japan} & g_{Japan,UK} & g_{Japan,US} \\ g_{UK,Japan} & g_{UK} & g_{UK,US} \\ g_{US,Japan} & g_{US,UK} & g_{US} \end{bmatrix}$$

$$Z = \begin{bmatrix} z_{Japan} & z_{Japan,UK} & z_{Japan,US} \\ z_{UK,Japan} & z_{UK} & z_{UK,US} \\ z_{US,Japan} & z_{US,UK} & z_{US} \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} \gamma_{Japan} & \gamma_{Japan,UK} & \gamma_{Japan,US} \\ \gamma_{UK,Japan} & \gamma_{UK} & \gamma_{UK,US} \\ \gamma_{US,Japan} & \gamma_{US,UK} & \gamma_{US} \end{bmatrix}$$

$$\Theta = \begin{bmatrix} \theta_{Japan} & \theta_{Japan,UK} & \theta_{Japan,US} \\ \theta_{UK,Japan} & \theta_{UK} & \theta_{UK,US} \\ \theta_{US,Japan} & \theta_{US,UK} & \theta_{US} \end{bmatrix}$$

where,

c_i = the constant of the conditional mean equation for national market i.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for regional market *i* over day t, with $x \in [Market, IR]$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* over the whole sample period. g_i represents the *FX* effect of the home currency over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* over the whole sample period. z_i represents the *FX_Var* effect of the home currency over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* during the crisis period. γ_i represents changes in the *FX* effect of the home currency during the crisis period.

$\theta_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market *j* towards the financial sector portfolio in regional market *i* during the crisis period. θ_i represents changes in the *FX_Var* effect of the home currency during the crisis period.

With *i* and *j* ∈ [*Japan, UK, US*]

The conditional mean equation can also be presented in scalar form, which is demonstrated as follow:

$$r_{i,t} = c_i + \sum \beta_{i,x} MF(X)_{i,t} + \sum g_{i,j} FX_{j,t} + \sum z_{i,j} FX\_Var_{j,t} + DUM \sum \gamma_{i,j,} FX_{j,t} + DUM \sum \theta_{i,j,} FX\_Var_{j,t} + \varepsilon_{j,t}$$

with *i* and *j* ∈ [*Japan, UK, US*].

where,

c_i = the constant of the conditional mean equation for national market i.

$\beta_{i,x}$ = the parameter for the two macroeconomic factors (*Market* and *IR*) for regional market *i* over day t, with $x \in [Market, IR]$.

$MF(X)_{i,t}$ = represents the two macroeconomic factors: 1) the market risk factor represents by domestic stock market index return (*Market*), and 2) the interest rate risk factor represents by the unexpected changes of long-term benchmark interest rate (IR) for national market i over day t, with $X \in [\,Market, IR]$.

$FX_{i,t}$ = the unexpected changes of trade weighted currency price index for currency in country j over day t, which is the estimated residual from a fitted ARMA-GARCH model.

$FX\_Var_{i,t}$ = the conditional variance of the trade weighted currency price index for country j over day t, which is generated from a fitting ARMA-GARCH model together with the $FX_{i,t}$.

$g_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market j towards the financial sector portfolio in regional market i over the whole sample period. g_i represents the *FX* effect of the home currency over the whole sample period.

$z_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market j towards the financial sector portfolio in regional market i over the whole sample period. z_i represents the *FX_Var* effect of the home currency over the whole sample period.

$\gamma_{i,j}$ = the parameter represents the impact of the *FX* effect from currency in regional market j towards the financial sector portfolio in regional market i during the crisis period. γ_i represents changes in the *FX* effect of the home currency during the crisis period.

$\theta_{i,j}$ = the parameter represents the impact of the *FX_Var* effect from currency in regional market j towards the financial sector portfolio in regional market i during the crisis period. θ_i represents changes in the *FX_Var* effect of the home currency during the crisis period.

DUM = a dummy variable represents the potential structural break in the crisis period. $DUM = 0$ before the *September 15, 2008*, and $DUM = 1$ afterwards.

C.2 Trade Weighted Currency Price Index

The relative currency value used in the current study is the trade weighted currency price index provided by Bank of England (BoE). The index represents the relative value of one currency against a basket of other currencies used by major industrial countries. The following table shows the industrial countries employed by Bank of England to derive the trade weighted currency price index.

Geographic Distribution			
Asian Pacific	**Europe**		**North America**
	Eurozone	**Non-Eurozone**	
Australia	Austria	Republic of Ireland	Canada
Netherlands	Belgium-Luxembourg	United Kingdom	United States
Japan	Denmark		
	Finland		
	France		
	Germany		
	Greece		
	Italy		
	Netherlands		
	Norway		
	Portugal		
	Spain		
	Sweden		
	Switzerland		

Note: the list of industrial countries is provided by BoE.

The weight for the trade weighted currency price index is generated based on relative competitiveness of the manufacturing sectors among these industrial countries. The formula for the trade weighted currency price index can be illustrated as follow:

$$Index_j = \sum_{i=1}^{20} N_i^{w_i}$$

where,

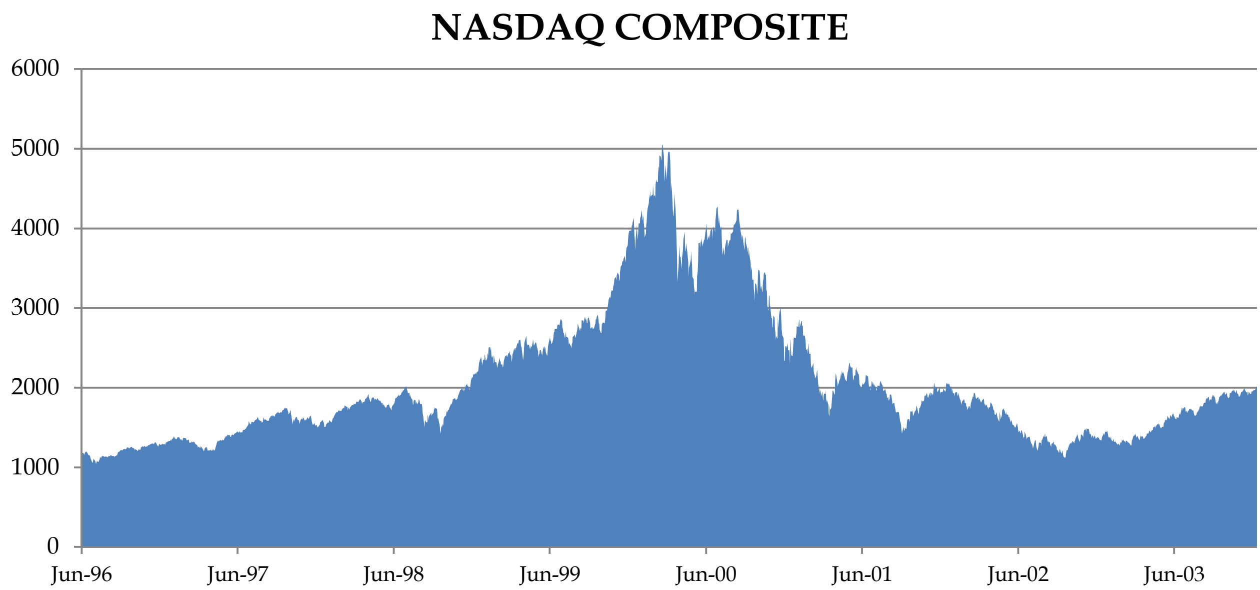
$Index_j$ = the trade weighted currency price index for national market j.

N_i = the bilateral exchange rate between the currency in national market j and the currency in national market i.

w_i = the weighting scheme of national market i in relation to national market j.

C.3 NASDAQ Composite Index during the Internet Bubble

The figure below demonstrates the price level of the NASDAQ Composite Index from *June 1996* till *December 2003*. The NASDAQ Composite Index covers all the common stocks listed on the NASDAQ stock market, which has more than 3000 components. It is commonly regarded as an indicator for the performances of technology firms and firms with high growth potential.

