Essays on the Empirical Analysis of Volatility Transmission in Petroleum Markets

by

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List of Abbreviations

ABEKK	Asymmetric version of Baba-Engle-Kraft-Kroner
ADF	Augmented Dickey-Fuller (1979) unit root test
ADL	Autoregressive Distributed Lag
ANS	Alaska North Slope
ARCH	Autoregressive Conditional Heteroskedasticity
BEKK	Baba-Engle-Kraft-Kroner
CCC	Constant Conditional Correlation
DCC	Dynamic Conditional Correlation
DE	Diversification Effectiveness Index
Eq.	Equation.
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GCC	Gulf Cooperation Council
HE	Hedging Effective Index
IAEE	International Association for Energy Economics
IPE	International Petroleum Exchange
JB	Jarque-Bera (1980) test for normality
KPSS	Kwiatkowski, Phillips, Schmidt and Shin (1992) unit root test
LPM	Lower Partial Moments
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
NYMEX	New York Mercantile Exchange
OECD	Organization for Economic Co-operation and Development
OHR	Optimal Hedging ratio
OPEC	Organization of Petroleum-Exporting Countries
PP	Phillips-Perron (1988) unit root test
QMLE	Quasi-Maximum Likelihood estimation
RMB	China Renminbi
VAR_AGARCH	Vector Autoregression – Asymmetric Generalized Autoregressive Conditional Heteroskedasticity
VAR-GARCH	Vector Autoregression – Generalized Autoregressive Conditional Heteroskedasticity
VIRF	Volatility Impulse Response Functions
WTI	West Texas Intermediate

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Declaration

I declare that this thesis is submitted to Cass Business School, City University of London, for the degree of Doctor of Philosophy in 2012. Excerpt, where acknowledged, the material contained in this thesis is my own work and that is has neither been previously published nor submitted elsewhere for the purpose of obtaining an academic degree.

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Abstract

Petroleum markets are undergoing rapid financialization and integration, leading to increased volatility and exposing participants to potentially much greater risks. This thesis addresses the explicit modeling of petroleum price volatility in a multivariate framework and analyzes the relative merits of multivariate models to describe change in the context of petroleum markets risk. The focus of this thesis will be on explaining the dynamic interdependencies in petroleum markets and further demonstrate whether the existence of such interdependencies prompt for the need to assess risk differently, by which this thesis contributes to the existing economic or econometric theories in three aspects. The first empirical part examines the importance of volatility spillovers and asymmetry in petroleum markets and their influence on optimal hedging strategy. To address in a realistic way the dynamic conditional correlation of petroleum spot and futures markets, we develop a new theoretical framework by accounting for the effect of time-varying conditional correlations in the conditional volatility processes of the VARMA-AGARCH model in what is termed the VARMA-AGARCH-DCC model. Results demonstrate that the proposed model is the best for OHR calculation in terms of the variance of portfolio reduction and tail risk analysis. The second empirical part, for the first time in the literature of energy economics, examines the volatility and correlation interdependence between oil market and China stock market at the sector-level. Results indicate that oil price fluctuations constitute a systematic asset price risk at the sector level and information content embedded in oil market volatility is an effective and valuable variable for constructing an optimal oil-stock holding. Finally, the third empirical part, for the first time in the literature of energy economics, investigates the volatility transmission mechanism among three benchmark oil markets and quantifies the size and persistence of these connections through employing the Volatility Impulse Response Function (VIRF) methodology. Results suggest markedly different responsiveness to historical events and volatility/correlation dynamics across crude oil benchmark markets. Overall, the findings of this thesis have important implications for crude oil market trading and risk management, as well as stock market investors, by providing valuable information on the oil price volatility dynamics and will help market participants develop efficient risk measurement schemes and devise sound risk management strategies.

Chapter 1

Introduction, Motivation, and Significance of the Study

1.1 Thesis motivation

Following the two oil price shocks and the development of derivatives markets in the 1980s, the total trading volume of oil-related futures contracts has far exceeded total world oil production.[1] Since then, crude oil markets have been transforming from a purely physical goods market into a sophisticated financial market, i.e. the 'paper' oil market. This transformation has been highlighted by two significant changes: the strengthening of the globalization trend of the oil markets and its increasing relation to the macroeconomic and financial markets such as the exchange rate market, stock market and bond market. The transformation of crude oil markets and their size, scope and complexity could allow a wide range of participants beyond the scope of traditional crude oil producers, physical traders, and refining and oil companies, to financial investors who consider it as a popular asset class. As a result, crude oil prices have experienced an unparalleled growth over the last decade with the most pronounced price boom between 2002 and mid-2008 and have been more volatile than prices of most other commodities since the oil crisis in 1973 (Fleming and Ostdiek, 1999; Regnier, 2007).[2] The main contributors of this phenomenon are geopolitical factors regarding the destabilization of the Middle East situation, as well as changes in supply-demand fundamentals. Oil-specific shocks, especially on the supply side, have generally played a key role in this respect. Rapidly growing demand for crude oil, especially in emerging economies, as well as the debate about the future use of fossil fuels in the light of global climate change, and about the link between crude oil production and climate

[1] Oil consumption has increased by more than 20 million barrels per day whereas the total trading volume of futures contracts has far exceeded total world oil production.
[2] Regnier (2007) finds that crude oil and energy prices are more volatile than prices for about 95% of other commodities sold by domestic producers over the period January 1945 through August 2005. Plourde and Watkins (1998) discover that crude oil price volatility is higher than price volatility for nine other commodities during the 1985-1994 periods.

change more generally, has clearly had an impact on recent oil price fluctuations beyond simple oil-specific shocks.

The volatile condition of crude oil markets has significant impacts and policy implications at both macroeconomic and microeconomic level.[3] Considerable oil price fluctuations often have great impacts on the macro economy. High volatility of crude oil prices creates uncertainty, as a result, the economic instability may be observed from both oil-exporting and oil-importing countries. Moreover, fluctuations in oil prices increase uncertainty about future prices and thus cause delays in business investments. Ferderer (1996) has shown that it is ideal for companies to postpone irreversible investment expenditures when they experience increased uncertainty concerning the future oil price. Volatility is an indispensable input for pricing oil derivatives and various financial instruments (Arouri et al., 2011). Furthermore, the volatility of crude oil markets suggests that individuals and firms trading in crude oil markets have to face significant challenges when trying to manage the risk associated with the changes, over time, in crude oil prices. Substantial changes in volatility of crude oil markets translate to significantly adverse effects for risk-averse investors.

Given the important role played by volatility of crude oil prices, forecasting crude oil prices, quantifying and managing the risks inherent to their frequent volatilities has become critical issues for both academicians and markets participants. Indeed, a better understanding of the return volatility of crude oil markets should allow the improvement of portfolio allocation using the estimated conditional variance matrix. An accurate measure of volatility also helps to improve the interference one can draw from an estimate. Therefore, the main motivation of this thesis is to build on modern quantitative techniques with a view to address several issues of oil price modelling and risk management which are very relevant topics in the industry. The driving force for developing such models of oil markets is the desire, by market participants, to ensure

[3] At the macroeconomic level, it can lead to the deterioration in the balance of payments and in public finances, and the associated uncertainty is likely to curtail investment and to significantly depress long-term growth. At the microeconomic level, high and volatile crude oil prices have severe impacts on the most vulnerable, especially energy-insecure households (UNCTAD, 2011)

accurate estimation of risk measures, successful implementation of hedging strategies as well as a thorough evaluation of investment policies. This thesis is a compilation of three closely related essays in petroleum risk modelling and risk management, dealing with several practically relevant issues in empirical energy economics. That said, three central aims are determined. The first is to develop a methodology for futures hedging designed to support risk management programmes in petroleum markets. The second is to understand and explore fundamental relationships and interdependencies between crude oil market and China stock market for optimal portfolio management. The third is to quantify the risk of the more liquid and volatile near to maturity crude oil contracts where market activity is mainly concentrated.

Empirical stylised facts of petroleum returns series suggest that volatility is time-varying. This thesis addresses the explicit modeling of petroleum price volatility in a multivariate framework and analyzes the relative merits of multivariate models to describe change in the context of petroleum markets risk. We argue that univariate models can capture the volatility dynamics of individual assets but cannot reveal the relationships among petroleum markets. Thus, the focus of this thesis will be on explaining the dynamic interdependencies in petroleum markets and further demonstrate whether the existence of such interdependencies for the need to assess risk differently. In doing so, we benefit from the flexible family of multivariate GARCH (MVGARCH) models that permit us to investigate hedging strategy, volatility spillover and correlations among petroleum markets or between petroleum markets and other financial markets. Haigh and Holt (2002) for instance, show that modeling of time-variation in hedging strategy according to MVGARCH models, and taking into account volatility spillover between markets can lead to significant reductions in uncertainty. The information content derived from MVGARCH models will be thoroughly discussed with the aim to assess their role and effectiveness in quantifying risk and to finally uncover fundamental interactions in a multivariate framework.

The topics studied range from risk quantification, volatility/correlation modelling, futures hedging as well as optimal portfolio management and Value-at-Risk analysis and management.

All essays have many things in common. First, they all focus on time series properties of petroleum prices. Second, they all explicitly model the return volatilities and correlations of these assets in a multivariate framework. Third, they all aim on accurate risk assessment and enhanced forecasting ability.

1.2 Thesis objectives and contribution

This thesis consists of three self-contained essays that discuss both theory and applications of multivariate GARCH models to petroleum markets. The thesis contributes to the existing literature by addressing three main issues: the development of the VARMA-AGARCH model with DCC structure and its application to minimum variance hedging in petroleum markets, the application of the asymmetric BEKK model to analyze volatility dependencies between crude oil and China stock market at the sector level with the aim of optimal portfolio management, and empirical evidence of volatility transmission mechanism among three benchmark oil markets with quantifying the size and persistence of these connections through the analysis of volatility impulse response functions. This thesis will provide useful information to energy traders and portfolio managers regarding risk control and profitable opportunities.

In the second chapter, we review fundamental concepts of the petroleum market structure and dynamics. The chapter begins with an introduction on why crude oil and its price volatility are important. This section is followed by an overview of the oil pricing mechanisms that make the oil markets special and the impact of financialization of oil markets on oil pricing mechanisms. After an outline of the underlying forces for oil price changes including market fundamentals (supply-demand) and speculative activities in oil derivative markets, we provide a literature review with the objective to present several applications of MGARCH models in energy economics, touching upon issues of volatility spillovers among oil markets or between oil and stock markets.

In the third Chapter, which is the first empirical chapter of the thesis, we propose the use of the VARMA-AGARCH model of McAleer et al. (2009) with dynamic conditional correlation structure (VARMA-AGARCH-DCC) in the petroleum markets for constructing optimal hedging strategy. Although volatility modeling and hedging strategies in a multivariate framework have been widely documented in crude oil markets, few studies have analyzed in depth the nature of volatility spillovers and asymmetric effects of spot and futures prices in oil-related products market, such as gasoline and heating oil markets. We develop a new theoretical framework by accounting for the effect of time–varying conditional correlations in the conditional volatility processes of the VARMA–AGARCH model in what is termed the VARMA-AGARCH-DCC model. To the best of our knowledge, this is the first time that the VARMA-AGRACH-DCC model is applied in petroleum markets. Implementing such model allows us to draw some new interesting insights regarding the effects of volatility spillovers, asymmetric effects and time–varying conditional correlations for petroleum markets hedging strategies. Our model specification is found superior in constructing optimal hedging strategy in comparison to the hedging strategies derived from other alternative multivariate GARCH models through applying the hedging effectiveness index. In addition, we link the new theoretical framework with tail estimation by examining the tails of the conditional distributions of the model and extending the above framework to a tail risk analysis. Overall, by identifying more accurate interaction between petroleum spot and futures markets, market participants may benefit from this analysis in terms of more accurate risk quantification.

In the fourth Chapter, we propose the use of the asymmetric version of the BEKK model introduced by Grier et al. (2004) to examine the volatility spillovers as well as asymmetric effects between oil and China stock market at the sector-level. This model offers the possibility to explore the time-varying conditional correlation as well as the conditional cross effects and volatility transmission between these markets, which permit a greater understanding of cross-correlation volatility spillovers between these interconnected markets. Only few studies have analysed in depth the nature of the volatility dependencies between crude oil and stock markets. No such study has been conducted explicitly so far to disentangle the role of oil price shocks from other underlying determinants driving China stock market volatilities. The innovation of this chapter is in analyzing the volatility dependencies between these markets at the sector level to allow for detailed discussion for optimal portfolio management, which has never been investigated in the literature of energy economics. We find significant evidence of volatility transmission between these markets at the sector-level, and the intensity of volatility transmission varies across the stock sectors, which supports the idea of cross-market hedging by investors and validates the argument that the sector perspective is more informative and generates more accurate implications for portfolio risk management. Then, we derive the implications of the estimated results on variances and covariances for effectuating optimal portfolio management in the presence of oil assets, which suggests that stock market investors in China should consider the additional source of uncertainty resulting from oil markets and then consider oil assets as a dynamic and valuable asset class that improves the risk–adjusted performance of a diversified portfolio of sector stocks. Overall, by identifying time-varying state dependent hedge ratios and optimal portfolio weights between oil and China stock market, market participants in China may be able to obtain significantly superior gains, measured in terms of variance reduction and increase in utility.

In the fifth Chapter, we apply the Volatility Impulse Response Functions model to investigate how a shock to one market influences the dynamic adjustment of volatility to another market and the persistence of these volatility transmission effects. Then, for the first time in the literature, we quantify the size and persistence of these connections through analyzing three historical shocks, namely the 2008 Financial Crisis, the BP Deepwater Horizon oil spill [4] and the OPEC

[4] The Deepwater Horizon Oil Spill is an oil spill in the Gulf of Mexico which flowed unabated for three months in 2010. It is the largest accidental marine oil spill in the history of the oil industry. It stemmed from a sea-floor oil gusher that resulted from the April 20, 2010, explosion of Deepwater Horizon. Please refer to http://en.wikipedia.org/wiki/Deepwater_Horizon_oil_spill for detailed explanation.

announcements[5]. Quantifying the impact of a shock on volatility is of practical interest to financial practitioners for determining the cost of capital, for assessing investment and leverage decisions, and for computing the optimal hedge ratio and portfolio weights as many financial instruments, especially options, are prices according to the entire price distribution as well as the distribution of volatility. While other financial markets, such as foreign exchange market, stock market and electricity market, have been thoroughly investigated in terms of volatility impulse response function, to our knowledge, no such study has been undertaken so far in crude oil markets. Therefore, it is within the context of previous limited empirical work that the present study is concentrated on the quantification of the impact of a shock on oil price volatility. Furthermore, for the first time in the literature of energy economics, we are able to test the responsiveness of different crude oil markets on historical shocks and then investigate the level to which crude oil markets are integrated. Results indicate that Brent and Dubai crude are highly responsive to market shocks, whereas WTI crude shows the least responsiveness of the three benchmarks, which creates questions about its predominance as a benchmark crude oil and its integration into global oil markets. Moreover, the fitted distributions are asymmetric showing that the probability of observing a large impact of a shock is lower while the probability of a relatively smaller impact is much higher. While the model can in principle be employed to analyze the impact of historical shocks on conditional volatility, we also aim to fill in the gap in the literature by providing a new approach to obtain forecasts of the Value-at-Risk. Results from this exercise indicate that only a "large" shock (derived from a smaller probability) will result in an increase in expected conditional volatilities. These results provide useful insights into the volatility transmission mechanism in crude oil markets and their associated risk estimation, and may have significant implications for various market participants and regulators.

[5] In 1982, OPEC established a system to regulate oil production among its members. Several times a year, the OPEC schedules a conference to agree on further oil production policies, based on its assessment of the current market condition. The OPEC's decision usually takes the form of an announcement, setting an overall oil production ceiling for the cartel and individual production quotas for its members (see OPEC Secretariat, 2003).

In the sixth Chapter, we conclude this thesis by summarizing the main empirical findings of this study. We also suggest a number of potential directions in which fruitful future research can be undertaken to some degree complement the study and consequently shed some light on the issues not covered in this thesis.

To sum up, for the first time in energy economics literature, all the above topics are examined in the particular approaches as offered by this thesis, thus making its contribution an original source of reference for academics and a practical tool for financial practitioners. The findings of this thesis have important implications for energy market participants who deal with trading and risk management by providing valuable information on volatility behaviour and transmission as well as their predictability. Overall, market participants may benefit from the thorough understanding of volatility transmission among energy markets and between energy markets and stock markets in terms of improving the forecasting accuracy and enhancing the performance of their hedging strategies.

1.3 Organization of the thesis

The original contribution of this study commences in Chapter 3 with empirical body of the thesis involving Chapter 3 to 5. Note that each chapter covers a topic on its own, so that they can be read independently of previous and subsequent chapter. Part of Chapter 4 was presented at the 2nd International Conference of the Financial Engineering and Banking Society of European Business School in London this June. Part of Chapter 5 has been published in the Journal of Energy Economics (Jin et al., 2012) and an earlier version was presented at the 34th International Association for Energy Economics (IAEE) Conference in Stockholm last June. The specific organisation of the thesis follows the objectives mentioned above in Section 1.2 and the rest of this study is organized as follows:

Chapter 2 offers an outlook of crude oil markets and the market structure, and also provides the necessary literature review on the employed MGARCH models in terms of volatility spillovers among energy markets or between oil and stock markets. Chapter 3 is the first empirical chapter of the thesis in which we propose the use of the VARMA-AGARCH-DCC model in the petroleum markets for constructing optimal hedging strategy. Chapter 4 investigates how and to what extent oil price shocks impact China stock market at sector level, emphasizing on the volatility transmission mechanisms by using an asymmetric version of BEKK model. Chapter 5 investigates crude oil markets integration on the second moment and further quantifies the size and persistence of these connections through the analysis of Volatility Impulse Response Functions for three historical shocks, namely the 2008 Financial Crisis, the BP Deepwater Horizon oil spill and the OPEC announcements. Finally, Chapter 6 summarizes the main empirical findings of this thesis, discusses the implications, and suggests potential interesting paths of future research as directed by the findings of this thesis.

Chapter 2

Introduction to Petroleum Markets

2.1 Introduction

Oil is the most important energy source, accounting for more than a third of the world primary energy mix. It is expected to continue to hold the largest share in the coming decades, although the share will decline marginally. In volume terms, oil production and consumption fell after the second oil crisis in 1979 and bottomed in 1983. Since then, however, the volume has been continuously increasing, despite variations in the price. In comparison to other physical commodities, the size, scope and complexity of global crude oil trade are unique. Currently more than 80 million barrels of oil are produced and consumed every day. Furthermore, the strategic importance of oil and the crucial role that it plays in the broad economy make it a commodity like no other.

Because of its importance in the world economy, the change of oil price has caused great concerns among academic researchers, policy makers as well as market participants. Volatility is a key input into macroeconomic models and option pricing formulas and oil price uncertainty has important implications on economic activity (Hamilton, 1983). Thus, it is of considerable interest to energy economists to understand and model oil price volatility and promote applications in risk management. For the purpose of capturing the dynamics of volatility, Engle's (1982) ARCH model and the generalized version developed by Bollerslev (1986) are arguably the most popular methods for modeling volatility of oil markets. However, univariate models can capture the volatility dynamics of individual assets but cannot reveal the dynamic relationship among petroleum markets. Thus, multivariate GARCH (MGARCH) models have been used to examine volatility spillover and correlations among energy markets or between energy markets and other financial markets. Empirical evidence suggests that volatility spillovers, asymmetric effects on the conditional variances and time-varying conditional correlations exist for most pairs of returns in major oil markets (see Chang et al., 2010).

The increasing integration of crude oil markets all over the world, spurred by deregulation, securitization, globalization and advances in information technology, has generated a good deal of interest in understanding the volatility spillover effects from one market to another. Malik and Ewing (2009) suggest that there are two plausible explanations as to why these spillovers exist. First, volatility spillovers may result from cross-market hedging and changes in common information, which may simultaneously alter expectations across markets. A second reason given to explain the volatility spillover effects is that of financial contagion, specifically, a shock to one country's asset market may cause changes in asset prices in another country's financial market.

In this chapter, we describe the structure of the oil markets. Section 2.2 presents an overview of oil pricing mechanisms that make the oil market special and the impact of financialization of oil markets on oil pricing mechanisms. Section 2.3 presents the underlying forces for oil price changes. Section 2.4 provides a brief introduction of MGARCH models with a selective overview of MGARCH literature in energy economics, touching upon issues of volatility spillovers among energy markets or between energy markets and stock markets. Section 2.5 concludes this chapter. The application of this multivariate framework is demonstrated in empirical analysis in later chapters.

2.2 Oil pricing mechanisms

It is important to distinguish between pricing mechanisms and the underlying forces which determine prices. The pricing mechanisms refer to the organization of trade, exchange and marketplaces, as well as the ways prices are determined. It does not necessarily shed an insight into what influences decision-making by buyers and sellers, nor about the resulting market balance and price level. The price mechanisms for crude oil can lead to a transparent and liquid market without any pressure for lower prices. However, the underlying forces which determine prices will have an influence on pricing mechanisms. In this section, we look into pricing mechanisms in the oil sector, particularly into the commodity-type pricing mechanisms that make oil special, which has developed since the official selling price system within long-term oil contracts established by OPEC[1] came to an end in the mid-1980s. The commodity pricing mechanism in the oil sector has gradually evolved from the spot trading to the oil derivatives markets. This section gives a brief review about the history and mechanism of the oil market with a small subsection focusing on the financialization of oil markets.

Commodity pricing in the oil sector is well established and spot markets for oil have developed the full range of commodity pricing instruments. The current spot markets have been developed since the early 1970s with the aim of fine-tuning oil demand and supply and cover no more than 3-5% international oil trade. Prior to the 1970s, however, the vertical value chain for internationally traded oil was almost under the full control of the Seven Sisters.[2] They held concessions covering vast areas, with only very low royalty payments. They received their oil mostly through long-term concession agreements with host countries and dominated the market through bilateral long-term contracts. During this period, almost all crude oil stayed within the integrated companies, and was transferred among affiliates, from producing via transport to refining-marketing affiliates. Crude oil prices were mostly internal transfer prices, kept low to minimise the rent-taking of producing countries. As transfer pricing dominated during this period, spot market was only served as a tool for the Seven Sisters to adjust surplus and deficiency and exchange oil products with each other.

[1] OPEC is the abbreviation of Organization of Petroleum Exporting Countries. OPEC is an intergovernmental organization of 12 oil-producing countries made up of Algeria, Angola, Ecuador, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, the United Arab Emirates, and Venezuela. According to its statues, one of the principal goals is to ensure the stabilization of prices in international oil markets with a view to eliminating harmful and unnecessary fluctuations

[2] Seven Sisters refer to the western oil companies dominating the global petroleum industry from the mid-1940s to the 1970s. For detailed history of oil market developments at their earlier stages, please see Yergin (1991) and other publications.

A structural transformation of the world petroleum industry began to occur in the early 1970s. The main symbol of this transformation was the establishment of the Organization of Petroleum-Exporting Countries (OPEC) and the decoupling of the upstream and downstream oil industry. The upstream assets of international oil companies in OPEC countries were nationalised and formed the basis on which the new national oil companies were created. Although the market was still dominated by long-term contracts, spot trading increased gradually and the spot market was no longer a residual market but became a marginal market which reflected the production and refinery cost of crude oil. As the share of volumes traded under long-term contracts diminished, their prices began to be established on the basis of spot deals, which were illustrated by the significant increase of volumes traded on the spot market. The spot market began to balance supply and demand and began to be used as a reference point for price levels both for exporters and importers.

In the early 1980s, new pricing mechanisms, including discounting government selling price and netback pricing, were introduced because the old-fashioned pricing mechanism adopted by OPEC in the 1970s could not withstand the formidable competitive pressures due to the combined impact of significant growth from non-OPEC production and decreasing world oil demand. Key benchmark grades, West Texas Intermediate (WTI), Brent and Dubai, emerged, and served as the reference for crude of similar qualities and locations. Previously the role was played by Arabian Light under OPEC's official selling price system. The main spot markets or trading centres for crude oil are Rotterdam for Europe, Singapore for Asia and New York for the United States. Their benchmarks are: Brent, Dubai and WTI. Accompanying the sharp fluctuations in spot oil prices was the introduction of risk management techniques into oil operations, which became the driving force for the standardized oil trade operations as one of the risk-management instruments operated at the existing commodities exchange and for the establishment of specialized oil exchange.

At the same time, futures markets have also developed in Western countries.[3] These arose from a desire on the part of oil companies to reduce risk in light of high price volatility. The New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE) are two major financial markets for oil. In 1979 heating oil became the first new futures contract at the NYMEX, and the International Petroleum Exchange (IPE) in London followed in 1981. Gasoline (petrol) futures trading started on the NYMEX in 1981. WTI trading started in 1983 on the NYMEX and Brent in 1988 on the IPE.

Finally, the "market" was ushered into the central stage following the collapse of the OPEC administered pricing mechanism in 1986. From then on, financial specialists began to involve in the oil markets, introducing the techniques of financial markets and specialized oil derivatives. By the end of the 1980s, the current complex contractual structure of the oil market was in place. By that time, the complex structure of interlinked oil markets which consisted of spot, forwards, futures, options and other derivatives markets declared the advent of the era of 'paper' oil markets.

It is now the oil exchange and over-the-counter where oil prices are determined mainly. It may be argumentative that the general trend of the oil markets has been moving from trade in 'physical' oil to trade in 'paper' oil, and it is oil derivatives that now play a predominant role in establishing oil prices. As oil derivatives have grown to be the dominant part of the oil pricing mechanisms, the role of price discovery in the market has moved away from physical markets to oil derivatives markets and financial innovations have become the bridge interlinking physical markets and derivatives markets of crude oil. Financial institutions, for example investment banks, pension funds, hedge funds, and sovereign investment funds, have been exerting influence in crude oil markets as traditional suppliers and demanders (see Haigh et al., 2006; Lombardi and Robays, 2011). Especially in recent years, the sharp fluctuations in oil prices and the sheer increase in

[3] Oil futures markets are not new. Price volatility in the early days of the US oil industry resulted in the first oil futures contracts in Pennsylvania in 1860s, which took the form of pipeline certificates.

volatility have spurred the possibility that crude oil has acquired the characteristics of financial assets such as stocks or bonds.

2.2.1 Financialization of oil markets

The striking increase in crude oil prices from the beginning of 2002 has been beyond the common expectation of academic community, and many arguments have been focused on the so-called financialization of oil markets, which means the vastly expanded role of financial motives, financial markets, financial factors and financial institutions in the operation of crude oil markets.[4] The participation of financial institutions into crude oil markets suggests that the fundamental analysis which only concentrates on physical supply-demand sides will present a biased view if it is not totally wrong. The core of the pricing mechanisms has been shifted from physical markets decided by the equilibrium of supply and demand to financial derivatives markets involving more stakeholders rather beyond producers and consumers alone. Some argue that the main reason for the rising of oil prices and the sheer volatility in the 21st century lies in the funds swarming into the oil futures markets from large banks, hedge funds and other speculative capital in recent years.

Crude oil is not only the industrial blood and economic lifeline but also one kind of investment product, similar to stocks and securities. Investors have been engaging in crude oil trading for the purpose of portfolio diversification ever since it became clear that crude oil futures contracts exhibited the same average returns as investments in equities, while over the business cycle their returns were negatively correlated with those on equities and bonds (see Gorton and Rouwenhorst, 2006). Crude oil market has been financialised and is now more like other traditional financial markets, which is illustrated in two aspects: the scale of financial derivatives has grown to surmount that of physical spot markets and financial participants have become

[4] Tang and Xiong (2011) suggest that the significant increase in oil prices since 2002 is the result of many financial institutions flooding into commodities markets as a new asset class following the collapse of equity markets in 2000. The asynchronous business cycle of equity and commodities markets suggests a negative correlation that is effective for portfolio management and investment diversification (see Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006).

more active than non-financial participants (Yin, 2008). Therefore, the dynamics of crude oil prices have been characterized by high volatility, high-intensity jumps, and strong upward drifts, and have been driven by underlying supply-demand factors of crude oil markets and potential impact of the participation of financial investors into crude oil markets. The process of financializaton of crude oil markets is likely to persist as long as commodity investment remains popular among financial investors as diversification incentives for portfolio management still motivate them to invest in commodities, and thus causing commodity prices to comove positively with other asset classes.

2.3 Underlying forces for oil price changes

Oil price changes have always been at the centre of academic research agenda not only because of their effect on the risk management of oil-related businesses, but also due to their far-reaching implications on economic growth and inflation, the price movements of other energy futures contracts, and other financial assets. Due to the importance of oil, resources deficiency and climate change, understanding the forces behind oil price changes gets unprecedented attention and is important in its own right. Particularly, since 2000, the international oil market has undergone significant changes in two aspects. First, the globalization trend of the oil markets has been strengthening. Second, the oil markets are becoming increasingly related to the macroeconomic and financial markets. As a result of these significant changes, oil prices are no longer fully subject to the impact of the market fundamentals measured by the supply-demand relationship, but show new characteristics. For example, many arguments have been focused on the so-called financialization of energy market. Indeed, energy commodities have become a recognized asset class within investment portfolios of financial institutions as a means to diversify risks such as inflation, or equity market weakness.

In this context, the long-standing debate surrounding the underlying forces for oil price changes has been more intensified due to the dramatic fluctuations in oil prices in recent years. This issue has been much investigated in the literature (see Kaufmann et al., 2008; Kilian, 2009; Kaufmann, 2011), the general findings among which suggest that oil price changes are driven by market fundamentals as well as speculative activities in oil derivatives markets.

2.3.1 Market fundamentals

Market fundamentals, i.e. supply- and demand-side factors, are the basis of analysing the formation of the global oil market and its operating principles. In the long run, oil price is mainly determined by demand-supply fundamentals, and all the other factors can have influence on oil price by changing the demand-supply relationship or people's expectation of the demand-supply relationship (see Chai et al., 2011).

On the supply side, crude oil markets all over the world have witnessed growing integration within as well as across boundaries, spurred by deregulation, globalization and advances in information technology. A considerable portion of the literature on crude oil markets focuses on the degree to which they are integrated (see Adelman, 1984; Bentzen, 2007). However, the supply-side of the global crude oil markets is yet imperfectly competitive, and many suggest that crude oil prices are partially affected by the different behaviour of two supplier groups, i.e. OPEC and non-OPEC nations. OPEC is the most important player in the oil market. Aiming to sustain world demand for oil rather than replacing it with alternative energy sources, OPEC has to balance market share and profits. The oil cartel's market power comes from three aspects. First, it has the largest size of proven oil reserves (891 billion barrels) and exports (19.5 million barrels per day) – 78.3% and 48.7% respectively of the 2003 world totals. Second, the Gulf countries within the cartel have the lowest production costs: USD 4.00 per barrel for Saudi Arabia or USD 4.50 for Iran, as compared with USD 9.85 for the North Sea and USD 12.50 for Brazil (Energy Intelligence, 2004). Third, most OPEC oil is produced by fully state-owned companies (Algeria, Iran, Kuwait, Qatar, Saudi Arabia and Venezuela) or majority state-owned companies (Libya, Nigeria and United Arab Emirates). Only in Indonesia is government participation in the oil sector very limited. The non-OPEC exporting countries, on the other hand, increased their international oil market share following the 1973-74 oil crises at the expense of OPEC and the resulting geographical dispersion of the oil fields served to smooth the supply process. However, by contrast with the Middle Eastern countries, their oil production is characterized by technological difficulties and high transportation costs, for instance in North Sea and Alaska. Kaufmann and Cleveland (2001) argue that non-OPEC nations generally are viewed as price takers and their output is negatively related to the cost of production and positively related to international oil price. In particular, unlike OPEC nations, there is little evidence for strategic considerations for non-OPEC producers (Kaufmann et al., 2004).

Blaming OPEC nations for the episodes of crude oil upsurge is quite understandable because of its central position in the global crude oil markets. In order to better understand the role played by OPEC nations in the global crude oil markets, many empirical analyses have devoted to investigate OPEC's behaviour. For example, Griffin (1985) tests OPEC's behaviour across the four alternative hypotheses including competitive, cartel, target revenues, and property rights models. His findings suggest that the partial market-sharing cartel model could be the most suitable one to explain OPEC's behaviour. Jones (1990) suggests that most OPEC members continue to behave like a "partial market sharing" while non-OPEC nations behave more competitively. Smith (2005) argues that there is a significant cooperative effort among OPEC nations to restrict output and then raise prices, which indicates that OPEC is much more than a non-cooperative oligopoly, but less than a frictionless cartel. However, Kaufmann et al. (2008) find that OPEC does not fit neatly into a single behavioural model. Actually, neither statistical tests nor economic theory supports modelling OPEC as a cartel or as a competitive model (see Alhajii and Huettner, 2000).

Unlike supply, demand for crude oil depends on the choices of many individual households and firms, given the transportation, industrial and residential needs. Obviously, this is directly linked to the global economic activity. Kilian (2009) finds that demand-driven shocks caused by the global economic activity result in a large, persistent and statistically significant increase in real price of crude oil, which has very different effects on the real price of crude oil from supply-driven shocks. He et al. (2010) also find that real futures prices of crude oil are significantly influenced by fluctuations in the global economic activity through both long-run equilibrium conditions and short-run impacts. However, due to oil's importance for the economy and national security, the demand side is also influenced by various private interest groups, for example the domestic oil refiners. Price controls and government policies, such as fiscal instruments, antitrust policies, public funds for alternative energy research, petroleum exploration activities and strategic oil reserves, are also key elements of the demand side.

Among the consuming countries, the United States is the dominant player, being the world's largest producer, consumer and importer of petroleum. In 2011 over 11 million bpd were imported in the United States. Canada, Mexico and South and Central America feed more than half of the US oil needs, whereas imports from the Middle East and Africa account for more than 17% and 15% of the total figure, respectively (see BP, 2011). Although worldwide demand still originates chiefly from OECD[5] countries, since the mid-1990s, emerging economies, especially China and India, have seen their consumptions surge.[6] After decades of self-sufficiency on its oil needs, China became a net importer of crude oil with accelerated volume since 1996, and almost at the same time, India follows China's step to import crude oil with increased volume. Some prevailing viewpoints forecast that China and India will continue to increasingly import crude oil and develop overseas resources for keeping their economy growing. This has become a "great concern" for many countries, and the role that emerging markets play in the global oil markets becomes the object of study for many academics.[7] This rapid growth may seem the driving force

[5] OECD is the abbreviation of Organization for Economic Co-operation and Development. OECD is an international economic organization of 34 countries founded in 1961 to stimulate economic progress and world trade. Most OECD members are developed, high-income economies.

[6] : According to the U.S. Department of Energy, OECD consumption represented 53% of world consumption in 2011 (see EIA, 2011).

[7] This concern is directly declared by CNN (2004) that "Surging Chinese demand is underpinning the recent spike in the price of oil, figures from the International Energy Agency (IEA) show. This 'China factor' has more bearing on oil prices than the 'risk factor' coming from global tensions, some experts say".

behind the recent rise in the world's energy demand and the surge in crude oil prices from 2002 to mid-2008 (see Hamilton, 2009a; Li and Lin, 2011).

2.3.2 Speculative activities

One striking characteristic of the oil markets in the past decades is that large financial institutions, hedge funds, and other investment funds have been investing billions of dollars in the futures market to take advantage of oil price changes (Masters, 2008). Hamilton (2009a) argues that speculators can affect the incentives faced by oil producers by purchasing large amount of future contracts and pushing future prices to even higher levels than current prices.[8] The unusual upsurge in oil future prices will finally be transmitted into oil spot markets. According to Hamilton (2009b), there is a case in which a futures bubble could lead to spot price increases with no clear storage effects. This would be, if the spot price is completely price inelastic in the short run. Then an increase in the futures price would increase the spot price with the exact same amount.

Although speculators serve an important role regarding market efficiency, transparency and enhancing liquidity, some side effects cause deviations from the equilibrium prices and increased volatility, at least temporarily. There is strong evidence showing that increasing speculation has been one of the important driving forces in the surge of oil prices since 2000. For example, Chevillon and Rifflart (2009) find that speculative activity is a driving force to explain the surge of oil prices since 2004. By investigating the information flows over the global crude oil spot and futures markets, Kaufmann and Ullman (2009) show that the upsurge of oil prices before 2008 is caused by fundamentals and speculative activity together. Moreover, by using a multivariate modified Capital Asset Pricing Model approach, Cifarelli and Paladino (2010) find evidence that speculative activity plays a significant role in the strong oil price changes in recent years. In particular, Kaufmann (2011) argues that repeated and extended break-downs in the

[8] Hamilton (2009a) that defines a speculator as a unit who does not produce or use the commodity, but risks his or her own capital trading futures in that commodity in hopes of making a profit on price changes.

cointegrating relationship between spot and far month futures prices since 2004 is an indication of the existence of speculation on crude oil markets.

To sum up, oil price at any point in time should reflect the balance between demand and supply fundamentals as well as the other factors that have influence on oil price by changing the demand-supply relationship or people's expectation of the demand-supply relationship. Short-run price elasticity of demand for crude oil is very low as there are no substitutes to its use that are readily available. The demand curve becomes elastic as quantity increases. The long-term demand curve is more elastic than the short-term demand curve (see Fattouh, 2007). An important characteristic of the oil supply curve is the existence of capacity constraints. The curve is elastic below the capacity constraint but becomes drastically inelastic as supply quantity approaches the constraint. It is almost vertical at the capacity limit. The short-run inelasticity and long-run elasticity imply that supply shortages or severe positive demand shocks are translated to large price movements, which in turn induce significant volatility and then have direct implications for market participants who deal with trading and risk managements.