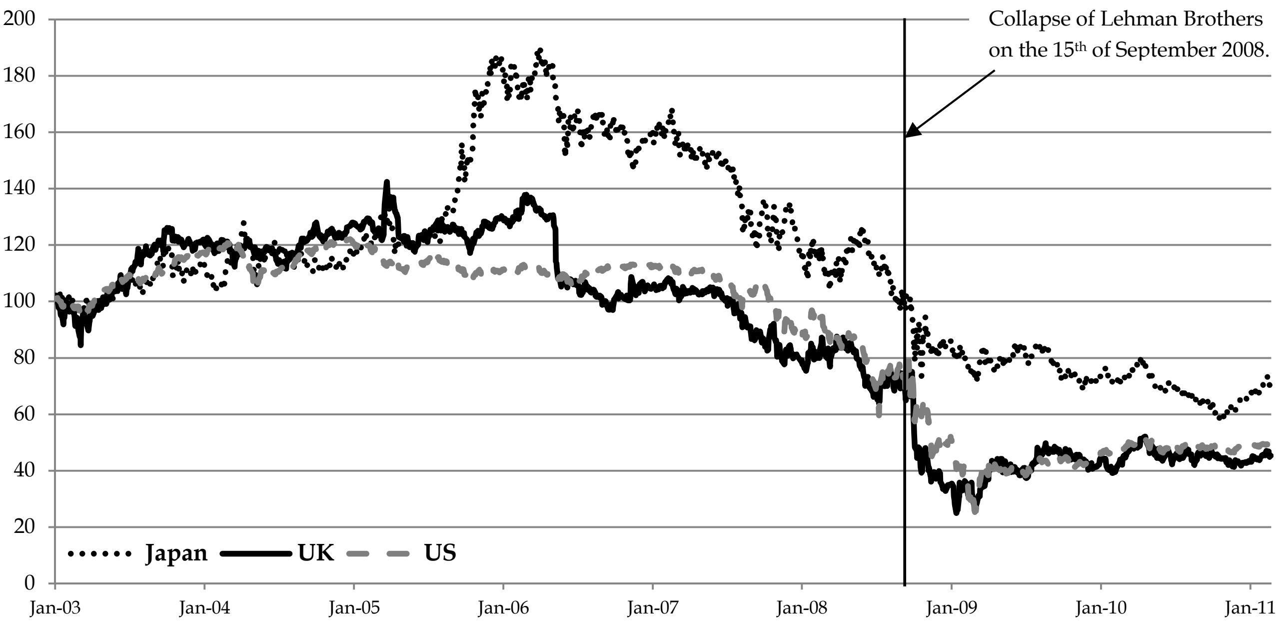


Note: the price information of the NASDAQ Composite Index is collected from DataStream International.

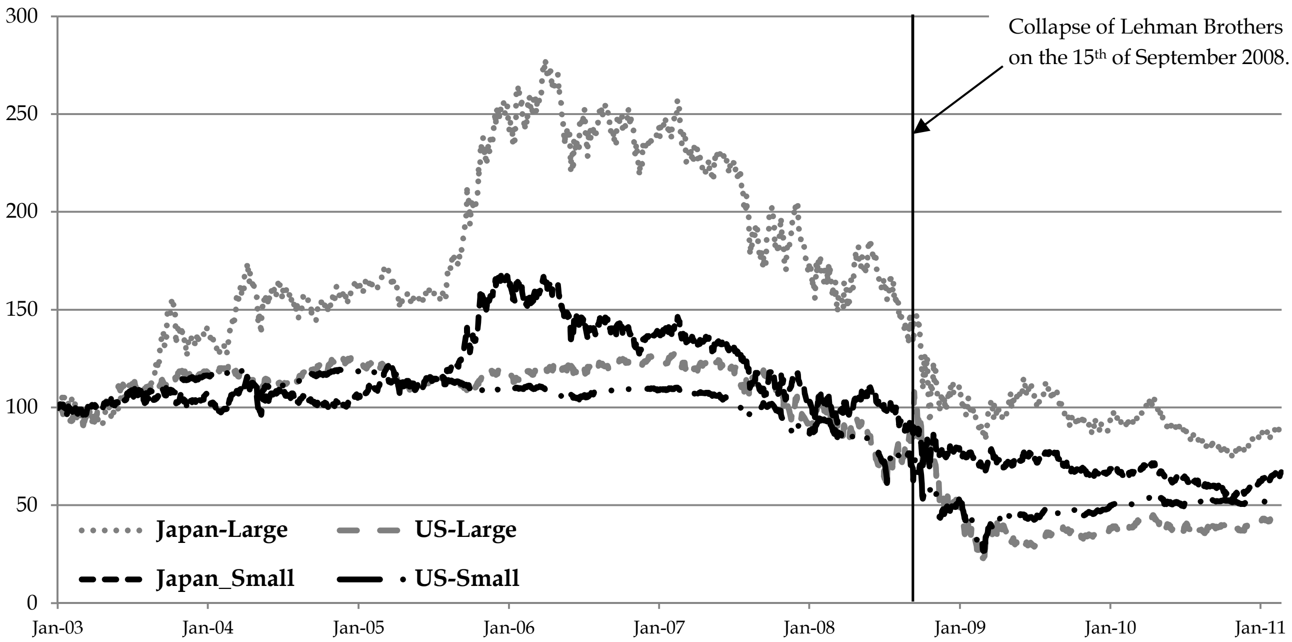
C.4 Time Series of Banking Sector Portfolios' Value

The figure below demonstrates the time series of banking portfolio value across the three national markets from the *January 1, 2003* till *March 31, 2011*. The value of the portfolios has been rescaled, which makes portfolio values equal to 100 at the beginning of the sample period.

Panel A: Banking Portfolios for the Japanese, UK and US markets.



Panel B: Large and Small Banking portfolios for the Japanese and US markets.

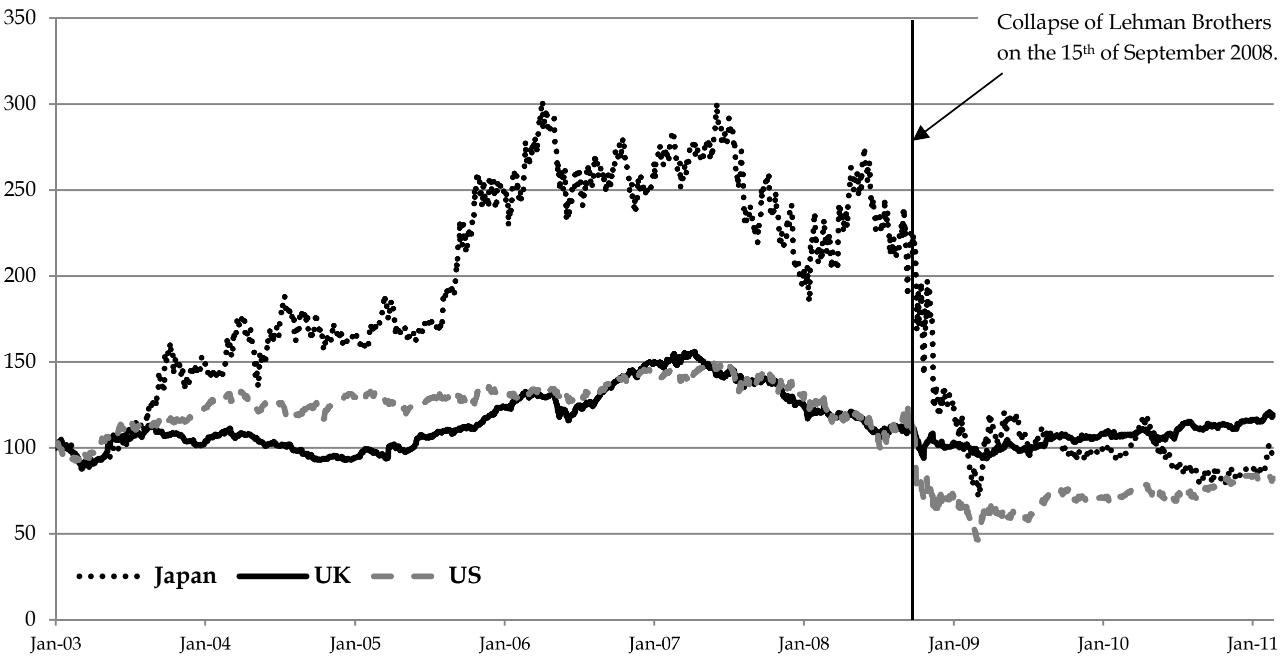


C.5 Time Series of Insurance Sector Portfolios' Value

The figure below demonstrates the time series of the insurance (life and non-life) portfolio value across the three national markets from the *January 1, 2003* till *March 31, 2011*. The value of the portfolios has been rescaled, which makes portfolio values equal to 100 at the beginning of the sample period.

Panel A: Life Insurance Portfolios for the UK and US markets.

Panel B: Non-Life Insurance Portfolios for the Japanese, UK and US markets.



C.6 Variance Inflation Factor Test

The variance inflation factor (VIF) test is a measure for multicolinearity for explanatory variables in a regression model. The VIF test statistics can be calculated in a three steps:

Step One: Run auxiliary regressions with the related explanatory variables.