2.4 Multivariate GARCH models and applications in the oil markets

Understanding and measuring the temporal interdependence in the second-order moments of assets returns is one of the hottest topics in finance as risk management, asset pricing, asset allocation, and the pricing of derivatives written on multiple assets all depend heavily on the forecast of the co-movement between financial assets. It is now widely accepted that financial asset returns volatility, covariance and correlations are time-varying with persistent dynamics. Recognizing these features through a multivariate modelling framework leads to more relevant empirical models than working with separate univariate models (Bauwens et al., 2006).

Since the seminal paper of Engle (1982), many considerations have been extended to multivariate GARCH (MGARCH) models to accommodate the co-movements of financial returns.

MGARCH models were initially developed in the late 1980s and the first half of the 1990s, and after a period of tranquility in the second half of the 1990s, this area seems to be experiencing again a quick expansion phase. There are generally two directions for modeling the multivariate time series, i.e. modeling variance-covariance matrix directly and modeling the correlation between the time series indirectly. Bollerslev, Engle, and Wooldridge (1988) proposed the first multivariate GARCH model for the conditional variance-covariance matrix, namely the VEC model. This VEC-GARCH model is a straightforward generalization of the univariate GARCH model. The generality of the VEC model is an advantage in the sense that the model is very flexible, but it also brings disadvantages as it is very difficult to impose the positive definiteness of the variance-covariance matrix. Bollerslev, Engle, and Wooldridge (1988) presented a simplified version of the VEC model, namely the Diagonal-VEC model. This model reduced the number of parameters greatly and it is relatively easier to derive the conditions to guarantee the positive definiteness of the variance-covariance matrix. However, this simplified VEC model seems too restrictive since no interaction is allowed between the different conditional variances and covariances.

A model that can be viewed as a restricted version of the VEC model is the Baba-Engle-Kraft-Kroner (BEKK) defined in Engle and Kroner (1995). The BEKK model has the attractive property that conditional variance-covariance matrix is positive definite by construction. The disadvantage of the BEKK model is that it is computationally complicated and the estimated coefficients for the variance-covariance matrix is not easy to be interpreted on an individual basis (see Caporin and McAleer, 2009). A further simplified version of the BEKK model which has diagonal matrices is the Diagonal-BEKK model. Diagonal-BEKK model faces the same problem of the Diagonal-VEC model even if the number of parameters has been reduced significantly. The most restricted version of the Diagonal-BEKK model is the Scalar-BEKK model. Scalar-BEKK model is too restrictive as it imposes the same dynamics to all the variances and covariances. On the other hand, a more complicated version of the BEKK model which accommodates the asymmetric effects is the Asymmetric version of the BEKK model introduced by Grier, Olan, Nilss, and Kalvinder (2004), namely the ABEKK model. The

ABEKK model relaxes the assumption of symmetry, thereby allowing for different relative responses to positive and negative shocks in the conditional variance-covariance matrix.

The main problem of multivariate GARCH models in most specification is the very large number of parameter. Those specifications which bypass this problem have to trade off the severe loss of generality. A potential way to reduce the number of parameters in the model is to introduce so-called factors. The so-called factor models are motivated by economic theory. Engle, Ng, and Rothschild (1990) introduced the first factor GARCH model. In this model it is assumed that the observations are generated by underlying factors that are conditionally heteroskedastic and possess a GARCH-type structure. The approach has the advantage that it can solve the problem of dimensionality by modeling the factors which is much less than the number of assets in terms of number. However, it has the undesirable property that the factors are generally correlated as it may turn out that several of the factors capture similar characteristics of the data. In order to avoid this disadvantage, several factors models with uncorrelated factors have been proposed in the literature, for example the Orthogonal-GARCH model of Alexander (2001) and the Generalized Orthogonal-GARCH model of Van Der Weide (2002). Furthermore, the Generalized Orthogonal Factor-GARCH model proposed by Lanne and Saikkonen (2007) can be seen as combining the advantages of both the factor models (having a reduced number of heteroskedastic factors) and the orthogonal models (relative ease of estimation due to the orthogonality of factors). However, one potential disadvantage of this approach is that it is difficult to interpret the parameters as the BEKK model.

Another direction for MGARCH models is to model the correlation indirectly between the time series instead of modeling the variance-covariance matrix directly. Correlation models are based on the decomposition of the conditional variance-covariance matrix into conditional standard deviations and correlations. Bollerslev (1990) first proposed a class of constant conditional correlation (CCC) models in which conditional correlation matrix is time-invariant and thus the conditional covariances are proportional to the product of the corresponding conditional standard deviations. In order to accommodate interdependencies of volatility across different assets and/or markets, Ling and McAleer (2003) proposed a vector autoregressive moving average (VARMA-) GARCH model. The VARMA-GARCH model assumes that negative and positive shocks of equal magnitude have identical impacts on the conditional variance. McAleer, Hoti and Chan (2009) extended the VARMA-GARCH model to accommodate the asymmetric impacts of the unconditional shocks on the conditional variance, and proposed the VARMA-AGARCH model. Both VARMA-GARCH and VARMA-AGARCH models assume constant conditional correlation matrix. Especially, the CCC-GARCH model of Bollerslev (1990) could be included into the VARMA-GARCH or VARMA-AGARCH model as special case. The estimation of MGARCH models with constant correlations is computationally attractive and the positive definiteness of the variance-covariance matrix is automatically guaranteed. However, the assumption of constant conditional correlations may be too restrictive and unrealistic in many empirical applications.

The CCC-GARCH model may be generalized by making the conditional correlation matrix time-varying. There are many ways to interpret the time-varying conditional correlation matrix. Tse and Tsui (2002) imposed GARCH type of dynamics on the conditional correlations in their VC-GARCH model in which the conditional correlations are functions of the conditional correlations of the previous period and a set of estimated correlations. Engle (2002) proposed a Dynamic Conditional Correlation (DCC-) GARCH whose dynamic conditional correlation matrix is similar to that of the VC-GARCH model. Both the VC- and the DCC-GARCH model extend the CCC-GARCH model, but do it with few extra parameters. However, compared to the CCC-GARCH models, the advantage of numerically simple estimation is lost, as the correlation matrix has to be inverted for each t during every iteration. Another disadvantage of the DCC-type models is that it restricts all the correlation processes to obey the same dynamic structure.

To avoid these limitations, several variants of the DCC-GARCH model are proposed in the literature. Billio and Caporin (2006) proposed a Quadratic Flexible DCC (GFDCC-) GARCH model, where the conditional correlations follow a BEKK structure. However, the number of parameters governing the correlations in the GFDCC-GARCH model in its fully general form is unfeasible in large systems. Cappiello, Engle, and Sheppard (2006) generalized the DCC-GARCH model in a similar manger, but also including asymmetric effects. In their Asymmetric Generalized DCC (AG-DCC) GARCH model the AG-DCC process allows for series-specific news impact and smoothing parameters and permits conditional asymmetries in conditional dynamics. The AG–DCC specification is well suited to examine correlation dynamics among different asset classes and investigate the presence of asymmetric responses in conditional variances and correlations to negative returns.

2.4.1 Evidence from the oil markets for volatility spillovers

Volatility is important in the oil markets and is typically unobservable, and volatility spillovers appear to be widespread in energy futures markets (see Lin and Tamvakis, 2001; Chang et al., 2010). The spillovers effect holds even when markets do not necessarily trade at the same time. Substantial research has been conducted to investigate volatility spillover effects in energy futures markets using various multivariate conditional volatility models. Lin and Tamvakis (2001) examine the volatility spillover effects between New York Mercantile Exchange (NYMEX) and International Petroleum Exchange (IPE) crude oil contracts in both non-overlapping and simultaneous trading hours. Their finding suggests that substantial spillover effects exist when both markets are trading simultaneously. Ewing et al. (2002) investigate the volatility transmission between the oil and natural gas markets using the BEKK model of Engle and Kroner (1995). Their finding indicates that changes in volatility in one market may have spillovers to the other market. Chang et al. (2009) examine the volatility spillovers and dynamic conditional correlations for the spot, forward and futures returns on Brent, WTI and Dubai crude oil markets using various multivariate conditional volatility models. Their finding indicates that there are significant volatility spillovers and the constant conditional correlations are not supported in the empirical analysis. Furio and Chulia (2012) investigate the volatility linkage between the Spanish electricity, Brent crude oil and Zeebrugge (Belgium) natural gas 1-month-ahead forward prices through employing the asymmetric version of the BEKK model proposed by Grier et al. (2004). Their finding suggests there are significant volatility spillovers and asymmetric effects between the Spanish electricity, Brent crude oil and Zeebrugge (Belgium) natural gas markets.

Significant volatility spillovers are also found between oil and stock markets (see Agren, 2006; Tansuchat et al., 2009). For example, Malik and Hammoudeh (2007) examined the volatility and shock transmission among U.S. equity, global crude oil market, and Gulf equity markets using the BEKK model of Engle and Kroner (1995). Their finding shows that Gulf equity markets are sensitive to volatility from the oil markets, while stock market volatility spills over into the oil markets only in Saudi Arabia. Malik and Ewing (2009) investigate volatility spillover between oil prices and five U.S. equity sector indices using the BEKK model of Engle and Kroner (1995) and find evidence of significant volatility transmission. Arouri et al. (2011) utilize the VAR-GARCH model of Ling and McAleer (2003) to examine the extent of volatility transmission between oil and stock markets in Europe and the United States at the sector-level. Their findings point to the existence of significant volatility spillover between oil and sector stock returns. However, the spillover is usually unidirectional from oil markets to stock markets in Europe, but bidirectional in the United States.

2.5 Conclusion

In this chapter we discussed the structure of the oil markets. We distinguished the oil pricing mechanisms and the underlying forces for oil price changes surrounding the markets from the basic fundamental forces (demand-supply) to the power of OPEC throughout time and the role of speculative activities. Finally, we gave a brief review of MGARCH models and some of the empirical evidence regarding the use of MGARCH models in the oil markets for detecting volatility spillover effects.

Next, in Chapter 3, we will focus on analyzing the nature of volatility spillovers, asymmetric effects and time-varying conditional correlations of spot and futures prices in petroleum markets and then constructing optimal hedging strategies. We extend previous research by including the time–varying conditional correlations in the specification of the VARMA–AGARCH model of McAleer et al. (2009) in what is termed the VARMA–AGARCH model with dynamic conditional correlation DCC structure. Our model specification is found superior in constructing optimal hedging strategy in comparison to the hedging strategies derived from other alternative multivariate GARCH models through applying the hedging effectiveness index.

Chapter 3

Volatility Spillovers, Asymmetries and Hedging Strategies in Petroleum Markets

3.1 Introduction

The past few years have witnessed a renewed interest in modeling petroleum price volatility and then constructing optimal hedging strategies.[1] A number of factors may have contributed to that interest. First, petroleum price volatility has significant effect on the risk management of oil-related business and far-reaching implications on the economic variables (Ferderer, 1996; Lardic and Mignon, 2006)[2] and other financial assets (Sadorsky, 2003; Aloui and Jammazi, 2009)[3]. Second, over the last decade, the financialization of petroleum markets has allowed a wide range of participants to hedge petroleum price risk. Third, a recent finding of Jalali-Naini and Manesh (2006) indicates that petroleum price is typically characterized by high volatility, which entails the necessity for market participants to actively search for an effective way to hedge petroleum price risk.

Among other strategies, an investor facing volatile price movements in spot markets could reduce uncertainty by simultaneously holding an opposite futures position on underlying assets.[4] It has been argued that the futures/spot hedging strategy can substantially reduce petroleum price volatility without significantly reducing returns, and with the added benefit of greater

[1] See for instance Cotter and Hanly (2010, 2012) and Chang et al. (2011).

[2] Further discussion about the impact of crude oil price volatility on the macroeconomy could be found in Hamilton (2003), Chang and Wong (2003), Doroodian and Boyd (2003), and Chen and Chen (2007).

[3] Further discussion about the impact of crude oil price volatility on the financial markets could be found in Sadorsky (1999, 2000), Ewing and Thompson (2007), and Driesprong et al. (2008).

[4] A futures contract is an agreement between underlying parties to buy and sell a given amount of a commodity at an agreed upon certain date in the future, at an agreed upon price, and at a given location. Furthermore, a futures contract is the tool primarily designed to minimize one's exposure to unwanted risk. Conceptually, hedging through holding futures contract is a process uses to restrain or reduce the risk of unfavourable price movements because futures prices and cash for the same commodity tend to move together. Therefore, changes in the value of a cash position are mitigated by changes in the value of an opposite futures position.

predictability and certainty.[5] Oil futures contracts have proven to be very popular among the participants in the oil industry and the volume of these derivatives has grown significantly since 2000. In addition, futures contracts are favoured as a hedging tool because of their liquidity, speed and lower transaction costs (Chang, et al., 2011).

In order to successfully reduce price risk of futures trading, it is important to employ the hedging strategy which is capable of capturing the dynamic interaction between futures and its underlying spot prices. Theoretically, the "optimal" hedge ratio (OHR) is a proper way to capture the dynamics between futures and its underlying spot prices. Under the mean-variance framework of Markowitz (1952) and the martingale assumption, the "optimal" hedge ratio (OHR) can be defined as a ratio of covariance between spot and futures returns to the variance of futures returns. However, as financial assets return volatility, covariances and correlations usually display time-varying characteristics with persistent dynamics, estimating a static hedge ratio may not be appropriate (see Baillie and Myers, 1991). Therefore, much literature has focused on identifying the optimal hedge ratio through employing various econometric models with time-varying characteristics.[6] Among other models, the multivariate GARCH models have been proven to be successful in capturing the time-varying variance-covariance matrix of financial variables and appear to be ideal for estimating time-varying OHRs.[7]

In the literature, research has been conducted on estimating time-varying hedge ratios of crude oil spot and futures returns using multivariate GARCH models.[8] However, few studies have been conducted to investigate the same issue for oil products markets. This chapter tends to fill this gap by modeling time-varying hedge ratios among crude oil (WTI), gasoline and heating oil futures contracts. Furthermore, volatility spillovers, asymmetric effects and time-varying conditional correlations between spot and futures markets for crude oil, gasoline and heating oil

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[5] See for instance Daniel (2001) and Chang et al. (2011).
[6] See for instance Baillie and Myers (1991), Myers (1991) and Bystrom (2003).
[7] For instance an earlier study by Baillie and Myers (1991) documents superior hedging effectiveness in the US agricultural commodities market through employing a multivariate GARCH model.
[8] See section 3.2 for detailed discussion.

are likely to be important for constructing optimal hedge ratios. Therefore, this chapter has three main objectives as follows. Firstly, we want to investigate the importance of volatility spillovers, asymmetric effects of negative and positive shocks of equal magnitude on the conditional variance for modeling petroleum price volatility in the returns of spot and futures prices. Secondly, we apply the estimated results to compute the optimal hedge ratios and optimal portfolio weights for optimal portfolio design and hedging strategies, which provides important policy implications for risk management in petroleum markets. Finally, the performance of the OHRs from the estimated models is compared through applying the hedging effectiveness index. Further analysis with regard to the tail risk in terms of semi-variance reduction and Value-at-Risk is also presented.

In doing so, the contributions of this chapter compare with the existing literature in at least two points. First, we employ the VARMA-AGARCH model of McAleer et al. (2009) to analyse in depth the nature of volatility spillovers and asymmetric effects of spot and futures prices in gasoline and heating oil markets, which has not been done previously. Second, we extend previous research by including the time-varying conditional correlations in the specification of the VARMA-AGARCH model of McAleer et al. (2009) in what is termed the VARMA-AGARCH model with dynamic conditional correlations (DCC) structure. A principal feature of this specification is that the assumption of constant conditional correlations may be too restrictive given changing economic conditions, thereby entailing the need to incorporate time-varying correlations (see Lanza et al., 2006). To the best of our knowledge, this is the first time the VARMA-AGARCH model with DCC structure is applied in petroleum markets.[9] Implementing such model allows us to draw some new interesting insights regarding the effects of volatility spillovers, asymmetric effects and time-varying conditional correlations for petroleum markets hedging strategies.

[9] Sadorsky (2012) applies the approach to investigate the correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies.

The plan of the chapter is as follows. Section 3.2 provides a brief literature review. Section 3.3 discusses the VARMA-AGARCH model with DCC structure to be estimated, and the derivation of the optimal portfolio weights, optimal hedge ratios and hedging effectiveness index. Section 3.4 explains the data, descriptive statistics, unit root test and cointegration test statistics. Section 3.5 describes the empirical results and presents the economic implications for optimal hedge ratios and optimal portfolio weights. Section 3.6 provides some concluding remarks.

3.2 Literature review

In the literature, substantial research has been undertaken on analyzing the volatility, as well as the correlations in the shocks to volatility, in petroleum spot, forward and futures markets. The dynamic conditional correlations are crucial for deciding whether or not to hedge against unforeseen circumstances, as well as for pricing options and other derivatives. Actually, there can be substantial differences among the estimated constant and dynamic conditional correlations. For example, Manera et al. (2006) estimate the volatility and dynamic conditional correlations in the returns on Tapis oil spot and one-month forward prices using various multivariate conditional volatility models. Their results suggest that there are significant interdependences in the conditional volatilities between the spot and forward markets and the significance of time-varying conditional correlations makes it clear that the assumption of constant conditional correlation is not supported empirically. Lanza et al. (2006) investigate the dynamic conditional correlations between WTI crude oil forward and futures markets by employing the constant conditional correlation model of Bollerslev (1990) and the dynamic conditional correlation model of Engle (2002). Their results suggest that the dynamic correlations offer a more comprehensive explanation of whether the shocks to the volatilities in the forward and futures returns are substitutes or complements. Chang et al. (2009) examine the volatility spillovers and dynamic conditional correlations for the spot, forward and futures returns on Brent, WTI and Dubai crude oil markets using various multivariate conditional volatility models. Their findings indicate that there are significant volatility spillovers and the constant conditional correlations are not supported in the empirical analysis.

With regard to the estimated time-varying hedge ratio using multivariate conditional volatility models, Haigh and Holt (2002) examine the hedging effectiveness of using crude oil, gasoline and heating oil futures contracts to reduce price uncertainty for energy traders by employing an innovative multivariate GARCH model allowing for time-varying variances/covariances and volatility spillovers in the volatility equations. The model performs relatively well and provides insightful information on risk management in the oil industry. Jalali-Naini and Manesh (2006) estimate the hedge ratios for WTI crude oil spot and futures contracts with different maturities by employing the BEKK model of Engle and Kroner (1995). Their results suggest that the optimal hedge ratios are time-varying and futures contract with longer maturity has higher perceived risk, higher OHR mean and standard deviations. Chang et al. (2010) estimate the OHR and optimal portfolio weights of the crude oil portfolio using only the VARMA-GARCH model of Ling and McAleer (2003) without comparing their results in terms of risk reduction such that their policy implications for risk management in crude oil markets may be misleading. Recently, Chang et al. (2011) estimate the OHR and optimal portfolio weights of the crude oil portfolio using a wide range of multivariate conditional volatility models and compare their results in terms of risk reduction or hedge strategies. However, they did not consider the asymmetric effect and time-varying conditional correlations within the same multivariate conditional volatility model specification.

3.3 Econometric models

3.3.1 Multivariate GARCH models

The econometric specification used in this chapter has two components. A vector autoregression (VAR) with two lags is used to model the returns.[10] This allows for autocorrelations and cross-autocorrelations in the returns. The multivariate GARCH models are used to model the time-varying variances and covariances.

In order to capture interdependencies of volatility across different markets and/or assets, Ling and McAleer (2003)[11] assumed symmetry in the effects of positive and negative shocks of equal magnitude on the conditional volatility, which is given by

$$Y_t = E(Y_t|F_{t-1}) + \varepsilon_t \tag{3.1}$$

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{3.2}$$

$$\varepsilon_t = D_t \eta_t \tag{3.3}$$

$$H_t = W_t + \sum_{l=1}^{r} A_l \overrightarrow{\varepsilon_{t-l}} + \sum_{l=1}^{s} B_l H_{t-l} \tag{3.4}$$

where Eq. (3.1) denotes the decomposition of Y_t into its predictable (conditional mean) and random components, F_{t-1} is the past information available at time t, $D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t}, \ldots., \eta_{mt})'$ is a sequence of independently and identically distributed (i.i.d.) random vectors, W_t, A_l and B_l are $m * m$ matrices, with typical elements a_{ij} and β_{ij} representing the ARCH and GARCH effect, respectively, $H_t = (h_{1t}, \ldots., h_{mt})'$, $\vec{\varepsilon} = (\varepsilon_{1t}^2, \ldots, \varepsilon_{mt}^2)'$, $\Phi(L) = I_m - \Phi_1 L - \cdots . -\Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - \cdots . -\Psi_q L^q$ are polynomials in L, the lag operator. Although Bollerslev (1986) argues that $GARCH(1,1)$ captures infinite ARCH process, on a practical level, a multivariate GARCH model with a greater number of lags can be problematic. Spillover effects, or the dependence of conditional variances across different markets/assets, are

[10] As is often the case in applied research, different criterion functions select different lag lengths for the VAR models. Preliminary regression analysis showed very little differences between a VAR with two lags compared to a VAR with one or three lags. Consequently, in the interest of parsimony and accuracy, a VAR with two lags is chosen.

[11] Recent examples of the VARMA-GARCH approach include Change et al. (2010), Hammoudeh et al. (2009) and Hammoudeh et al. (2010).

given in the conditional volatility for each market/asset in Eq. (3.4) as it allows large shocks to one variable to affect the variances of the other variables.

The abovementioned model assumes that positive and negative shocks of equal magnitude have identical impacts on the conditional variance. However, this may not be the case in some empirical analysis. Therefore, McAleer et al. (2009) extended the VARMA-GARCH model to accommodate the asymmetric impacts of the unconditional shocks on the conditional variance, and proposed the VARMA-AGARCH specification of the conditional variance as follows:

$$H_t = W_t + \sum_{i=1}^{r} A_i \overrightarrow{\varepsilon_{t-\iota}} + \sum_{j=1}^{s} B_j H_{t-j} + \sum_{l=1}^{r} C_i I_{t-i} \overrightarrow{\varepsilon_{t-\iota}} \tag{3.5}$$

where C_i are $m * m$ matrices for $i = 1, \dots, r$ with typical element γ_{ij} , and $I_t = diag(I_{1t}, \dots, I_{mt})$, is an indicator function, given as:

$$I(\eta_{it}) = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \leq 0 \end{cases} \tag{3.6}$$

If $m = 1$, Eq. (3.5) reduces to the asymmetric GARCH (or GJR) model of Glosten et al. (1992). Meanwhile, the VARMA-AGARCH model reduces to the VARMA-GARCH model when $C_i = 0$ for all i. If $C_i = 0$ and A_i and B_j are diagonal matrices for all i and j, then the VARMA-AGARCH model reduces to the constant conditional correlation (CCC) multivariate GARCH model of Bollerslev (1990). For further details about the necessary and sufficient conditions for stationarity and ergodicity of the VARMA-AGARCH model, please see McAleer et al. (2009). The parameters of Eq. (3.1) to Eq. (3.5) are obtained by maximum likelihood estimation (MLE) using a joint normalized distribution. However, it is well known that the normality of the innovations is always rejected in most applications dealing with daily data in commodity markets. In particular, the kurtosis of most commodities prices returns is larger than three, which means that they have too many extreme values to be normally distributed and could be considered as conditional leptokurtosis. Harvey et al. (1992) and Fiorentini et al. (2003) indicate that an alternative to the multivariate Gaussian distribution is the Student's t distribution, which has an extra scalar parameter, the degrees of freedom parameter, denoted ν hereafter. Therefore, when η_t does not follow a joint multivariate normalized distribution, the appropriate estimator is Quasi-Maximum Likelihood Estimation (QMLE).[12]

With regard to the conditional correlation, we can assume it to follow the Bollerslev (1990) model, in which the conditional volatility matrix is defined as:

$$H_t = D_t \Gamma D_t \tag{3.7}$$

where $D_t = diag(h_1^{1/2}, \ldots., h_m^{1/2})$, m is the number of returns, and $t = 1, \ldots, n$, and $\Gamma = \mathrm{E}(\eta_t \eta_t' | F_{t-1}) = \mathrm{E}(\eta_t \eta_t')$, where $\Gamma = \{\rho_{ij}\}$, for $i, j = 1, \ldots m$, is the constant conditional correlation matrix of the unconditional shocks, η_t is equivalent to the constant conditional covariance matrix of the conditional shocks, ε_t, from Eq. (3.1), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, and $\mathrm{E}(\varepsilon_t \varepsilon_t' | F_{t-1}) = H_t = D_t \Gamma D_t$, where H_t is the conditional covariance matrix. The conditional covariance matrix is positive definite if and only if all the conditional variances are positive and Γ is positive definite.

As the assumption that the conditional correlations across different markets are constant may seem unrealistic in many empirical analyses (see Lanza et al., 2006; Manera et al., 2006), it will be appropriate to use the dynamic conditional correlation (DCC) structure proposed by Engle (2002) to capture the time-dependent conditional correlation matrix Γ_t, which is defined as:

$$\Gamma_t = \{diag(Q_t)^{-\frac{1}{2}}\} Q_t \{diag(Q_t)^{-\frac{1}{2}}\} \tag{3.8}$$

where $Q_t = (q_{ij,t})$ is a $m * m$ symmetric positive definite matrix given by:

$$Q_t = [1 - \theta_1 - \theta_2]\overline{Q} + \theta_1 \eta_{t-1} \eta_{t-1}' + \theta_2 Q_{t-1} \tag{3.9}$$

where θ_1 is a positive and θ_2 a non-negative scalar parameter to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional

[12] Please refer to McAleer et al. (2009) for detailed log likelihood function. They state that since η_t is not necessarily assumed to be normal, the estimation of the log likelihood function is the QMLE.

correlation respectively. Their sum is less than unity to ensure the positive definite of the variance-covariance matrix H_t. $\overline{Q}$ is the 2x2 unconditional correlation matrix of the standardized residuals η_{t-1}. Engle (2002) presents the conditional correlation as a weighted sum of past correlations. For the DCC structure, the null hypothesis of $\theta_1 = \theta_2 = 0$ is tested to determine whether imposing constant correlations is relevant. When $\theta_1 = \theta_2 = 0$, Q_t in Eq. (3.9) is equivalent to the CCC structure. The disadvantage of the DCC specification is that θ_1 and θ_2 are scalars, therefore, the conditional correlations feature the same dynamics. This is a necessary condition to ensure Γ_t is positive definite for all *t.* The DCC structure may be estimated simply using a two-step method based on the likelihood function (see Caporin and McAleer, 2009).

An alternative dynamic conditional correlation model featuring the volatility transmission effects is the BEKK model of Engle and Kroner (1995), which has the attractive property that the conditional covariance matrices are positive definite. However, McAleer et al. (2009) argue that the BEKK model suffers from the so-called "curse of dimensionality". The BEKK model for multivariate GARCH (1, 1) is given as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}'A' + BH_{t-1}B' \tag{3.10}$$

where the individual element for the matrices $C, A\ and\ B$ are given as:

$$C = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

for a two-market/asset portfolio with $\sum_{j=1}^{q}\sum_{k=1}^{K}(A_{kj}\otimes A_{kj}) + \sum_{j=1}^{q}\sum_{k=1}^{K}(B_{kj}\otimes B_{kj})$, where $\otimes$ denotes the Kronecker product of two matrices, are less than one in the modulus for covariance stationary (Silvennoinen and Terasvirta, 2008). Matrix A measures the extent to which conditional variances are correlated with past squared unexpected returns and consequently the effects of shocks on volatility. At the same time, matrix B depicts the extent to which current level of conditional variance-covariance matrix is related to past conditional variance-covariance matrices. The disadvantage of the BEKK model is that it is computationally complicated and the estimated coefficients for the variance-covariance matrix cannot be interpreted on an individual basis (see Caporin and McAleer, 2009).

3.3.2 Optimal hedge ratios and optimal portfolio weights

The objective of market participants in futures markets is to minimise risk of their portfolio without reducing their expected returns. Consider an investor in petroleum markets intending to protect their exposure to petroleum price fluctuations, the return on the investor's portfolio of spot and futures positions can be denoted as:

$$R_{H,t} = R_{S,t} - \gamma_t R_{F,t} \tag{3.11}$$

where $R_{H,t}$ is the return on holding the portfolio between $t-1$ and t, $R_{S,t}$ and $R_{F,t}$ are the returns on holding spot and futures positions between $t-1$ and t, and γ_t is the hedge ratio, which is the number of futures contracts that the hedger should sell for each unit of spot commodity on which price risk is borne.[13]

Johnson (1960)[14] explains that the variance of the returns of the hedged portfolio, conditional on the information set available at time $t-1$, is described as:

$$Var(R_{H,t}|\Omega_{t-1}) = Var(R_{S,t}|\Omega_{t-1}) - 2\gamma_t Cov(R_{S,t}, R_{F,t}|\Omega_{t-1}) + \gamma_t^2 Var(R_{F,t}|\Omega_{t-1}) \tag{3.12}$$

where $Var(R_{S,t}|\Omega_{t-1})$, $Var(R_{F,t}|\Omega_{t-1})$ and $Cov(R_{S,t}, R_{F,t}|\Omega_{t-1})$ are the conditional variance and covariance of the spot and futures returns, respectively. Therefore, the optimal hedge ratio (OHR) is defined as the value of γ_t which minimizes the conditional variance (the proxy of risk) of the hedged portfolio returns. Baillie and Myers (1991) derive the OHR from Eq. (3.12) after taking the partial derivative of Eq. (3.12) with respect to γ_t, setting it equal to zero and solving for γ_t, as:

[13] In this chapter we assume that a hedger in petroleum markets, such as petroleum producers or consumers, is always short on the futures contracts. Similar discussion could be attained for someone who is short on the physical and has to buy it at some future time.

[14] Please also see Stein (1961) and Ederington (1979).

$$\gamma_t^*|\Omega_{t-1} = \frac{Cov(R_{S,t}, R_{F,t}|\Omega_{t-1})}{Var(R_{F,t}|\Omega_{t-1})} \tag{3.13}$$

in which the returns are defined as the logarithmic differences of spot and futures prices.

Based on the VARMA-AGARCH model described previously, the OHR could be described as:

$$\gamma_t^*|\Omega_{t-1} = \frac{h_{SF,t}}{h_{F,t}} \tag{3.14}$$

where $h_{SF,t}$ is the conditional covariance between spot and futures returns, and $h_{F,t}$ is the conditional variance of futures returns. This equation is consistent with the function given by Kroner and Sultan (1993). In order to minimize risk, a long position of one dollar taken in one petroleum spot asset should be hedged by a short position of $\$\gamma_t^*$ in its corresponding futures asset at time t (see Hammoudeh et al., 2009).

Alternatively, estimating the right time-varying variance-covariance matrix is essential for the optimal portfolio design. Following Kroner and Ng (1998)'s instruction, we assume here that the expected returns are zero, making the problem equivalent to estimating the risk-minimizing portfolio weights. Then we can define

$$w_{SF,t} = \frac{h_{F,t} - h_{SF,t}}{h_{S,t} - 2h_{SF,t} + h_{F,t}} \tag{3.15}$$

Under the assumption of a mean-variance utility function, the optimal portfolio weight of petroleum spot/futures holding is given by:

$$w_{SF,t} = \begin{cases} 0, & if\ w_{SF,t} < 0 \\ w_{SF,t}, & if\ 0 < w_{SF,t} < 1 \\ 1, & if\ w_{SF,t} > 0 \end{cases} \tag{3.16}$$

where $w_{SF,t}$ and $1 - w_{SF,t}$ are the optimal weight of the spot and futures in a one dollar portfolio of petroleum commodity spot/futures at time t.

Furthermore, it would be interesting to look into hedging effectiveness (HE) by actually running the portfolio simulations with the optimal portfolio designs. The effectiveness of the portfolio diversification is measured by comparing the realized risk and return characteristics of the considered portfolio. Ku et al. (2007) propose that the effectiveness of hedging across each considered portfolio can be evaluated by examining the realized hedging errors, which is given by:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{3.17}$$

where the variance of the hedged portfolio is obtained from the variance of the rate of return, $R_{H,t}$, and the variance of the unhedged portfolio is the variance of spot returns (see, Arouri et al., 2011). A higher HE ratio suggests superior hedging effectiveness in terms of the portfolio's variance reduction, which thus implies that the associated investment method can be deemed a better hedging strategy.

3.4 Data

The data set for this chapter comprises daily synchronous closing prices of spot and the nearby futures contract (that is, the contract for which the maturity is closest to the current date) for three petroleum commodities: NYMEX WTI crude oil, gasoline, and heating oil from October 7, 2005 to October 23, 2012.[15] All daily closing prices of 1768 observations are obtained from the Energy Information Agency of US government website.[16] The returns of petroleum commodity i at time t in a continuous compound basis are calculated as $r_{i,t} = \log(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of petroleum commodities i for days t and $t-1$, respectively.

[15] The reason for us to choose this particular starting date is that the futures contract with regard to gasoline has changed specification in late 2005. In order to keep datasets consistency across three petroleum commodities, we have chosen this particular date.

[16] The abbreviation for the spot prices of WTI crude oil, gasoline and heating oil are WTI_S, GASO_S and HEAT_S, respectively. The abbreviation for the futures prices of WTI crude oil, gasoline and heating oil are WTI_F, GASO_F and HEAT_F, respectively.

The criteria for selecting the data set for this analysis include: (1) the petroleum commodities must be actively traded; (2) F.O.B. price is preferable. F.O.B. price (Free on board, which is the price charged at the exporting country's port of loading) for oil products will eliminate the impact of transportation and insurance cost in comparison with C.I.F. price (Cost, Insurance and Freight, which is the price charged at the importing country's port of discharging).

Table 3.1
Descriptive statistics.

Returns	Mean (%)	Std. Dev. (%)	Skew.	Kurt	Max	Min	JB	$Q(10)$	$Q^2(10)$
WTI_S	0.019	2.533	0.105	7.877	0.164	-0.128	1754.7^{+++}	35.387^{+++}	1065.3^{+++}
WTI_F	0.019	2.525	0.130	7.942	0.164	-0.131	1803.3^{+++}	25.051^{+++}	1121.9^{+++}
GASO_S	0.018	3.090	0.111	7.255	0.222	-0.187	1336.3^{+++}	13.798	349.02^{+++}
GASO_F	0.023	2.544	-0.162	6.357	0.153	-0.135	837.5^{+++}	19.437^{++}	372.74^{+++}
HEAT_S	0.026	2.141	-0.094	4.490	0.106	-0.099	166.2^{+++}	3.179	299.05^{+++}
HEAT_F	0.025	2.122	-0.125	4.852	0.088	-0.102	257.2^{+++}	4.396	449.16^{+++}

Notes: This table reports the basic statistics of the return series of WTI crude oil, gasoline and heating oil, including mean (Mean), standard deviation (Std. Dev), skewness (Skew.), kurtosis (Kurt.), minimum (Min), and maximum (Max). JB refers to the empirical statistic of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis. Q(10) represents the Ljung-Box (1978) tests for autocorrelations of order 10 applied to standardized residuals. $Q^2(10)$ represents the Engle's (1982) ARCH test, carried out as the Ljung–Box (1978) Q statistics on the squared series. $^{+++}$ and $^{++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 1% and 5% levels, respectively.

Table 3.1 reports the descriptive statistics of the return series. The means of the six return series are quite small in comparison to the standard deviations, but the corresponding volatility of returns measured by standard deviation is much higher. Both skewness and kurtosis statistics, accompanied with extreme value statistics (Minimum and Maximum), indicate essentially that pre-eminence of large jumps in the datasets leads up to the rejection of the normality assumptions for the return series, which is also confirmed by the Jarque-Bera (1980) test. The Ljung and Box (1978) Q statistic on the first ten lags of the sample autocorrelation function is significant only in the WTI crude oil market at the 1% significance level. Engle's (1982) ARCH test, carried out as the Ljung-Box Q statistic on the squared series, indicates the existence of heteroscedasticity for all six return series.

Table 3.2 reports the results of unit roots tests for the price and returns series of petroleum markets based on Augmented Dickey-Fuller (1979) (ADF) and Phillips and Perron (1988) (PP) unit root tests. Under the hypothesis of both intercept and trend in test equations, both ADF and PP test statistics fail to reject the null hypothesis of a unit root for all price series. For each of the return series, the results of a stationary process can be obtained from unit root tests. Thus, we can say that the petroleum price process follows a unit root, whereas the return process is stationary. The market efficiency hypothesis requires that the current futures prices and the future spot price are cointegrated, meaning that futures prices are unbiased predictors of spot prices at maturity (see Moosa, 1996). Consequently, the agent can buy or sell a contract in the futures market for a commodity and undertakes to receive or deliver the commodity at a certain time in the future, based on a price determined today (Chang et al., 2011).

Table 3.2
Unit root tests.