Assume there are three highly related variables, namely x_1, x_2 and x_3. In the first step, for each variable we run an auxiliary regression with this variable as dependent variable and the remaining two as the independent variables. The R^2 for each of the auxiliary regression will be calculated and recorded.

$$x_1 = c_1 + a_1 x_2 + \beta_1 x_3 + \varepsilon_1 => R_1^2$$
$$x_2 = c_2 + a_2 x_1 + \beta_2 x_3 + \varepsilon_2 => R_2^2$$
$$x_3 = c_3 + a_3 x_1 + \beta_3 x_2 + \varepsilon_3 => R_3^2$$

where,

c_i = the constant for auxiliary regression with x_i as dependent variable.

a_i/b_i = the regression parameter for auxiliary regression with x_i as dependent variable.

ε_i = the estimated error for x_i.

$R^2{}_i$ = the R2 of the auxiliary regression with x_i as dependent variable.

with $i \in [1, 2, 3]$.

Step Two: Calculate the VIF statistics for Auxiliary Regressions.

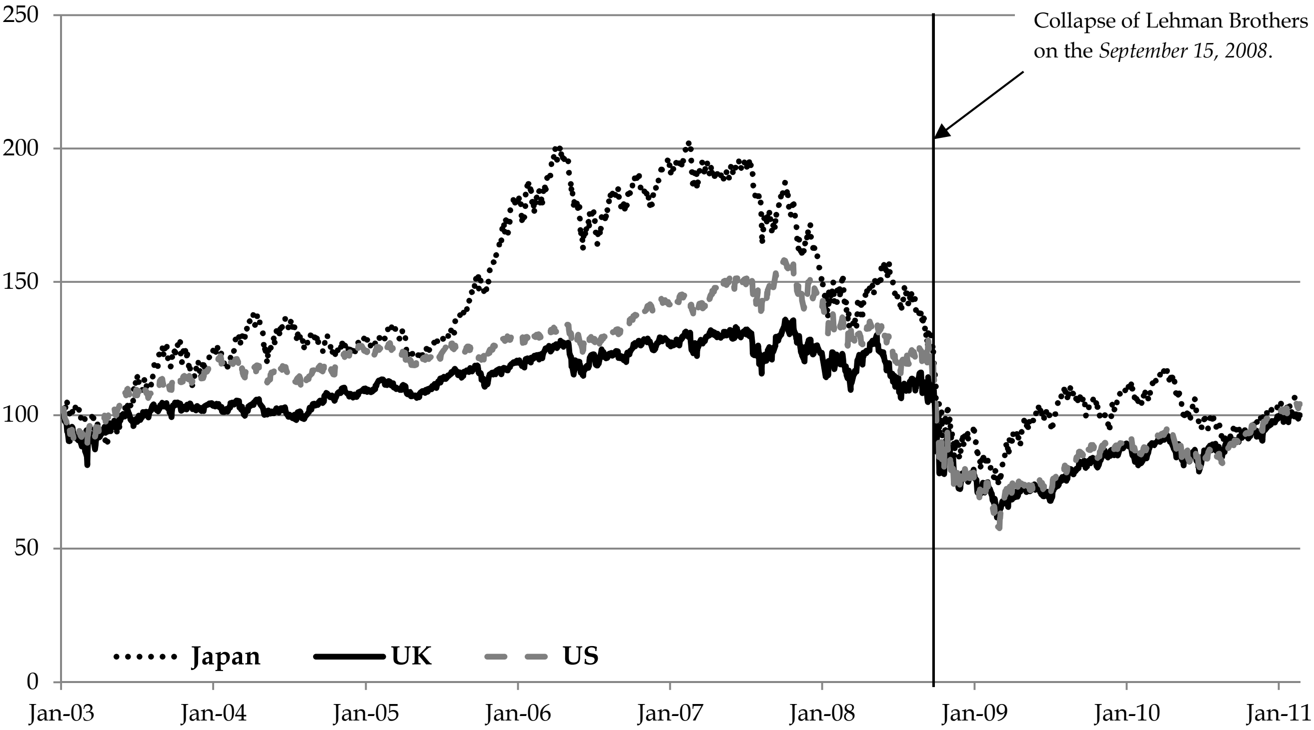
$$VIF_i = \frac{1}{1-R_i^2}\text{; with } i \in [1, 2, 3].$$

Step Three: Compare the VIF statistics with Critical Value.

The commonly used critical value for VIF test is 5. If test statistics (VIF_i) is large than 5, then we suggest the multicolinearity among the three related explanatory variables is high, and one should not incorporate all the three variables into the regression model at once.

C.7 Time Series of National Stock Market Index

The figure below demonstrates the time series of the three national stock market indices from the *January 1, 2003* till *March 31, 2011*. The value of the index price has been rescaled, which makes all the index values equal to 100 at the beginning of the sample.



Note: the stock market indices used in the above figure are the *S&P 500 Composite Index*, the *FTSE 100 Stock Market Index*, and the *NIKKEI 225 Stock Market Ind*ex for the Japanese, UK and US market, respectively.

SECTION D

D.1 Technique Aspects of the DCC MGARCH model

Dynamic Conditional Correlation MGARCH, for a two-asset case, follows the process

$$r_t = H_t^{1/2} \xi_t$$

$$H_t = \begin{bmatrix} h_{1,t} & \rho_t \sqrt{h_{1,t} h_{2,t}} \\ \rho_t \sqrt{h_{1,t} h_{2,t}} & h_{2,t} \end{bmatrix}$$

where the conditional variances are specified as

$$h_{1,t} = \omega_1 + \alpha_1 \ r_{1,t-1}^2 + \beta_1 h_{1,t-1}$$

and

$$h_{2,t} = \omega_2 + \alpha_2 \ r_{2,t-1}^2 + \beta_2 h_{2,t-1}$$

and $\rho_t = h_{12,t} / \sqrt{h_{1,t}^* h_{2,t}^*}$ comes from

$$h_{1,t}^* = (1 - \theta_1 - \theta_2) + \theta_1 \ \varepsilon_{1,t-1}^2 + \theta_2 h_{1,t-1}^*$$

$$h_{2,t}^* = (1 - \theta_1 - \theta_2) + \theta_2 \ \varepsilon_{2,t-1}^2 + \theta_2 h_{2,t-1}^*$$

and

$$h_{12,t} = \phi_{12} \ (1 - \theta_1 - \theta_2) + \theta_1 \ \varepsilon_{1,t-1} \varepsilon'_{2,t-1} + \theta_2 \ h_{12,t-1}$$

with ϕ_{12} equal to the average sample correlation of returns. Finally, $\varepsilon_{1,t} = \mu_{1,t} / \sqrt{h_{1,t}}$ and $\varepsilon_{2,t} = \mu_{2,t} / \sqrt{h_{2,t}}$.

D.2 Technique Aspects of the A-DCC MGARCH model

Asymmetric Generalized Dynamic Conditional Correlation MGARCH model gives higher tail dependence for both the upper and lower tails of the multi-period joint density. However, it may be interesting to have higher tail dependence in the lower tail of the multi-period density. This situation can be studied by using A-DCC. An A-DCC estimator has the following structure in a two assets case

$$r_t = H_t^{1/2} \xi_t$$

$$H_t = \begin{bmatrix} h_{1,t} & \rho_t \sqrt{h_{1,t} h_{2,t}} \\ \rho_t \sqrt{h_{1,t} h_{2,t}} & h_{2,t} \end{bmatrix}$$

where

$$h_{1,t} = \omega_1 + \alpha_1 \; r_{1,t-1}^2 + \beta_1 \, h_{1,t-1}$$

and

$$h_{2,t} = \omega_2 + \alpha_2 \, r_{2,t-1}^2 + \beta_2 \, h_{2,t-1}$$

and $\rho_t = h_{12,t} / \sqrt{h_{1,t}^* h_{2,t}^*}$, comes from

$$h_{1,t}^* = (1 - \theta_1 - \theta_2 - \theta_3/2) + \theta_1 \, \varepsilon_{1,t-1}^2 + \theta_2 \, h_{1,t-1}^* + \theta_3 \, d_{1,t-1} \varepsilon_{1,t-1}^2$$

$$h_{2,t}^* = (1 - \theta_1 - \theta_2 - \theta_3/2) + \theta_1 \, \varepsilon_{2,t-1}^2 + \theta_2 \, h_{2,t-1}^* + \theta_3 \, d_{2,t-1} \varepsilon_{2,t-1}^2$$

and

$$h_{12,t} = \phi_{12} \, (1 - \theta_1 - \theta_2) - \phi_3 \, \theta_3 + \theta_1 \, \varepsilon_{1,t-1} \varepsilon'_{2,t-1} + \theta_2 \, h_{12,t-1} + \theta_3 \, (d_{1,t-1} \varepsilon_{1,t-1}) \, (d_{2,t-1} \varepsilon_{2,t-1})'$$

The variables $d_{1,t}$ and $d_{2,t}$ are dummies for $r_{1,t}$ and $r_{2,t}$ that assume value *1* whenever these variables are negative and *0* otherwise, and the coefficient $\theta_3/2$ relies on the assumption that ε_1 and ε_2 have a symmetric distribution. ϕ_{12} and ϕ_3 are the average correlation of returns and the average asymmetric component $(d_{1,t-1} \varepsilon_{1,t-1}) \, (d_{2,t-1} \varepsilon_{2,t-1})'$, and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are defined as before.