Panel A: price series						
Prices	ADF test			PP test		
	None	Cons.	Cons. & trend	None	Cons.	Cons. & trend
WTI_S	-0.2103	-2.1099	-2.2077	-0.1728	-2.0452	-2.1366
WTI_F	-0.2041	-2.1025	-2.1979	-0.1673	-2.0581	-2.0985
GASO_S	-0.2822	-2.3689	-2.6822	-0.3357	-2.5027	-2.8346
GASO_F	-0.0702	-2.0175	-2.2925	-0.1051	-1.9998	-2.2166
HEAT_S	0.1644	-1.4240	-1.8661	0.1817	-1.4113	-1.8556
HEAT_F	0.1541	-1.4347	-1.8811	0.1686	-1.4179	-1.8653
Panel B: return series						
Returns	ADF test			PP test		
	None	Cons.	Cons. & trend	None	Cons.	Cons. & trend
WTI_S	-19.418^{+++}	-19.416^{+++}	-19.411^{+++}	-42.396^{+++}	-42.388^{+++}	-42.377^{+++}
WTI_F	-24.212^{+++}	-24.207^{+++}	-24.201^{+++}	-44.067^{+++}	-44.058^{+++}	-44.046^{+++}
GASO_S	-43.057^{+++}	-43.047^{+++}	-43.035^{+++}	-43.081^{+++}	-43.069^{+++}	-43.057^{+++}
GASO_F	-41.685^{+++}	-41.677^{+++}	-41.665^{+++}	-41.686^{+++}	-41.677^{+++}	-41.665^{+++}
HEAT_S	-43.536^{+++}	-43.530^{+++}	-43.521^{+++}	-43.532^{+++}	-43.526^{+++}	-43.517^{+++}
HEAT_F	-42.812^{+++}	-42.806^{+++}	-42.797^{+++}	-42.818^{+++}	-42.812^{+++}	-42.803^{+++}

Notes: ADF is the Augmented Dickey-Fuller (1979) unit root test statistic. PP is the Phillips-Perron (1988) unit root test statistic. The null hypothesis in the ADF and PP tests is that the underlying series has a unit root. +++ indicates the rejection of the null hypothesis at the significance levels of 1%. Numbers of augmenting lags are chosen using the Hannan-Quinn Criterion. Significance levels probabilities from MacKinnon (1996) use the number of observations. Asymptotic values have a higher significance level.

The Johanson (1995) cointegration test between spot and futures prices is reported in Table 3.3 through employing the trace (λ_{trace}) and maximal (λ_{max}) eigenvalue test statistics. Both tests suggest that the null hypothesis of no cointegrating vector, $k = 0$, can be rejected at the significance level of 1%, while the alternative hypothesis of at least one cointegrating vector, $k = 1$, can not be rejected at the significance level of 10% at least. Therefore, we can draw the conclusion that spot and futures prices are cointegrated with one cointegrating vector.

Table 3.3
Cointegration test using the Johansen approach.

Market	Lag number	λ_{trace}		λ_{max}	
		$k = 0$	$k \leq 1$	$k = 0$	$k \leq 1$
WTI	2	381.3^{+++}	4.125	377.2^{+++}	4.126
GASO	2	64.608^{+++}	4.431	60.177^{+++}	4.431
HEAT	2	101.5^{+++}	3.585	97.9^{+++}	3.586

Notes: +++ indicates the rejection of the null hypothesis at the significance levels of 1%. Significance levels probabilities from MacKinnon (1996) use the number of observations. Asymptotic values have a higher significance level.

Fig. 3.1 displays the evolution of the synchronous petroleum commodities prices. All prices move in the same pattern, suggesting they are contemporaneously correlated. The behaviour of petroleum commodities prices shows distinctly three main patterns: a modest stable trend from October 2005 to February 2007, followed by a strong upward deterministic trend and persistence over the period from March 2007 to July 2008, with prices rising progressively to cross the peak point in July 2008, showing no sign for stability around a mean. However, following the impact of financial crisis of 2008, the persistent upward trend is dramatically reversed within a very short period from August 2008 to December 2008. Subsequently, the upward trend comes back and becomes predictable. Fig. 3.2 shows the plot of petroleum commodities returns, which indicates that the periods of high volatilities are followed by the periods of relative tranquillity. Fig. 3.3 presents the dynamics of volatilities of petroleum commodities, whereas volatilities are proxied by the squared daily returns.[17] These plots also confirm the existence of volatility clustering.

Table 3.4
Engle and Ng (1993) tests for sign and size bias in variance.

Variable	Sign	Negative size	Positive size	Joint
WTI_S	2.375^{++}	6.801^{+++}	9.119^{+++}	133.95^{+++}
WTI_F	2.262^{++}	7.056^{+++}	6.929^{+++}	111.16^{+++}
GASO_S	0.315	5.469^{+++}	3.941^{+++}	46.28^{+++}
GASO_F	1.935^{+}	4.317^{+++}	6.883^{+++}	66.79^{+++}
HEAT_S	0.073	5.096^{+++}	2.857^{+++}	37.76^{+++}
HEAT_F	0.049	4.679^{+++}	1.577	30.13^{+++}

Notes: $^{+++}$, $^{++}$ and $^{+}$ indicate the rejection of the null hypothesis of the Engle and Ng (1993) test at the 1%, 5% and 10% levels, respectively.

Finally, as we are interested in the asymmetry of the volatility response to news, in Table 3.4, we present Engle and Ng (1993) test statistics for "sign bias", "negative size bias", "positive size bias" and their "Joint effect". As can be seen from Table 3.4, the conditional volatilities of petroleum commodities prices are sensitive to the sign and size of the innovation. In particular, the joint test for both sign and size bias is significant at 1% significance level.

[17] Kang et al. (2009) take the same approach to assess daily actual volatility (variance). Another way to measure the daily volatility is to calculate the square of the estimated residuals of the returns series from an ARMA (1, 1) process (see Chang et al., 2011). The plotted patterns are similar no matter which approach has been employed, which suggests the existence of volatility clustering.

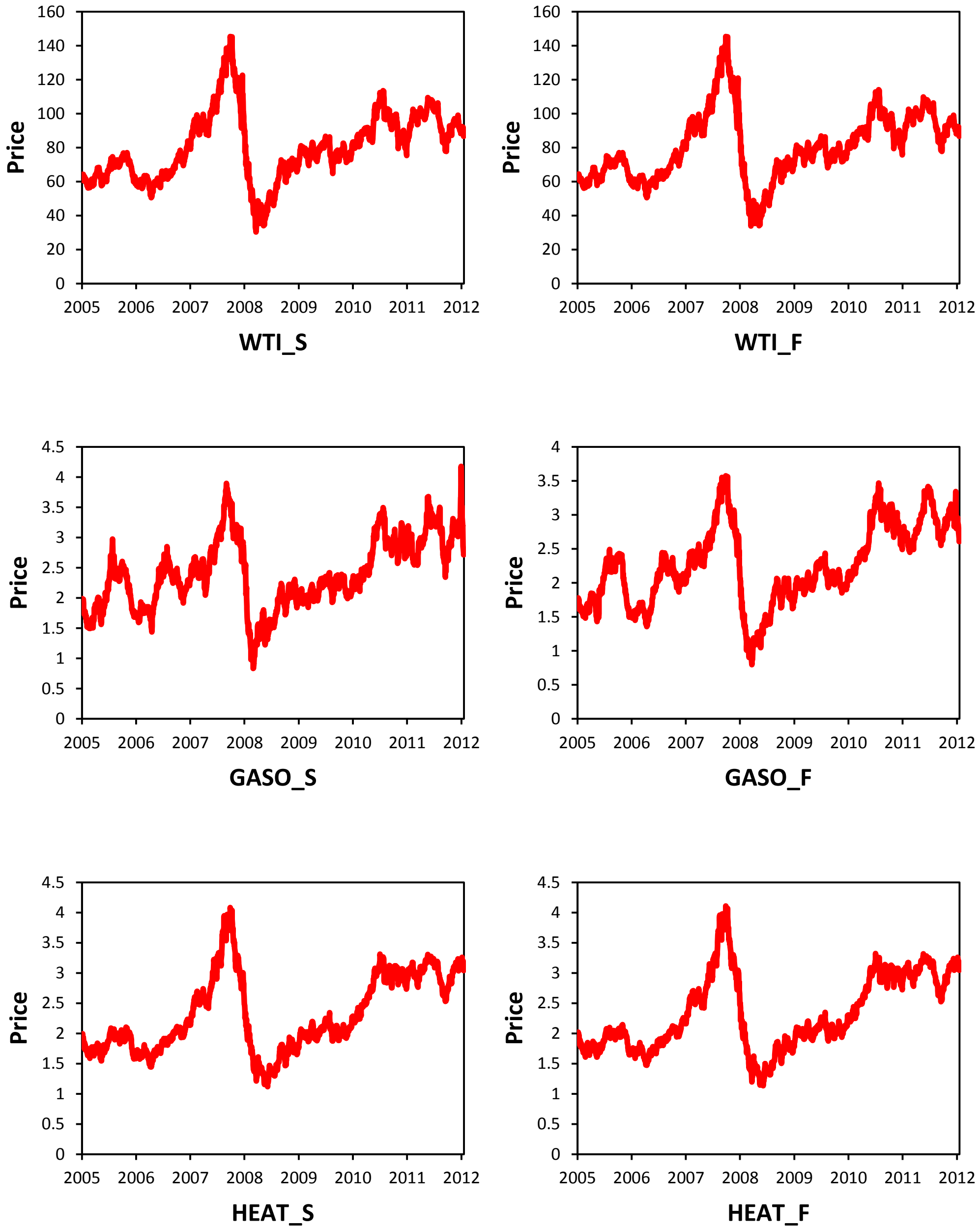


Fig. 3.1 Petroleum commodities spot and futures prices.

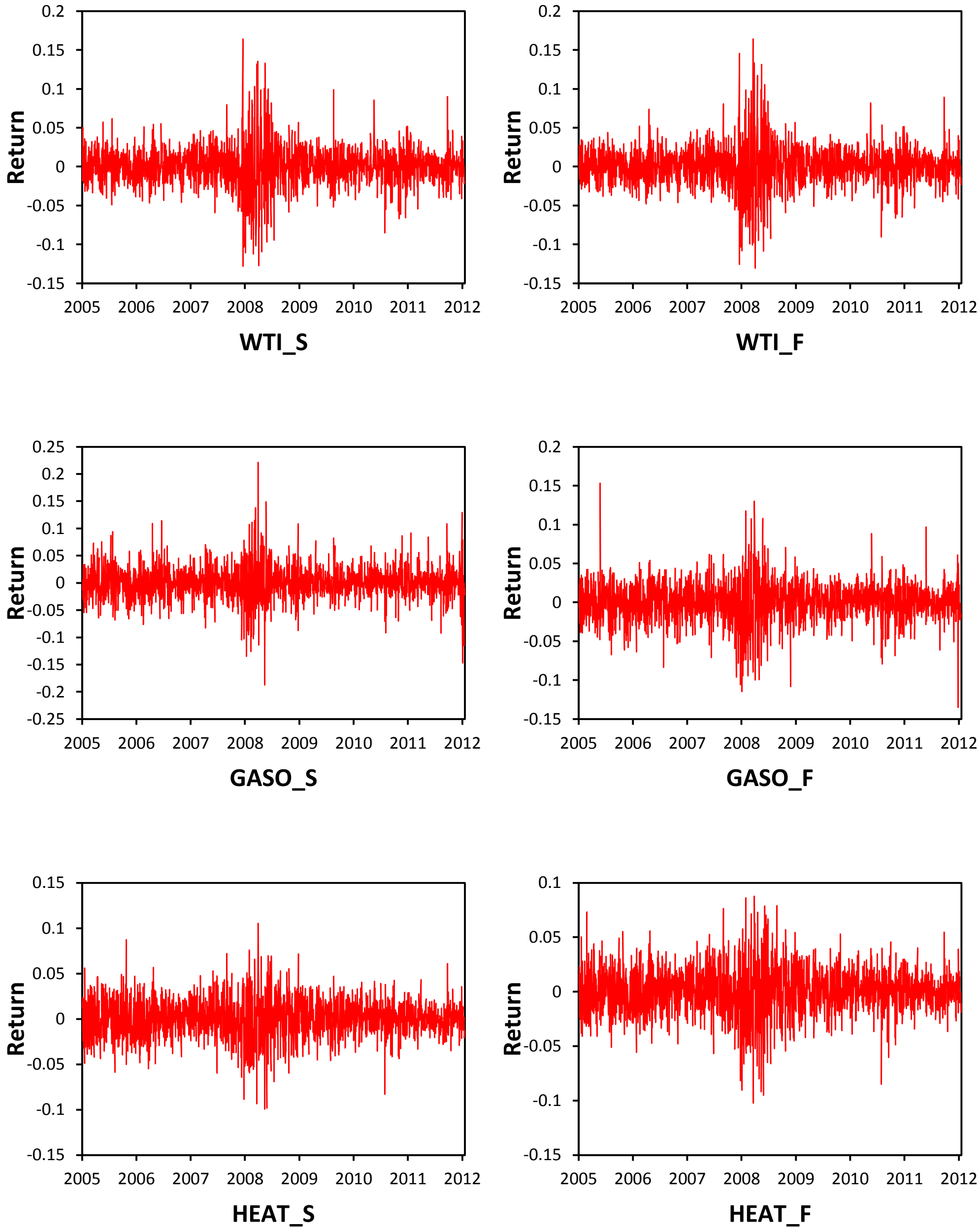


Fig. 3.2 Logarithm of daily petroleum commodities spot and futures returns.

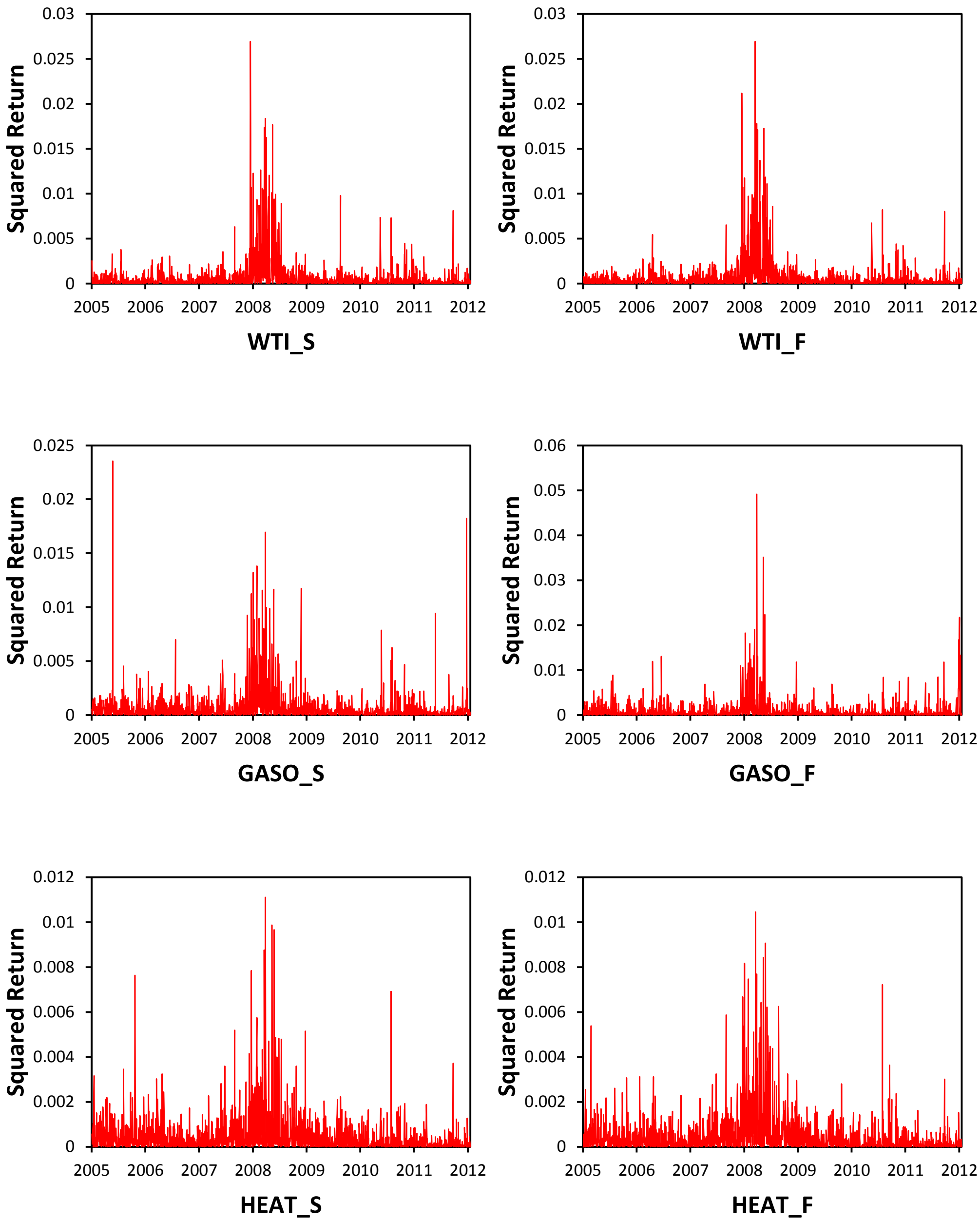


Fig. 3.3 Squared returns of daily petroleum commodities spot and futures prices.

3.5 Empirical results

In this section, we will first discuss our findings related to volatility transmission between petroleum commodities spot and futures markets within the empirical framework of the VARMA-AGARCH model with DCC structure[18]. We will then use the estimation results to compute the optimal weights as well as the optimal hedge ratios and to discuss the optimal hedging strategies.

Table 3.5 reports the estimates of the conditional mean and variance for VAR (2)-AGARCH (1, 1) models with DCC structure.[19] The results with regard to the conditional mean equation indicate that returns for all petroleum spot and futures prices are interdependent but these interdependencies are not the same across the petroleum markets. In order to investigate the information flow between petroleum spot and futures returns, we also examine the daily Granger-causality relationship in returns. Granger causality test (Granger, 1969) is designed to detect causal direction between two time series. More precisely, Granger causality test detects a correlation between the current value of one variable and the past values of another variable. Based on Granger's definition of causality, Sims (1980) provided a variant. Consider a bivariate VAR model with two time series for up to five lags[20]:

$$r_i^S = a_1 + \sum_{j=1}^{5} b_{1j} r_{t-j}^S + \sum_{j=1}^{5} c_{1j} r_{t-j}^F + \varepsilon_{1t} \qquad (3.18a)$$

$$r_i^F = a_1 + \sum_{j=1}^{5} b_{2j} r_{t-j}^F + \sum_{j=1}^{5} c_{2j} r_{t-j}^S + \varepsilon_{2t} \qquad (3.18b)$$

where r_i^S and r_i^F are the log returns on petroleum markets spot and futures prices, ε_t is an error term, b and c are parameters for estimation. The VAR model is estimated using ordinary

[18] The other two models, i.e. the VARMA-AGARCH model with CCC structure and the BEKK model, are also estimated, but the results are not shown here as they are used especially to compare the results of hedging effectiveness. Both models are estimated under the distributional assumption of a joint normalized distribution. The computations presented in this study were conducted by means of RATS and R programs.

[19] Note that we also estimated the models under the distributional assumption of a joint normalized distribution. Model parameters were found to be robust irrespective of the distribution chosen and results were similar to those reported in Table 3.5.

[20] We use five lags to represent a typical trading week. The results are robust to differing numbers of lags.

least squares with heteroskedasticity-consistent standard errors. To test whether the Granger causality runs from spot to futures market or from futures to spot market, the null hypothesis is:

$$H_{0,1}: c_{1j} \text{ and } c_{2j} = 0 \text{ for all } j = 1, \dots, 5$$

$$H_{0,2}: \sum_j c_{1j} \text{ and } \sum_j c_{2j} = 0$$

The first null hypothesis tests that all of the cross-market coefficients are jointly equal to zero. The second tests that the sum of all the coefficients is equal to zero. Hereafter, the first and second tests are defined as the joint and sum coefficient tests, respectively. The results for the Granger-causality tests are reported in Table 3.6. For the WTI crude oil market, there is significant bi-directional lead-lag relationship between spot and futures markets, since the joint tests are significant at the 1% level. The results for the heating oil markets are also significant. Regarding the gasoline market, the results demonstrate that neither gasoline spot market returns lead futures market returns nor do futures market returns lead spot market returns as both the joint and sum tests are not significant in either direction.

3.5.1 Volatility dependencies and dynamic conditional correlations

The results with regard to the conditional volatility equation show that the volatility sensitivity to its own lagged conditional volatility (GARCH terms) is significant for all spot and futures returns series. Changes in the current conditional volatility of both spot and futures returns are also dependent upon their own lagged shocks (ARCH terms), which are indicated by the significance of the estimates of ARCH coefficients. Furthermore, the larger magnitude of GARCH-term estimates, combined with the smaller size of ARCH-term estimates, indicates the gradual fluctuations of conditional volatility over time for petroleum markets, which suggests that investors participating in petroleum markets may consider active asset management strategies based on volatility persistence and current market trends. These properties can be further apprehended through plotting the time-variations of conditional volatility estimated over the sample period in Fig. 3.4.

Table 3.5
Estimates of VAR (2)-AGARCH (1, 1) model with DCC structure.

Variables	WTI_S-WTI_F		GASO_S-GASO_F		HEAT_S-HEAT_F	
	WTI_S	WTI_F	GASO_S	GASO_F	HEAT_S	HEAT_F
Conditional mean equation						
Constant	0.0002	0.0002	0.0001	0.0002	0.0002	0.0002
$AR(1)^S$	0.1058	0.0374	-0.0698^{**}	0.0079	-0.2275^{***}	0.2958^{***}
$AR(1)^F$	-0.1204	-0.0822	2.1701^{**}	0.0017	0.2095^{***}	-0.3002^{***}
$AR(2)^S$	-0.1493^{***}	0.1527^{***}	-0.0111	-0.0176	-0.0085	0.1847^{***}
$AR(2)^F$	1.9207^{*}	-0.1969^{***}	-0.0335	-0.0156^{**}	0.0072	-0.1834^{***}
Conditional variance equation						
Constant	0.00004^{***}	0.00004^{***}	0.00001^{**}	0.00002^{**}	0.00001^{**}	0.00002^{*}
$(\varepsilon_{t-1}^S)^2$	-0.0924^{***}	0.4884^{***}	0.1265^{***}	-0.1241^{***}	0.0193^{**}	-0.0719^{***}
$(\varepsilon_{t-1}^F)^2$	0.4759^{***}	-0.0765^{**}	-0.0056^{*}	-0.0045^{*}	0.0952^{***}	-0.0506^{***}
h_{t-1}^S	0.6968^{***}	-0.0378^{**}	0.8085^{***}	0.1723^{***}	0.9541^{***}	0.0155^{*}
h_{t-1}^F	0.0753	0.5827^{***}	0.2437^{***}	0.7492^{***}	-0.0954^{***}	1.0954^{***}
Asymmetry	0.3312^{***}	0.3324^{***}	0.0544^{**}	0.0736^{***}	0.0296^{***}	0.0354^{***}
$Shape(v)$	3.19^{***}		4.88^{***}		6.61^{***}	
Dynamic Conditional Correlation (DCC)						
θ_1	0.4075^{***}		0.0364^{***}		0.0779^{***}	
θ_2	0.5862^{***}		0.9557^{***}		0.9157^{***}	
$\theta_1 + \theta_2$	0.9937		0.9921		0.9936	
Average DCC	0.9656 (0.0909)		0.6799 (0.1211)		0.9428 (0.0780)	
Diagnostic statistics						
Log L	11807.2		8736.3		11207.1	
JB	207.4^{+++}	171.6^{+++}	134.5^{+++}	197.9^{+++}	41.13^{+++}	51.76^{+++}
ARCH(10)	14.971	16.817^{+}	19.001^{++}	19.977^{++}	9.409	7.483
Q(10)	5.987	8.251	4.749	10.896	4.212	3.764

Notes: *, **, and *** indicate significance at the 10%, 5% and 1% respectively. Model is estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. The Log L (Log Likelihood) criterion measures the relative goodness of fit of the estimated model. JB, ARCH(10), and Q(10) refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 10, and the Ljung-Box (1978) tests for autocorrelations of order 10 applied to standardized residuals in levels. The Average DCC refers to the average value of dynamic conditional correlations between petroleum spot and futures markets. The two entries for each Average DCC are their respective value and the corresponding standard deviation. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% respectively.

Table 3.6
Granger causality in returns.

$$r_i^S = a_1 + \sum_{j=1}^{5} b_{1j} r_{t-j}^S + \sum_{j=1}^{5} c_{1j} r_{t-j}^F + \varepsilon_{1t} \qquad (3.18a)$$

$$r_i^F = a_1 + \sum_{j=1}^{5} b_{2j} r_{t-j}^F + \sum_{j=1}^{5} c_{2j} r_{t-j}^S + \varepsilon_{2t} \qquad (3.18b)$$

	r_i^S		r_i^F	
Panel A: WTI Crude oil				
	$\chi^2(5)$ statistic	p-value	$\chi^2(5)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	2.9452	0.0098***	3.2419	0.00645***
$H_{0,2}$: Sum coefficient test	1.3167	0.2512	12.722	0.0004***
Panel B: Gasoline	r_i^S		r_i^F	
	$\chi^2(5)$ statistic	p-value	$\chi^2(5)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	1.5476	0.1719	0.3228	0.8995
$H_{0,2}$: Sum coefficient test	2.4517	0.1174	0.3507	0.5537
Panel C: Heating Oil	r_i^S		r_i^F	
	$\chi^2(5)$ statistic	p-value	$\chi^2(5)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	2.6132	0.0231**	5.6585	0.0001***
$H_{0,2}$: Sum coefficient test	2.2722	0.1317	15.341	0.0001***

Notes: This table presents results for the initial Granger-causality tests specified by Eq. (3.18a) and (3.18b). *** and ** indicate the null hypothesis is significant at the 1% and 5% level, respectively.

The estimates of volatility spillovers and asymmetric effects between spot and futures returns are also found in all petroleum markets. This means that the conditional variances of spot returns of petroleum markets are affected by the previous short run shocks and long run persistence from their corresponding futures returns and the conditional variances of futures returns of petroleum markets are also affected by the previous short run shocks and long run persistence from their corresponding spots returns. Furthermore, the significance of the coefficients associated with asymmetry indicates that the positive and negative shocks of equal magnitude have different impacts on the conditional variance, which in turn suggests that the VARMA-AGARCH model is more appropriate than the VARMA-GARCH model in terms of modeling dynamic volatility of petroleum markets.

The DCC estimates of the conditional correlations between the volatilities of spot and futures returns are also given in Table 3.5. The estimated coefficients on θ_1 and θ_2 are each positive and statistically significant at the 1% level, which indicates that the assumption of constant conditional correlation for petroleum markets is not supported empirically. The short run persistence of shocks on the dynamic conditional correlations is greatest for WTI crude oil at 0.4075, while the largest long run persistence of shocks to the conditional correlations is 0.9937 (=0.4075+0.5862) for WTI crude oil. Furthermore, these estimated coefficients sum to a value which is less than one, meaning that the dynamic conditional correlations are mean-reverting.

The time-varying conditional correlations between spot and futures returns are plotted in Fig. 3.5. It is clear that there is significant variation in the conditional correlations over time, especially in the spot and futures returns of gasoline which has the highest standard deviation of the dynamic conditional correlations reported in Table 3.5. It is also observed that the dynamic conditional correlations can vary a lot from the average conditional correlations ($DCC_{WTI} = 0.9656, DCC_{Gasoline} = 0.6799, and\ DCC_{Heatingoil} = 0.9428$) emphasizing the need to compute dynamic conditional correlations. The time series plots in Fig. 3.5 show that, for each pair of series, the dynamic conditional correlations provide much more useful information than do the correlations from the constant conditional correlations model, which indicates that any calculations associated with correlations from the constant conditional correlation model would have been very misleading.

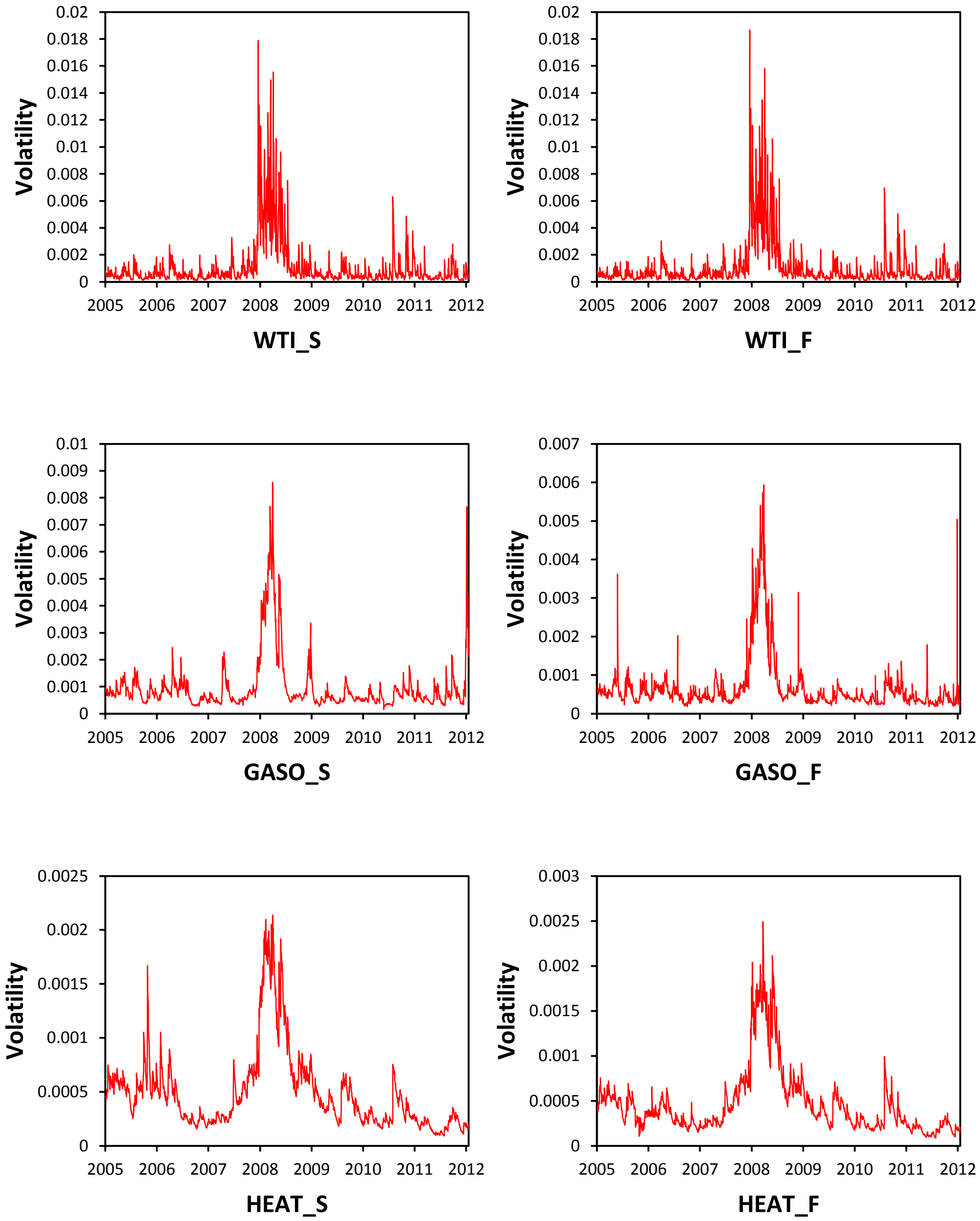


Fig. 3.4 Time-variations of conditional volatility for petroleum markets.

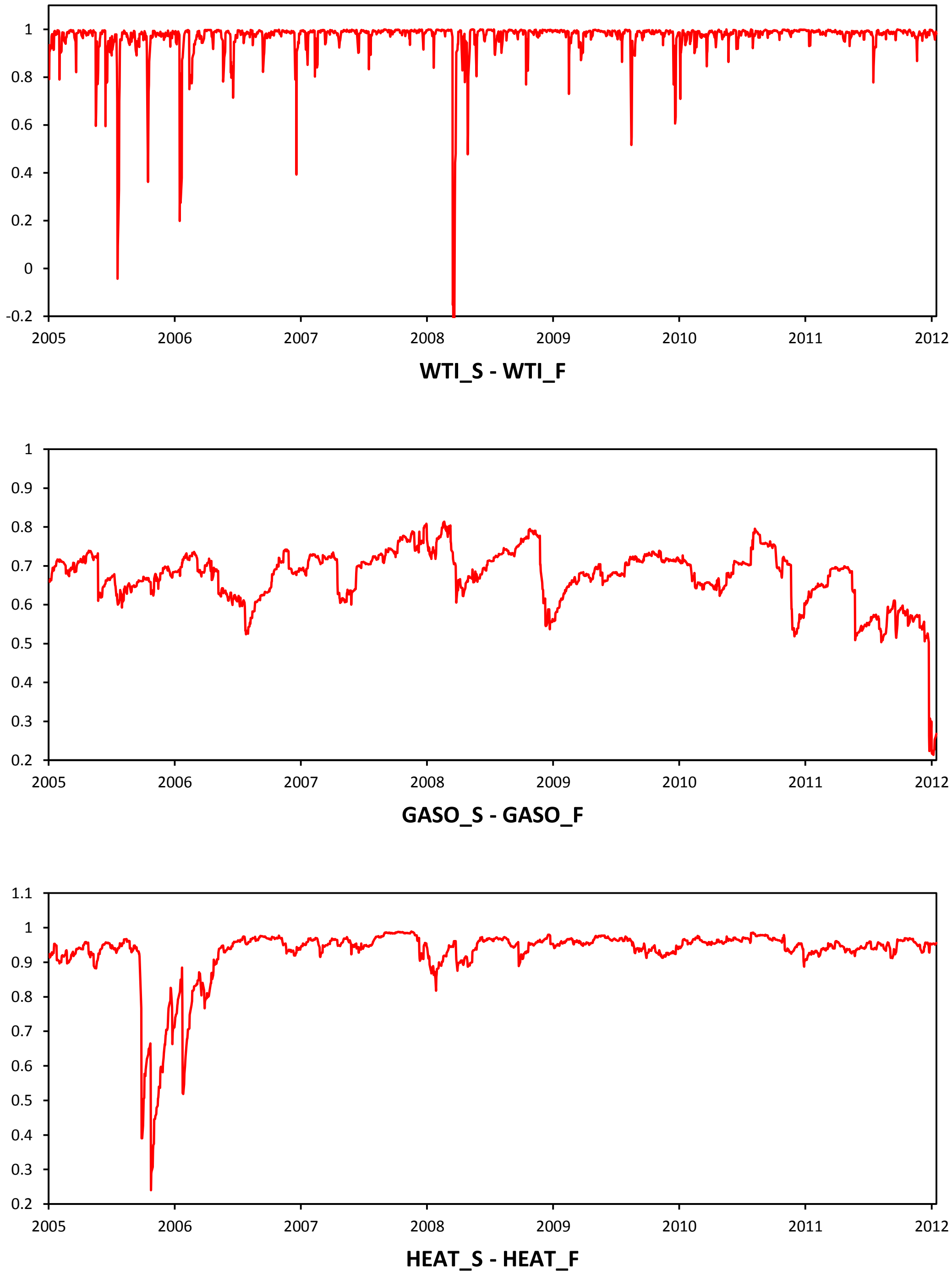


Fig. 3.5 Time-varying conditional correlations for petroleum markets.

Table 3.7
Diagnostic tests based on the news impact curve.

	$(\varepsilon_t^S)^2 - h_t^S$	$\varepsilon_t^S \varepsilon_t^F - h_t^{SF}$	$(\varepsilon_t^F)^2 - h_t^F$
WTI_S – WTI_F			
$I(\varepsilon_{t-1}^S < 0)$	0.9656	0.8589	0.8732
$I(\varepsilon_{t-1}^F < 0)$	0.9569	0.8717	0.8260
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F < 0)$	0.9268	0.8233	0.7882
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F > 0)$	0.0902	0.0742	0.1213
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F < 0)$	0.1887	0.1856	0.2475
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F > 0)$	2.3659^{++}	2.2142^{++}	2.0932^{++}
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	0.5119	1.9254^{+}	0.0064
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^F < 0)$	5.4003^{+++}	5.9963^{+++}	0.7884
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^S < 0)$	0.3379	0.1704	0.0345
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^F < 0)$	0.4618	0.1572	0.1287
GASO_S – GASO_F			
$I(\varepsilon_{t-1}^S < 0)$	0.2759	1.4307	0.9226
$I(\varepsilon_{t-1}^F < 0)$	0.1766	1.8176^{+}	0.6727
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F < 0)$	1.0940	2.2088^{++}	0.8657
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F > 0)$	0.2489	5.4369^{+++}	0.5131
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F < 0)$	0.7479	0.5022	0.4690
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F > 0)$	1.3954	0.7341	1.5672
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	0.0836	0.3853	2.7016^{+++}
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^F < 0)$	0.3643	1.0421	2.8634^{+++}
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^S < 0)$	2.9182^{+++}	0.1296	2.5521^{++}
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^F < 0)$	0.2515	0.1809	0.3001
HEAT_S – HEAT_F			
$I(\varepsilon_{t-1}^S < 0)$	1.3263	1.9530^{+}	1.8736^{+}
$I(\varepsilon_{t-1}^F < 0)$	1.1812	1.8902^{+}	1.8189^{+}
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F < 0)$	1.2745	1.9404^{+}	1.8377^{+}
$I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F > 0)$	0.2145	0.2399	0.1578
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F < 0)$	0.2274	0.1789	0.2393
$I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F > 0)$	2.5182^{++}	1.5289	2.9194^{++}
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	0.0476	0.2041	0.4436
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^F < 0)$	0.6928	2.3199^{++}	0.8892
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^S < 0)$	0.3469	0.3701	0.2522
$(\varepsilon_{t-1}^F)^2 I(\varepsilon_{t-1}^F < 0)$	1.5917	0.5971	0.1463

Notes: $^{+++}$, $^{++}$ and $^{+}$ indicate the rejection of the null hypothesis of t of no asymmetric effects at the 1%, 5% and 10% significance levels, respectively.

Lastly, the results of diagnostic tests based on standardized residuals are also shown in Table 3.5. The diagnostic tests for the standardized residuals and standardized residuals squared show no evidence of serial autocorrelation and ARCH effects at the significance level of 1%. However, the JB statistics still reject the normality hypothesis even though that departure from normality is greatly reduced. We regard the departure from normality as well as the significance of the estimated degrees of freedom for the Student's t distribution as strong evidence for favouring a Student's t distribution for ε_t.

The diagnostic tests suggested by Engle and Ng (1993) and Kroner and Ng (1998), based on the 'generalized residuals', defined as $\varepsilon_t^S \varepsilon_t^F - h_t^{SF}$, are also conducted. A generalized residual can be thought of as the distance between a point on the scatter plot of $\varepsilon_t^S \varepsilon_t^F$ from a corresponding point on the news impact curve. If the conditional heteroskedasticity part of the model is correct, generalized residuals should be uncorrelated with all information known at time $t-1$. The Engle and Ng (1993) and Kroner and Ng (1998) misspecification indicators test whether we can predict the generalized residuals by some variables observed in the past, but which are not included in the model. In this regard, we follow Kroner and Ng (1998) and Shields et al. (2005) and define two sets of misspecification indicators. In a two dimensional space, we first partition $(\varepsilon_{t-1}^S, \varepsilon_{t-1}^F)$ into four quadrants in terms of the possible sign of the two residuals. Then, we define the series of indicator functions as $I(\varepsilon_{t-1}^S < 0)$, $I(\varepsilon_{t-1}^F < 0)$, $I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F < 0)$, $I(\varepsilon_{t-1}^S < 0, \varepsilon_{t-1}^F > 0)$, $I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F < 0)$, and $I(\varepsilon_{t-1}^S > 0, \varepsilon_{t-1}^F > 0)$, where $I(\cdot)$ equals one if the argument is true and zero otherwise. Furthermore, we further define a second set of indicator functions, $(\varepsilon_{t-1}^S)^2 I(\varepsilon_t^S < 0)$, $(\varepsilon_{t-1}^S)^2 I(\varepsilon_t^F < 0)$, $(\varepsilon_{t-1}^F)^2 I(\varepsilon_t^F < 0)$, and $(\varepsilon_{t-1}^F)^2 I(\varepsilon_t^S < 0)$, to examine the possible effect of both the size and the sign of a shock. These indicators are technically scaled versions of the former ones, with the magnitude of the shocks as a scale measure. We conduct indicator tests and report the results in Table 3.7. It can be observed from Table 3.7 that most of the indicators fail to reject the null hypothesis of no misspecification - all test statistics in Table 3.7 are distributed as $\chi^2(1)$. Hence, our model captures the effects of all sign bias and size-sign scale depended shocks in predicting volatility and there is no significant model misspecification error in the standardized residuals. Therefore, the VARMA-AGARCH model with DCC structure provides a sufficient and parsimonious representation of the volatility process of petroleum commodities returns in terms of volatility spillovers, asymmetric effects and time-varying conditional correlations.

Summarizing all, the empirical VARMA-AGARCH model with DCC structure appears to satisfactorily capture the volatility transmission for all petroleum markets under consideration. The analysis of volatility interdependence shows significant volatility spillovers and asymmetric effects between petroleum spot and futures markets. It is worth noting that the estimation results will allow us to compute the optimal weights as well as the optimal hedge ratios and to discuss the optimal hedging strategies in the following section.

3.5.2 Portfolio management with optimal hedging strategies

Our previous findings suggest that potential gains from diversification are substantial by investing in both petroleum spot and futures markets. However, their volatility transmissions require investors to quantify the optimal weights and hedging ratios in order to deal adequately with the risk. To illustrate this purpose, we now consider a portfolio composed of petroleum spot and futures assets for which we attempt to minimize the risk without reducing expected returns. The average values of optimal portfolio weights ($w_{SF,t}$) using estimates from various multivariate models, namely the VARMA-AGARCH model with DCC or CCC structure and the BEKK model, are presented in the second, third and fourth columns of Table 3.8.

For all petroleum markets, the optimal portfolio weights from each model are not particularly different, suggesting that the portfolio constructions give similar results. In the case of the WTI crude oil market, the largest average value of $w_{SF,t}$ of the portfolio consisting of crude oil spot and futures from the VARMA-AGARCH model with CCC structure is 0.6714, meaning that investors should have more crude oil spot than futures in their portfolio in order to minimize risk without lowering expected returns. In addition, the optimal holding of spot in a one-dollar spot-future market portfolio should be 67.14 cents, and the remaining budget of 32.86 cents is invested in futures. With regard to the gasoline market, the largest average value of $w_{SF,t}$ obtained from the VARMA-AGARCH model with CCC structure, which is 0.7411, suggests that investors should have more gasoline spot than futures in their portfolio and the optimal holding of spot in a one-dollar spot-future market portfolio should be 74.11 cents, and the remaining budget of 25.89 cents is invested in futures. In the case of the heating oil market, the largest average value of $w_{SF,t}$ obtained from the BEKK model, which is 0.4533, suggests that investors should have less heating oil spot than futures in their portfolio and the optimal holding of spot in a one-dollar spot-future market portfolio should be 45.33 cents, and the remaining budget of 54.67 cents is invested in futures.

Table 3.8
Optimal hedging strategies.

Model	Optimal portfolio weights			Optimal hedge ratio		
	WTI	Gasoline	Heating oil	WTI	Gasoline	Heating oil
VARMA-AGARCH with DCC	0.6420	0.7343	0.4473	0.9578	0.5762	0.9638
VARMA-AGARCH with CCC	0.6714	0.7411	0.4197	0.9682	0.5941	0.9673
BEKK	0.6356	0.7123	0.4533	0.9442	0.5929	0.9546

Note: The optimal portfolio weights given are for the spot crude oil/gasoline/heating oil, and thus 1-spot weights for futures in the portfolio are warranted.

The average values of the optimal hedge ratio (γ_t^*) using estimates from various multivariate models are presented in the fifth, sixth and seventh columns of Table 3.8. It can be observed that different multivariate conditional volatility models generate different OHR. The average OHR values of the gasoline market obtained from different multivariate conditional volatility models are lowest among all three petroleum commodities markets. By following the estimated hedge strategy from the VARMA-AGARCH model with DCC structure, the average value of the optimal hedge ratio between spot and futures petroleum commodities is 0.9578, 0.5762, and 0.9638 for WTI crude oil, gasoline and heating oil, respectively. These results are important in establishing that a one-dollar long position in spot WTI crude oil market can be hedged for 95.78 cents with a short position in futures WTI crude oil market; A one-dollar long position in spot gasoline market can be hedged for 57.62 cents with a short position in futures gasoline market; and a one-dollar long position in spot heating oil market can be hedged for 96.38 cents with a short position in futures heating oil market. Fig. 3.6 presents the calculated time-varying optimal hedge ratios (OHRs) from the VARMA-AGARCH model with DCC structure.[21]

Table 3.9
Hedging effectiveness.

	Mean	Variance (%)	$Return(\%)^*$	HEI (%)	$VaR_{5\%}(\$)$	Semi-Variance	HEII (%)
WTI_S – WTI_F							
Unhedged	0.0173	0.0641	0.6837	---	41642.2	0.0240	---
VARMA-AGARCH-DCC	0.0273	0.0089	2.9050	86.17	15486.8	0.0045	81.19
VARMA-AGARCH-CCC	0.0213	0.0097	2.1626	86.13	15558.3	0.0046	81.17
BEKK	0.0112	0.0106	1.0878	83.45	16942.8	0.0047	80.26
GASO_S – GASO_F							
Unhedged	0.0180	0.0956	0.5817	---	50871.4	0.0349	---
VARMA-AGARCH-DCC	0.0315	0.0573	1.3159	40.08	39379.5	0.0208	40.31
VARMA-AGARCH-CCC	0.0304	0.0576	1.2667	39.80	39469.3	0.0211	39.62
BEKK	0.0298	0.0584	1.2331	38.94	39751.6	0.0210	39.92
HEAT_S – HEAT_F							
Unhedged	0.0239	0.0458	1.1178	---	35219.7	0.0165	---
VARMA-AGARCH-DCC	0.0258	0.0071	3.0619	84.41	13798.5	0.0034	79.64
VARMA-AGARCH-CCC	0.0245	0.0080	2.7392	82.52	14724.3	0.0041	75.31
BEKK	0.0196	0.0084	2.1385	81.65	13907.1	0.0037	77.58

Notes: This table reports the realized risk-adjusted returns, portfolio variance, semi-variance, Value-at-Risk (VaR) and hedging effectiveness ratios. $Return^*$ is the realized risk-adjusted returns, measured by calculating the ratio of each portfolio's mean to its standard deviation, of different portfolios. Variance denotes the variance of the unhedged/hedged portfolios. Semi-variance denotes the semi-variance of the unhedged/hedged portfolio. $VaR_{5\%}$ is the Value-at-Risk estimated using Eq. (3.19) with $\Phi(c)$ equal to the normal distribution 5% quantile, i.e. 1.645. HEII denotes the hedging effectiveness. HEI denotes the hedging effectiveness and measures the incremental variance reduction of various models. HEII denotes the hedging effectiveness and measures the incremental semi-variance reduction of various models.

[21] The time-varying optimal hedge ratios (OHRs) from the VARMA-AGARCH model with CCC structure and the BEKK model are presented in Appendix 3.A and 3.B respectively.

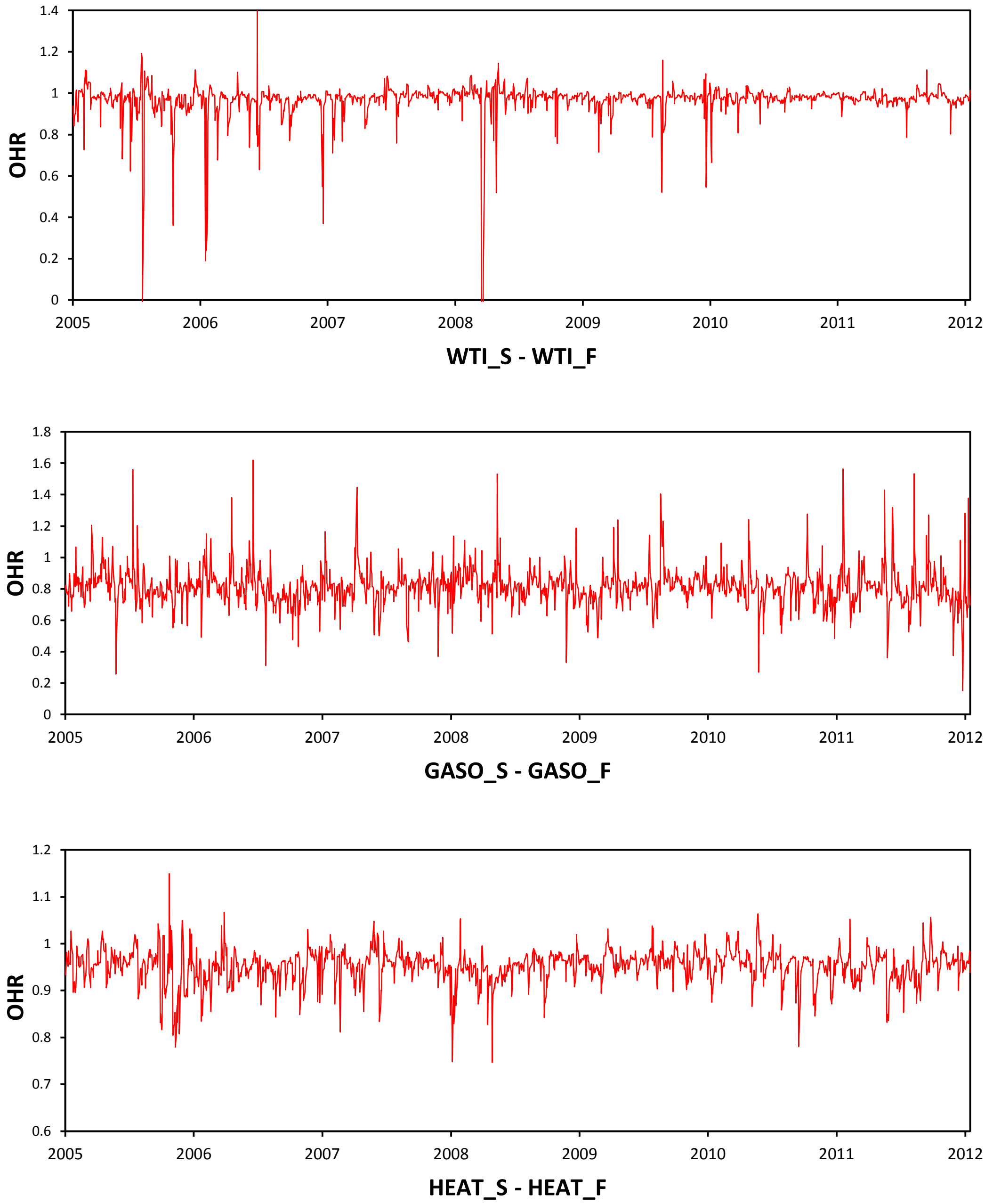


Fig. 3.6 Optimal hedge ratios for petroleum markets from VARMA-AGARCH model with DCC structure.

The results from portfolio simulations in the second, third and fourth columns of Table 3.9 show that the risk-adjusted return ratios have been improved in the hedged portfolios. More importantly, these results hold for all cases and for all models we consider. The benchmark VARMA-AGARCH model with DCC structure provides the best risk-adjusted return ratios in all markets. The hedging effectiveness documented in the fifth column of Table 3.9 show that all numbers are positive, implying the superior performance of hedged portfolios over unhedged portfolios. All three multivariate conditional volatility models effectively reduce the variance of the portfolio, and perform better in the WTI crude oil and heating oil markets than in the gasoline market (the HE indices are above 80% for WTI crude oil and heating oil markets and only around 40% for gasoline market). Among all three multivariate conditional volatility models, the VARMA-AGARCH model with DCC structure produces the highest hedging performance across all petroleum markets, such that the VARMA-AGARCH model with DCC structure is the best model for OHR calculation in terms of the variance of portfolio reduction. In contrast, the lowest HE value in all markets is obtained from the BEKK model. Therefore, the BEKK model is the worst model in terms of the variance of portfolio reduction.[22]

The relatively poor performance of all three models for gasoline market could be explained as follows. First, as the volume and open interest of gasoline is lower than crude oil or heating oil, in terms of the volume or the number of market participants, gasoline has lower liquidity than crude oil or heating oil. Second, as traders profit from wide price swings, increasing volatility makes it more expensive for producers and consumers to use futures as a hedge. Table 3.1 shows that the standard deviation of the gasoline returns is higher than for crude oil and heating oil.

Similarly, we can consider the economic benefits from the proposed hedging strategies through investigating the reduction in the Value-at-Risk (VaR) exposure. Under the assumption of a normal distribution, if we denote W_0 as the initial value of the portfolio and $\Phi(c)$ the inverse of

[22] Even we consider the transaction costs, the changes in hedging effectiveness resulting from including transaction costs is found to be very small and mostly negative. In this case, the VARMA-AGARCH model with DCC structure is still the best model for calculating the optimal hedge ratio and the BEKK model is the worst. Similar approach has been adopted by Alexander et al. (2012).

the standard Gaussian cumulative distribution function, the portfolio VaR is simply a constant multiple of the diversified portfolio standard deviation where the multiple is determined by the VaR confidence level $1 - c$:

$$VaR = W_0 \left[E(r_d) + \Phi(c)\sqrt{Var(r_d)} \right] \tag{3.19}$$

with r_d representing the returns from the hedged portfolio.

The results of the daily VaR for a portfolio value of $1m with 95% confidence level are reported in the sixth column of Table 3.9, which indicates that the VaRs have been reduced in the hedged portfolios for all petroleum commodities and across all models we consider. For example, the results for the WTI crude oil market indicates that one obtains a daily VaR=-$41642.2 if the unhedged portfolio is considered and a VaR of -$15486.8 when the hedge ratio derived from the VARMA-AGARCH model with DCC structure is used. Hence, by using the VARMA-AGARCH model with DCC structure, hedgers in the market can benefit from a decrease in the average daily VaR of $26155 over the unhedged portfolio. Similarly, hedgers can also benefit from a decrease in the average daily VaR of $ 11492 and $ 21421 by using the VARMA-AGARCH model with DCC structure in the gasoline and heating oil markets, respectively. Among all three models, the VARMA-AGARCH model with DCC structure produces the highest decrease in the average daily VaR across all petroleum markets, which is consistent with the results derived from the hedging effectiveness (HE) ratio previously. Therefore, investors would prefer the hedging strategy derived from the VARMA-AGARCH model with DCC structure to the hedging strategies derived from other models or unhedged portfolio.

Another way of considering the hedging effectiveness from the proposed hedging strategies is to look at the reduction at the downside risk, arising from the different hedging strategies. The motivation for investigating this stems from both the pitfalls associated with variance as a measure of hedging effectiveness and the specific properties inherent in the VARMA-AGARCH model.

Because the variance metric assigns the same weight to positive gains and negative losses, it may not be the appropriate measure for the risk averse investor who is more concerned about the downside risk of a hedged portfolio. In practice a number of metrics have been proposed in the literature that is able to deal with possible asymmetries in the profile of risk averse investors. For instance, Cotter and Hanly (2006) evaluate the hedging performance based on Lower Partial Moments (LPM) and find differences in terms of the best strategy compared to the traditional variance metric. On the other hand, it is of interest to examine whether the VARMA-AGARCH model is capable of adequately capturing the skewness and kurtosis typical of financial data and, if this is true, whether this can be used effectively to eliminate downside risk within the minimum-variance framework. In this regard, we propose to use the semi-variance metric that acts as a measure for a downside risk averse investor. Mathematically, this can be expressed as:

$$sv_{(-)} = \frac{1}{T}\sum_{i=1}^{T}\{\min(0, r_{t+1} - u)\}^2 \tag{3.20}$$

This is equivalent to the second order lower partial moment (LPM) where the target return u is set to zero in order to distinguish between positive and negative realized portfolio returns r_{t+1}. A short hedging position is equivalent to selling futures contracts against the purchase of the underlying spot assets; hence the investor is more concerned about negative semi-variance.

The seventh and eighth columns of Table 3.9 present the negative semi-variance figures where negative semi-variance reflects the downside variation in the performance of short hedging strategies and the hedging effectiveness ratios. Overall, the results indicate that the improvement in the semi-variance using the VARMA-AGARCH model with DCC structure is best across all petroleum markets, thus supporting the suggested strategy.

3.6 Conclusion

The main purpose of this chapter is to examine the optimal hedging strategies in petroleum markets using the VARMA-AGARCH model of McAleer et al. (2009) with DCC structure. The rationale behind the use of this model stems from the fact that there may be volatility spillovers and asymmetric effects between petroleum spot and futures markets and the assumption of constant conditional correlations between petroleum spot and futures markets is not supported empirically. Therefore, by applying the VARMA-AGARCH model with DCC structure, one may obtain more efficient volatility estimates and hence, superior hedging strategy compared to the methods which are currently being employed, such as the BEKK model or the VARMA-AGARCH model with CCC structure.

The empirical results show that, for the WTI crude oil and gasoline market, the optimal portfolio weights obtained from all multivariate volatility models suggest holding spot in larger proportion than futures. On the contrary, for the heating oil market, the optimal portfolio weights obtained from all multivariate volatility models suggest holding futures in larger proportion than spot. In the case of minimizing risk by using a hedge, a long position of one dollar in the petroleum spot markets should be shorted by a large cents in the petroleum futures markets. The hedging effectiveness indices indicate that the VARMA-AGARCH model with DCC structure is the best for OHR calculation in terms of the variance and semi-variance of portfolio reduction.

The findings of this chapter offer several avenues for future research. First, our empirical results are available for only in-sample time horizon. So it would be interesting to assess the optimal hedging strategy for the out-of-sample time horizon which in turn may provide more information about petroleum markets risk to central governments and businesses. Second, our results may be sensitive to the choice of the return innovation's distribution. Thus, it would be interesting to consider other innovation's distributions. Finally, it would be interesting to expand the current study to cover wider energy market, such as natural gas market and electricity market.

In the following chapter, we will turn our attention to the impact of oil price changes on stock markets. Crude oil plays a pivotal role in modern economies. Stock markets, as a barometer of the state of our economy, are unlikely to escape the influence from oil market fluctuations. Therefore, we will investigate how and to what extent the information embedded in oil price shocks is transmitted into China stock market. We will focus our research on the volatility transmission between oil markets and China stock market. The potential findings will help investors optimize their portfolio management.

Appendix 3.A

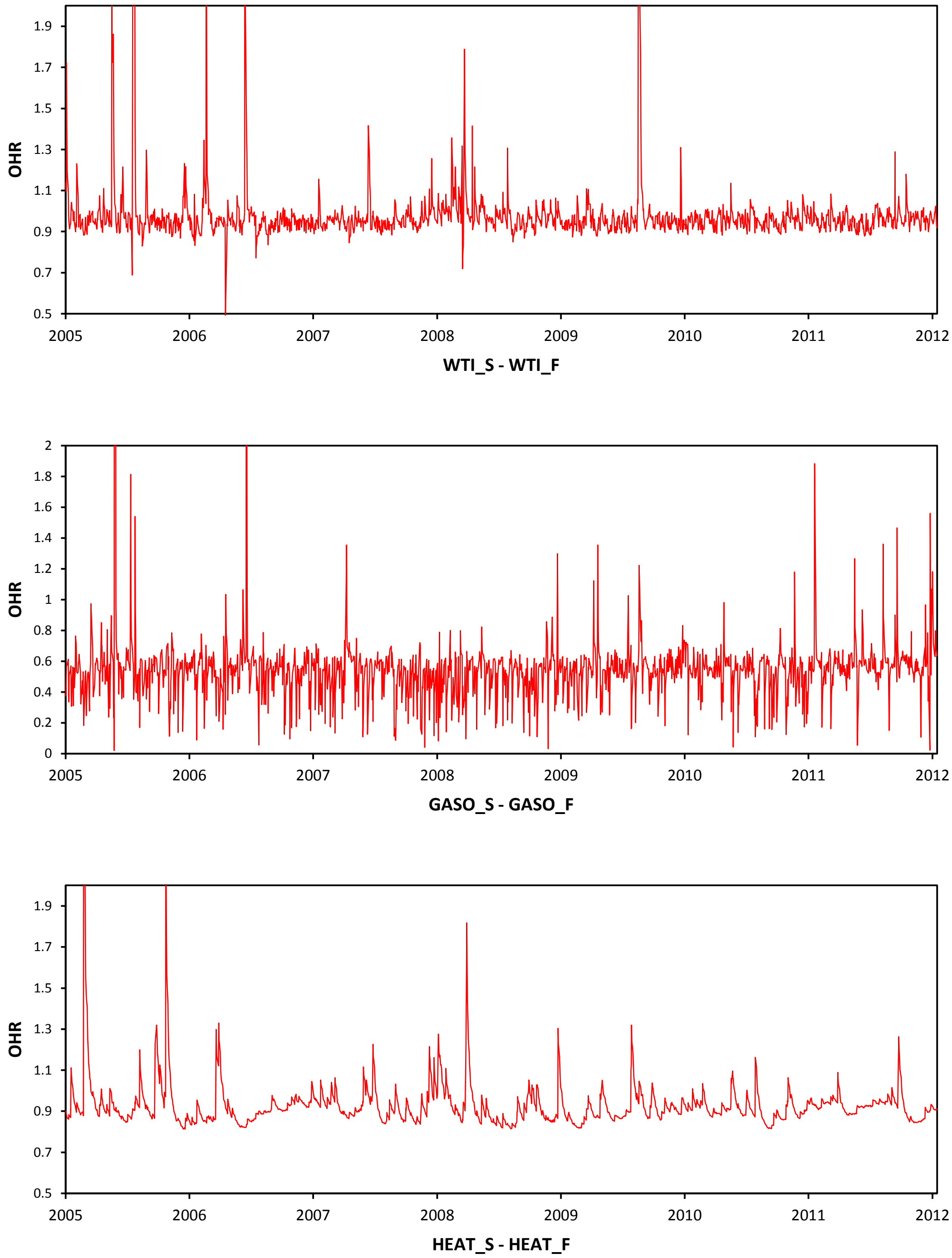


Fig. 3.A Optimal hedge ratios for petroleum markets from VARMA-AGARCH model with CCC structure.

Appendix 3.B

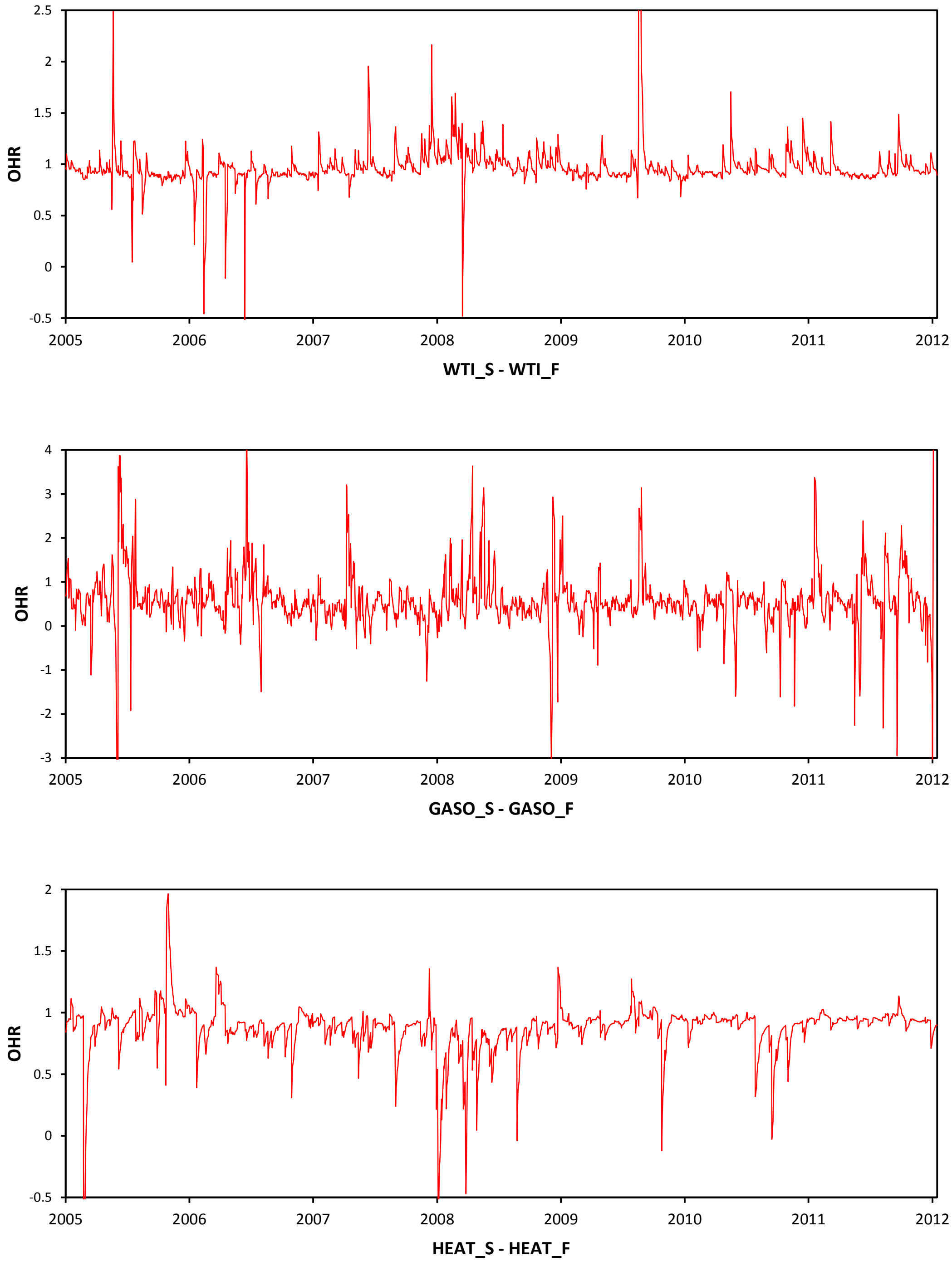


Fig. 3.B Optimal hedge ratios for petroleum markets from BEKK model.

Chapter 4

Volatility Spillovers and Asymmetries between Oil Prices and Chinese Stock Sector Returns: Implications for Portfolio Management

4.1 Introduction

The financialization of energy market means that crude oil has become a recognized asset class within investment portfolios of financial institutions as a means to diversify risks such as inflation, and/or equity market weakness (see Gorton and Rouwenhorst, 2006). This has resulted in increased inter-relationship between stock markets and oil prices. It is a common theoretical assumption that stock prices should equal the sum of discounted values of expected future cash flows at different investment horizons. Therefore, it will be central for market participants to identify the factors affecting these discounted cash flows to support their decision making. Empirical analysis in the energy finance literature has documented several channels through which oil shocks are transmitted to stock markets. For example, on the one hand, changes on the prices of oil, a key factor in the production process, affect financial performance or cash flows of firms, which in turn influence equity prices (e.g. Huang et al., 1996; Jones and Kaul, 1996). On the other hand, oil prices affect interest rates in the economy via inflation and monetary policy of the central bank, which in turn influence discount rate and equity prices (e.g. Apergis and Miller, 2009). Furthermore, the interaction between oil and stock markets does not dwell on the level of return variables, it also appears in volatility. Tauchen and Pitts (1983) and Ross (1989) suggest that it is the volatility of an asset rather than its return that is related to the rate of information flow in a market. This information flow is the pivotal point of risk management, asset pricing as well as its underlying derivatives pricing.

Although understanding the comovements of volatility between oil and stock markets is of great practical importance, relatively little empirical work has been conducted on the extent of volatility transmission between oil and stock markets at the sector-level and such study may provide interesting insights into the nature of the volatility interaction between different asset classes. Work has been carried out in the OECD[1] countries to detect the impact of oil shocks on the stock markets of these largely oil-importing nations. To the best of our knowledge, no such study has been undertaken for Chinese stock market. It is within the context of previous limited empirical work that the present chapter is conducted to fill this gap by examining the information flow between oil and Chinese stock market. In the meantime, one of the most important motivations for considering Chinese stock market is that China is considered the growth engine of the world economy and its stock market is a very promising area for regional and global portfolio diversification. The impact of oil markets on the stock market and their sector-based stocks may have significant implications for investors. Furthermore, China is now the second largest oil importer in the world and its economy is increasingly dependent on imported oil. Variations in economic growth may well be reflected in stock markets, then transmitted directly into oil prices (Li and Lin, 2011). Our results would have significant implications for oil users, traders, regulators and investors.

In this study we aim to examine the extent of volatility transmission between oil and Chinese stock market from a sector perspective. This permits a greater understanding of information transmission via volatility flows among these interconnected markets. Five major industrial sectors are studied: Basic Materials, Consumer Goods, Consumer Services, Financials, and Industrials sectors. Our next objective is to apply the estimated results to derive optimal portfolio weights and hedge ratios, which will effectuate optimal portfolio management in the presence of oil assets.

[1] OECD is the abbreviation of Organization for Economic Co-operation and Development. OECD is an international economic organization of 34 countries founded in 1961 to stimulate economic progress and world trade. Most OECD members are developed, high-income economies.

We employ the asymmetric version of the BEKK model introduced by Grier et al. (2004) to examine the volatility spillovers as well as asymmetric effects between oil and stock markets (sectors) in China. Using daily data over the period from November 1, 2000 through October 31, 2011, we examine volatility transmission between five industrial sectors and crude oil benchmark. The empirical results offer four major findings. Firstly, there is evidence that the correlation between oil and stock markets (sectors) in China is not constant but time-varying. It tends to increase with the volatility in the market. Secondly, there is significant transmission of shocks and volatility between oil and stock sectors. Thirdly, the extent of volatility transmission varies across the five stock sectors, which validates the argument that the sector perspective is more informative and generates more accurate implications for portfolio risk management. Finally, our analysis shows that Chinese stock market investors should consider the additional source of uncertainty resulting from the strong connection between crude oil and Chinese stock markets in terms of volatility transmission and then consider oil assets as a dynamic and valuable asset class that improves the risk-adjusted performance of a diversified portfolio of sector stocks.

The remainder of this chapter is organized as follows. Section 4.2 provides a brief literature review. Section 4.3 presents the data. Section 4.4 describes the multivariate GARCH framework to be used in the analysis. Section 4.5 discusses the empirical results. Section 4.6 shows the implications on portfolio management in the presence of oil assets. Section 4.7 provides some concluding remarks along with a few possible areas for future research.

4.2 Literature review

The relationship between oil price and macroeconomic variables is well documented in the literature through the studies on the impact of oil price changes on macroeconomic variables (e.g. Hooker, 1996; Hamilton, 2008). The majority of these studies have found that rising oil prices and price volatility serve to stifle economic activity (Hamilton, 2003), whereas a reduction in oil prices does not necessarily lead to noticeable output growth (Mork and Olsen, 1994). Recently, the interconnection between oil price and stock markets has been added to the literature (Jones and Kaul, 1996; Jones et al., 2004).[2] This research aims to uncover the information flow between the two markets. Detailed analysis has been conducted to examine the relationship between sector indices and oil prices.

From a theoretical perspective, stock market returns and their price levels should reflect the effects of current and expected future impacts of oil price shocks (Jones et al., 2004). The study by Kaul and Seyhun (1990) is the first to examine the reaction of stock markets to oil shocks. The authors consider the US stock market over 1949-1984 and report a detrimental effect of oil price shocks on the US stock market. Jones and Kaul (1996) propose a standard cash flow/dividends valuation model to examine stock market efficiency in the US, Canada, Japan, and UK in terms of the degree to which stock prices change in response to oil price changes. They find that the changes of oil price on the current and future cash-flows have a partially decisive effect on the four countries' real stock returns. A similar conclusion is drawn from the Greek stock market as positive oil price shocks suppress real stock returns (Papapetrou, 2001). As to oil-exporting countries, stock market prices are expected to be affected positively by oil price changes through positive income and wealth effects[3], which has been confirmed by Park and Ratti's (2008) findings that stock markets in Norway, an oil-exporting country, respond positively to oil price shocks.[4] Furthermore, as global economy shifts to emerging markets, the importance of the oil factor for stock prices is also discovered as Basher and Sadorsky (2006) suggest that emerging economies are more exposed to oil price shocks than more developed economies because they

[2] In comparison with the research on the links between oil prices and macroeconomic variables, the strand of research on the potential links between oil prices and stock markets has gained ground only recently. The possible explanation for the less emphasis on this issue is that oil price shocks are not the only factor affecting the stock price and oil price shocks influence various industries' stock prices differently (Cong, et al., 2008). However, if oil plays an important role in the economy, one would expect oil price changes to affect stock markets (Huang et al., 1996), and oil shocks on real cash flows can partly account for fluctuation in aggregate stock prices (Jones and Kaul, 1996).

[3] The wealth effect is an economic term referring to an increase (decrease) in spending that accompanies an increase (decrease) in perceived wealth. Mehra and Ptersen (2005) indicate that changes in oil prices have asymmetric influence on consumption expenditures via wealth transfers. The negative impact of an increase in oil prices is greater than the stimulus of economic growth as a result of a fall in oil prices.

[4] Jones and Kaul (1996) argue that the impact of oil price shocks to a country's economy of which reflected on stock returns are likely to vary across countries depending on their oil production and consumption level.

are less able to reduce oil consumption and thus more energy intensive, which causes significant changes in stock returns over both the short-run and long-run.

A number of studies have investigated the impact of oil price changes on the stocks of individual sectors, as it is important to know which sector indices are more sensitive to oil price fluctuations. A common belief is that oil price shocks are beneficial for oil-related companies (e.g. El-sharif et al., 2005; Boyer and Filion, 2007) and also have an impact on other sectors (e.g. Arouri and Nguyen, 2010; Arouri et al., 2011). Recently, Elyasiani et al. (2011) examine the impact of changes in the oil returns and oil return volatilities on excess stock returns and return volatilities of thirteen US industries and show that oil fluctuations constitute a systematic asset price risk at the industry level as nine of the thirteen sectors analysed show a statistically significant relationship between oil-futures return distribution and industry excess return. Surprisingly, the paper of Cong et al. (2008) shows that oil price shocks do not exert a statistically significant impact on the real stock returns of most Chinese stock market sectors indices, except for manufacturing index and some oil companies.

More recently, the research emphasis has broadened to include not only the effects of changes in the oil price level but also the effects of price volatility. The evidence confirms that oil volatility has a considerable influence on the stock market. For example, Malik and Ewing (2009) employ a bivariate GARCH model to detect volatility spillover between oil prices and five different US stock sector indexes, i.e. Financials, Industrials, Consumer Services, Health Care, and Technology. They find evidence of significant volatility transmission between oil prices and some of the examined market sectors. Arouri et al. (2011) use a VAR-GARCH (1, 1) model of Ling and McAleer (2003) to study the volatility transmission from oil prices to European equity markets. The authors show strong evidence of volatility spillover from oil to the sector stock markets studied.

In summary, volatility spillovers among oil and stock markets have been tested in several countries. However, little is known about how volatility is transmitted between oil and stock markets in China. This chapter tries to fill this gap and also adds to the literature on financial liberalisation and integration in a global context.

4.3 Data

Our sample data for the equity segments cover five industrial sectors in China (DataStream Global Sector Indices): Basic Materials, Consumer Goods, Consumer Services, Financials, and Industrials.[5] One market-wide index, the DataStream Global Country Index, is also included to compare the empirical results across sector and market level.[6] The use of sector data allows us to uncover relationships between individual sectors with crude oil market, hence equipping us better for making risk management and portfolio diversification decisions. Furthermore, by design, the sector indices may offer an alternative view of the performance of the Chinese equity market. All stock sectors data are extracted from DataStream International database and all indices are expressed in local currencies.

For the crude oil market, we choose the Brent crude oil price, taken from DataStream International database. In this study, we use the nearby futures contract (that is, the contract for which the maturity is closest to the current date) because of the advantage of its liquidity, transparency, and flexibility in comparison to spot prices (Sadorsky, 2001). The spot prices are more heavily affected by temporary random noise than the futures prices. Finally, we convert Brent futures prices into local currency using the US dollar exchange rates from DataStream International database.