D.3 Quasi–Maximum Likelihood (QML) Estimation

The two-step estimation of DCC and AG-DCC MVGARCH model assume that

$$r_t \,|\, \Omega_{t-1} \sim N(0, H_t) \sim N(0, D_t\, R_t\, D_t)$$

The normality assumption of r_t gives rise to a log-likelihood function. Without the normality assumption, the estimator will still have the QML interpretation. The log likelihood for this estimator can be written as

$$L = -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + log\, |H_t| + log\, |R_t| + r'_t\, H_t^{-1}\, r_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + log\, |D_t\, R_t\, D_t| + r'_t\, D_t^{-1} R_t^{-1} D_t^{-1}\, r_t\right)$$

Since the standardized residual, $\varepsilon_t = r_t \,/\, \sqrt{h_t} = D_t^{-1}\, r_t$, the log-likelihood function can be expressed as

$$L = -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + 2\, log\, |D_t| + log\, |R_t| + \varepsilon'_t\, R_t^{-1}\, \varepsilon_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + 2\, log\, |D_t| + r'_t\, D_t^{-1} D_t^{-1}\, r_t - \varepsilon'_t \varepsilon_t + log\, |R_t| + \varepsilon'_t\, R_t^{-1}\, \varepsilon_t\right)$$

It is clear that there are two separate parts of the log-likelihood function, the volatility part containing D_t and the correlation part containing R_t. This gives rise to the two stage estimation procedure. In the first stage, each of D_t can be considered as an univariate GARCH model, therefore the log-likelihood of the volatility term is simply the sum of the log-likelihoods of the individual GARCH equations for the involved return series

$$L = -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + 2\, log\, |D_t| + r'_t\, D_t^{-1} D_t^{-1}\, r_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + 2\, log\, |D_t| + r'_t\, D_t^{-2}\, r_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T} \left(n\, log(2\pi) + \sum_{i=1}^{n} \left(log(h_{it}) + r_{it}^2 / h_{it}\right)\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{n} \left(T\, log(2\pi) + \sum_{i=1}^{T} \left(log(h_{it}) + r_{it}^2 / h_{it}\right)\right)$$

In the second stage, the parameters of the correlation evolution are estimated using the specified log-likelihood of the correlation part, conditioning on the parameters estimated in the first stage likelihood

$$L_C = -\frac{1}{2}\sum_{t=1}^{T} \left(log\, |R_t| + \varepsilon'_t\, R_t^{-1}\, \varepsilon_t - \varepsilon'_t \varepsilon_t\right)$$

The properties of the QMLE and related test statistics in dynamic models that jointly parameterize conditional means and conditional covariances are discussed in Bollerslev and Wooldridge (1992).

It should be noted that the two step estimation of the likelihood function means that estimation is inefficient, though consistent (Engle and Sheppard, 2001; Engle, 2002).

D.4 GARCH-type Model Selection for the Two-Step MGARCH Estimation

Panel A: Sector Indices from the Japanese Equity market

Series	Models	c	a	b	e	LLF	AIC	SIC
ENG	GARCH	0.000	0.131	0.830		3940.9	-10.56	5.51
	EGARCH	-0.479	-0.049	0.959	0.207	3945.6	-8.56	12.87
BML	GARCH	0.000	0.099	0.873		4471.4	-10.81	5.26
	EGARCH	-0.325	-0.054	0.977	0.172	4474.0	-8.81	12.61
IND	GARCH	0.000	0.080	0.904		4505.6	-10.826	5.24
	EGARCH	-0.279	-0.045	0.979	0.136	4506.7	-8.827	12.60
CGS	GARCH	0.000	0.088	0.886		4403.8	-10.78	5.29
	EGARCH	-0.359	-0.020	0.973	0.172	4398.4	-8.78	12.65
HCR	GARCH	0.000	0.085	0.847		4796.2	-10.95	5.12
	EGARCH	-0.472	-0.063	0.960	0.148	4799.0	-8.95	12.47
CSV	GARCH	0.000	0.083	0.858		4734.0	-10.93	5.14
	EGARCH	-0.419	-0.070	0.964	0.134	4735.2	-8.93	12.50
TEL	GARCH	0.000	0.106	0.894		4069.2	-10.62	5.45
	EGARCH	-0.281	-0.031	0.984	0.209	4071.5	-8.62	12.80
UTL	GARCH	0.000	0.146	0.785		5023.8	-11.04	5.02
	EGARCH	-0.849	-0.055	0.928	0.243	5021.7	-9.04	12.38
FIN	GARCH	0.000	0.124	0.836		4072.3	-10.62	5.44
	EGARCH	-0.505	-0.056	0.958	0.222	4072.6	-8.62	12.80
TEC	GARCH	0.000	0.072	0.926		4043.0	-10.61	5.46
	EGARCH	-0.157	-0.013	0.992	0.129	4071.7	-8.62	12.80

Note: The table above indicates the univariate GARCH parameters for the 10 industry sector series returns in the Japanese equity market. The sample period is from July/1/1996 to June/28/2002. The 'c' is the constant parameter in the GARCH model; the 'a' is the parameter of the ARCH factor; the 'e' is the parameter of the EGARCH factor; the 'b' is the parameter of the GARCH factor. LLF is the log-likelihood value; the AIC is the Akaike Information Criterion, $AIC = 2 \times K - 2 \times ln(LLF)$, where K is the number of parameter; the SIC is the Schwarz Information Criterion, $SIC = K \times ln(LLF) - 2 \times ln(LLF)$.

Panel B: Sector Indices from the UK Equity market

Series	Models	c	a	b	e	LLF	AIC	SIC
ENG	GARCH	0.000	0.069	0.917	0.109	4367.3	-10.76	5.30
	EGARCH	-0.211	-0.049	0.985		4371.2	-8.77	12.66
BML	GARCH	0.000	0.232	0.681	0.377	4986.8	-11.03	5.04
	EGARCH	-1.295	-0.043	0.890		4990.1	-9.03	12.39
IND	GARCH	0.000	0.163	0.827	0.200	4475.4	-10.81	5.25
	EGARCH	-0.433	-0.070	0.966		4492.5	-8.82	12.60
CGS	GARCH	0.000	0.060	0.935	0.116	4116.5	-10.65	5.42
	EGARCH	-0.173	-0.031	0.989		4119.1	-8.65	12.78
HCR	GARCH	0.000	0.060	0.928	0.106	4655.4	-10.90	5.18
	EGARCH	-0.204	-0.043	0.986		4662.6	-8.90	12.53
CSV	GARCH	0.000	0.103	0.886	0.177	4979.1	-11.03	5.04
	EGARCH	-0.329	-0.061	0.979		4978.7	-9.03	12.40
TEL	GARCH	0.000	0.066	0.934	0.125	4178.0	-10.68	5.39
	EGARCH	-0.179	-0.035	0.990		4177.4	-8.68	12.75
UTL	GARCH	0.000	0.082	0.859	0.153	5045.1	-11.05	5.02
	EGARCH	-0.591	-0.049	0.948		5039.9	-9.05	12.37
FIN	GARCH	0.000	0.074	0.910	0.073	4470.800	-10.81	5.26
	EGARCH	-0.234	-0.089	0.979		4494.700	-8.82	12.60
TEC	GARCH	0.000	0.155	0.753	0.068	3314.1	-10.21	5.86
	EGARCH	-0.178	-0.031	0.982		3332.1	-8.22	13.20

Note: The table above indicates the univariate GARCH parameters for the 10 industry sector series returns in the Japanese equity market. The sample period is from July/1/1996 to June/28/2002. The 'c' is the constant parameter in the GARCH model; the 'a' is the parameter of the ARCH factor; the 'e' is the parameter of the EGARCH factor; the 'b' is the parameter of the GARCH factor. LLF is the log-likelihood value; the AIC is the Akaike Information Criterion, $AIC = 2 \times K - 2 \times ln(LLF)$, where K is the number of parameter; the SIC is the Schwarz Information Criterion, $SIC = K \times ln(LLF) - 2 \times ln(LLF)$.

Panel C: Sector Indices from the US Equity market

Series	Models	c	a	b	e	LLF	AIC	SIC
ENG	GARCH	0.000	0.051	0.935		4445.8	-10.80	5.27
	EGARCH	-0.218	-0.070	0.983	0.091	4459.2	-8.81	12.62
BML	GARCH	0.000	0.097	0.898		4510.0	-10.83	5.24
	EGARCH	-0.241	-0.057	0.983	0.128	4516.7	-8.83	12.59
IND	GARCH	0.000	0.071	0.921		4539.7	-10.84	5.23
	EGARCH	-0.241	-0.112	0.978	0.072	4589.2	-8.86	12.56
CGS	GARCH	0.000	0.074	0.911		4577.1	-10.86	5.21
	EGARCH	-0.231	-0.080	0.982	0.098	4600.4	-8.87	12.56
HCR	GARCH	0.000	0.101	0.853		4779.5	-10.94	5.12
	EGARCH	-0.471	-0.135	0.959	0.136	4812.6	-8.96	12.47
CSV	GARCH	0.000	0.108	0.887		4598.8	-10.87	5.20
	EGARCH	-0.321	-0.130	0.974	0.127	4638.1	-8.88	12.54
TEL	GARCH	0.000	0.065	0.911		4500.8	-10.82	5.24
	EGARCH	-0.463	-0.069	0.958	0.139	4507.1	-8.83	12.60
UTL	GARCH	0.000	0.085	0.910		5024.2	-11.04	5.02
	EGARCH	-0.276	-0.037	0.984	0.169	5025.2	-9.04	12.38
FIN	GARCH	0.000	0.077	0.896		4395.1	-10.78	5.29
	EGARCH	-0.309	-0.094	0.973	0.113	4416.2	-8.79	12.64
TEC	GARCH	0.000	0.083	0.901		3757.1	-10.46	5.60
	EGARCH	-0.352	-0.114	0.965	0.112	3787.5	-8.48	12.94

Note: The table above indicates the univariate GARCH parameters for the 10 industry sector series returns in the Japanese equity market. The sample period is from July/1/1996 to June/28/2002. The 'c' is the constant parameter in the GARCH model; the 'a' is the parameter of the ARCH factor; the 'e' is the parameter of the EGARCH factor; the 'b' is the parameter of the GARCH factor. LLF is the log-likelihood value; the AIC is the Akaike Information Criterion, $AIC = 2 \times K - 2 \times ln(LLF)$, where K is the number of parameter; the SIC is the Schwarz Information Criterion, $SIC = K \times ln(LLF) - 2 \times ln(LLF)$.

D.5 Technical Details of the Welch's Student's t-test

In the current study, four MGARCH estimators have the structural break specification. They are the DCC and ADCC Break MVGARCH models with both the scalar and diagonal parameter settings. As shown in the equation, for each break model, two sets of dynamic parameters need to be estimated for the pre- and post-break period.

Since the coefficients for pre- and post-break period have different population ($t_1 = 910$ for the pre-break period and $t_2 = 655$ for the post-break period), and is assumed to have different variance, we deployed the *Welch's Student's t-test* (Welch, 1947) to assess the statistical significance of the difference between the two sets of parameters.

The Welch's t-test can be showed as follows

$$t = \frac{\left| X_1 - X_2 \right|}{S_{1-2}}$$

$$S_{1-2} = \sqrt{\left| \frac{S_1^2}{N_1} - \frac{S_2^2}{N_2} \right|}$$

where t is the t-test statistic; X_1 and X_2 are the corresponding coefficients for the pre- and post-break period; S_1 and S_2 are the variance for the parameter X_1 and X_2; S_{1-2} is the pooled variance between the two parameter; and the N_1 and N_2 are the number of observations to estimate the two coefficients.

In the Welch's t-test, the degree of freedom of the Student-t distribution is differently defined from the simple t-test, which can be written as

$$d.f. = \frac{\left(\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2} \right)^2}{\frac{\left(\frac{S_1^2}{N_1} \right)^2}{N_1 - 1} + \frac{\left(\frac{S_2^2}{N_2} \right)^2}{N_2 - 1}}$$

D.6 Welch's Student's t-test for the Significance of Structural Break

The Tables below showed the result of structural break tests of the various MVGARCH models. The sample period is from *July 1, 1996* till *May 31, 2007*. The "a" is the parameter of the ARCH factor in the second step of the DCC-type MVGARCH model; the "b" is the parameter of the GARCH factor in the second step of the DCC-type MVGARCH model; the "g" is the parameter of the asymmetry effect in the second step of the DCC-type MVGARCH model estimation. The structure break is set on the date: *January 1, 1999*. The test statistics is generated based on the Welch's student's t-test. The Mean (abs.) is the absolute value of the difference between the two parameters before and after the structural break; the S.D. refers to the standard deviation of the pool variance (S_{1-2}); the d.f. refers to degree of freedom of the test.

Panel A: Structural Break Test for the Japanese Sector Portfolio

DCC-Break

Period 1			Period 2			Difference					
	Mean	**S.E.**		**Mean**	**S.E.**	**Mean(abs.)**	**S.D.**	**t-test**	**d.f.**	**p-value**	**Significance**
a_1	0.0233	0.0001	**a_2**	0.0136	0.0000	0.0098	0.0000	4.5460	614.7252	0.0000	***
b_1	0.8777	0.0063	**b_2**	0.9802	0.0001	0.1024	0.0003	6.4431	612.1951	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

A-DCC-Break

Period 1			Period 2			Difference					
	Mean	**S.E.**		**Mean**	**S.E.**	**Mean(abs.)**	**S.D.**	**t-test**	**d.f.**	**p-value**	**Significance**
a_1	0.0233	0.0001	**a_2**	0.0108	0.0002	0.0125	0.0000	5.0634	2088.1199	0.0000	***
b_1	0.8777	0.0079	**b_2**	0.9796	0.0001	0.1019	0.0003	5.7062	612.1200	0.0000	***
g_1	0.0000	0.0006	**g_2**	0.0039	0.0003	0.0039	0.0000	0.8029	685.1310	0.2112	-

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

G-DCC-Break

Series	Period 1			Period 2			Difference					
		Mean	**S.E.**		**Mean**	**S.E.**	**Mean(abs.)**	**S.D.**	**t-test**	**d.f.**	**p-value**	**Significance**
ENG	**a_1^2**	0.0109	0.0001	**a_2^2**	0.0089	0.0000	0.0020	0.0000	1.0866	618.5728	0.1388	-
	b_1^2	0.8935	0.0135	**b_2^2**	0.9609	0.0005	0.0673	0.0005	2.8819	612.4368	0.0020	***
BML	**a_1^2**	0.0310	0.0003	**a_2^2**	0.0214	0.0000	0.0096	0.0000	2.9536	612.9713	0.0016	***
	b_1^2	0.8744	0.0065	**b_2^2**	0.9701	0.0000	0.0957	0.0003	5.9233	612.0216	0.0000	***
IND	**a_1^2**	0.0130	0.0000	**a_2^2**	0.0189	0.0000	0.0060	0.0000	6.1553	959.2652	0.0000	***
	b_1^2	0.9728	0.0013	**b_2^2**	0.9782	0.0000	0.0054	0.0001	0.7494	612.4228	0.2270	-
CGS	**a_1^2**	0.0087	0.0000	**a_2^2**	0.0140	0.0000	0.0053	0.0000	5.2054	741.2654	0.0000	***
	b_1^2	0.9467	0.0006	**b_2^2**	0.9860	0.0000	0.0394	0.0000	8.1658	612.1761	0.0000	***
HCR	**a_1^2**	0.0065	0.0000	**a_2^2**	0.0119	0.0000	0.0054	0.0000	5.9201	2153.1145	0.0000	***
	b_1^2	0.8980	0.0009	**b_2^2**	0.9767	0.0001	0.0787	0.0000	13.4344	616.8350	0.0000	***
CSV	**a_1^2**	0.0109	0.0000	**a_2^2**	0.0213	0.0000	0.0104	0.0000	7.4185	643.2957	0.0000	***
	b_1^2	0.9521	0.0053	**b_2^2**	0.9621	0.0001	0.0100	0.0002	0.6853	612.0910	0.2467	-
TEL	**a_1^2**	0.0088	0.0002	**a_2^2**	0.0200	0.0000	0.0111	0.0000	4.1966	623.7042	0.0000	***
	b_1^2	0.9581	0.0662	**b_2^2**	0.9510	0.0004	0.0070	0.0027	0.1362	612.0182	0.4459	-
UTL	**a_1^2**	0.0124	0.0000	**a_2^2**	0.0030	0.0000	0.0093	0.0000	6.8821	612.0055	0.0000	***
	b_1^2	0.8327	0.0066	**b_2^2**	0.9970	0.0000	0.1643	0.0003	10.0876	612.0049	0.0000	***
FIN	**a_1^2**	0.0557	0.0011	**a_2^2**	0.0369	0.0002	0.0188	0.0000	2.7999	619.7722	0.0026	***
	b_1^2	0.8896	0.0070	**b_2^2**	0.9328	0.0010	0.0431	0.0003	2.5537	619.3290	0.0054	***
TEC	**a_1^2**	0.0235	0.0001	**a_2^2**	0.0229	0.0000	0.0005	0.0000	0.2562	644.7617	0.3989	-
	b_1^2	0.9404	0.0005	**b_2^2**	0.9681	0.0001	0.0277	0.0000	6.3116	636.2847	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