[5] A representative sample of 100 stocks has been chosen for Chinese stock market. Using FTSE Actuaries classifications, the constituent stocks are allocated into industries/sectors, and the DataStream Global Indices calculated. DataStream classifies each company by industry, and a sector is any group of stocks with the same industrial classification. Each sector on the DataStream system comprises a representative sample of major stocks within that market and with that industrial classification. DataStream uses these constituent stocks when calculating an index for a specific sector. An aggregate index of all sectors is the Market Index. The abbreviation for the five sectors indices of Basic Materials, Consumer Goods, Consumer Services, Financials, and Industrials are BASIM, CONSG, CONSS, FINAN, and INDUS, respectively.

[6] For Chinese stock market, the Market Index is the China A index comprising of class A shares of mainland Chinese companies traded on Shanghai and Shenzhen exchanges and is investable only by Chinese nationals. The abbreviation for the Market Index is MARKT.

We employ daily data over the period from November 1, 2000 through October 31, 2011 with 2870 observations. Although some empirical analyses suggest that weekly data is superior to daily data when being employed to examine the oil-stock market relationships (see Arouri and Nguyen, 2010), daily data is more convenient and effective to capture the information content of changes in volatilities due to avoiding time aggregation and compensation effects associated with other data frequencies. As usual, stock market, sectors, and oil returns are computed by taking the natural log of the ratio between two successive prices. It is worth noting that all data are expressed in RMB (China's currency unit) inasmuch as our primary focus is on China where the links between oil prices and Chinese stock sector returns have received only little attention.

Table 4.1
Summary statistics for daily returns.

Returns	Mean (%)	Std. Dev. (%)	Skew.	Kurt.	JB	$Q^2(10)$	Q(10)	Corr. with oil
BRENT	0.035	2.125	-0.104	6.877	1801.9^{+++}	243.5^{+++}	13.242	
MARKT	0.005	1.629	-0.079	7.370	2286.2^{+++}	329.1^{+++}	20.550^{++}	0.0646***
BASIM	0.018	1.946	-0.200	6.293	1315.1^{+++}	516.0^{+++}	33.272^{+++}	0.0738***
CONSG	0.025	1.758	-0.223	6.620	1590.5^{+++}	389.2^{+++}	27.499^{+++}	0.0271*
CONSS	0.023	1.814	-0.350	6.909	1885.5^{+++}	504.9^{+++}	29.821^{+++}	0.0297*
FINAN	0.004	1.838	0.125	6.569	1530.2^{+++}	279.9^{+++}	11.758	0.0442**
INDUS	-0.034	1.759	-0.266	6.927	1877.6^{+++}	441.8^{+++}	23.754^{+++}	0.0503***

Notes: This table reports the basic statistics of return series of oil and stock sectors indices, including mean (Mean), standard deviation (Std. Dev), skewness (Skew.), kurtosis (Kurt.), and correlation between stock sectors and crude oil Brent (Corr. with oil). JB refers to the empirical statistic of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis. Q(10) represents the Ljung-Box (1978) tests for autocorrelations of order 10 applied to standardized residuals. $Q^2(10)$ represents the Engle's (1982) ARCH test, carried out as the Ljung–Box (1978) Q statistics on the squared series. $^{+++}$ and $^{++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 1% and 5% levels, respectively. With regard to the correlation between stock sectors and crude oil Brent, we calculate the Spearman's rank correlation coefficient. ***, ** and * indicates significance at the 1%, 5% and 10% levels, respectively.

The summary statistics for the log return series are shown in Table 4.1. The crude oil market experiences higher returns than Chinese equity segments over our study period. With regard to the equity segments, Consumer Goods has the highest sector returns (0.025%) and Industrials has the lowest sector returns (-0.034%). It is clearly shown that the means of the return series are relatively small compared to the corresponding standard deviations. Kurtosis coefficients are significantly greater than three and all return series, except the Financials sector have negative skewness values, which indicate that the distribution of almost all return series are typically asymmetric and that the probability of observing large negative returns is higher than that of a normal distribution. As a result, the Jarque-Bera (1980) test statistics (JB) clearly confirm the rejection of the null hypothesis of normality for all return series at the significance level of 1%. Results from the Ljung-Box (1978) Q statistic indicate the presence of serial autocorrelations for five of seven return series. Engle's ARCH test (1982), carried out as the Ljung-Box Q statistic on the squared return series, indicates the existence of heteroscedasticity for all return series at the 1% level, which thus supports the argument to employ a GARCH modeling approach to examining volatility spillovers between oil and stock markets. We also calculate the Spearman's rank correlation coefficient of equity and oil returns.[7] It varies substantially across industries: from 0.0271 (Consumer Goods) to 0.0738 (Basic Materials), which are all positive and significantly from zero. This finding suggests that oil price increases over the last decade may be indicative of higher expected economic growth and corporate earnings (Arouri et al., 2011).[8]

A battery of unit root tests is conducted in Table 4.2 for the prices and log returns series of crude oil and Chinese equity segments. As can be seen, according to the Augmented Dickey-Fuller (1979) (ADF) and Phillips and Perron (1988) (PP) unit root tests, performed on the levels and log-differences, all prices series under consideration follow the unit root processes, while their first differences are stationary as large negative values support the rejection of the null hypothesis of a unit root at the 1% significance level. We thus conclude that the return series of Brent crude oil and Chinese equity segments are stationary.

[7] We prefer the copula based Rank correlation measure, i.e. the Spearman's rank correlation coefficient, to the Pearson correlation measure. The estimation process is implemented through MatLab.
[8] The weak positive correlation between stock and oil market is also observed in the Europe and Gulf Cooperation Council (GCC) countries.

Table 4.2
Unit root tests.

Panel A: index series

Indices	ADF test			PP test		
	None	Cons.	Cons. & trend	None	Cons.	Cons. & trend
BRENT	0.3584	-1.1365	-2.2413	0.3471	-1.1494	-2.2617
MARKT	-0.3803	-1.2788	-1.5246	-0.3736	-1.2768	-1.5246
BASIM	-0.3916	-1.4414	-1.8075	-0.4653	-1.5635	-1.9632
CONSG	0.2806	-0.9090	-1.7746	0.3192	-0.8767	-1.7333
CONSS	-0.2846	-1.3329	-1.7680	-0.2398	-1.2878	-1.6941
FINAN	-0.4680	-1.3532	-1.5735	-0.4791	-1.3747	-1.6026
INDUS	-2.3761^{++}	-2.8914^{++}	-2.4968	-2.2389^{++}	-2.8576^{++}	-2.5114

Panel B: return series

Returns	ADF test			PP test		
	None	Cons.	Cons. & trend	None	Cons.	Cons. & trend
BRENT	-54.362^{+++}	-54.366^{+++}	-54.358^{+++}	-54.355^{+++}	-54.360^{+++}	-54.352^{+++}
MARKT	-53.665^{+++}	-53.656^{+++}	-53.649^{+++}	-53.681^{+++}	-53.672^{+++}	-53.665^{+++}
BASIM	-50.674^{+++}	-50.669^{+++}	-50.661^{+++}	-50.947^{+++}	-50.941^{+++}	-50.933^{+++}
CONSG	-51.385^{+++}	-51.386^{+++}	-51.391^{+++}	-51.402^{+++}	-51.401^{+++}	-51.405^{+++}
CONSS	-51.052^{+++}	-51.049^{+++}	-51.042^{+++}	-51.053^{+++}	-51.051^{+++}	-51.043^{+++}
FINAN	-53.425^{+++}	-53.715^{+++}	-53.707^{+++}	-53.726^{+++}	-53.717^{+++}	-53.709^{+++}
INDUS	-51.586^{+++}	-51.597^{+++}	-51.622^{+++}	-51.736^{+++}	-51.731^{+++}	-51.749^{+++}

Notes: ADF is the Augmented Dickey-Fuller (1979) unit root test statistic. PP is the Phillips-Perron (1988) unit root test statistic. The null hypothesis in the ADF and PP tests is that the underlying series has a unit root. +++ indicates the rejection of the null hypothesis at the significance levels of 1%. Numbers of augmenting lags are chosen using the Hannan-Quinn Criterion. Significance levels probabilities from MacKinnon (1996) use the number of observations. Asymptotic values have a higher significance level.

Finally, as we are interested in the asymmetry of the volatility response to news, we report Engle and Ng (1993) test statistics for “sign bias”, “negative size bias”, “positive size bias” and their “Joint effect” in Table 4.3. The sign bias test examines the impact that positive and negative shocks have on volatility. In particular, if the response of volatility to shocks is asymmetric, then the “sign bias” statistics will be statistically significant. Furthermore, the size of the shock could also affect volatility. Therefore, the “negative size bias” statistics focuses on the different effects that large and small negative shocks have on volatility and the “positive size bias” statistics focuses on the different effects that large and small positive shocks have on volatility. And the “joint test” statistics focuses on the joint effects of sign and size on volatility. It can be observed that the conditional volatility of Brent crude oil is sensitive to the sign and size of the innovations. In particular, there is strong evidence of sign and both positive and negative size bias in the Brent crude oil volatility, and the joint test for both sign and size bias is highly significant. Also, the conditional volatilities of the change in Chinese equity segments indexes display both negative and positive size bias and the joint test for both sign and size bias is significant at conventional significance levels.

Table 4.3
Engle and Ng (1993) tests for sign and size bias in variance.

Variable	Sign	Negative size	Positive size	Joint
BRENT	1.7796^{+}	3.0072^{+++}	2.4102^{++}	23.5017^{+++}
MARKT	0.2691	5.9704^{+++}	4.5318^{+++}	56.8166^{+++}
BASIM	1.0224	6.9614^{+++}	3.6940^{+++}	62.2075^{+++}
CONSG	0.0172	7.5869^{+++}	4.5434^{+++}	79.7997^{+++}
CONSS	0.2174	8.1053^{+++}	4.5274^{+++}	87.0229^{+++}
FINAN	1.6599^{+}	3.7313^{+++}	4.4914^{+++}	40.0577^{+++}
INDUS	0.3115	6.5144^{+++}	4.8467^{+++}	66.0611^{+++}

Notes: $^{+++}$ and $^{++}$ indicate the rejection of the null hypothesis of the Engle and Ng (1993) test at the 1% and 5% levels, respectively.

4.4 Econometric methodology

Multivariate GARCH (MGARCH) models have been commonly used to estimate the volatility spillover effects among different markets. Andersen et al. (1999) show that MGARCH models perform well relative to competing alternatives, for example, the continuous stochastic diffusion models. Especially, MGARCH models have been used in the energy economics and finance literature to study oil prices (see Chang et al., 2010, 2011)[9], and to study volatility transmissions in equity markets (see Khan and Batteau, 2011)[10]. Given the evidence of volatility spillovers and asymmetric effects in Brent crude oil and Chinese equity segments, we characterize the joint data

[9] Further discussion about this issue could be found in Jalali-Naini and Kazemi-Manesh (2006) and Lanza et al. (2006).
[10] Further discussion about this issue could be found in Hassan and Malik (2007) and Büttner and Hayo (2011).

generating process underlying the return series of Brent crude oil and Chinese equity segments as follows:

$$\begin{aligned} R_t &= \mu + \sum_{i=1}^{p} \Phi_i R_{t-i} + \varepsilon_t\,, \quad \varepsilon_t | I_{t-1} \sim (\mathbf{0}, \boldsymbol{H_t}) \\ \varepsilon_t &= \eta_t H_t^{1/2} \end{aligned} \tag{4.1}$$

where $R_t = \begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix}$ is the vector of the returns on Brent oil price and Chinese equity segments indices respectively, $\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$ is the deterministic vector specifying the unconditional means of R_t and R_{t-i} is used to model the interdependence between oil and equity segments return series with its coefficient matrix given as $\Phi_i = \begin{bmatrix} \gamma_{11}^{(i)} & \gamma_{12}^{(i)} \\ \gamma_{21}^{(i)} & \gamma_{22}^{(i)} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$ is the stochastic vector specifying the random error term of the mean equation for the returns on Brent oil price and Chinese equity segments indices respectively, $\eta_t = \begin{bmatrix} \eta_{1,t} \\ \eta_{2,t} \end{bmatrix}$ is a sequence of independently and identically distributed (i.i.d.) random vectors. The market information available at time $t-1$ is denoted as I_{t-1}, and $H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}$ is the matrix of conditional variances of oil and stock returns.

Multivariate GARCH models require that we specify volatility matrix H_t. Several different specifications have been proposed in the literature, including the VECH model of Bollerslev et al. (1988), the CCORR model of Bollerslev (1990), the BEKK model of Engle and Kroner (1995), the DCC model of Engle (2002), and the VARMA-GARCH model proposed by Ling and McAleer (2003). However, none of these specifications is capable of capturing the asymmetry of the volatility response to news.[11] In this regard, given the asymmetric effects of news on volatility in the return series of Brent crude oil and Chinese equity segments, we use an asymmetric version of the BEKK model, introduced by Grier et al. (2004), as follows:

[11] McAleer et al. (2009) extended the VARMA-GARCH model to accommodate the asymmetric impacts of the unconditional shocks on the conditional variance, and proposed the VARMA-AGARCH specification of the conditional variance. However, the VARMA-AGARCH model does not accommodate the time-varying conditional correlations which are more realistic in many empirical analyses. In chapter 3, we take the extended version of the VARMA-AGARCH model with dynamic conditional correlations to analyze empirical issues. In this chapter, we choose the asymmetric version of the BEKK model to accommodate volatility spillovers, asymmetry and dynamic conditional correlations simultaneously.

$$H_t = C'C + \sum_{k=1}^{g} A_k' \varepsilon_{t-k}\varepsilon_{t-k}' A_k + \sum_{j=1}^{f} B_j' H_{t-j} B_j + D' u_{t-1} u_{t-1}' D \qquad (4.2)$$

where C, $A_k, B_j, and\ D$ are $2 * 2$ matrices (for all values of j and k)[12], $u_t = \max(\varepsilon_t, 0)$ are the Glosten et al. (1993) dummy series collecting the stylized negative asymmetry from the shocks, with C being a triangular matrix to ensure positive definiteness of H_t. Matrix A measures the extent to which conditional variances are correlated with past squared unexpected returns and consequently the effects of shocks on volatility. At the same time, matrix B depicts the extent to which current level of conditional variance-covariance matrix is related to past conditional variance-covariance matrices. Matrix D shows the asymmetric volatility effect. This specification allows past volatilities, H_{t-j}, as well as lagged values of $\varepsilon_{t-k}\varepsilon_{t-k}'$ and $u_{t-1}u_{t-1}'$, to show up in estimating current volatilities of oil and equity, where $u_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$ captures potential asymmetric responses. In particular, if the price of oil is higher than expected, we consider that in general to be bad news to Chinese equity market, although oil price shocks may have differential effects on Chinese equity segments. In addition, the introduction of the $u_{t-1}u_{t-1}'$ term in Eq. (4.2) extends the BEKK model by relaxing the assumption of symmetry, thereby allowing for different relative responses to positive and negative shocks in the conditional variance-covariance matrix, H_t.

Estimation is done by maximum likelihood, where the contribution of ε_t to the joint Gaussian log-likelihood of a sample with T observations is given by:

$$L_T = -\frac{1}{2}\sum_{t=1}^{T} \log|H_t| - \frac{1}{2}\sum_{t=1}^{T} \varepsilon_t' H_t^{-1} \varepsilon_t \qquad (4.3)$$

In empirical application of univariate GARCH processes it has often been found that standardized residuals have excess kurtosis. To take the conditional leptokurtosis into account, Bollerslev (1986) advocates to evaluate and maximize the sample log-likelihood under the assumption of

[12] The coefficient matrices are described as $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, $B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, D= $\begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$, and C= $\begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}$.

Student's t-distributed innovations. For this reason we alternatively use a product of standardized univariate t distributions to specify the log-likelihood function, which is given by:

$$L_T = \sum_{t=1}^{T} \log F\left(H_t^{-\frac{1}{2}}\varepsilon_t\right) + \sum_{t=1}^{T} |H_t^{-\frac{1}{2}}| \tag{4.4}$$

with F is the density function of the multi standardized Student's t distribution. Because the conditional distribution of ε_t is governed by a non-normal distribution, i.e. Student's t distribution, the estimation procedure given by Eq. (4.4) is interpreted as quasi-maximum likelihood (QML) estimation.

Therefore, the econometric specification used in this chapter has two components. A vector autoregression (VAR) given in Eq. (4.1) is used to model the returns. This allows for autocorrelations and cross-autocorrelations in the returns. A multivariate GARCH model given in Eq. (4.2) as the asymmetric version of the BEKK model is used to model the volatility spillovers, asymmetry and dynamic conditional correlations. As is often the case in applied research, different criterion functions select different lag lengths for the VAR models. Preliminary regression analysis showed very little difference between a VAR with two lags compared to a VAR with one or three lags. Consequently, in the interest of parsimony and accuracy, a VAR with two lags is chosen. Furthermore, in order to deal with estimation problems in the large parameter space which is clearly the case of Eq. (4.2), we assume that $f = g = 1$ in Eq. (4.2), which is consistent with recent empirical evidence regarding the superiority of GARCH (1, 1) models (see Hansen and Lunde, 2005). Therefore, the conditional variance for Brent crude oil $(h_{11,t+1})$ and Chinese equity segments $(h_{22,t+1})$ returns can be expanded as:

$$h_{11,t+1} = c_{11}^2 + a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 + b_{11}^2h_{11,t} + 2b_{11}b_{12}h_{12,t}$$
$$+b_{21}^2h_{22,t} + d_{11}^2u_{1,t}^2 + 2d_{11}d_{12}u_{1,t}u_{2,t} + d_{21}^2u_{2,t}^2 \tag{4.5}$$

$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2\varepsilon_{2,t}^2 + b_{12}^2h_{11,t} + 2b_{12}b_{22}h_{12,t}$$

$$+b_{22}^2h_{22,t} + d_{12}^2u_{1,t}^2 + 2d_{12}d_{22}u_{1,t}u_{2,t} + d_{22}^2u_{2,t}^2 \quad (4.6)$$

In Eq. (4.5) and Eq. (4.6), the elements contained in the matrices of Eq. (4.2) are given by their corresponding lowercase letters, where subscripts (k, j, t) denote row, column and time period, respectively. Eq. (4.5) and Eq. (4.6) reveal how shocks and volatility are transmitted across time and across the Brent crude oil and Chinese stock sectors.[13]

4.5 Empirical results and analysis

In this section we estimate the VAR(2) – ABEKK(1,1) model for all pairs of oil and stock market (sector) returns in China using quasi maximum likelihood methods and allow necessary adjustments for standard errors by using robust versions. We used a range of starting values to ensure that the estimation procedure converged to the global maximum.[14]

Table 4.4 shows the estimation results of our $VAR(2) - ABEKK(1,1)$ model for six pairs of oil-stock market returns in China, together with statistical tests applied to standardized residuals. Taking a close look at the conditional mean equations for all equity segments, we find that the returns for Brent crude oil and Chinese equity segments are not interdependent as current oil returns in all cases are only affected by the one-period or two-period lagged oil returns, denoted by $AR(1)^O$ and $AR(2)^O$, respectively. This finding thus suggests some evidence of short-term predictability in oil price changes through time and corroborates the conclusions of some recent papers that the weak-form informational efficiency of international oil markets is rejected most of the time (see Elder and Serletis, 2008; Arouri et al., 2010). At the same time, none of the

[13] In Eq. (4.2), the elements of $A, B, and\ D$ matrices cannot be interpreted individually. Instead, we have to interpret the non-linear functions of the parameters which form the intercept terms and the coefficients of the lagged variances, covariances and error terms presented in Eq. (4.5) and Eq. (4.6). We follow Kearney and Patton (2000) and calculate the expected value and the standard error of those non-linear functions. The expected value of a non-linear function of random variables is calculated as the function of the expected value of the variables. In order to calculate the standard errors of the function, a first-order Taylor approximation is used. This linearizes the function by using the variance–covariance matrix of the parameters as well as the mean and standard error vectors.

[14] The computations presented in this study were conducted by means of RATS and R programs.

autoregressive terms in the return-generating process for the stock market is statistically significant from zero, which indicates that past information of Chinese stock returns do not help predict current Chinese stock returns. Our finding is consistent with Arouri et al. (2011)'s conclusion with regard to the European and U.S. stock markets that past realizations of stock returns do not help predict stock returns.

Moreover, in order to assess the information flow between oil price and Chinese stock market returns, the daily Granger-causality relationship among the oil and Chinese stock markets returns is examined through the VAR model using two lags[15], which is given as:

$$r_i^O = a_1 + \sum_{j=1}^{2} b_{1j} r_{t-j}^O + \sum_{j=1}^{2} c_{1j} r_{t-j}^S + \varepsilon_{1t} \qquad (4.7a)$$

$$r_i^S = a_1 + \sum_{j=1}^{2} b_{2j} r_{t-j}^S + \sum_{j=1}^{2} c_{2j} r_{t-j}^O + \varepsilon_{2t} \qquad (4.7b)$$

where r_i^O and r_i^S are the log return on the respective crude oil and stock markets. The VAR model is estimated using ordinary least squares with heteroskedasticity-consistent standard errors. The coefficients b_{1j} and b_{2j} in Eq. (4.7a) and (4.7b) describe the lead-lag relationship between the respective crude oil and stock markets own returns, while the coefficients c_{1j} and c_{2j} quantify Granger-causality between the respective crude oil and stock markets. In order to test the significance of the lead-lag relationships, two restriction tests are employed on the cross-market coefficients c_{1j} and c_{2j}, in Eq. (4.7a) and (4.7b) as follows:

$$H_{0,1}: c_{1j}\ and\ c_{2j} = 0\ for\ all\ j = 1,2$$

$$H_{0,2}: \sum_j c_{1j}\ \ and\ \ \sum_j c_{2j} = 0$$

The first null hypothesis tests that all of the cross-market coefficients are jointly equal to zero. The second tests that the sum of all the coefficients is equal to zero. Hereafter, the first and second tests are defined as the joint and sum coefficient tests, respectively. The results for the

[15] The results are robust to differing numbers of lags.

Granger-causality tests described in Table 4.5 suggest that there is no Granger-causality relationship between the oil and Chinese stock market returns.[16] None of the coefficient tests for the oil and Chinese stock market returns reject the null hypothesis of no lead-lag relationship among all the cross-market coefficients at the significance level of 1%.[17]

[16] In order to examine the separate effects of signed returns, the VAR model is modified to include the effects of lagged positive and negative returns describing Granger causality from positive and negative shocks from Brent crude oil and Chinese stock markets. The results suggest that there is no evidence that significant lead-lag relationships persist among Brent crude oil and Chinese stock markets positive/negative returns.

[17] It is noteworthy that the dynamic relationship between oil and stock returns is sensitive to the stage of the business cycle, and if this dependence is not accounted for, it may become unstable. In particular, when the economy is down and subject to high uncertainty, as in the aftermath of the recent financial crisis of 2007-2010, oil prices may not reflect expected future macroeconomic conditions accurately. Therefore, we examined the coefficients stability of the mean equation in Eq. (4.1) across business cycles by extending our model to include a dummy variable indicating the aftermath of the financial crisis of 2007-2010 following the bankruptcy of Lehman Brothers on September 15, 2008. For the most part, the results support the argument that the returns for Brent crude oil and Chinese equity segments are not interdependent. Elyasiani et al. (2011) take the similar method to clarify the impact of business cycle on the dynamic relationship between oil and stock returns.

Table 4.4
Estimates of VAR (2) – ABEKK (1, 1) model with Student's t distribution for oil and equity segments indices in China

Returns	*Conditional mean equation*					*Conditional volatility equation*										*Diagnostics statistics*			
	C	$AR(1)^O$	$AR(1)^S$	$AR(2)^O$	$AR(2)^S$	Cons.	$\varepsilon_{1,t}^2$	$\varepsilon_{1,t}\varepsilon_{2,t}$	$\varepsilon_{2,t}^2$	$h_{11,t}$	$h_{12,t}$	$h_{22,t}$	$u_{1,t}^2$	$u_{1,t}u_{2,t}$	$u_{2,t}^2$	Log L	JB	ARCH(10)	Q(10)
Panel A: BRENT_MARKET INDEX																			
BRENT	0.0003	-0.0161^{**}	0.0266	0.0083	-0.0229	0.000004^{***}	0.001190	0.001642	0.001399^{**}	0.968650^{***}	0.003149^{***}	0.000040^{***}	0.039283^{***}	-0.001150^{**}	0.000106^{**}	15358	248.9^{+++}	18.073^{+}	7.154
MARKT	0.00002	0.0388	-0.0058	-0.0089	-0.0117	0.000003	0.000566	0.010072	0.044775^{***}	0.000003^{***}	0.003085^{***}	0.929489^{***}	0.000008^{**}	-0.008855^{**}	0.023287^{**}		1186.2^{+++}	4.007	22.664^{++}
$Shape(v)$	6.3	Average DCC		0.0682 (0.0737)															
Volatility persistence comparison																			
Brent oil price return					0.9761														
Chinese stock market index					0.9880														
Panel B: BRENT_BASIC MATERIALS INDEX																			
BRENT	0.0003	-0.0170	0.0301	0.0080^{**}	-0.0237	0.000004^{***}	0.001109	-0.001092	0.000166^{**}	0.968453^{***}	0.000787^{***}	0.000001^{**}	0.039164^{***}	0.001860^{***}	0.000177^{***}	14901	249.6^{+++}	18.329^{+}	7.299
BASIM	0.0001	0.0639	0.0501	-0.0094	-0.0246	0.000002	0.000269	-0.008066	0.060467^{***}	0.000001^{***}	0.000771^{***}	0.929682^{***}	0.000022^{***}	0.001090^{***}	0.013456^{***}		836.3^{+++}	3.452	19.028^{++}
$Shape(v)$	6.9	Average DCC		0.0738 (0.0711)															
Volatility persistence comparison																			
Brent oil price return					0.9694														
Chinese equity segment (Basic Materials) index					0.9831														

Table 4.4 (continued.1)
Estimates of VAR (2) – ABEKK (1, 1) model with Student's t distribution for oil and equity segments indices in China

Returns	*Conditional mean equation*					*Conditional volatility equation*										*Diagnostics statistics*			
	C	$AR(1)^O$	$AR(1)^S$	$AR(2)^O$	$AR(2)^S$	Cons.	$\varepsilon_{1,t}^2$	$\varepsilon_{1,t}\varepsilon_{2,t}$	$\varepsilon_{2,t}^2$	$h_{11,t}$	$h_{12,t}$	$h_{22,t}$	$u_{1,t}^2$	$u_{1,t}u_{2,t}$	$u_{2,t}^2$	Log L	JB	ARCH(10)	Q(10)
Panel C: BRENT_CONSUMER GOODS INDEX																			
BRENT	0.0003	-0.0151	0.0099	0.0089**	-0.0236	0.000001***	0.005198**	0.002812	0.000169	0.964128***	-0.013354	0.000010	0.042148***	0.004640	0.001648	15085	227.9+++	14.215	6.816
CONSG	0.0002	0.0068	0.0423	-0.0141	−0.0390*	0.000006	0.000380	-0.009512	0.059487***	0.000046*	-0.012867	0.895105***	0.000128	0.004970	0.048356***		614.7+++	11.626	20.905++
$Shape(v)$	7.2	Average DCC		0.0344 (0.0571)															
Volatility persistence comparison																			
Brent oil price return					0.9590														
Chinese equity segment (Consumer Goods) index					0.9326														
Panel D: BRENT_CONSUMER SERVICES INDEX																			
BRENT	0.0003	−0.0153***	0.0143	0.0085	-0.0174	0.000004***	0.009025***	0.002223	0.000437	0.966092***	0.000983	0.000022***	0.033856***	0.009126*	0.002372**	15084	235.2+++	15.276	6.904
CONSS	0.0002	0.0154	0.0481	-0.0109	-0.0249	0.000005	0.005941	0.064465	0.000001***	0.000001	0.000947***	0.897567***	0.000615*	−0.010575*	0.045454***		848.1+++	4.377	18.080+
$Shape(v)$	7.1	Average DCC		0.0344 (0.0528)															
Volatility persistence comparison																			
Brent oil price return					0.9788														
Chinese equity segment (Consumer Services) index					0.9691														

Table 4.4 (continued.2)
Estimates of VAR (2) – ABEKK (1, 1) model with Student's t distribution for oil and equity segments indices in China

Returns	*Conditional mean equation*					*Conditional volatility equation*										*Diagnostics statistics*			
	C	$AR(1)^O$	$AR(1)^S$	$AR(2)^O$	$AR(2)^S$	Cons.	$\varepsilon_{1,t}^2$	$\varepsilon_{1,t}\varepsilon_{2,t}$	$\varepsilon_{2,t}^2$	$h_{11,t}$	$h_{12,t}$	$h_{22,t}$	$u_{1,t}^2$	$u_{1,t}u_{2,t}$	$u_{2,t}^2$	Log L	JB	ARCH(10)	Q(10)
Panel E: BRENT_FINANCIALS INDEX																			
BRENT	0.0003	-0.0155^{***}	0.0181	0.0084	-0.0205	0.000004^{***}	0.013806^{***}	-0.001575	0.000571	0.962361^{***}	0.005297^{***}	0.000050^{**}	0.028934^{***}	0.003912^{*}	0.000571^{*}	14915	232.8^{+++}	14.576	7.051
FINAN	0.00001	0.0361	-0.0059	-0.0033	-0.0137	0.013853	0.000045	-0.002779	0.043015^{***}	0.000007^{***}	0.005219^{***}	0.934122^{***}	0.000132^{*}	-0.003241^{*}	0.019853^{***}		776.9^{+++}	7.875	16.194^{+}
$Shape(v)$	6.5	Average DCC		0.0469 (0.0704)															
Volatility persistence comparison																			
Brent oil price return					0.9805														
Chinese equity segment (Financials) index					0.9796														
Panel F: BRENT_INDUSTRIALS INDEX																			
BRENT	0.0004	-0.0164^{***}	0.0372	0.0081	-0.0168	0.000004^{***}	0.011686^{***}	0.002746^{**}	0.000734^{**}	0.964520^{***}	0.000786^{*}	0.000023^{**}	0.031471^{***}	0.007202^{*}	0.003807^{***}	15180	223.3^{+++}	14.472	7.229
INDUS	-0.0003	0.0199	0.0358	-0.0157	-0.0017	0.000002	0.000161^{**}	0.005974^{**}	0.055319^{***}	0.000001^{*}	0.000769^{*}	0.923521^{***}	0.000412^{*}	-0.007077^{*}	0.030380^{***}		981.1^{+++}	5.082	21.199^{++}
$Shape(v)$	6.7	Average DCC		0.0508 (0.0658)															
Volatility persistence comparison																			
Brent oil price return					0.9805														
Chinese equity segment (Industrials) index					0.9857														

Notes: Oil and stock are oil price returns, stock sector (market) index returns respectively. *, **, and *** indicate significance at the 10%, 5% and 1% respectively. Model is estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. The Log L (Log Likelihood) criterion measures the relative goodness of fit of the estimated model. JB, ARCH(2), and Q(10) refer to the empirical statistics of the Jarque-Bera (1980) test for normality based on skewness and excess kurtosis, the Engle (1982) test for conditional heteroscedasticity of order 2, and the Ljung-Box (1978) tests for autocorrelations of order 10 applied to standardized residuals in levels. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% respectively. Average DCC refers to the average value of dynamic conditional correlations between oil and stock market. The two entries for each Average DCC are their respective value and the corresponding standard deviation.

Table 4.5
Granger causality in returns.

$$r_i^O = a_1 + \sum_{j=1}^{2} b_{1j} r_{t-j}^O + \sum_{j=1}^{2} c_{1j} r_{t-j}^S + \varepsilon_{1t} \qquad (4.7a)$$

$$r_i^S = a_1 + \sum_{j=1}^{2} b_{2j} r_{t-j}^S + \sum_{j=1}^{2} c_{2j} r_{t-j}^O + \varepsilon_{2t} \qquad (4.7b)$$

	r_i^O		r_i^S	
Panel A: Market Index	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	1.0413	0.3531	1.7592	0.1511
$H_{0,2}$: Sum coefficient test	0.0109	0.9167	2.0151	0.1621
Panel B: Basic Materials	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	1.6792	0.1867	3.1588	0.0645*
$H_{0,2}$: Sum coefficient test	0.0543	0.8158	4.9240	0.0265**
Panel C: Consumer Goods	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	0.6198	0.5381	0.5197	0.5948
$H_{0,2}$: Sum coefficient test	0.1909	0.6621	0.1109	0.7391
Panel D: Consumer Services	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	0.5032	0.6046	0.7099	0.4918
$H_{0,2}$: Sum coefficient test	0.0105	0.9185	0.0396	0.8422
Panel E: Financials	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	0.8029	0.4481	2.5190	0.0807*
$H_{0,2}$: Sum coefficient test	0.0059	0.9389	2.0163	0.1556
Panel F: Industrials	$\chi^2(2)$ statistic	p-value	$\chi^2(2)$ statistic	p-value
$H_{0,1}$: Joint coefficient test	1.5910	0.2039	1.3631	0.2560
$H_{0,2}$: Sum coefficient test	0.4193	0.5173	0.0371	0.8473

Notes: This table presents results for the initial Granger-causality tests specified by Eq. (4.7a) and (4.7b). ** and * indicate the null hypothesis is significant at the 5% and 10% level, respectively.

4.5.1 Volatility spillovers and asymmetric effects: the market-level perspective

The results of estimating the ABEKK parameterization from the market-level perspective are reported in Panel A of Table 4.4. Our findings indicate that volatility (conditional variance) in oil returns is directly affected by its own volatility and by the volatility in the Chinese stock index returns. High level of conditional volatility in the past are associated with higher conditional volatility in the current period (see the positive and significant coefficients on $h_{11,t}$ and $h_{22,t}$). Moreover, the coefficient for the covariance term (h_{12}) in the conditional variance equation for oil returns is statistically significant. This latter finding implies indirect volatility transmission through the covariance term from Chinese stock index returns to oil returns. Thus, we find significant direct and indirect transmission of volatility from the Chinese stock market to the Brent crude oil market. Furthermore, our results indicate that volatility in oil returns is also affected by shocks originating in the Chinese stock market (note the significant estimated coefficient on $\varepsilon_{2,t}^2$) but not shocks originating in the oil market (note the insignificant estimated coefficient on $\varepsilon_{1,t}^2$). In addition, the estimated coefficient on the cross-error term ($\varepsilon_{1,t}\varepsilon_{2,t}$) is insignificant, suggesting the absence of an indirect effect of shocks in the Chinese stock market on the Brent oil market.[18] Finally, the coefficients on $u_{1,t}^2$ and $u_{2,t}^2$ are significant indicating that Brent oil market volatility responds asymmetrically to its own shocks and Chinese stock market shocks, i.e. negative events originating in these markets increase volatility more than positive shocks.

The behaviour of stock return volatility is similar to that of oil. The results indicate that volatility in stock returns is directly affected by its own volatility and by the volatility in the oil returns (note the significant estimated coefficient on $h_{11,t}$ and $h_{22,t}$). Moreover, the coefficient for the covariance term (h_{12}) in the conditional variance equation for stock returns is statistically significant. This latter finding implies indirect volatility transmission through the covariance

[18] The analysis of the impacts of the previous day's shocks of crude oil and stock markets on the conditional variance of crude oil market and the conditional variance of stock market, in some degree, is similar to the news impact surfaces analysis developed by Kroner and Ng (1998), which is a multivariate generalization of the univariate news impact analysis of Engle and Ng (1993) involving plotting conditional variance against lagged shocks.

term from oil returns to Chinese stock index returns. Thus, we find significant direct and indirect transmission of volatility from the Brent crude oil market to the Chinese stock market. Moreover, our results indicate that volatility in stock returns is also affected by shocks originating in the Chinese stock market (note the significant estimated coefficient on $\varepsilon_{2,t}^2$) but not shocks originating in the oil market (note the insignificant estimated coefficient on $\varepsilon_{1,t}^2$). In addition, the estimated coefficient on the cross-error term ($\varepsilon_{1,t}\varepsilon_{2,t}$) is insignificant, suggesting the absence of an indirect effect of shocks in the Brent oil market on the Chinese stock market. Finally, the stock returns volatility responds asymmetrically to its own shocks and to shocks originating in the oil market ($u_{1,t}^2$ and $u_{2,t}^2$ are both significant), suggesting that negative events in these markets increase volatility more than positive shocks.

Panel A of Table 4.4 also provides estimates of the persistence in volatility for each return series.[19] The estimates of volatility persistence will provide clue about the extent to which future conditional variance is influenced by past shocks and volatility. The greater the persistence, the more weight should be given to recent observations of volatility in terms of explaining future volatility. On the contrary, less weight on recent observations of volatility should be given under the condition of lesser degrees of persistence for forecasting future values of volatility. This is because the volatility of the series will return to its unconditional variance faster than would be the case when there is greater persistence. In the case of no persistence, forecasts of future volatility will simply be given by the long-run variance of the series. The results presented here indicate that both Brent crude oil and Chinese stock returns series are persistent with their persistence value and the reversion of volatility to its long-run value is a little bit of quicker for stock than for oil returns.

In general, the estimated conditional volatility series do not change very rapidly under the impulsion of return innovations given the small size of the coefficients associated with shocks.

[19] Analogous to the univariate GARCH model, the persistence of volatility in the multivariate GARCH model is computed by taking the sum of coefficients of lagged variances, covariances, squared error terms and cross-product of error terms (see Ewing et al., 2002).

They tend instead to evolve gradually over time with regard to substantial effects of past volatility given the large values of the coefficients associated with current volatility. Accordingly, investors seeking profit from trading oil and Chinese stock assets may consider active investment strategies based on volatility persistence and current market trends and should keep in mind that the viability of such strategies depends on the stability and the strength of performance between successive periods.

The volatility interdependence between the Brent oil market and the Chinese stock market may result from the fact that China's oil consumption has quadrupled during the last three decades, and it has become the second largest oil consumer only after the US. At the same time, because the domestic oil production of China has reached its full capacity in recent years, the increase in consumption is mainly satisfied by increases in import such that China has turned from an oil exporter into the world's second largest oil importer. Furthermore, China has accounted for the largest increase in world oil consumption. Therefore, one would expect fluctuations in oil market would have a significant impact on China's stock market as a result. Unambiguously, with its amount of oil consumption, higher dependence on imported oil supply and more market-oriented domestic oil pricing mechanism, the interaction between the world oil price and China's macro-economy and its stock market should have been more significant (Du et al., 2010).

4.5.2 Volatility spillovers and asymmetric effects: the sector-level perspective

The results for oil and basic materials models are reported in Panel B of Table 4.4. Our findings indicate that volatility (conditional variance) in oil returns is directly driven by past volatilities in oil and sector returns, as well as indirectly influenced by the covariance term from sector returns to oil returns. Thus, we find significant direct and indirect transmission of volatility from basic materials sector to the Brent crude oil market. Moreover, only past sector shocks are found to drive volatility changes in oil market. Furthermore, crude oil volatility responds asymmetrically to its own shocks and to shocks originating in the basic materials sector. On the other hand, the behaviour of sector return volatility is similar to that of oil as both direct and indirect transmission of volatility from the Brent crude oil market to the basic materials sector has been detected. Interestingly, only unexpected changes in sector returns influence sector return volatility. Furthermore, sector volatility responds asymmetrically to its own shocks and to shocks originating in the oil market. Finally, the estimates of the persistence in volatility suggest that both Brent crude oil and basic materials returns series are persistent and the reversion of volatility to its long-run value is a little bit of quicker for sector returns than for oil returns. The possible explanation for the volatility transmissions between crude oil and basic materials sector is that the relatively heavy use of oil in the basic materials sector is a key determinant of the oil effects (see Arouri et al., 2011). Indeed, the sector return volatility could be intensified by oil prices increases through changes in the oil supply for this industry as well as consumer demand for its manufactured products. Therefore, it is their own interest to minimize the unfavorable impact of rising oil prices through an effective hedging strategy.

For the oil-consumer goods model reported in Panel C of Table 4.4, our finding suggests that there are no significant direct and indirect cross-volatility effects and shock transmissions from sector returns to oil returns. Volatility in oil returns depends on own past return innovations and own past volatility. On the other hand, we essentially find unilateral volatility transmission from oil returns to sector returns as volatility in sector returns is driven by not only its own past shocks and volatility but also past volatility in oil returns. The unilateral volatility transmission from crude oil to consumer goods sector is expected as rising oil prices are likely to strongly influence consumer and investment sentiment, and consequently their appetite for consumer goods. With respect to the asymmetric effects, our finding suggests that oil and sector returns only respond asymmetrically to their own shocks. In addition, the estimates of the persistence in volatility suggest that both Brent crude oil and consumer goods returns series are persistent with their persistence value and sector returns are slower than oil returns in terms of the reversion of volatility to its long-run value.

The results for oil and consumer services model reported in Panel D of Table 4.4 reveal bidirectional volatility transmissions even though the transmission patterns are not similar for oil and sector returns. Volatility (conditional variance) in oil returns is only driven by past volatilities in oil and sector returns. On the other hand, volatility in sector returns is directly driven by own past volatility as well as indirectly influenced by the covariance term from oil returns to sector returns. Furthermore, there are no significant direct and indirect shock transmissions between sector and oil returns as only own unexpected changes influence volatility. The significant volatility transmissions from oil returns to sector returns may be primarily the result of the direct impact of oil price changes on uncertainty over demand for the products of companies in consumer services sector. In addition, both oil and sector volatilities respond asymmetrically to the shocks originating in the oil and sector markets. Finally, the estimates of the persistence in volatility suggest that both Brent crude oil and consumer services returns series are persistent with their persistence value to be very close to one and the return of volatility to its long-run value is a little bit of slower for sector returns than for oil returns.

For the oil-financials sector model reported in Panel E of Table 4.4, our finding suggests that there are no significant direct and indirect shock transmissions between sector returns and oil returns. However, we essentially find bidirectional volatility transmissions as there are direct and indirect interaction for volatility in oil and sector returns. Although financial institutions are not directly involved with oil production or consumption, their association with oil occurs via their lending to and/or holdings of corporate bonds issued by firms with significant exposure to oil price fluctuations, their speculative positions in oil-related instruments, and portfolio readjustments that take place by market players in response to oil price movements (see Elyasiani et al., 2011). In addition, both oil and sector volatilities respond asymmetrically to the shocks originating in the oil and sector markets..

The results reported in Panel F of Table 4.4 reveal that the industrials sector and the oil market experience significant direct and indirect shock transmissions and cross-volatility effects. Their conditional volatility depend on both own and counterpart past return innovations and past volatilities. As a heavy user of petroleum and related products and the limited development of effective hedges against the impact of oil price fluctuations, it is not surprising to observe the volatility transmission effects for industrials sector in China. Our results are the counterevidence of Malik and Ewing (2009), who note that the development of effective hedges against the effects of oil price changes is the most likely explanation of the insignificant volatility transmission from the world oil markets to the US industrials sector. In addition, both oil and sector volatilities respond asymmetrically to the shocks originating in the oil and sector markets. Finally, the estimates of the persistence in volatility indicate that both Brent crude oil and industrials returns series are persistent and the return of volatility to its long-run value is a little bit of quicker for sector returns than for oil returns.

4.5.3 Dynamic conditional correlations and diagnostic tests

Fig. 4.1 shows the time-varying conditional correlations from the ABEKK model. The dynamic conditional correlations can vary a lot from their average value reported in Table 4.4 emphasizing the need to compute dynamic conditional correlations. Up until 2008 there was no significant trend in each pair of correlations. After 2008, there is a slight upward trend in each pair of correlations. It has been observed that the dynamic conditional correlations for each series are all smaller than 0.5. This indicates that there is sufficient scope for portfolio diversification between Brent crude oil and Chinese stock sectors. Furthermore, these dynamic conditional correlations do alternate in sign and cover a range of values between -0.2 and 0.4. These periods of negative correlations provide an opportunity for meaningful portfolio diversification. Furthermore, the significant variation in the conditional correlations over time indicates that any inferences from the constant conditional correlation model would be misleading.

Lastly, the results of diagnostic tests based on standardized residuals are also shown in Table 4.4. Tests on the standardized residuals and standardized residuals squared indicate that there are no significant signs of autocorrelation and ARCH effects at the 1% significance level. However, the JB statistics still reject the normality hypothesis even though that departure from normality is greatly reduced. We regard the departure from normality as well as the significance of the estimated degrees of freedom for the Student's t distribution as strong evidence for favouring a Student's t distribution for ε_t.

We also present diagnostic tests suggested by Engle and Ng (1993) and Kroner and Ng (1998), based on the 'generalized residuals', defined as $\varepsilon_t^O \varepsilon_t^S - h_t^{OS}$. For all symmetric GARCH models, the news impact curve is symmetric and centred at $\varepsilon_{t-1} = 0$ (see Engle and Ng, 1993). A generalized residual can be thought of as the distance between a point on the scatter plot of $\varepsilon_t^O \varepsilon_t^S$ from a corresponding point on the news impact curve. Therefore, if the conditional heteroskedasticity part of the model is correct, generalized residuals should be uncorrelated with all information known at time $t-1$. In other words, the unconditional expectation of $\varepsilon_t^O \varepsilon_t^S$ should be equal to its conditional one, h_t^{OS}. The Engle and Ng (1993) and Kroner and Ng (1998) misspecification indictors test whether we can predict the generalized residuals by some variables observed in the past, but which are not included in the model. In this regard, we follow Kroner and Ng (1998) and Shields et al. (2005) to define a battery of misspecification indicators. In a two dimensional space, we partition $(\varepsilon_{t-1}^O, \varepsilon_{t-1}^S)$ into four quadrants in terms of the possible sign of the two residuals. Then, to shed light on any possible sign bias of the model, we define the set of indicator functions as $I(\varepsilon_{t-1}^O < 0)$, $I(\varepsilon_{t-1}^S < 0)$, $I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$, $I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$, $I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$, and $I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$, where $I(\cdot)$ equals one if the argument is true and zero otherwise. Significance of any of these indicator functions indicates that the model, Eq. (4.2), is incapable of predicting the effects of some shocks to either oil or stock markets. Moreover, due to the fact that the possible effect of a shock could be a function of both the size and the sign of the shock, we define another set of indictor functions, $(\varepsilon_{t-1}^O)^2 I(\varepsilon_t^O < 0)$,

$(\varepsilon_{t-1}^{O})^2 I(\varepsilon_t^S < 0)$, $(\varepsilon_{t-1}^{S})^2 I(\varepsilon_t^S < 0)$, and $(\varepsilon_{t-1}^{S})^2 I(\varepsilon_t^O < 0)$. These indicators are technically scaled versions of the former ones, with the magnitude of the shocks as a scale measure. We conducted indicator tests and report the results in Table 4.6. As can be seen in Table 4.6, most of the indicators fail to reject the null hypothesis of no misspecification – all test statistics in Table 4.6 are distributed as $\chi^2(1)$. Hence, our model captures the effects of all sign bias and sign-size scale depended shocks in predicting volatility and there is no significant model misspecification error in the standardized residuals. Therefore, the $VAR(2) - ABEKK(1,1)$ model we employ is flexible enough to capture the dynamics of oil and Chinese stock returns in terms of volatility spillovers, asymmetric effects and time-varying conditional correlations.

In summary, our results imply the existence of widespread volatility transmissions between oil and stock sector returns. Moreover, the degree of volatility transmissions from oil market to stock market varies from one sector to another, which confirms the argument that the degree with which stock sector returns are sensitive to oil volatility depends on several industry-specific factors such as the degree of oil consumption, competition and concentration in the industry, and the effectiveness of hedging oil risk (see Arouri et al., 2011). It is obvious that the significant volatility transmissions we show previously require portfolio managers to quantify the optimal weights and optimal hedge ratios to properly deal with oil risk.

Table 4.6
Diagnostic tests based on the news impact curve.

	$(\varepsilon_t^O)^2 - h_t^O$	$\varepsilon_t^O \varepsilon_t^S - h_t^{OS}$	$(\varepsilon_t^S)^2 - h_t^S$
BRENT_MARKET INDEX			
$I(\varepsilon_{t-1}^O < 0)$	3.6251^{+++}	1.4249	1.7606^{+}
$I(\varepsilon_{t-1}^S < 0)$	1.1915	1.1914	1.3574
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	0.9247	0.5865	1.4529
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	1.2748	1.4003	0.3238
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.5709	1.1422	0.3993
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.2390	1.3745	0.9887
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	0.6757	1.2871	0.0167
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.8880	1.6612^{+}	0.0010
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0066	0.5344	0.0889
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	2.6402^{+++}	2.1334^{++}	0.8066
BRENT_BASIC MATERIALS INDEX			
$I(\varepsilon_{t-1}^O < 0)$	3.4832^{+++}	2.2074^{++}	0.7355
$I(\varepsilon_{t-1}^S < 0)$	1.3113	1.0738	1.7011^{+}
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	0.9348	0.8193	2.1244^{++}
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	0.0225	1.6111	0.6471
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.5577	1.0881	0.5302
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.2830	1.0684	1.2082
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	0.7627	0.4794	0.3362
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.9218	0.6258	0.2704
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0013	0.3793	0.4356
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	3.0229^{+++}	1.3850	1.6349
BRENT_CONSUMER GOODS INDEX			
$I(\varepsilon_{t-1}^O < 0)$	0.1364	0.9588	0.6236
$I(\varepsilon_{t-1}^S < 0)$	1.0592	0.4860	0.5753
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	0.9373	1.5524	0.9109
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	1.0215	1.9259^{+}	0.2969
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.7353	0.0281	0.6310
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.0703	0.9255	0.3861
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	0.7315	1.4279	0.0001
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.9327	0.0239	0.1934
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0074	0.4427	0.8112
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	2.6828^{+++}	1.1667	0.6626
BRENT_CONSUMER SERVICES INDEX			
$I(\varepsilon_{t-1}^O < 0)$	0.1820	0.7626	1.8117^{+}
$I(\varepsilon_{t-1}^S < 0)$	1.0388	1.4052	0.2864
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	0.8886	1.3856	1.4485
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	1.1090	1.8629^{+}	0.6539
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.7669	1.8382^{+}	0.1880
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.5368	0.8753	1.3239
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	1.0110	0.7573	0.1147
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.9608	0.4394	0.2067
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0039	0.4499	0.0107
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	2.8875^{+++}	0.6844	1.9499^{++}

Table 4.6 (continued.)
Diagnostic tests based on the news impact curve.

	$(\varepsilon_t^O)^2 - h_t^O$	$\varepsilon_t^O \varepsilon_t^S - h_t^{OS}$	$(\varepsilon_t^S)^2 - h_t^S$
BRENT_FINANCIALS INDEX			
$I(\varepsilon_{t-1}^O < 0)$	0.1537	1.1579	0.9273
$I(\varepsilon_{t-1}^S < 0)$	1.2505	0.4933	0.7642
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	1.0216	0.7534	0.2465
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	1.2257	0.9984	0.1340
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.6844	1.6030	1.3547
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.2445	1.5922	0.9440
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	0.7407	3.3198^{+++}	0.1259
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.9098	0.5849	0.3039
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0025	0.0279	0.1081
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	2.1449^{++}	1.7531^{+}	1.6822^{+}
BRENT_INDUSTRIALS INDEX			
$I(\varepsilon_{t-1}^O < 0)$	0.0634	1.0234	1.8374^{+}
$I(\varepsilon_{t-1}^S < 0)$	1.0342	1.0558	0.6697
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S < 0)$	0.7625	0.8867	1.6044
$I(\varepsilon_{t-1}^O < 0, \varepsilon_{t-1}^S > 0)$	1.4455	1.5956	0.8231
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S < 0)$	0.6930	1.4424	0.0514
$I(\varepsilon_{t-1}^O > 0, \varepsilon_{t-1}^S > 0)$	0.2490	0.7386	0.3218
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^O < 0)$	0.8622	0.8082	0.4915
$(\varepsilon_{t-1}^O)^2 I(\varepsilon_{t-1}^S < 0)$	0.8583	0.3113	0.1626
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^O < 0)$	0.0053	0.0925	0.3182
$(\varepsilon_{t-1}^S)^2 I(\varepsilon_{t-1}^S < 0)$	2.1606^{++}	1.8145^{+}	0.4176

Notes: $^{+++}$, $^{++}$ and $^{+}$ indicate the rejection of the null hypothesis of no asymmetric effects at the 1%, 5% and 10% significance levels, respectively.

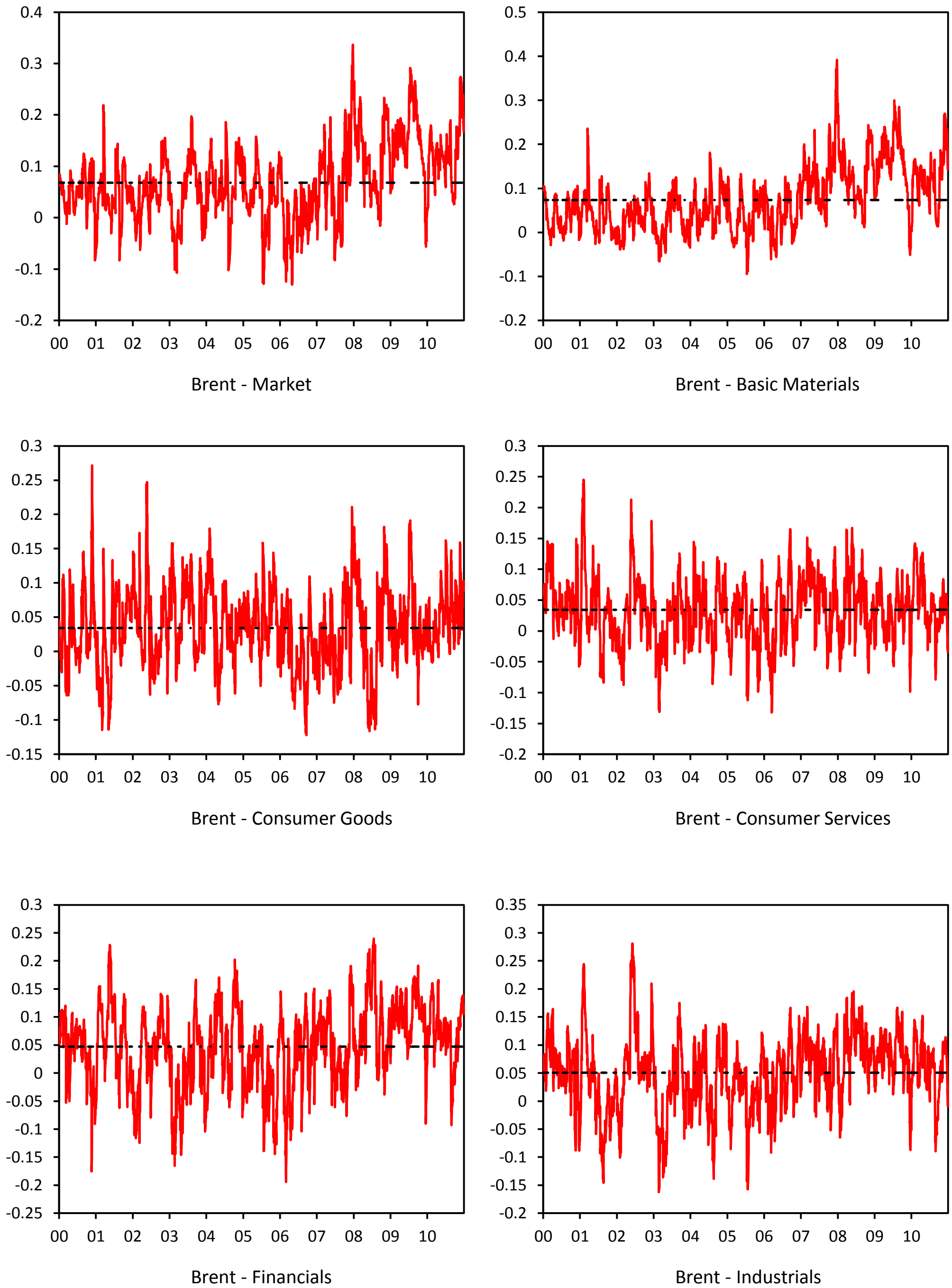


Fig.4.1 Time-varying conditional correlations (red lines) and corresponding average value of dynamic conditional correlations (dotted black lines) for pairs of Brent crude oil and stock sector indices in China.

4.6 Implications for portfolio management

The additional source of uncertainty resulting from the strong connection between oil and stock markets in China may present a new challenge, and the same time, a new opportunity for stock markets participants. Investors may need to re-evaluate their risk management strategy to deal with this additional source of risk.

To illustrate the implications of our findings on optimal portfolio design and oil risk hedging, we consider a portfolio of oil and stocks in which an investor attempts to minimize portfolio risk without lowering expected returns.[20] Let h_t^O, h_t^S, and h_t^{OS} be the conditional volatility of the oil market, the conditional volatility of the stock market (sector), and the conditional covariance between oil and stock returns at time t, respectively. According to Kroner and Ng (1998) and Hammoudeh et al. (2010), define

$$w_t^{OS} = \frac{h_t^S - h_t^{OS}}{h_t^O - 2h_t^{OS} + h_t^S} \tag{4.8}$$

Then it is easy to show that, under the condition of a mean-variance utility function, the optimal portfolio weight of oil-stock holding is

$$w_t^{OS} = \begin{cases} 0, if\ w_t^{OS} < 0 \\ w_t^{OS}, if\ 0 \leq w_t^{OS} \leq 1 \\ 1, if\ w_t^{OS} > 1 \end{cases}$$

where w_t^{OS} and $(1 - w_t^{OS})$ are the optimal weight of the oil and stock assets in a one-dollar portfolio of oil-stock at time t.

Summary statistics for portfolio weights computed from the $VAR(2) - ABEKK(1,1)$ model are reported in Table 4.7. A glance at the coefficients shows that the optimal weights for the oil asset in the oil-stock portfolios vary substantially across sectors. At the aggregate market level, we observe that, to maximize the risk-adjusted return of the one-dollar oil-stock portfolio, China investors should have more stock assets than oil assets in their portfolio in order to minimize risk without lowering expected returns. In addition, the optimal holding of oil assets in a

[20] In order to avoid forecasting expected returns, we assume here that the expected returns are zero, making the problem equivalent to estimating the risk-minimizing portfolio weights, which is consistent with Kroner and Ng (1998).

one-dollar oil-stock portfolio should be 33.12 cents, and the remaining budget of 66.88 cents is invested in stock assets. By sector, the optimal weight for oil ranges from 36.86% (Industrials) to 41.55% (Basic Materials) from the $VAR(2) - ABEKK(1,1)$ model for China sector-based portfolios. This result suggests that for Industrials the optimal allocation for oil in a one-dollar oil-stock portfolio should be 36.86 cents, with the remainder, 63.14 cents, invested in the Industrials stock sector index. For Basic Materials, these optimal investments are 41.55 cents for oil and 58.45 cents for stocks. On the whole, our results indicate that, to minimize the risk without lowering the expected return, investors in China should have more stocks than oil in their portfolios.

Table 4.7
Portfolio weights summary statistics.

	Mean	St. Dev.	Min	Max
BRENT_MARKT	0.3312	0.0231	0.0747	0.7491
BRENT_BASIM	0.4155	0.0362	0.0783	0.8467
BRENT_CONSG	0.3778	0.0257	0.0396	0.8368
BRENT_CONSS	0.3820	0.0329	0.0313	0.8581
BRENT_FINAN	0.4013	0.0207	0.1088	0.7891
BRENT_INDUS	0.3686	0.0320	0.0001	0.8461

Notes: This table reports the basic statistics of portfolio weights for oil, including mean (Mean), standard deviation (Std. Dev), minimum value (Min) and maximum value (Max) using conditional variance and covariance estimated from the VAR(2)-ABEKK(1,1) model. The oil asset is represented by the Brent crude oil of future contracts, whereas investment in stocks is represented by the DataStream Global Country Indices (China) or each of five stock sector indices in China represented by the DataStream Global Sector Indices.

As to the optimal hedge ratios, Kroner and Sultan (1993) consider a two-asset portfolio, equivalent to a portfolio composed of oil and the stock market (sector) index in our analysis. To minimize the underlying portfolio risk, a long position of one-dollar on the stock segment should be hedged by a short position of β_t^{SO} dollars on the oil assets, where β_t^{SO} is given by

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^{O}} \tag{4.9}$$

Fig. 4.2 plots the calculated time-varying optimal hedge ratios from the $VAR(2) - ABEKK(1,1)$ model. For all of the hedge ratios, the graphs show considerable variability after January 2007. For many of the hedge ratios it is also the case that the maximum value was recorded after January 2007.

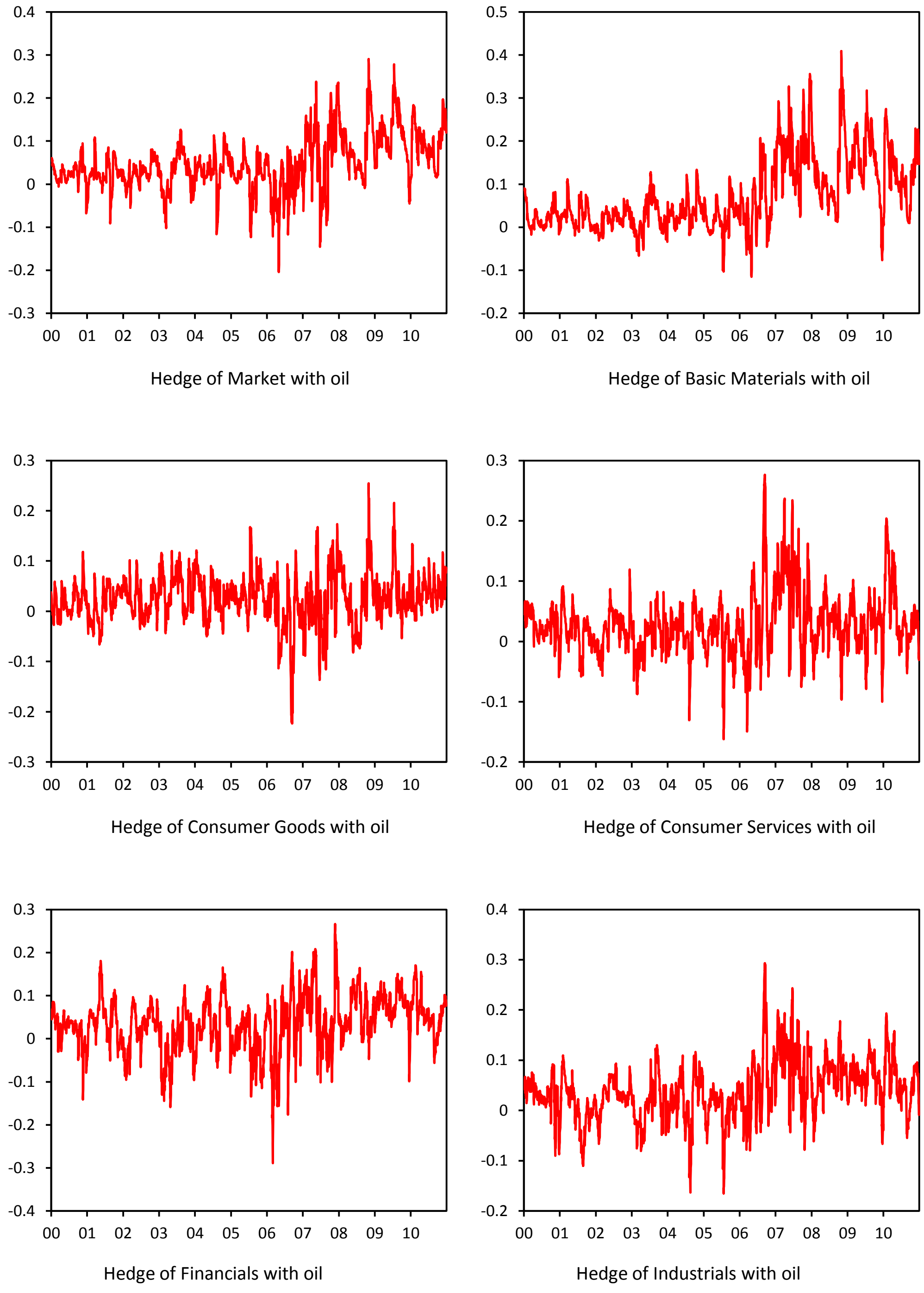


Fig.4.2 Time-varying hedge ratios computed from the VAR(2)-ABEKK(1,1) model.

Summary statistics for hedge ratios computed from the $VAR(2) - ABEKK(1,1)$ model are reported in Table 4.8. A glance at the average optimal hedge ratio (β_t^{SO}) provides insightful information for short hedgers. First, the low ratios suggest that stock investment risk can be hedged by taking a short position in oil markets or oil futures markets. At the aggregate market level, the ratio, 0.0471, means that one-dollar long (buy) in the Chinese stock market index should be shorted (sell) by 4.71 cents of oil futures. Second, similar to the optimal portfolio weights, the optimal hedge ratios differ across sectors ranging from 0.0245 (Consumer Goods) to 0.0714 (Basic Materials). Summing up these together, our findings for optimal hedge ratios support the argument that oil assets should be an integral part of a diversified portfolio of stocks and then improve the risk-adjusted performance of the hedged portfolio.

Table 4.8
Hedge ratio (long/short) summary statistics.

	Mean	St. Dev.	Min	Max
BRENT_MARKT	0.0471	0.0038	-0.2039	0.2899
BRENT_BASIM	0.0714	0.0064	-0.1153	0.4091
BRENT_CONSG	0.0245	0.0023	-0.2228	0.2541
BRENT_CONSS	0.0278	0.0025	-0.1617	0.2759
BRENT_FINAN	0.0364	0.0039	-0.2889	0.2661
BRENT_INDUS	0.0400	0.0031	-0.1649	0.2928

Notes: This table reports the basic statistics of hedge ratio (long/short) for oil and stock sectors indices, including mean (Mean), standard deviation (Std. Dev), minimum value (Min) and maximum value (Max) using conditional variance and covariance estimated from the VAR(2)-ABEKK(1,1) model. The oil asset is represented by the Brent crude oil of future contracts, whereas investment in stocks is represented by the DataStream Global Country Indices (China) or each of five stock sector indices in China represented by the DataStream Global Sector Indices.

We now look into diversification effectiveness by actually running the portfolio simulations with our optimal portfolio designs. We use the estimates of the ABEKK model to build two portfolios: a portfolio of stocks and a weighted oil-stock portfolio with optimal weights provided in Table 4.7. The effectiveness of the portfolio diversification is judged by comparing the realized risk and return characteristics of the considered portfolios. A higher diversification effectiveness (DE) ratio indicates greater diversification effectiveness in terms of the portfolio's variance reduction, which thus implies that the associated investment method can be deemed a better diversification strategy.

Table 4.9
Diversification effectiveness.

	Mean (%)	Variance (%)	$Return(\%)^{*}$	DEI (%)	$VaR_{5\%}(\$)$	Semi-Variance	DEII (%)
BRENT_MARKT							
Undiversifie	0.0043	0.0265	0.2612	---	26883.7	0.0106	---
Diversified	0.0163	0.0166	1.2626	37.46	22142.2	0.0063	40.82
BRENT_BASIM							
Undiversifie	0.0173	0.0379	0.8867	---	32119.1	0.0153	---
Diversified	0.0283	0.0201	2.0002	47.08	24885.4	0.0075	50.88
BRENT_CONSG							
Undiversifie	0.0249	0.0309	1.4136	---	29017.2	0.0123	---
Diversified	0.0275	0.0173	2.0880	44.09	22958.4	0.0065	47.47
BRENT_CONSS							
Undiversifie	0.0425	0.0517	1.8715	---	37512.5	0.0118	---
Diversified	0.0285	0.0201	1.9981	61.20	26842.1	0.0084	29.03
BRENT_FINAN							
Undiversifie	0.0160	0.0463	0.7448	---	35518.6	0.0096	---
Diversified	0.0195	0.0168	1.5033	63.65	25357.3	0.0065	32.29
BRENT_INDUS							
Undiversifie	0.0258	0.0458	1.2062	---	35292.4	0.0104	---
Diversified	0.0267	0.0184	1.9713	59.87	26030.9	0.0076	27.42

Notes: This table reports the realized risk-adjusted returns, portfolio variance, semi-variance, Value-at-Risk (VaR) and diversification effectiveness ratios. $Return^{*}$ is the realized risk-adjusted returns, measured by calculating the ratio of each portfolio's mean to its standard deviation, of different portfolios. Variance denotes the variance of the undiversified/diversified portfolios. Semi-variance denotes the semi-variance of the undiversified/diversified portfolio. $VaR_{5\%}$ is the Value-at-Risk estimated by using Eq. (4.10) with $\Phi(c)$ equal to the normal distribution 5% quantile, i.e. 1.645. DEI denotes the diversification effectiveness and measures the incremental variance reduction of the ABEKK model, which is estimated using the formula:
$[Var(Diversified\ portfolio) - Var(Undiversified\ portfolio]/Var(Undiversified\ portfolio)$.
DEII denotes the diversification effectiveness and measures the incremental semi-variance reduction of the ABEKK model, which is estimated using the formula:
$[SVar(Diversified\ portfolio) - SVar(Undiversified\ portfolio]/SVar(Undiversified\ portfolio)$.
The diversified portfolio is a weighted oil-stock portfolio in which the weights are given by the optimal weights reported in Table 4.7.

The results from portfolio simulation in the second and fourth columns of Table 4.9 show that adding the oil asset to the diversified portfolios improves their risk-adjusted return ratios. More importantly, this result holds for all equity sectors we consider. We then focus on the fifth column of Table 4.9, in which the diversification effectiveness ratios (DEI) are reported. The results show that diversification strategies involving oil and stock assets make it possible to reduce portfolio risk (variance) considerably with the variance reduction ranging from 37.46% (Market index) to 63.65% (Financial index). Moreover, this variance reduction differs significantly across equity sectors.

Another way of considering the economic benefits from the proposed portfolio diversification is to look at the reduction in the Value-at-Risk (VaR) exposure, arising from the diversification strategy. Assuming a normal distribution, if we denote as W_0 the initial value of the portfolio and $\Phi(c)$ the inverse of the standard Gaussian cumulative distribution function, the portfolio VaR is simply a constant multiple of the diversified portfolio standard deviation where the multiple is determined by the VaR confidence level $1 - c$:

$$VaR = W_0 \left[E(r_d) + \Phi(c)\sqrt{Var(r_d)}\right] \quad (4.10)$$

with r_d representing the returns from the diversified portfolio.

Results of the daily VaR for a portfolio value of $1m with 95% confidence level reported in the sixth column of Table 4.9 indicate that one obtains a daily VaR of -$26883.7 if the undiversified portfolio is considered and a VaR of -$22142.2 when the diversified portfolio is considered for the China market index, which results in a decrease in VaR of $4741. Similar results are obtained across all equity sectors in terms of the reduction of VaR. Therefore, investors would prefer the ABEKK-based strategy to diversify their investment portfolio.

Although variance reduction gives the overall picture about how well a diversification strategy performs, it does not consider the tail risk of the diversification strategy. The motivation for investigating this stems from the pitfalls associated with variance as a measure of diversification effectiveness. Variance assigns the same weight to positive gains and negative losses, which may not be the case for the risk averse investors. A number of metrics have recently been proposed in the literatures that are able to deal with possible asymmetries in the profile of risk averse investors. For example, Cotter and Hanly (2006) evaluate the diversification performance based on Lower Partial Moments and find differences in terms of the best strategy compared to the traditional variance metric. In order to remove the effect of upside gains from the variance, we employ the semi-variance metric which acts as a measure for a downside risk averse investor, who is more concerned about the variability of negative losses. This can be expressed as:

$$sv_{(-)} = \frac{1}{N}\sum_{i=1}^{N}\{\min(0, r_{n+1} - u)\}^2 \tag{4.11}$$

This is equivalent to the second order lower partial moment (LPM) where the target return u is set to zero in order to distinguish between positive and negative realized portfolio returns r_{n+1}. The seventh and eighth columns of Table 4.9 present the negative semi-variance figures where negative semi-variance reflects the downside variation in the diversified strategies and the diversification effectiveness ratios. Overall, all numbers are positive, implying the superior performance of the diversified portfolio over undiversified portfolio with the semi-variance reduction ranging from 27.42% (Industrials index) to 50.88% (Basic Materials index). Moreover, this semi-variance reduction differs significantly across equity sectors.

4.7 Conclusion

The main purpose of this chapter is to investigate the extent of volatility transmission and its implication for portfolio management in oil and stock market in China from a sector perspective. The rationale for doing so is that market-level index may mask the industry-specific characteristics, and different industry may react differently to oil shocks as well. Arouri et al. (2011) argue that with regard to portfolio management, studies focusing on sector sensitivities to oil price shocks are of particular interest since they offer insight into sectors that still provide valuable opportunities for international diversification during large swings in oil prices.

After considering the evidence of volatility spillovers and asymmetric effects in Brent crude oil and Chinese stock market, by taking the asymmetric version of the BEKK model approach which permits volatility spillover and asymmetric effects, we find significant volatility interdependence in oil and stock market sectors. Empirical evidence also points out to the heterogeneous intensity of volatility transmissions across the five stock sectors. Furthermore, we find that the correlations between oil and stock markets (sectors) are time-varying and must be modelled as such. Finally, out investigation of optimal portfolio weights and hedge ratios indicates that optimal portfolios should have more stocks than oil assets and that the stock investment risk can be hedged with relatively low hedging costs by taking a short position in the oil futures markets. Overall, our analysis suggests that oil assets can be treated as a dynamic and valuable asset class that help improve the risk-adjusted performance of a well-diversified portfolio of sector stocks and serves to hedge oil risk more effectively.

Future research may focus on simulation and analysis of government intervention regarding how to alleviate the impact of oil price fluctuations on equity markets. Additional insight may also be gained by exploring regime changes in the role of oil price fluctuations in explaining the equity market behaviour as well as employing the spillover index from the Diebold and Yilmaz (2009) framework to shed new direction on the volatility spillover between oil and stock markets in China.

In the following chapter, we will focus on the investigation of crude oil markets integration in terms of volatility transmission. We also quantify the size and persistence of these connections through the analysis of Volatility Impulse Response Functions (VIRFs) for three historical shocks, namely the 2008 Financial Crisis, the BP Deepwater Horizon oil spill and the OPEC Announcements. The potential findings will provide useful insights into the volatility transmission mechanism in crude oil markets and their associated risk estimation, and may have significant implications for various market participants and regulators.

Chapter 5

Volatility Transmission and Volatility Impulse Response Functions in Crude Oil Markets[1]

5.1 Introduction

Since the reverse oil price shocks of 1986 and the move to a market-driven pricing mechanism, the behaviour of oil prices has been under scrutiny practically on a daily basis and for a variety of reasons. Trading in crude oil has also changed, with physical and paper trading attracting numerous types of market participants, not just parties with commercial interests, but also those who treat oil as an investment vehicle. In the last few years, trading in the paper markets has become even more widespread and accessible for close to 24 hours and for almost every day of the year. At the same time, there is relatively easy access to multiple markets, particularly so for the all-important European and US markets, where two of the key benchmark oils, Brent and West Texas Intermediate, are traded.

There is increasing integration of major financial markets throughout the world, enabling convergence of risk-adjusted returns on the assets of similar maturities across markets. With the introduction of crude oil as an alternative asset in investment portfolios, crude oil markets all over the world have witnessed growing integration, spurred by deregulation, securitization, globalization and advances in information technology.