Panel A: CONT'D

AG-DCC-Break													
Series	**Period 1**			**Period 2**			**Difference**						
		Mean	**S.E.**		**Mean**	**S.E.**	**Mean(abs.)**	**S.D.**	**t-test**	**d.f.**	**p-value**	**Significance**
ENG	a_1^2	0.0222	0.0001	a_2^2	0.0050	0.0000	0.0172	0.0000	7.7777	614.1362	0.0000	***
	b_1^2	0.7843	0.0050	b_2^2	0.9928	0.0002	0.2086	0.0002	14.6363	612.7172	0.0000	***
	g_1^2	0.0459	0.0004	g_2^2	0.0021	0.0000	0.0439	0.0000	10.7778	613.2082	0.0000	***
BML	a_1^2	0.0508	0.0001	a_2^2	0.0197	0.0000	0.0311	0.0000	16.0145	618.0269	0.0000	***
	b_1^2	0.8036	0.0028	b_2^2	0.9717	0.0000	0.1681	0.0001	15.8035	612.0863	0.0000	***
	g_1^2	0.0036	0.0003	g_2^2	0.0047	0.0000	0.0011	0.0000	0.3159	613.4456	0.3761	-
IND	a_1^2	0.0162	0.0001	a_2^2	0.0209	0.0000	0.0047	0.0000	3.0369	676.6740	0.0012	***
	b_1^2	0.8746	0.0116	b_2^2	0.9677	0.0001	0.0931	0.0005	4.2989	612.0120	0.0000	***
	g_1^2	0.0016	0.0003	g_2^2	0.0101	0.0000	0.0086	0.0000	2.5526	613.7777	0.0055	***
CGS	a_1^2	0.0067	0.0001	a_2^2	0.0230	0.0002	0.0163	0.0000	7.1913	2607.5316	0.0000	***
	b_1^2	0.9786	0.0754	b_2^2	0.9489	0.0005	0.0297	0.0030	0.5385	612.0220	0.2952	-
	g_1^2	0.0001	0.0012	g_2^2	0.0056	0.0002	0.0055	0.0000	0.7925	618.7239	0.2142	-
HCR	a_1^2	0.0061	0.0000	a_2^2	0.0125	0.0001	0.0064	0.0000	5.1557	2079.4644	0.0000	***
	b_1^2	0.9929	0.0000	b_2^2	0.9405	0.0002	0.0524	0.0000	25.2888	2281.4312	0.0000	***
	g_1^2	0.0001	0.0000	g_2^2	0.0356	0.0002	0.0355	0.0000	18.3614	2063.0446	0.0000	***
CSV	a_1^2	0.0264	0.0000	a_2^2	0.0207	0.0000	0.0057	0.0000	3.9859	678.7185	0.0000	***
	b_1^2	0.7740	0.0052	b_2^2	0.9517	0.0001	0.1777	0.0002	12.2452	612.1477	0.0000	***
	g_1^2	0.0057	0.0203	g_2^2	0.0082	0.0000	0.0024	0.0008	0.0857	612.0053	0.4659	-
TEL	a_1^2	0.0096	0.0001	a_2^2	0.0197	0.0000	0.0102	0.0000	5.3641	620.2024	0.0000	***
	b_1^2	0.8788	0.0039	b_2^2	0.9454	0.0001	0.0666	0.0002	5.3374	612.2894	0.0000	***
	g_1^2	0.0222	0.0001	a_2^2	0.0050	0.0000	0.0010	0.0000	0.5553	631.3602	0.2894	-
UTL	a_1^2	0.7843	0.0050	b_2^2	0.9928	0.0002	0.0026	0.0000	2.2504	613.6808	0.0124	**
	b_1^2	0.0459	0.0004	g_2^2	0.0021	0.0000	0.0692	0.0000	73.0599	612.9495	0.0000	***
	g_1^2	0.0508	0.0001	a_2^2	0.0197	0.0000	0.0140	0.0000	53.5417	2063.0016	0.0000	***
FIN	a_1^2	0.8036	0.0028	b_2^2	0.9717	0.0000	0.0599	0.0000	10.6134	613.4746	0.0000	***
	b_1^2	0.0036	0.0003	g_2^2	0.0047	0.0000	0.1380	0.0001	14.5986	621.4085	0.0000	***
	g_1^2	0.0162	0.0001	a_2^2	0.0209	0.0000	0.0036	0.0001	0.4954	616.1851	0.3102	-
TEC	a_1^2	0.8746	0.0116	b_2^2	0.9677	0.0001	0.0087	0.0000	1.8543	614.1952	0.0321	**
	b_1^2	0.0016	0.0003	g_2^2	0.0101	0.0000	0.0035	0.0031	0.0623	612.0051	0.4752	-
	g_1^2	0.0067	0.0001	a_2^2	0.0230	0.0002	0.0089	0.0003	0.5229	612.0197	0.3006	-

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

Panel B: Structural Break Test for the UK Sector Portfolio

DCC-Break

	Period 1			Period 2		Difference					
	Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
a_1	0.0152	0.0001	a_2	0.0141	0.0000	0.0011	0.0000	0.4741	652.4188	0.3178	-
b_1	0.9101	0.0013	b_2	0.9750	0.0006	0.0649	0.0001	8.9532	707.5547	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

A-DCC-Break

	Period 1			Period 2		Difference					
	Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
a_1	0.0097	0.0008	a_2	0.0112	0.0010	0.0014	0.0000	0.2257	1231.1827	0.4107	-
b_1	0.9136	0.0031	b_2	0.9742	0.0005	0.0606	0.0001	5.4590	641.1645	0.0000	***
g_1	0.0131	0.0032	g_2	0.0046	0.0018	0.0085	0.0001	0.7377	753.9945	0.2305	-

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

G-DCC-Break

		Period 1			Period 2		Difference					
		Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
ENG	a_1^2	0.0113	0.0025	a_2^2	0.0110	0.0000	0.0002	0.0001	0.0238	631.0378	0.4905	-
	b_1^2	0.8929	0.3491	b_2^2	0.9819	0.0002	0.0891	0.0139	0.7565	631.0048	0.2248	-
BML	a_1^2	0.0077	0.0000	a_2^2	0.0126	0.0000	0.0049	0.0000	4.2881	710.2178	0.0000	***
	b_1^2	0.9890	0.0002	b_2^2	0.9789	0.0001	0.0101	0.0000	4.0326	743.2111	0.0000	***
IND	a_1^2	0.0196	0.0005	a_2^2	0.0162	0.0000	0.0034	0.0000	0.7722	633.0463	0.2201	-
	b_1^2	0.8972	0.0281	b_2^2	0.9755	0.0002	0.0783	0.0011	2.3429	631.0191	0.0097	***
CGS	a_1^2	0.0353	0.0033	a_2^2	0.0070	0.0001	0.0282	0.0001	2.4610	631.1081	0.0071	***
	b_1^2	0.7324	0.0612	b_2^2	0.9930	0.0007	0.2606	0.0024	5.2841	631.0501	0.0000	***
HCR	a_1^2	0.0349	0.0001	a_2^2	0.0221	0.0000	0.0128	0.0000	6.2703	710.7134	0.0000	***
	b_1^2	0.8941	0.0013	b_2^2	0.9659	0.0002	0.0718	0.0001	10.1063	637.0755	0.0000	***
CSV	a_1^2	0.0473	0.0024	a_2^2	0.0157	0.0000	0.0317	0.0001	3.2780	631.0156	0.0006	***
	b_1^2	0.7729	0.0476	b_2^2	0.9754	0.0000	0.2025	0.0019	4.6602	631.0050	0.0000	***
TEL	a_1^2	0.0222	0.0005	a_2^2	0.0170	0.0000	0.0052	0.0000	1.2278	631.2870	0.1100	-
	b_1^2	0.9166	0.0020	b_2^2	0.9696	0.0000	0.0530	0.0001	5.9452	631.1518	0.0000	***
UTL	a_1^2	0.0021	0.0000	a_2^2	0.0085	0.0000	0.0064	0.0000	5.9600	677.9991	0.0000	***
	b_1^2	0.8835	0.0593	b_2^2	0.9777	0.0001	0.0942	0.0024	1.9418	631.0067	0.0263	**
FIN	a_1^2	0.0215	0.0001	a_2^2	0.0190	0.0000	0.0025	0.0000	1.3271	647.5504	0.0925	*
	b_1^2	0.9331	0.0005	b_2^2	0.9714	0.0001	0.0382	0.0000	8.5359	634.7351	0.0000	***
TEC	a_1^2	0.0004	0.0000	a_2^2	0.0098	0.0000	0.0095	0.0000	13.4598	2257.3954	0.0000	***
	b_1^2	0.9497	0.0105	b_2^2	0.9810	0.0001	0.0313	0.0004	1.5304	631.0537	0.0632	*

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

Panel B: CONT'D

AG-DCC-Break

		Period 1			Period 2		Difference					
		Mean	**S.E.**		**Mean**	**S.E.**	**Mean(abs.)**	**S.D.**	**t-test**	**d.f.**	**p-value**	**Significance**
ENG	a_1^2	0.0000	0.0002	a_2^2	0.0099	0.0000	0.0099	0.0000	3.5152	634.1530	0.0002	***
	b_1^2	0.7864	43.8370	b_2^2	0.9782	0.0002	0.1918	1.7410	0.1453	631.0047	0.4422	-
	g_1^2	0.0653	3.6437	g_2^2	0.0103	0.0002	0.0549	0.1447	0.1444	631.0047	0.4426	-
BML	a_1^2	0.0044	0.0001	a_2^2	0.0137	0.0000	0.0092	0.0000	5.7882	680.1105	0.0000	***
	b_1^2	0.9489	2.4159	b_2^2	0.9767	0.0001	0.0278	0.0959	0.0897	631.0047	0.4643	-
	g_1^2	0.0182	0.0319	g_2^2	0.0009	0.0000	0.0173	0.0013	0.4847	631.0047	0.3140	-
IND	a_1^2	0.0064	0.0003	a_2^2	0.0183	0.0001	0.0119	0.0000	3.6427	644.4849	0.0001	***
	b_1^2	0.9054	0.2511	b_2^2	0.9733	0.0002	0.0679	0.0100	0.6801	631.0050	0.2484	-
	g_1^2	0.0459	0.0058	g_2^2	0.0004	0.0000	0.0455	0.0002	2.9925	631.0049	0.0014	***
CGS	a_1^2	0.0155	0.0021	a_2^2	0.0066	0.0000	0.0089	0.0001	0.9791	631.0059	0.1640	-
	b_1^2	0.7855	0.0745	b_2^2	0.9947	0.0000	0.2092	0.0030	3.8474	631.0048	0.0001	***
	g_1^2	0.0300	0.0016	g_2^2	0.0014	0.0000	0.0286	0.0001	3.5832	631.0088	0.0002	***
HCR	a_1^2	0.0161	0.0025	a_2^2	0.0194	0.0000	0.0033	0.0001	0.3327	631.0298	0.3698	-
	b_1^2	0.8843	0.4763	b_2^2	0.9615	0.0001	0.0772	0.0189	0.5615	631.0047	0.2873	-
	g_1^2	0.0289	0.0200	g_2^2	0.0143	0.0001	0.0146	0.0008	0.5197	631.0083	0.3017	-
CSV	a_1^2	0.0082	0.0035	a_2^2	0.0160	0.0000	0.0078	0.0001	0.6621	631.0195	0.2541	-
	b_1^2	0.7388	0.0953	b_2^2	0.9741	0.0001	0.2353	0.0038	3.8257	631.0049	0.0001	***
	g_1^2	0.1036	0.0155	g_2^2	0.0016	0.0000	0.1020	0.0006	4.1059	631.0048	0.0000	***
TEL	a_1^2	0.0564	0.1452	a_2^2	0.0151	0.0000	0.0413	0.0058	0.5445	631.0047	0.2931	-
	b_1^2	0.8951	0.0053	b_2^2	0.9705	0.0000	0.0754	0.0002	5.2002	631.0288	0.0000	***
	g_1^2	0.0000	0.0002	a_2^2	0.0099	0.0000	0.0094	0.0003	0.5560	631.0069	0.2892	-
UTL	a_1^2	0.7864	43.8370	b_2^2	0.9782	0.0002	0.0032	0.0002	0.2180	631.0058	0.4138	-
	b_1^2	0.0653	3.6437	g_2^2	0.0103	0.0002	0.9173	2.9161	0.5372	631.0047	0.2957	-
	g_1^2	0.0044	0.0001	a_2^2	0.0137	0.0000	0.0087	0.0006	0.3489	631.0059	0.3637	-
FIN	a_1^2	0.9489	2.4159	b_2^2	0.9767	0.0001	0.0015	0.0000	0.5633	633.9865	0.2867	-
	b_1^2	0.0182	0.0319	g_2^2	0.0009	0.0000	0.0447	0.0083	0.4912	631.0047	0.3117	-
	g_1^2	0.0064	0.0003	a_2^2	0.0183	0.0001	0.0159	0.0001	1.6948	631.0268	0.0453	**
TEC	a_1^2	0.9054	0.2511	b_2^2	0.9733	0.0002	0.0091	0.0002	0.6652	631.0074	0.2531	-
	b_1^2	0.0459	0.0058	g_2^2	0.0004	0.0000	0.0212	0.2403	0.0432	631.0047	0.4828	-
	g_1^2	0.0155	0.0021	a_2^2	0.0066	0.0000	0.0001	0.0000	0.0529	631.0449	0.4789	-

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

Panel C: Structural Break Test for the US Sector Portfolio

DCC-Break

	Period 1			Period 2		Difference					
	Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
a_1	0.0230	0.0002	a_2	0.0110	0.0000	0.0120	0.0000	4.6157	631.6411	0.0000	***
b_1	0.8965	0.0057	b_2	0.9868	0.0007	0.0902	0.0002	5.9687	635.4971	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

A-DCC-Break

	Period 1			Period 2		Difference					
	Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
a_1	0.0151	0.0022	a_2	0.0100	0.0014	0.0051	0.0001	0.5316	784.7248	0.2976	-
b_1	0.9077	0.0118	b_2	0.9868	0.0006	0.0791	0.0005	3.6583	630.9578	0.0001	***
g_1	0.0121	0.0061	g_2	0.0011	0.0016	0.0110	0.0002	0.7037	656.9000	0.2409	-