In crude oil markets more specifically, we have witnessed the strength of Brent crude oil as a benchmark of world oil prices, but also its changing relationship with West Texas Intermediate crude oil (henceforth WTI), which seems to increasingly reflect US domestic, rather than world,

[1] Part of this chapter has been published in Energy Economics (Jin et al., 2012). We would like to thank the Editor (Richard Tol) and two anonymous referees for their constructive comments and helpful feedback. An earlier version is presented at the 34th IAEE International Conference in Stockholm (June 19th-22nd, 2011).

markets. In addition, the increased trade flows from the Middle East to the developed and emerging markets of East Asia have given more prominence to the use of Dubai Fateh crude oil (henceforth Dubai) as a pricing benchmark for these crude oil flows. It is therefore of interest and practical significance to investigate further the relationship among these three crude oils.

Within this context, the behaviour of crude oil prices and returns has been the subject of much attention from the academic community and financial practitioners. Numerous econometric studies have examined the dynamic and distributional properties of price and/or return time series in leading crude oil markets. The majority of these studies are devoted to the analysis of a univariate time-series. A natural extension to this interest is to investigate crude oil markets in higher moments of a distribution, i.e. volatility. Although some research has been done on the second moment with regard to the existence of volatility transmission, there are no direct findings about how a shock to one market influences the dynamic adjustment of volatility to another market and the persistence of these transmission effects.

The importance of measuring volatility cannot be overstated. It is equally important, however, to understand how volatility is transmitted between markets and assets. In physical oil markets, agents often have exposures to a number of different grades of crude oil, which may be priced off one or more of the benchmarks; in paper oil markets, agents frequently build portfolios which include some or all of the benchmarks. More generally, an understanding of volatility and how it is transmitted is important for determining the cost of capital, for assessing investment and leverage decisions, and for computing the optimal hedge ratio and portfolio weights. Substantial changes in volatility in crude oil markets may have significant negative effects on risk-adverse investors.

In this chapter we focus on volatility aspects of crude oil markets and aim to achieve two objectives: (1) to investigate the volatility transmission mechanism, using a multivariate conditional volatility model, within and across benchmark markets, i.e. WTI, Dubai and Brent;

and (2) to apply the volatility impulse response function analysis to uncover the impact of historical innovations on conditional volatility by utilizing the above transmission mechanism and to quantify the risk on a future horizon. We choose to study WTI, Brent and Dubai markets because they represent major demand-supply activities in the world oil trade.

To achieve the first goal, a multivariate conditional volatility model, namely the full BEKK model by Engle and Kroner (1995), is used to facilitate the study of volatility transmissions within the three benchmark markets as well as across them. The results will have significant implications on how volatilities are being transmitted among major oil markets, and hence indicate the pattern of information flow and to some extent the relative strength of three benchmarks. For the second goal, the volatility impulse response function (VIRF) methodology developed by Hafner and Herwartz (2006) is applied. It allows us to analyse the impact of external shocks on oil market volatilities. Three major historical events, i.e. the 2008 Financial Crisis, the BP oil spill of 2010[2], and the OPEC announcements[3], are examined, followed by the creation of an empirical distribution of possible random shocks. The latter further facilitates the quantification of Value-At-Risk estimation. Results generated from these analyses could have implications for trading, risk management and policy issues in crude oil markets.

By focusing on the volatility aspects of crude oil markets, this chapter contributes to the existing literature in two aspects. The first contribution of this chapter is to show that volatilities within and across WTI, Dubai and Brent markets follow a “meteor shower”[4] process, indicating that volatility spillovers across crude oil markets should be considered for crude oil volatility modelling. In particular, we empirically examine the trivariate time-series properties of crude oil

[2] The Deepwater Horizon Oil Spill is an oil spill in the Gulf of Mexico which flowed unabated for three months in 2010. It is the largest accidental marine oil spill in the history of the oil industry. It stemmed from a sea-floor oil gusher that resulted from the April 20, 2010, explosion of Deepwater Horizon. Please refer to http://en.wikipedia.org/wiki/Deepwater_Horizon_oil_spill for detailed explanation.

[3] In 1982, OPEC established a system to regulate oil production among its members. Several times a year, the OPEC schedules a conference to agree on further oil production policies, based on its assessment of the current market condition. The OPEC’s decision usually takes the form of an announcement, setting an overall oil production ceiling for the cartel and individual production quotas for its members (see OPEC Secretariat, 2003). We will consider a series of OPEC announcements which correspond with our data period.

[4] This concept is developed by Engle et al. (1990) to describe volatilities reacting to shocks in other markets and a volatility process whose estimation is not improved by using innovations in other markets.

returns. The multivariate volatility model we employ is robust, in which it is capable of handling non-linear effects on the variances of each time-series, as well as allowing for the possibility that changes in volatility in one crude oil market may transmit into the other crude oil markets through conditional variance and conditional covariance channel. As we have argued previously, an understanding of volatility and how it is transmitted are very important for financial market practitioners to understand the volatility transmission mechanism across time and markets in order to facilitate optimal portfolio allocation decisions, which provide important policy implications for risk managements in crude oil markets.

The second contribution of this chapter is to quantify the impact of three historical observed shocks, i.e. the 2008 Financial Crisis, the BP Deepwater Horizon oil spill and the OPEC announcements, on the volatilities within the WTI, Dubai and Brent markets adapting Sims's (1980) impulse response function to the volatility setting. To do so, by using a recently developed technique, i.e. Hafner and Herwartz' (2006) VIRF methodology, we estimate the corresponding VIRFs implied by the specification of each model. To the best of our knowledge, no other study has employed this innovative technique of VIRFs to study volatility dynamics in crude oil markets. More importantly, in comparison with another technique derived by Lin (1997) in a context of MGARCH model and Gallant et al. (1993)' definition of impulse response analysis, there are some crucial features of the VIRFs which should be addressed. The VIRFs depend on both the volatility state and the unexpected returns vector when the shock occurs, which indicates that a given shock will not always increase expected conditional volatility. Because of the application of Jordan's decomposition, this approach avoids typical orthogonalization and ordering problems which would be hardly feasible in the case of high-frequencies financial time-series.

The VIRF clearly shows us that different historical shocks have significantly different impacts on expected conditional volatilities, in which the 2008 Financial crisis around the bankruptcy of Lehman Brothers on September 15, 2008 exerts the highest positive impacts on expected conditional volatilities within WTI, Dubai and Brent markets and followed by the BP Deepwater

Horizon oil spill. By contrast, the OPEC announcements only exert relatively small negative impacts on expected conditional volatilities.[5] Another interesting finding is that even if the shocks are absorbed by crude oil markets simultaneously as we have assumed, the dynamics of the impact of shocks are largely specific: Dubai and Brent crude oils are more volatile and sensitive than crude oil WTI in terms of the volatility impulse response analysis. Alternatively, we can say that crude oil Dubai and Brent are more responsive to market shocks, and WTI shows the least responsiveness of the three benchmarks, which put its predominance as a world oil price benchmark to question.

The variance forecasting ability shown in our analysis provides important practical guidelines for financial practitioners and policy implications to determine the cost of capital, assess investment and leverage decisions, and compute the optimal hedge ratio and portfolio weights as many financial instruments, especially options[6], are priced according to the entire price distribution as well as the distribution of volatility[7].

The chapter comprises six sections. Following this introduction, section 5.2 gives some background on previous contributions to the study of crude oil markets integration and volatility transmission, and the concept of volatility impulse response function analysis. Section 5.3 explains the dataset and descriptive statistics. Section 5.4 discusses the econometric methodology of volatility impulse response function in conjunction with the multivariate GARCH model to be estimated. Section 5.5 describes the empirical estimates and some diagnostic tests of the multivariate model, discusses results for different historical shocks within the framework of volatility impulse response analysis, and presents the estimated distributions of the volatility impulse response function for different forecast horizons obtained through the simulation of

[5] The possible explanation for the opposite pattern of VIRFs is that OPEC announcements are not purely random events which cannot be anticipated and forecasted, such that market rational expectation about OPEC announcements result in the subsequent decrease of crude oil volatility no matter which scenario emerges. By contrast, the bankruptcy of Lehman Brothers in the peak of the 2008 Financial Crisis and the BP Deepwater Horizon oil spill were random events and occurred without sufficient anticipation. These kinds of unanticipated events will cause the increase of conditional volatility subsequently.

[6] For example, put options for negative skewed assets are more expensive thus indicating that volatility is not a sufficient criterion to price derivatives.

[7] Hull and White (1987) suggest that this is of much concern for option pricing using stochastic volatility.

random shocks. Section 5.6 provides some concluding remarks along with a few possible areas for future research.

5.2 Literature review

5.2.1 Crude oil markets integration and volatility transmission

There has been a considerable interest in the financial literature in examining whether or not different crude oils produced in a variety of countries or locations constitute a homogeneous world oil market. For example, Weiner (1991) analyses correlations and regression results on price adjustment across regions, indicating that world oil market is far from unified and crude oil prices do not move together around the world. Adelman (1992) rejects Weiner's (1991) results and argues that based on the 'Law of One Price', arbitrage opportunities will be eliminated if the price differential between crude oils from two different regions is less than the transaction costs (e.g. transportation) between these regions and quality differentials (e.g. sulphur content, API gravity index) between the crude oils.

More recent studies tend to support the view advocated by Adelman (1992) that world oil markets behave like one common market. Gulen (1999) applies cointegration tests to a series of oil markets with pairwise comparisons on post-1990 data, and concludes that prices of similar quality crude oils have grown more unified during the period 1994-1996 as compared with the period 1991-1994. Ewing and Harter (2000) find that Alaska North Slope (ANS) and UK Brent oil prices follow a random walk and share a long-run common trend, suggesting the two markets are "unified". Using daily price data for five very different crude oils, i.e. WTI, Brent, ANS, Dubai and Indonesian Arun, and the error correction model proposed by Engle and Granger (1987), Bachmeier and Griffin (2006) conclude that the world oil market is a single, highly integrated economic market. Bentzen (2007) re-confirms this postulation while analysing WTI, Brent and Dubai, for the time period 1988 to 2004. The bi-directional causality among these crude oil prices suggests the globalization of crude oil markets. There seems to be a general consensus of empirical findings which support the hypothesis that global crude oil market is integrated.

The increasing integration of major crude oil markets has generated interest in understanding the effects of information transmission on returns and volatilities across markets. Lin and Tamvakis (2001) investigate information transmission with regards to returns between the New York Mercantile Exchange (NYMEX) and London's International Petroleum Exchange (IPE) crude oil contracts in both non-overlapping and simultaneous trading hours. They find that substantial transmission effects do exist when both markets are trading simultaneously, although IPE morning prices seem to be considerably affected by the close of the previous day on NYMEX. Ewing et al. (2002) examine how volatility in the oil and natural gas sectors are transmitted between each other using the BEKK model and daily returns data. Their findings indicate that there exists direct and indirect transmission from one market to the other. Chang et al. (2009) analyse conditional volatility and conditional correlation relationships among spot, forward and future returns for Brent, WTI and Dubai markets respectively. Their empirical findings show the presence, as well as the asymmetry, of volatility transmission in the conditional volatilities within each of the markets.

5.2.2 Volatility impulse response function (VIRF) method

The idea of impulse response, or error shock methodology, which measures the time profile of the effect of a shock on the behaviour of a time series, is put forward by Sims (1980) and refined by Doan et al. (1984) and others subsequently. Initially, the so-called impulse response analysis is a comprehensive tool kit of methods for exploring the dynamics of a linear process and comparing them to the predictions of an economic model.

With regard to the idea of impulse response analysis, two issues have been raised. Firstly, many works have focused on linear models rather than nonlinear ones. Beaudry and Koop (1993), Pesaran and Potter (1994), and Potter (1995) argue that linear models are too restrictive for attempting to measure the persistence effect of shocks on macroeconomic time series because the symmetry property of the linear model does not facilitate different features generated by shocks occurring in a recession period and shocks from an expansion period. Secondly, a better understanding of the persistence of shocks can be provided within the framework of vector linear multiple time series (Blanchard and Quah, 1989). Some applications of extending the basic linear univariate model to linear multivariate models have been implemented by Pesaran et al. (1993) and Lee and Pesaran (1993).

The definition of impulse response of non-linear econometric structures to shocks has been addressed in a number of papers, most notably Gallant et al. (1993) and Koop et al. (1996). Gallant et al. (1993) provide a methodology for computing the impulse response for a non-linear time series model by computing the differences between the baseline approach and the conditional moment profile using a semi-parametric methodology. The shock which inflicts the difference between the "shocked" and the baseline trajectories is a perturbation in the conditionally heteroskedastic error term, which is supposed to be either observable or estimated. Koop et al. (1996) develop the concept and derive rigorously what is termed as generalized non-linear impulse response functions for the conditional expectation by using the difference between the mean of the response vector conditional on both history and a present shock and the mean that only conditions on history.

Building on the definition by Gallant et al. (1993), Lin (1997) derives a measure in the context of an MGARCH model and assesses the finite sample properties of the standard errors that surround the impulse response function by means of a Monte Carlo simulation. The main critique for Gallant's et al. (1993) approach is discussed by Koop et al. (1996) and Hafner and Herwartz (2006). They argue that the method of obtaining shocks from the conditionally heteroskedastic error term is a priori for analyzing macroeconomic systems and then hardly feasible for high-frequency financial time series. Following Koop's et al. (1996) methodology, Hafner and Herwartz (2006) demonstrate a model of impulse response functions tracing the time pattern of the effects of independent shocks on volatility. In order to avoid the typical orthogonalization and ordering problems, they apply a Jordan decomposition to retrieve an independent and realistic shock from the conditionally heteroskedastic error term.

Panopoulou and Pantelidis (2009) argue that the VIRF approach developed by Hafner and Herwartz (2006) is a convenient way to analyse volatility transmission and has a number of advantages in comparison with traditional impulse response functions developed by Sims (1980). First, this approach allows practitioners to determine precisely how a shock to one market influences the dynamic adjustment of volatility in another market and the persistence of these spillover effects. Second, VIRFs depend on both the volatility state and the unexpected returns vector when the shock occurs, which indicates that a given shock will not always increase expected conditional volatility. Third, contrary to traditional impulse response functions, this specific methodology avoids typical orthogonalization and ordering problems, which would be hardly feasible in the case of high-frequency financial time series.

5.3 Data

In this chapter, we use daily futures prices for the three crude oil benchmarks: WTI, Brent and Dubai. We do so because futures prices have the advantage of liquidity, transparency and flexibility. In all cases, the nearest to expiry contract is used, rolling forward to the next nearby on the first business day of the delivery month in order to mitigate the impact of thin trading and expiration effects in the estimation results.[8] The oil prices cover the period from 1 July 2005 to 30 June 2011 with 1565 observations.[9] Prices are quoted in US dollars per barrel and are obtained from Bloomberg.

[8] Nomikos and Pouliasis (2011) take the similar method to pass from one contract to another in the case of succession of front contract to make sure that the large kurtosis is not due to outliers occurring around the contract switch dates. Further example could be found in Chang et al. (2009).

[9] The sample period is restricted by data availability of Dubai crude futures contract. It would be better to update it to the range of 2013 in the revised version. However, due to the unavailability of the access to DataStream, the dataset would be left at its original range.

There are two considerations that should be mentioned for the selection of the datasets. Firstly, future prices are preferable to spot prices. Schwarz and Szakmary (1994) find that future prices dominate price discovery relative to spot prices. This finding is corroborated by Silvapulle and Moosa (1999), in which they argue that some evidence proves the existence of causal relationship from future prices to spot prices for crude oil. Oil future prices are appropriate predictors of future oil spot prices. Secondly, the same closing time (NYMEX close) is critical which ensures information content embedded in the price series are synchronized (see Lin and Tamvakis, 2001).

5.3.1 Preliminary analysis

For the purpose of this study, all daily sample prices are converted into continuously compounded daily returns, which are computed as follows:

$$r_t^i = \ln\left(X_t^i / X_{t-1}^i\right) \tag{5.1}$$

For $t = 1,2, \ldots .T$, in which $r_t^i$is the log return for crude oil prices at time t, X_t^i is the current price, $X_{t-1}^i$is the previous day's price, i represents different crude oil, i.e. WTI, Brent and Dubai.

Descriptive statistics are reported in Table 5.1. From panel A, we can observe that all price returns share similar statistical properties in relation to third and fourth moments. All the returns are skewed and have higher kurtosis value than standard normal distribution, which indicate that they do not conform to the normal distribution assumption. Based on the Jarque-Bera (1980) test statistic, we can reject the null hypothesis of Gaussian distribution. Furthermore, based on the Box-Pierce Q^2 statistic of order 10, we can also reject the null hypothesis of white noise and assert that all the time series are autocorrelated.

In panel B, we present the results of the Augmented Dickey-Fuller (1979) (ADF) and Phillips-Perron (1988) (PP) unit root tests, and the Kwiatkowski, Phillips, Schmidt and Shin (1992) (KPSS) stationarity test. The ADF and PP tests undoubtedly reject the null hypothesis of unit root for all the crude oils returns time series at the 1% significance level. Meanwhile KPSS test of stationarity cannot be rejected at the significance level of 1% for all three crude oil returns time series. As the result, we can conclude that all the three return series are stationary.

Table 5.1
Summary statistics, unit root and stationarity tests for daily returns

	WTI	Dubai	Brent
Panel A: Descriptive statistics			
Nu of Obs.	1565	1565	1565
Mean	0.000295	0.000445	0.000430
Median	0.000000	0.000531	0.000747
Maximum	0.152819	0.203841	0.158267
Minimum	-0.106556	-0.105361	-0.109452
Std. Dev.	0.023301	0.024146	0.023016
Annul Vol.	0.369892	0.383306	0.365368
Skewness	0.102577	0.261531	-0.038124
Kurtosis	6.888152	8.756687	7.105626
Panel B: Unit root and stationarity tests			
J-B	987.9146*	2177.417*	1098.839*
$Q^2(10)$	619.617*	525.801*	767.235*
ADF test	-41.25613^*	-43.60221^*	-41.71571^*
PP test	-41.24039^*	-43.64751^*	-41.74526^*
KPSS test	0.069844	0.084406	0.092736

Note: * denotes significance at a 1% level. J-B test is the Jarque-Bera (1980) normality test statistic. The test follows a χ^2 distribution with 2 degrees of freedom. $Q^2(10)$ is the Box-Pierce Q-statistic of order 10 on the squared returns. ADF is the Augmented Dickey-Fuller (1979) unit root test statistic. PP is the Phillips-Perron (1988) unit- root test statistic. KPSS is the Kwiatkowski, Phillips, Schmidt and Shin (1992) stationarity test statistic.

5.4 Econometric methodology

5.4.1 The BEKK model

We follow the BEKK (Engle and Kroner, 1995) by modelling return series of WTI, Dubai and Brent crude oil prices as a vector random process $\{r_t\}$ of dimension 3. We condition $\{r_t\}$ on the sigma field, denoted by I_{t-1}, of past information until time $t-1$, as follows:

$$r_t = \mu_t + \varepsilon_t;\ \varepsilon_t = H_t^{1/2}(\theta) z_t \tag{5.2}$$

where μ_t is the conditional mean vector and could be governed by a vector autoregression (VAR), $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t})'$ is the vector of the zero-mean error terms, z_t is the $3*1$ random vector following two moments: $E(z_t) = 0$ and $Var(z_t) = I_N$ (the identity matrix of order 3). ε_t has a time-varying conditional variance governed by H_t with a finite vector of parameters denoted by θ , which is a $3*3$ positive definite symmetric matrix. In a BEKK (1, 1), H_t has the following representation:

$$H_t = C * C' + A * \varepsilon_{t-1} * \varepsilon'_{t-1} * A' + G * H_{t-1} * G' \tag{5.3}$$

where C is a lower triangular matrix, and A and G are 3*3 parameter matrices. Matrix A measures the extent to which conditional variances is correlated with past squared one lag unexpected returns (i.e. deviation from the conditional mean) and consequently the effects of shocks on volatility. At the same time, matrix G depicts the extent to which current levels of the conditional variance-covariance matrix are related to past one lag conditional variance-covariance matrices.

The procedure most often used in estimating Eq. (5.3) involves the maximization of a likelihood function constructed under the auxiliary assumption of an independent and identical distribution for the standardized innovations z_t. The most commonly employed distribution in the literature is the multivariate normal distribution, uniquely determined by its first two moments. In this case, the likelihood function is given by:

$$L_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T} \log|H_t| - \frac{1}{2}\sum_{t=1}^{T} \varepsilon'_t H_t^{-1} \varepsilon_t \tag{5.4}$$

If the conditional distribution of ε_t is not normal, then maximizing Eq. (5.4) is interpreted as quasi maximum likelihood (QML) estimation. Results for the asymptotic properties of the QML-estimator have been derived by Jeantheau (1998) and Comte and Lieberman (2003). However, it is well known that the normality of the innovations is always rejected in most applications dealing with daily data in commodity markets, which is obviously the case in our analysis as we have rejected the null hypothesis of gaussianity based on the Jarque-Bera (1980) test statistic reported in Table 5.1. In particular, the kurtosis of prices returns of crude oil WTI, Dubai and Brent are larger than three, which means that they have too many extreme values to be normally distributed and could be considered as conditional leptokurtosis. Following Bollerslev's advocations (1986), Harvey et al. (1992) and Fiorentini et al. (2003) argue that a natural alternative to the multivariate Gaussian distribution is the Student's t distribution, which has an extra scalar parameter, the degrees of freedom parameter, denoted ν hereafter. The density of a multi standardized t distribution is given by:

$$f(z_t|\theta,\nu)=\frac{\Gamma(\frac{\nu+N}{2})}{\Gamma(\frac{\nu}{2})[\pi(\nu-2)]^{\frac{N}{2}}}[1+\frac{z_t'z_t}{\nu-2}]^{-\frac{N+\nu}{2}} \tag{5.5}$$

where $\Gamma(\cdot)$ is the gamma function.

Under this assumption the conditional distribution of ε_t is given by:

$$\varepsilon_t|I_{t-1}\sim f\left(H_t^{-\frac{1}{2}}\varepsilon_t\right)|H_t^{-\frac{1}{2}}| \tag{5.6}$$

and the contribution of ε_t to the log-likelihood function reads as:

$$L_T(\theta)=\sum_{t=1}^{T}\log f\left(H_t^{-\frac{1}{2}}\varepsilon_t\right)+\sum_{t=1}^{T}|H_t^{-\frac{1}{2}}| \tag{5.7}$$

5.4.2 Volatility impulse response functions (VIRF)

5.4.2.1 The vech representation

Equation (5.3) of BEKK model can also be represented by the VEC model proposed by Bollerslev et al. (1988) with variables within the model being stacked up as

$$vech(H_t)=vech(C)+R*vech(\varepsilon_{t-1}*\varepsilon_{t-1}')+F*vech(H_{t-1}) \tag{5.8}$$

where $vech(\cdot)$ denote the operator that stacks the lower fraction of an $3*3$ matrix into an $N^* = N*(N+1)/2$ dimensional vector. R and F are parameter matrices each containing $(N^*)^2$ parameters, whereas $vech(C)$ contains N^* coefficients.[10]

5.4.2.2 Identification of independent shocks

Hafner and Herwartz (2006) argue that a shock is inherently independent over time and consider a shock appearing in one time series as independent from a shock appearing in another time series if they appear at the same time. This assumption enables the VIRF to be constructed based on the definition of data generating process of Koop et al. (1996), which indicates that independent shocks can be traced or obtained from historical data sets for the VIRF analysis within a multivariate framework.

However, because of the characteristics of contemporaneous correlation of the error vector ε_t within a multivariate framework, it is not easy to identify the effect of shock on one of its components without taking into account the changes in the others. Therefore, the error components in ε_t cannot be directly treated as shock coming from independent sources. To filter out the effects of independent sources, we need to look at the orthogonality of residuals.

In practice, Choleski decomposition is often employed to identify z_t, by which the elements of z_t depend recursively on the elements of ε_t and therefore the ordering of variables in ε_t. Another solution is to apply the structural analysis of dynamic macroeconomic systems, which is hard to apply to financial data or other high frequency data because of the unclear links of causation. Therefore, Jordan decomposition[11] was employed by Hafner and Herwartz (2006) to decompose H_t such that identical and independent shocks can be retrieved from Eq. (5.2). The symmetric matrix of $H_t^{1/2}$ is decomposed as:

$$H_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t' \tag{5.9}$$

[10] See Appendix 5.A for the derivation of the equivalent vec-representation of a BEKK model.
[11] We also calculated VIRFs using spectral decomposition. Results are similar. However we adopt Jordan Decomposition as a preferred method as the former does not always generate a solution.

in which $\Lambda_t = diag(\lambda_{1t}, \lambda_{2t}, \lambda_{3t})$ is the diagonal matrix whose components $\lambda_{it}, i = 1, \ldots, 3$ denotes the eigenvalues of H_t. $\Gamma_t = (\gamma_{1t}, \gamma_{2t}, \gamma_{3t})$ is the matrix $3 * 3$ of the corresponding eigenvectors. Therefore, the independent shocks are defined as

$$z_t = H_t^{-1/2} \varepsilon_t \tag{5.10}$$

Hafner and Herwartz (2006) show that under the hypothesis of a non-Gaussian distribution, z_t is uniquely defined, which may be treated as shocks from the past that could affect each of the markets in the future.

Hafner and Herwartz (2006) show that if ε_t is normally distributed, Jordan decomposition cannot generate a unique shock vector z_t; however, if ε_t is not normally distributed, i.e. Student's t distribution, a unique z_t can be attained through the Jordan decomposition in Eq. (5.10) and may be treated as shocks from the past that could affect each of the markets in the future. The requirement of non-Gaussin distribution works well with empirical evidence that residuals are fat tailed (Meade, 2010).

5.4.2.3 Volatility impulse response functions

Hafner and Herwartz (2006) define the VIRF as the expectation of volatility conditional on an initial shock and history, subtracted by the baseline expectation that only conditions on history, which is given by:

$$V_t(z_0) = E[vech\,(H_t)|I_{t-1}, z_0] - E[vech\,(H_t)|I_{t-1}] \tag{5.11}$$

in which z_0 is an initial specific shock hitting the system at time 0, estimated from Eq. (5.10), I_{t-1} is the observed history up to time $t-1$, and $V_t(z_0)$ is the $N^* = N(N+1)/2$ vector of the impact of the identical and independent shock components of z_0 on the t-step ahead conditional variance-covariance matrix components. For a BEKK (1, 1) model with the number of dimension equal to 3, there will be 6 components in the $vech$ representation model of Eq. (5.11). Therefore, the first, fourth and sixth elements of $V_t(z_0)$ (denoted as $v_{1,t}$, $v_{4,t}$ and $v_{6,t}$

respectively) represent the reaction of the conditional variance of the first, second and third variable respectively to the shock, z_0, that occurred t periods ago.

Applied to a BEKK (1,1) and then the $vech$ representation, the one-step ahead VIRF is obtained as:

$$V_1(z_0) = R * \{vech(H_0^{1/2} z_0 z_0' H_0^{1/2}) - vech(H_0)\}$$

$$= RD_N^{+}(H_0^{1/2} \otimes H_0^{1/2}) D_N vech(z_0 z_0' - I_N) \quad (5.12)$$

in which H_0 is the conditional variance-covariance matrix at initial time 0, D_N denotes the duplication matrix defined by the property $vech(Z) = D_N vech(Z)$ for any symmetric $(N * N)$ matrix Z, D_N^{+} denotes the Moore-Penrose inverse of matrix Z, I_N is the identify matrix, $\otimes$ is the Kronecker Tensor product and R is identical to that specified in Eq. (5.8). And for any $t \geq 2$, the VIRF is:

$$V_t(z_0) = (R + F)^{t-1} RD_N^{+}(H_0^{1/2} \otimes H_0^{1/2}) D_N vech(z_0 z_0' - I_N)$$

$$= (R + F) * V_{t-1}(z_0) \quad (5.13)$$

Equation (5.13) shows that Hafner and Herwartz (2006) VIRF has the following distinctive properties in comparison with traditional Choleski decomposition impulse response function analysis of the conditional mean in linear systems:

1. The VIRF is a symmetric function of the shock, as opposed to an odd function in the traditional analysis, which can be shown by the feature of $V_t(z_0) = V_t(-z_0)$.
2. The VIRF is not a homogeneous function of any degree, in contrast to the traditional linear analysis.
3. The VIRF depends on the history through the volatility state H_0 at the time when the initial shock occurs. In contrast, the traditional impulse response functions do not depend on the history of the process.

4. The decay or persistence of shocks is measured by the moving average matrices $\Phi_t = (R + F)^{t-1}R$, which is analogous to the traditional analysis.

Hafner and Herwartz (2006) suggest that if z_t is a random variable with an identical and independent distribution, the response for the random shocks drawn from this predefined distribution at any time horizon can be calculated and a non-parametric estimation method, i.e. kernel estimation, could be applied to construct the distribution of volatility impulse responses. Moreover, if the baseline (the initial conditional variance-covariance state H_0) is also randomly drawn from an unconditional distribution, another distribution of volatility impulse responses at any time horizon could be estimated, again based on the same kernel estimation. Because of the flexibility of the VIRF method, there are several possible applications.

In our application, we focus on considering specific historical shocks, i.e. the 2008 Financial crisis, the BP Deepwater Horizon oil spill and the OPEC announcements. Our aim is to investigate the impact of an observed historical shock given the observed volatility at the date the shock occurs, which will give some empirical evidence on a past event. Another choice we have made is to consider random shocks and an observed conditional baseline from history, in which case we will be able to forecast the expectation of future conditional volatility given this level of volatility (baseline) and a specific level of shock. By then a value-at-risk estimation of a specific level of shock could be attained. This would be a particularly interesting point for a market participant when optimizing his/her portfolio when taking into risks into consideration.

5.5 Empirical analysis

In this section, we illustrate how return and volatility series are modelled and the VIRF analysis for crude oil markets. We focus on investigating several historical shocks that fall into our sample period. We fit the VIRF distribution[12] for random innovations generated from a predefined

[12]Note that we adopt the VIRF methodology developed by Hafner and Herwartz (2006) on the basis of a fully symmetric BEKK model. Other versions of BEKK, such as the diagonal and scalar BEKK models, are nested within our specification.

distribution, followed by the three significant historical events mentioned above, within the sample period.

5.5.1 Dynamic interdependencies in returns

A trivariate dynamics vector autoregression (VAR) model is set up to examine the market return behaviour. The residuals saved would allow us to further investigate a trivariate volatility dynamics model for discovering volatility transmission and then analysing volatility impulse response functions. The VAR analyses would show whether there exist interdependencies in the returns of oil prices within and across the three crude oil markets:

$$r_t^i = \{r_t^{WTI}, r_t^{DUBAI}, r_t^{Brent}\}$$

where $r_t^{WTI}, r_t^{DUBAI}, r_t^{Brent}$ stand for the returns of WTI, Dubai and Brent crude oil prices at time t. The lag length for the VAR model is determined using model information selection criteria, which indicate that the vector of three return time series are appropriately modelled by the VAR model with three lags.

The estimation results and diagnostic results are summarized in Table 5.2. The results in Panel A of Table 5.2 indicate that returns for all crude oil prices are interdependent but these interdependencies are not the same across the variables. r_t^{WTI} is dependent on by its first and third-lagged values, the third- lagged value of $r_t^{DUBAI}$and the first-lagged value of r_t^{Brent}. By contrast, r_t^{DUBAI} depends on its own first and third-lagged values, the first, second and third-lagged value of $r_t^{WTI}$and the first and second-lagged value of r_t^{Brent}. r_t^{Brent} has its dependence on all lagged values of r_t^{WTI}, r_t^{DUBAI} and its own displayed in Table 5.2.

The results of the diagnostic tests are reported in Panel B of Table 5.2. The Box-Pierce Portmanteau Q test on the standardized residuals show that serial correlation has been eliminated for all variables up to 12 lagged orders. The LM-ARCH test rejects the homoskedasticity hypothesis at the significance level of 1% up to 20 lagged orders for all variables. All residual processes show excess kurtosis, such that the normality assumption tested by the Jarque-Bera test is strongly violated at the significance level of 1%.

Table 5.2

Estimates of the VAR for returns of crude oil prices

	r_t^{WTI}		r_t^{DUBAI}		r_t^{Brent}	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Panel A: Estimation results						
Constant	0.000313	0.00059	0.000539	0.00060	0.000503	0.00058
r_{t-1}^{WTI}	-0.111844^{***}	0.06204	0.113951^{***}	0.06372	0.111395^{***}	0.06108
r_{t-2}^{WTI}	0.0533854	0.06187	0.130894^{**}	0.06355	0.111940^{***}	0.06092
r_{t-3}^{WTI}	0.201788^{*}	0.05846	0.268998^{*}	0.06004	0.231032^{*}	0.05755
r_{t-1}^{DUBAI}	-0.122972	0.1020	-0.393557^{*}	0.1047	-0.229695^{**}	0.1004
r_{t-3}^{DUBAI}	-0.172228^{*}	0.05662	-0.252543^{*}	0.05815	-0.219796^{*}	0.05574
r_{t-1}^{Brent}	0.205795^{***}	0.1107	0.206847^{***}	0.1137	0.0739988	0.1090
r_{t-2}^{Brent}	-0.0793701	0.06307	-0.173299^{*}	0.06478	-0.150058^{**}	0.06209
RSS	0.83739		0.88338		0.81169	
Panel B: Model Diagnostic						
Portmanteau (12)	5.25846		4.90572		6.93857	
Jarque-Bera Test	333.59^{*}		564.54^{*}		384.94^{*}	
LM-ARCH 1-20 Test	17.957^{*}		21.726^{*}		25.880^{*}	

Note: *, ** and *** denotes significance at the 1%, 5% and 10% level, respectively.

It is clearly indicated from the estimations and diagnostic analysis that a Student's t distribution rather than a Gaussian distribution may be employed to model the residuals obtained from the VAR system for constructing the volatility dynamics model.

5.5.2 Dynamic interdependencies in volatilities

We follow the trivariate BEKK model described in Eq. (5.3). The estimation of the BEKK model is implemented under normal and Student's t distribution assumptions for ε_t, namely

$\varepsilon_t|I_{t-1} \sim N(0, H_t)$ and $\varepsilon_t|I_{t-1} \sim g(\mathrm{H}_t^{-1/2})|\mathrm{H}_t^{-1/2}$, respectively. The estimated parameters of the conditional variances and covariances with associated standard deviation in parentheses and the likelihood function values are given in Table 5.3 and Table 5.4 for normal distribution and Student's t distribution, respectively. Generally, for both distributions, the conditional variance-covariance equations incorporated into the BEKK methodology effectively capture the volatility and cross volatility dynamics among the variables under consideration. Therefore, useful insights are uncovered by examining the changes in volatility transmission across crude oil markets.

For both distributions, some off-diagonal coefficients of A and G are statistically significant (reported in Table 5.3 and Table 5.4), implying that volatility spillovers are transmitted through the cross product of innovations as well as the squared innovations. This result indicates that volatility spillovers across crude oil markets should be included for crude oil volatility modelling. Higher levels of conditional volatility in the past are associated with higher conditional volatility in the current period. The estimated degree of freedom parameter of the Student's t distribution is $\nu = 4.02$[13] at the significance level of 1%. Comparing the log likelihood value for the BEKK model with different distribution assumptions, we find that the BEKK model with a Student's t distribution has a higher log likelihood value than the BEKK model with a normal distribution. We can regard both the significance of the estimated degree of freedom for the Student's t distribution and the higher log likelihood value achieved by the Student's t distribution as strong evidence for favouring a Student's t distribution for ε_t.

[13] Note that a Student's t-distribution tends to normality as its degree of freedom ν increases. A value close to 4 indicates a leptokurtic distribution for the residuals.

Table 5.3

Estimates of BEKK (1,1) model for crude oil returns with normal distribution $\varepsilon_t|\psi_{t-1} \sim N(0, \Sigma_t)$

C_0			A_{11}			G_{11}		
0.0028^{*}	0	0	0.3415^{*}	0.0594	0.0847^{***}	0.8796^{*}	-0.0503^{**}	-0.0623^{**}
(0.0005)			(0.0441)	(0.0454)	(0.0461)	(0.0249)	(0.0238)	(0.0265)
0.0027^{*}	0.0017^{*}	0	0.2211^{*}	0.4635^{*}	0.2890^{*}	-0.0624^{*}	0.9044^{*}	-0.0713^{*}
(0.0005)	(0.0002)		(0.0644)	(0.0628)	(0.0669)	(0.0231)	(0.0194)	(0.0206)
0.0029^{*}	0.0014^{*}	4.6e-8	-0.4089^{*}	-0.3239^{*}	-0.1564^{**}	0.1639^{*}	0.1115^{*}	1.0907^{*}
(0.0005)	(0.0002)	(0.0008)	(0.0710)	(0.0675)	(0.0716)	(0.0283)	(0.0222)	(0.0255)
λ_i								
0.9482 + 0.0456i	0.9482 - 0.0456i	0.9825	0.9685 + 0.0185i	0.9685 - 0.0185i	0.9649	0.9706 + 0.0154i	0.9706 - 0.0154i	0.9626
$Log\ (L)$	15313.983							

Note: standard errors in parentheses. $Log\ (L)$ is the value of the log – likelihood. The λ_i are the eigenvalues of the matrix $A_{11} \otimes A_{11} + G_{11} \otimes G_{11}$. *, **, and *** denotes significance at a 1%, 5% and 10% level, respectively.