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

G-DCC-Break

		Period 1			Period 2		Difference					
		Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
ENG	a_1^2	0.0081	0.0001	a_2^2	0.0201	0.0176	0.0120	0.0004	0.6135	2112.1983	0.2698	-
	b_1^2	0.9628	0.0008	b_2^2	0.9799	0.0118	0.0172	0.0003	1.0694	2169.2249	0.1425	-
BML	a_1^2	0.0086	0.0000	a_2^2	0.0143	0.0012	0.0057	0.0000	1.1056	2115.4189	0.1345	-
	b_1^2	0.9894	0.0002	b_2^2	0.9857	0.0012	0.0037	0.0000	0.7073	2364.7307	0.2397	-
IND	a_1^2	0.0200	0.0001	a_2^2	0.0131	0.0082	0.0069	0.0002	0.5155	2113.6416	0.3031	-
	b_1^2	0.9454	0.0006	b_2^2	0.9869	0.0097	0.0415	0.0002	2.8405	2171.2988	0.0023	***
CGS	a_1^2	0.0154	0.0001	a_2^2	0.0178	0.0259	0.0025	0.0006	0.1045	2112.4386	0.4584	-
	b_1^2	0.9535	0.0009	b_2^2	0.9815	0.0379	0.0280	0.0008	0.9765	2120.5623	0.1645	-
HCR	a_1^2	0.0170	0.0001	a_2^2	0.0106	0.0084	0.0063	0.0002	0.4693	2113.2503	0.3195	-
	b_1^2	0.9414	0.0002	b_2^2	0.9822	0.0196	0.0408	0.0004	1.9745	2113.3328	0.0242	**
CSV	a_1^2	0.0133	0.0001	a_2^2	0.0100	0.0001	0.0033	0.0000	1.7087	2441.0398	0.0438	**
	b_1^2	0.9468	0.0001	b_2^2	0.9801	0.0014	0.0334	0.0000	5.9747	2163.5899	0.0000	***
TEL	a_1^2	0.0200	0.0079	a_2^2	0.0065	0.0067	0.0135	0.0003	0.7286	913.0074	0.2332	-
	b_1^2	0.8661	0.0035	b_2^2	0.9935	0.0233	0.1274	0.0005	5.5518	2400.3183	0.0000	***
UTL	a_1^2	0.0607	0.0067	a_2^2	0.0154	0.0004	0.0453	0.0003	2.7736	631.2365	0.0029	***
	b_1^2	0.7320	0.0197	b_2^2	0.9846	0.0005	0.2526	0.0008	9.0368	630.2120	0.0000	***
FIN	a_1^2	0.0149	0.0001	a_2^2	0.0031	0.0000	0.0118	0.0000	7.8081	816.8628	0.0000	***
	b_1^2	0.9580	0.0003	b_2^2	0.9815	0.0008	0.0235	0.0000	5.2433	2682.0946	0.0000	***
TEC	a_1^2	0.0198	0.0000	a_2^2	0.0092	0.0001	0.0106	0.0000	6.0037	2717.9268	0.0000	***
	b_1^2	0.9316	0.0006	b_2^2	0.9901	0.0003	0.0585	0.0000	11.7066	695.9265	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

Panel C: CONT'D

AG-DCC-Break		Period 1		Period 2			Difference					
		Mean	S.E.		Mean	S.E.	Mean(abs.)	S.D.	t-test	d.f.	p-value	Significance
ENG	**a_1^2**	0.0041	0.0120	**a_2^2**	0.0084	0.0010	0.0044	0.0005	0.2008	632.7202	0.4205	-
	b_1^2	0.9995	0.0087	**b_2^2**	0.9886	0.0061	0.0110	0.0004	0.5682	819.8899	0.2850	-
	g_1^2	0.0059	0.0115	**g_2^2**	0.0001	0.0000	0.0058	0.0005	0.2703	630.0047	0.3935	-
BML	**a_1^2**	0.0053	0.0006	**a_2^2**	0.0192	0.0002	0.0139	0.0000	2.8091	654.6019	0.0026	***
	b_1^2	0.9420	0.0272	**b_2^2**	0.9747	0.0003	0.0327	0.0011	0.9950	630.0609	0.1601	-
	g_1^2	0.0312	0.0132	**g_2^2**	0.0045	0.0000	0.0267	0.0005	1.1675	630.0051	0.1217	-
IND	**a_1^2**	0.0103	0.0001	**a_2^2**	0.0176	0.0000	0.0073	0.0000	5.0574	639.3582	0.0000	***
	b_1^2	0.9353	0.0004	**b_2^2**	0.9726	0.0000	0.0373	0.0000	9.3896	632.3203	0.0000	***
	g_1^2	0.0231	0.0003	**g_2^2**	0.0061	0.0000	0.0170	0.0000	4.8683	630.4757	0.0000	***
CGS	**a_1^2**	0.0059	0.0004	**a_2^2**	0.0146	0.0000	0.0087	0.0000	2.2461	632.9299	0.0125	**
	b_1^2	0.9331	0.0015	**b_2^2**	0.9788	0.0001	0.0457	0.0001	5.8981	632.3411	0.0000	***
	g_1^2	0.0290	0.0005	**g_2^2**	0.0073	0.0000	0.0217	0.0000	4.6686	630.7740	0.0000	***
HCR	**a_1^2**	0.0134	0.0009	**a_2^2**	0.0115	0.0004	0.0019	0.0000	0.3117	715.5929	0.3777	-
	b_1^2	0.9346	0.0032	**b_2^2**	0.9862	0.0019	0.0516	0.0001	4.4649	763.1073	0.0000	***
	g_1^2	0.0151	0.0005	**g_2^2**	0.0015	0.0000	0.0136	0.0000	3.1863	631.0204	0.0008	***
CSV	**a_1^2**	0.0048	0.0002	**a_2^2**	0.0150	0.0000	0.0102	0.0000	4.1101	631.2099	0.0000	***
	b_1^2	0.9452	0.0004	**b_2^2**	0.9779	0.0000	0.0327	0.0000	7.8125	631.8012	0.0000	***
	g_1^2	0.0169	0.0002	**g_2^2**	0.0068	0.0000	0.0101	0.0000	3.6467	631.0081	0.0001	***
TEL	**a_1^2**	0.0231	0.0021	**a_2^2**	0.0096	0.0001	0.0135	0.0001	1.4594	630.2467	0.0725	*
	b_1^2	0.8804	0.0199	**b_2^2**	0.9811	0.0003	0.1007	0.0008	3.5810	630.0799	0.0002	***
	g_1^2	0.0137	0.0002	**g_2^2**	0.0000	0.0000	0.0137	0.0000	5.5175	630.0047	0.0000	***
UTL	**a_1^2**	0.0707	0.0045	**a_2^2**	0.0062	0.0000	0.0645	0.0002	4.8326	630.0049	0.0000	***
	b_1^2	0.7464	0.0162	**b_2^2**	0.9898	0.0000	0.2435	0.0006	9.6084	630.0057	0.0000	***
	g_1^2	0.0000	0.0005	**g_2^2**	0.0000	0.0000	0.0000	0.0000	0.0001	630.0047	0.5000	-
FIN	**a_1^2**	0.0036	0.0000	**a_2^2**	0.0133	0.0000	0.0097	0.0000	12.3916	666.4326	0.0000	***
	b_1^2	0.9150	0.0282	**b_2^2**	0.9821	0.0000	0.0672	0.0011	2.0046	630.0049	0.0227	**
	g_1^2	0.0651	0.0040	**g_2^2**	0.0016	0.0000	0.0635	0.0002	5.0122	630.0048	0.0000	***
TEC	**a_1^2**	0.0086	0.0000	**a_2^2**	0.0141	0.0000	0.0055	0.0000	5.0435	863.3517	0.0000	***
	b_1^2	0.9247	0.0017	**b_2^2**	0.9760	0.0001	0.0513	0.0001	6.2342	630.4631	0.0000	***
	g_1^2	0.0370	0.0005	**g_2^2**	0.0051	0.0000	0.0320	0.0000	7.0611	630.6271	0.0000	***

The "*"s indicates the parameter's significance level: *** -- 99%, ** -- 95%, * -- 90%.

D.7 Exact New Impact Surface for Correlation

$$f\left(e_1,e_2\right)=\frac{c_{ij}+\left(a_i a_j+g_i g_j\right)e_i e_j+b_i b_j \rho_{ij,t}}{\sqrt{\left(c_{ii}+\left(a_i^2+g_i^2\right)e_i^2+b_i^2\right)\left(c_{jj}+\left(a_j^2+g_j^2\right)e_j^2+b_i^2\right)}}\text{, for } e_1, e_2 < 0$$

$$f\left(e_1,e_2\right)=\frac{c_{ij}+a_i a_j e_i e_j+b_i b_j \rho_{ij,t}}{\sqrt{\left(c_{ii}+\left(a_i^2+g_i^2\right)e_i^2+b_i^2\right)\left(c_{jj}+a_j^2 e_j^2+b_i^2\right)}}\text{, for } e_1 < 0,\ e_2 > 0$$

$$f\left(e_1,e_2\right)=\frac{c_{ij}+a_i a_j e_i e_j+b_i b_j \rho_{ij,t}}{\sqrt{\left(c_{ii}+a_i^2 e_i^2+b_i^2\right)\left(c_{jj}+\left(a_j^2+g_j^2\right)e_j^2+b_i^2\right)}}\text{, for } e_1 > 0,\ e_2 < 0$$

$$f\left(e_1,e_2\right)=\frac{c_{ij}+a_i a_j e_i e_j+b_i b_j \rho_{ij,t}}{\sqrt{\left(c_{ii}+a_i^2 e_i^2+b_i^2\right)\left(c_{jj}+a_j^2 e_j^2+b_i^2\right)}}\text{, for } e_1, e_2 > 0$$

where ε_i, i = 1, 2 are the standardized residuals; c_{ij} is the corresponding element of the constant matrix in the correlation equation (*i.e.* the matrix C_j in eq.5 in page 271); a_i and g_i are the corresponding elements of matrices A and G.

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