Table 5.4

Estimates of BEKK (1,1) model for crude oil returns with Student's t distribution $\varepsilon_t|\psi_{t-1} \sim g\left(\Sigma_t^{-\frac{1}{2}}\right)|\Sigma_t^{-\frac{1}{2}}$

C_0			A_{11}			G_{11}		
0.0026^{*}	0	0	0.2212^{*}	-0.0534	-0.0257	0.9639^{*}	0.0144	0.0099
(0.0005)			(0.0469)	(0.0507)	(0.0461)	(0.0113)	(0.0132)	(0.0114)
0.0029^{*}	-0.0022^{*}	0	0.2623^{*}	0.7428^{*}	0.2885^{*}	-0.0874^{*}	0.6994^{*}	-0.1106^{*}
(0.0006)	(0.0002)		(0.0689)	(0.0762)	(0.0663)	(0.0206)	(0.0259)	(0.0031)
0.0022^{*}	-0.0008^{*}	0.0011^{*}	-0.3039^{*}	-0.4957^{*}	-0.0693	0.1070^{*}	0.2664^{*}	1.0812^{*}
(0.0005)	(0.0002)	(0.0002)	(0.0783)	(0.0792)	(0.0760)	(0.0225)	(0.0161)	(0.0122)
λ_i								
0.9992	0.9705	0.8685 + 0.0120i	0.8685 - 0.0120i	0.8944	0.9828	0.9828	0.8831 + 0.0045i	0.8831 - 0.0045i
$Log\ (L)$	15683.701							
ν	4.02							

Note: standard errors in parentheses. $Log\ (L)$ is the value of the log – likelihood. The λ_i are the eigenvalues of the matrix $A_{11} \otimes A_{11} + G_{11} \otimes G_{11}$. *, **, and *** denotes significance at a 1%, 5% and 10% level, respectively. ν is the estimated degree of freedom of the Student's t distribution.

Fig. 5.1 plots the estimated conditional variances, covariances and correlation dynamics obtained from the BEKK model with a Student's t distribution for crude oil WTI, Dubai and Brent. All three benchmarks crude oils show signs of volatility clustering, with Dubai having the highest value of conditional variance and WTI having the lowest during the course of the 2008 Financial crisis. The volatility spikes are caused by the unprecedented increase in fundamental uncertainty and speculative behaviour in crude oil futures markets (Kaufmann, 2011), which correspondingly causes the disconnection between markets, or downward spikes in the conditional correlations between WTI-Dubai and WTI-Brent. Among conditional covariance dynamics, those between Dubai and Brent have the highest value and that between Brent and WTI has the lowest. Correspondingly, the conditional correlation between WTI and Dubai is the most volatile and has the lowest value, followed by that between WTI and Brent. Furthermore, the most volatile period for the conditional variances, covariances and correlations is from July 2008 to July 2009, which coincides with the course of the 2008 Financial crisis, as well as the meteoric rise and subsequent collapse of the oil price.

We also report λ, the eigenvalues of the estimate of $A \otimes A + G \otimes G$[14] in Table 5.3 and Table 5.4. Their magnitudes are less than one but close to it, which suggests that covariances are stationary but with a high level of persistence in volatility transmission across markets, indicating that the duration of volatility transmissions is likely to increase. The high level of persistence suggests that more weight should be given to recent observations of volatility in terms of explaining future volatility. The high level of persistence in volatility transmissions is more significant for the BEKK model with a Student's t distribution than the BEKK model with a normal distribution because the largest eigenvalues reported in Table 5.4 are only slightly smaller than one. Given the data characteristics, we adopt Student's t distribution and Quasi Maximum Likelihood estimation for our analyses.

[14] $\otimes$ is the Kronecker Tensor product.

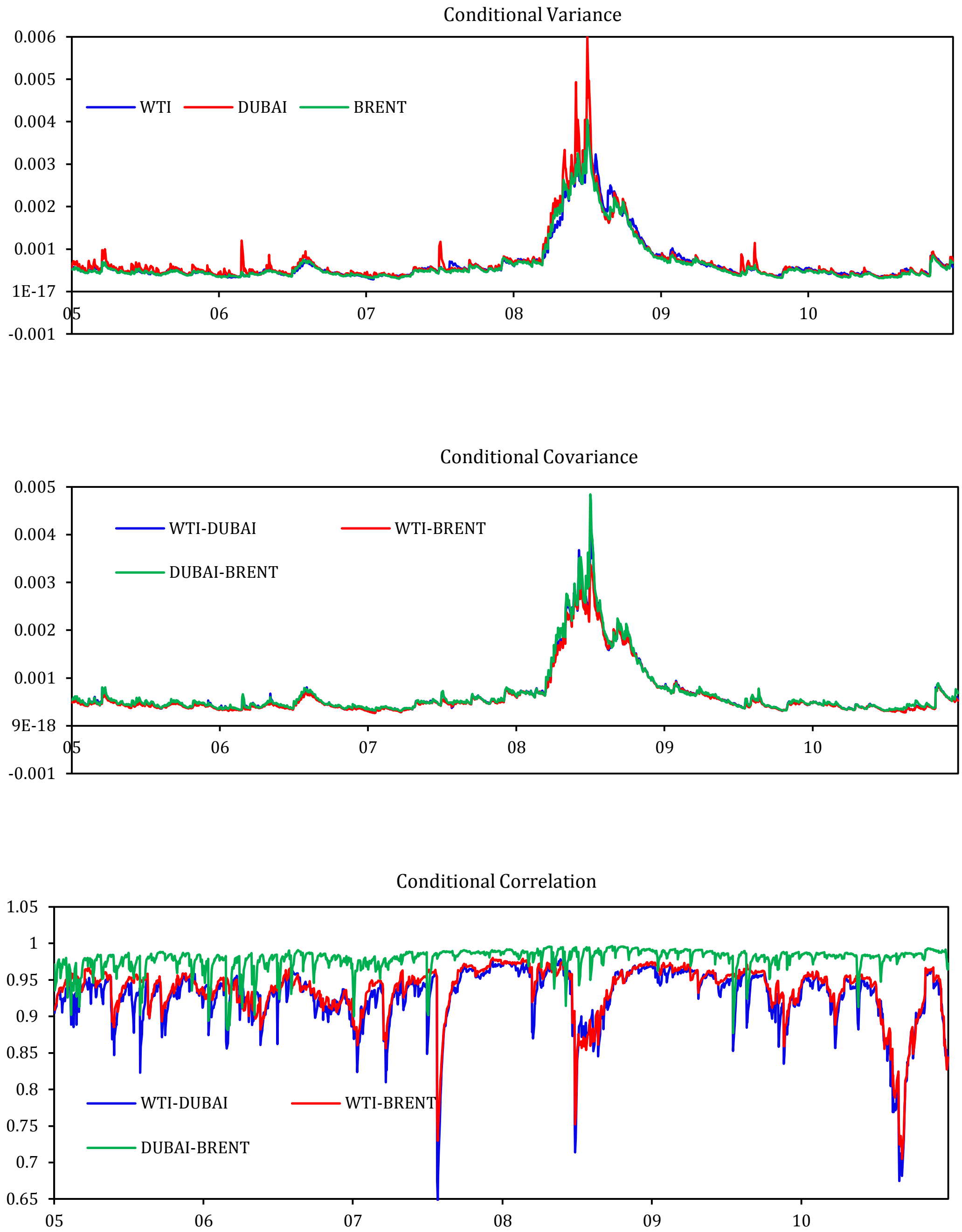


Fig. 5.1 Conditional variances, covariances and correlations for WTI, Dubai and BRENT crude oil returns obtained from the BEKK model with a Student's t-distribution.

5.5.3 Volatility impact from past events

In this section, we illustrate the VIRF analysis for crude oil markets. We first focus on investigating several historical shocks that fall into our sample period. We then fit the VIRF distribution for random innovations generated from a predefined distribution, followed by three significant historical events within the sample period, namely the 2008 Financial crisis (Lehman Brothers Bankruptcy), the BP Deepwater Horizon oil spill and the OPEC announcements. The estimated residual ε_t and the estimated covariance matrix H_t from the BEKK model with a Student's t distribution at the time of the historical shocks are used to calculate the $V_t(z_0)$. The impulse responses are scaled with respect to the estimated conditional volatilities at the time the shock occurred. This allows us to interpret the scales as percentage deviations of the 'shock scenario' with respect to the 'baseline scenario'.

5.5.3.1 Onset of the 2008 Financial crisis -Lehman Brother Bankruptcy

The 2008 Financial Crisis was triggered by the liquidity shortfall in the United States banking system caused by the collapse in the domestic housing market. The crisis culminated on September 15, 2008 with Lehman Brothers filing for bankruptcy. Why would this event, however, be relevant to the oil market? One of the many effects of the crisis was the reluctance of financial institutions to lend money either to each other or to commercial entities. For example, Aubouin (2009) observe "supply-driven shortages of trade finance have a potential to inflict further damages to international trade. Even if the lack of trade finance may not to be blamed entirely for the drop in world trade in the aftermath of the crisis, it is quite reasonable to assume that the uncertainty around the prospects of world economic growth permeated all commodity business (oil baseness in particular) is closely associated with changes in economic activity (Asmundson et al., 2011). It is, therefore, not an unreasonable proposition to examine the 2008 Financial Crisis in relation to oil prices.

To our knowledge, the impact of the 2008 Financial Crisis on crude oil markets has not been investigated so far. Therefore, we will employ the VIRF methodology to investigate the effect of the event on crude oil volatility in the returns of future prices within and across the WTI, Dubai and Brent markets.

Although spanning a period of at least several months, the news of the bankruptcy of Lehman Brothers on September 15, 2008 signaled the unraveling of a series of events that came to be known as the 2008 Financial Crisis. We therefore set this date as the base point for our analysis. However, we do not merely focus on analyzing the impact of the single shock on conditional expected volatility, but rather compare the average impulse responses obtained over a symmetric time window located around the bankruptcy of Lehman Brothers since numerous similar events took place after the Lehman Brothers filing for bankruptcy.

For a symmetric time window located around the bankruptcy of Lehman Brothers covering 31 trading days, Fig. 5.2 depicts the time profile of the average impulse response of volatilities of before the bankruptcy of Lehman Brothers (red lines) and after the event (blue lines) for crude oil WTI, Dubai and Brent, respectively. They show that on average there are large volatility increases resulting from the shock of the 2008 Financial crisis on all three conditional variances post-bankruptcy and relatively smaller volatility decreases resulting from the shocks on all three conditional variances pre-bankruptcy. This indicates the 2008 Financial crisis has a significant impact on oil markets across the globe. However, the size of the impacts is not the same for all crude oil markets. The smallest positive impact for the post-period can be observed for the returns of WTI as its one-step ahead expected conditional variance is only increased by 4%. The positive impact for the post-period in expected conditional variance of Dubai and Brent returns are about 100% and 70% respectively for the one-step ahead expected conditional variance. By contrast, the absolute magnitudes of the negative impact for the pre-period are relatively smaller than the corresponding ones of the positive impact for the post-period. The latter ones are 1.5%, 40% and 30% for the one-step ahead expected conditional variance of WTI, Dubai and Brent returns, respectively.

The results reported above indicate that both Brent and Dubai exhibit a high responsiveness to shocks (as seen by the scale on the Y-axis of the VIRF graphs in Figure 5.2) and their magnitudes are higher than that exhibited by WTI. This finding may reflect the position of Brent a leading price benchmark, followed by Dubai and WTI. WTI's position at the third place is reflected by its being increasingly decoupled from international oil marketplaces and becoming a domestic US crude. It may also coincide with a reversion of the WTI-Brent spread for the last 18 months or so. Furthermore, we have found similar patterns for WTI, Dubai and Brent from Fig. 5.3 to Fig. 5.4 (discussed in section 5.5.3.2 and section 5.5.3.3 below), which indicates that it is not simply because WTI was more responsive to previous news from the U.S. financial markets and has already adjusted downwards and demonstrated higher volatility at an earlier time.

Furthermore, a striking phenomenon of the effects of the shock is that the lengths of the impacts are relatively protracted, such that they cannot be cancelled even after about 50 days. This feature is attributable to the fact that several eigenvalues of the matrix $A \otimes A + G \otimes G$ reported in Table 5.3 and Table 5.4 are very close to unity.

To sum up our results, we can find that the window horizon after the Lehman Brothers bankruptcy can be described as a more volatile period than the window horizon before the event and the shocks that hit the returns at the window horizon of post Lehman Brothers bankruptcy are larger compared to their previous values for the year 2008, even before the bankruptcy of Lehman Brothers. Another interesting finding is that even if the shocks are absorbed by crude oil markets simultaneously, the responsiveness of crude oil markets from the impact of shocks are largely specific: Dubai and Brent are more volatile and sensitive than WTI in terms of the volatility impulse response analysis on the information source of Lehman Brothers bankruptcy.

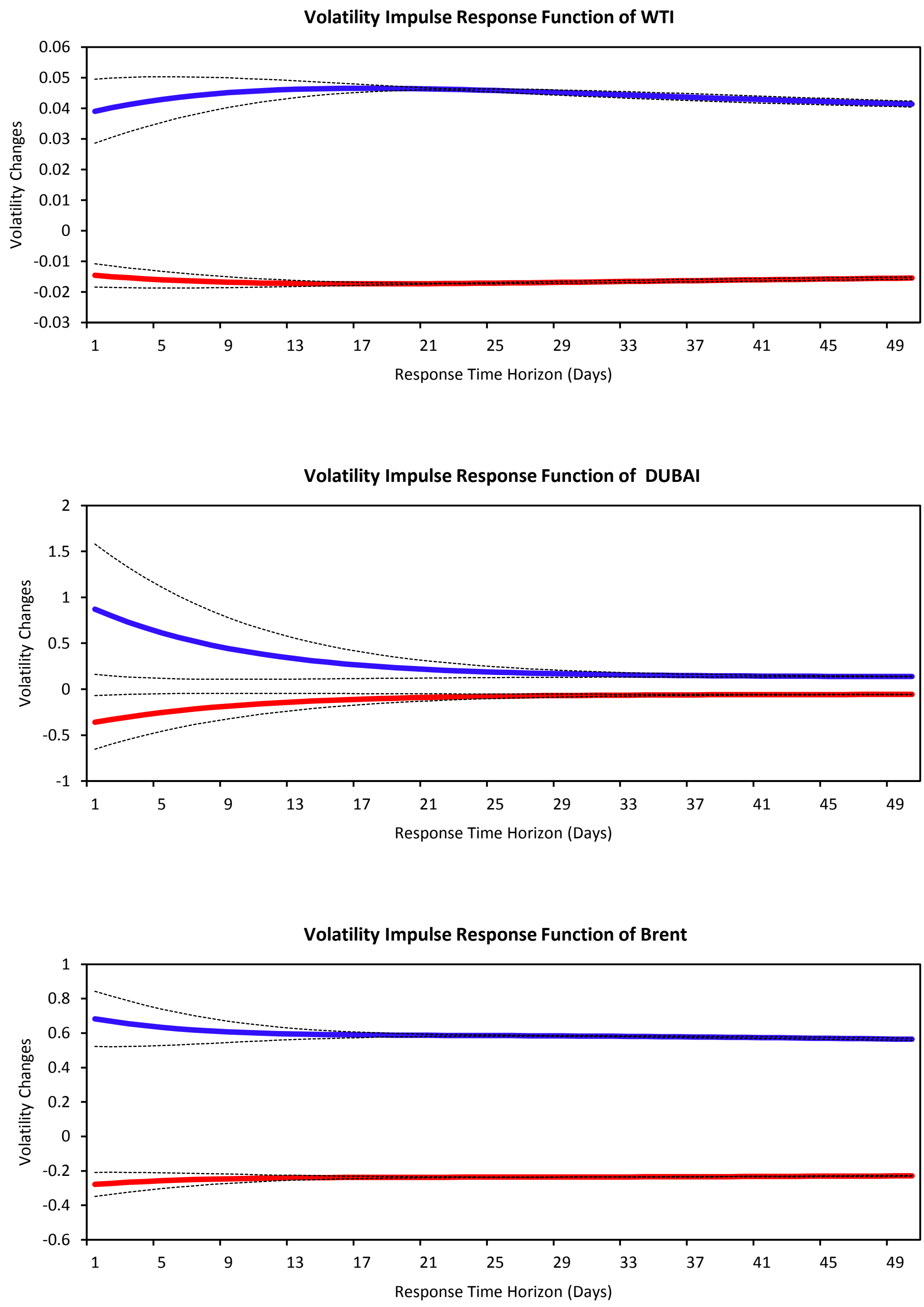


Fig. 5.2 Volatility impulse responses functions for the 2008 Financial Crisis around the bankruptcy of Lehman Brothers. The blue lines are averages of VIRF over a period from the filing of Lehman Brothers bankruptcy on September 15, 2008, until 15 days after it; the red lines are averages of VIRF over a period from 15 days prior to the filing until the day before the filing. The dotted black lines are the corresponding 95% confidence intervals.

5.5.3.2 BP deepwater Horizon oil spill

The Deepwater Horizon oil spill (Reuters, 2010) is a well documented event in the Gulf of Mexico, which followed the explosion of the offshore oil-drilling platform, Deepwater Horizon, on April 20, 2010. The leak was eventually stopped by capping the gushing wellhead on July 15, 2010 (Petroleum Economist, 2010). The event is of course directly linked to the oil industry, but it is of particular interest for two reasons: firstly, because of the short-term disruption it could cause to the supply of oil in the US Gulf (see Evans, 2010) and; secondly because of the ramifications it could have on the issue of new leases for oil exploration in the area and the implications for the mid- to long-term oil supply to the US market (see Hoyos, 2010).

In this study, we look into the impact of this event on crude oil volatility. We look into several specific dates rather than the whole time horizon during the period of oil spill because we are more concerned with the direct impact of the shocks of the first notice of oil spill on crude oils volatility. The timeline of the spill is summarized as follows:

- April 20, 9:45 p.m. Central Time Zone (North America): gas, oil and concrete from the Deepwater explode up the wellbore onto the deck and then catch fire.
- April 21: The platform continues to burn.
- April 22: The rig sinks and an oil leak is discovered in the afternoon when a large oil slick begins to spread around the former rig site.

We select April 23, 2010, as the event day of the spill for the purpose of our analysis, using the volatility impulse response function methodology. By this date the whole information on the oil leak following the explosion had been completely transmitted to crude oil markets and would be reflected in crude oil prices and their volatilities.

In Fig. 5.3 the estimated volatility impulse responses functions are presented for f crude oil WTI, Dubai and Brent, respectively. The volatility impulse responses to the shock on April 23 indicate that a positive impact has been exerted onto the expected conditional variance. For all three crude oil markets, the impact is instantaneous. In this context, Dubai is the crude oil with the most responsive pass-through from the shock to the one-step-ahead expected conditional variance illustrated by a 34% increase. For Brent, the expected conditional variance is significantly influenced by the spill shock. The one-step ahead conditional variance is increased by 14%. For WTI, the expected conditional variance is also significantly influenced by the spill shock with one-step ahead conditional variance increased by 12%. This result indicates that, as mentioned earlier, Dubai and Brent again demonstrate a higher responsiveness to the shock in comparison to WTI, which may infer a declining use of the latter as a global benchmark and more as a US domestic benchmark instead.

We also depict the time profile of the impulse response of expected conditional variance for the shocks of the rig catching fire (April 21), the rig sinking (April 22) and the first trading day following the information of oil spill (April 26). Obviously, for all three crude oil markets, the impact is instantaneously recorded. However, two significant differences, in comparison with the previous mentioned response from the oil spill on April 23, have been observed. Firstly, the impacts are negative, which mean that expected conditional variance following the shocks tends to decrease rather than increase as described in the previous case. Secondly, the size of the shocks in these cases is relatively smaller than in the previous case correspondingly. The comparison indicates that the impact of shocks depend on the current level of volatility and therefore only “large” shocks compared to the current level of volatility will result in an increase in expected conditional volatilities and relative “small” shocks seem to decrease expected conditional volatility.

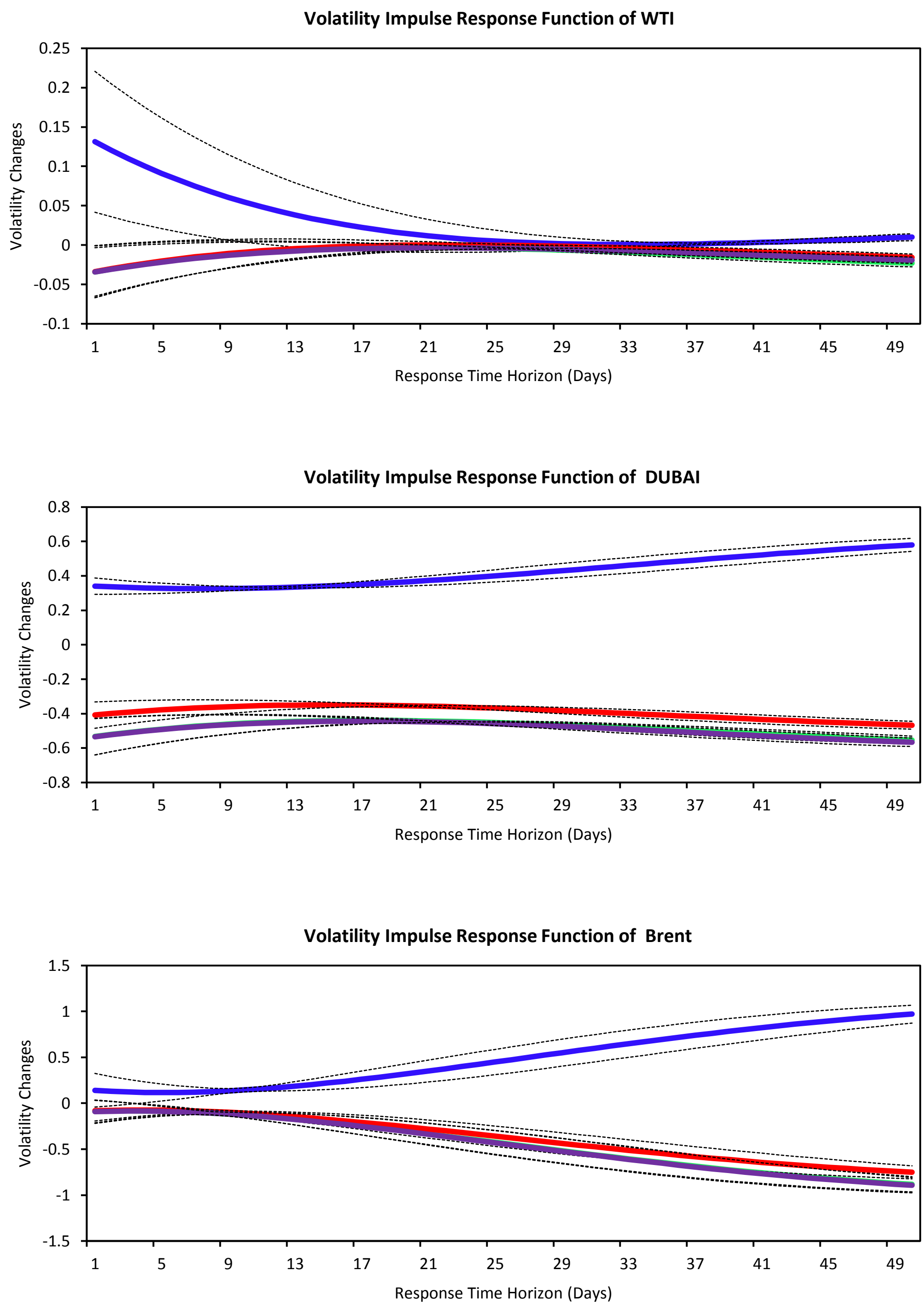


Fig. 5.3 Volatility impulse responses functions for the BP Deepwater Horizon oil spill on April 23, 2010. The blue lines are VIRF for shocks on April 23, 2010, the red lines are VIRF for shocks on April 21, 2010, the green lines are VIRF for shocks on April 22, 2010, and the purple lines are VIRF for shocks on April 26. The dotted black lines are the corresponding 95% confidence intervals.

5.5.3.3 OPEC Announcements

Many factors have been brought forth to explain the extreme movements in oil prices, among which OPEC's ability to effectively cartelize the oil market is the object of ongoing discussion (see Loderer, 1985; Smith, 2005; Fattouh, 2007). In 1982, OPEC established a system in which it regulates oil production among its members. Several times a year, OPEC schedules a conference to discuss on further oil production policies, based on its assessment of the current market condition.[15] OPEC's decision usually takes the form of an announcement, which sets an overall oil production ceiling for the cartel and individual production quotas for its members (see OPEC Secretariat, 2003). As a consequence of the announcements, there will be a particular channel through which OPEC can induce volatility: prior to OPEC conferences, there is usually rampant speculation about which decision on production levels (increase, no change, or decrease) the cartel will agree on (Schmidbauer and Rosch, 2012). However, empirical analyses on whether oil price changes are significantly triggered around OPEC meetings are ambiguous.[16]

In this analysis, we explore the information content of the OPEC announcements and attempt to identify whether the patterns of impact from the OPEC announcements are uniform with respect to the type of decision. For this purpose, we examine meeting summaries from the Official Resolutions and Press Releases published by the OPEC Secretariat and compile a list of official announcements on production decisions. In our analysis, each official press release is considered an event. Having compiled a list of events, we then classify each OPEC announcement in terms of production quotas increase, no change, and decrease. Overall, as reported in Table 5.5, a total of 24 OPEC meetings have been examined, of which 2 resulted in a production hike, 5 in a

[15] OPEC meets twice a year on prescheduled dates for 'ordinary' conferences but they also call for 'extraordinary' conferences with short notice. The ministerial meetings are held occasionally to resolve operational and monitoring problems in the organization; and sometimes they decide to change production levels. In our analysis, we do not intend to distinguish between scheduled and unscheduled events.

[16] Deaves and Krinsky (1992) examine the reaction of crude oil futures to OPEC meetings during the period 1970 – 1990. They find that the oil futures markets respond efficiently to OPEC announcements of "good news" in terms of bearish outcomes, but on the average, futures prices underreact to bullish outcomes. Horan et al. (2004) examine the implied volatility of crude oil options and provide evidence on the pre-meeting rise in implied volatility followed by a post-meeting drop in implied volatility, implying OPEC has a significant impact on oil prices. At a further comprehensive step, Lin and Tamvakis (2010) suggest that there exists significant differentiation in the magnitude and significance of market responses to OPEC quota decisions under different price bands. Further discussion about this issue could be found in Demirer and Kutan (2010).

production cut, and 17 in no change in production levels. We will not merely focus on analyzing the impact of a single announcement on expected conditional volatility, but rather compare the average impulse responses of the same type of decision.

Table 5.5

OPEC announcements summary

Date	OPEC announcement		
	Increase	No change	Decrease
2005-09-20	*		
2005-12-09		*	
2006-01-31		*	
2006-03-08		*	
2006-06-01		*	
2006-09-11		*	
2006-10-19			*
2006-12-14			*
2007-02-01			*
2007-03-15		*	
2007-09-11	*		
2007-12-05		*	
2008-02-01		*	
2008-03-05		*	
2008-10-24			*
2008-12-17			*
2009-03-16		*	
2009-05-28		*	
2009-09-09		*	
2009-12-22		*	
2010-03-17		*	
2010-10-14		*	
2010-12-11		*	
2011-06-08		*	

Fig. 5.4 depicts the time profile of the impulse response of volatilities for crude oil WTI, Dubai and Brent, respectively. There is a large negative impact of the OPEC's announcement with all types of decision on all three expected conditional variances. However, the size of the impact originating from the same type of decision is different for all oil markets. With regard to OPEC's decision to increase the production level, the largest decrease can be observed for Dubai crude oil

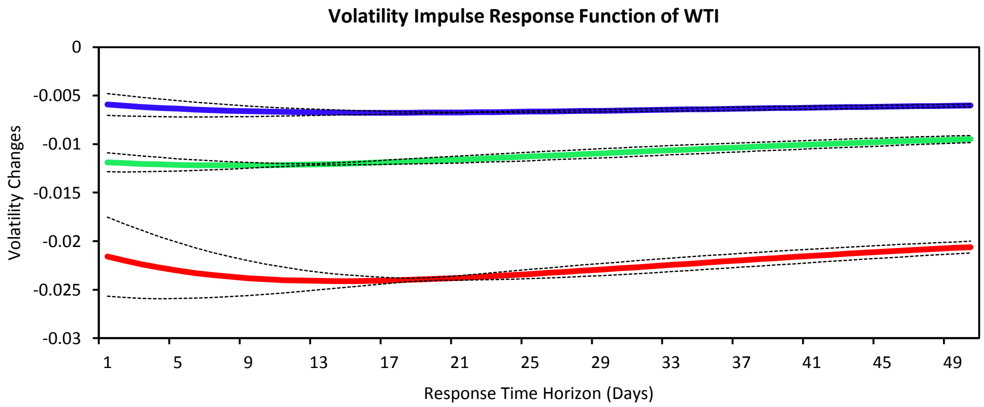
as its one-step ahead expected conditional variance is decreased by near 40%. The one-step ahead expected conditional variance for crude oil Brent is decreased by almost 35%. By contrast, the response of WTI crude oil is relatively small as its one-step ahead expected conditional variance is only decrease by 2%. A similar but less responsive pattern is also observed in the case of decisions to cut or maintain the production level for all crude oil markets.

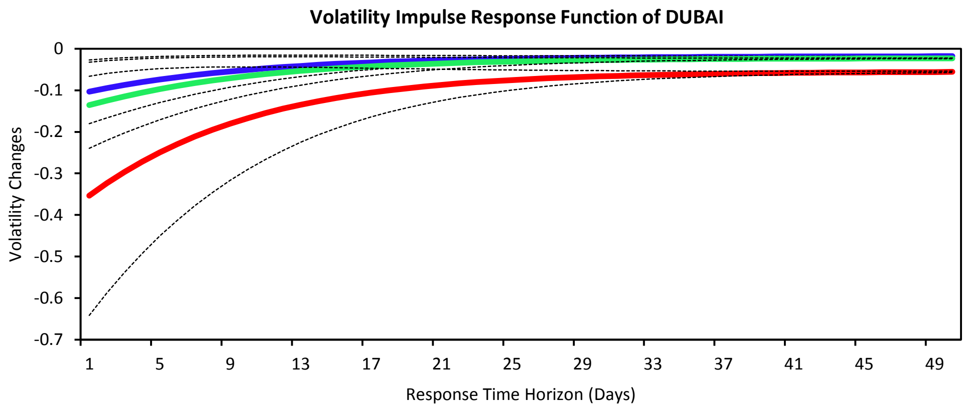
To sum up our analysis, the VIRF clearly shows us at least three findings. First, the patterns of impact from the OPEC announcements appear non-uniform with respect to the type of decision. Anticipation effects on volatility appear to be highly pronounced in the case of decisions to increase production level, which is illustrated by the largest decrease in expected conditional variance.[17] Second, there is significant differentiation in terms of the magnitude of market responses to OPEC decisions, in which Dubai crude oil absorbs the shock more efficiently and then reflected by the largest decline in one-step ahead expected conditional variance. Third, the negative impact of OPEC decisions on crude oil volatility gives rise to a hypothesis that information leakage is crucial in the creation of volatility as OPEC decisions are strongly anticipated by market players and then incorporated into the volatility of price changes in the post-announcement period. The drop in conditional variance after the OPEC announcements corroborates the finding of a post-meeting drop in implied volatility by Horan et al. (2004).[18] Our results reinforce the conception of the cartel's meetings as a "channel through which the OPEC can induce volatility" (Fattouh, 2005; Schmidbauer and Rosch, 2012).[19]

[17] This is in line with existing literature (e.g. Schmidbauer and Rosch, 2012).

[18] Wirl and Kujundzic (2004) conclude that, with data ending in 2001, OPEC's impact on the crude oil markets has weakened after 1985 and at best restricted to meetings recommending price increases.

[19] The rationale behind the significantly opposite pattern of VIRFs among the 2008 Financial crisis, the BP Deepwater Horizon oil spill and the OPEC announcements could be argued by the fact that OPEC announcements are not purely random events which cannot be anticipated and forecasted, such that market rational expectation about OPEC announcements result in the subsequent decrease of crude oil volatility no matter which scenario emerges. By contrast, the bankruptcy of Lehman Brothers in the peak of the 2008 Financial Crisis and the BP Deepwater Horizon oil spill were stochastic events and occurred without sufficient anticipation. These kinds of unanticipated events will cause the increase of conditional volatility subsequently.





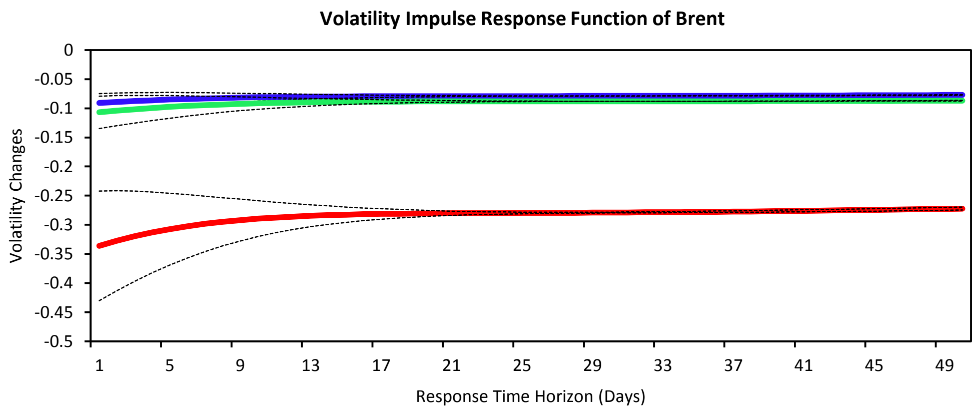


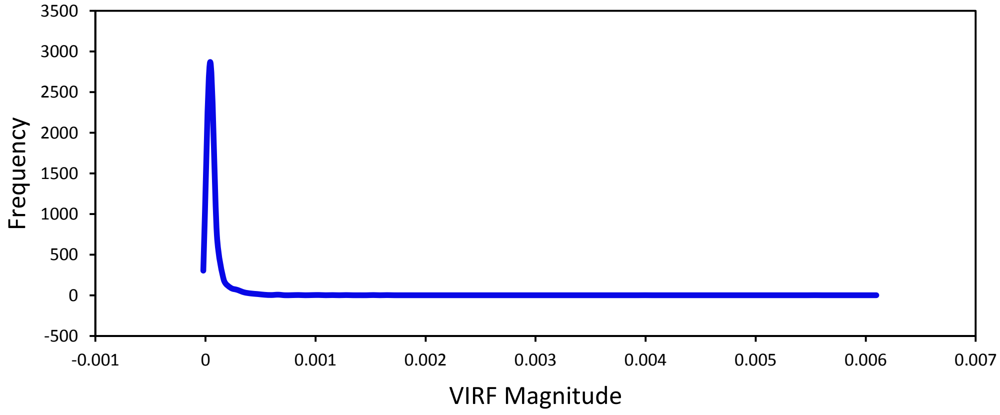
Fig. 5.4 Volatility impulse responses functions for the OPEC announcements with current production levels decreased (blue lines), unchanged (green lines) and increased (red lines). The dotted black lines are the corresponding 95% confidence intervals.

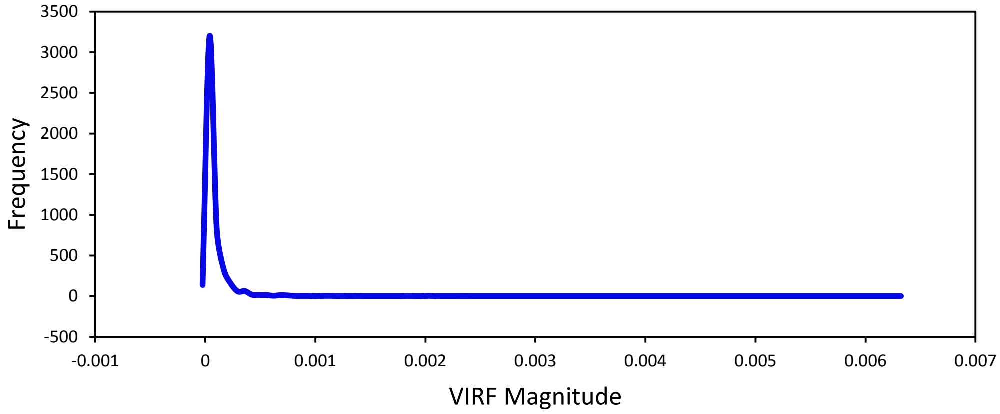
5.5.4 Simulated volatility impulse response distributions

Having demonstrated the impacts of historical events on expected conditional volatility of crude oil markets in previous section, we now estimate hypothetical random shocks and their associated volatility impulse responses to uncover the volatility impact of possible future shocks. The impact of a random shock can be measured by the notion of dispersion of the distribution of VIRF. However, Hafner and Herwartz (2006) prove that the distribution of VIRF will be asymmetric and far from being Gaussian, which indicates that only calculating the dispersion of the distribution of VIRF is not enough to generate the whole feature about the impact of a random shock on VIRF. Therefore, we simulate 100,000 realizations of the shock z_0 from an independent, standardized Student's t distribution with $\nu = 4.02$. The VIRF can then be calculated according to Eq. (5.13) using the estimated BEKK model, obtaining 100,000 realizations of VIRF for various time horizons. For three random horizons, h=1, h=5 and h=20, which corresponds with one-day, one-week and one-month forecasting, we then estimate the density by kernel density estimation.

We apply the observed conditional variance-covariance matrix obtained from the BEKK model on the date of Lehman Brother Bankruptcy (15 September, 2008)[20] to simulate shocks from a Student's t distribution with degree of freedom $\nu = 4.02$. The VIRF for abovementioned date is estimated subsequently.

[20] The dates are randomly chosen. We also tested the volatility impulse response distribution for simulated random shocks from other dates. The inferences were found to be robust irrespective of the dates chosen and results were similar to those reported in Fig. 5.5 to Fig. 5.7.





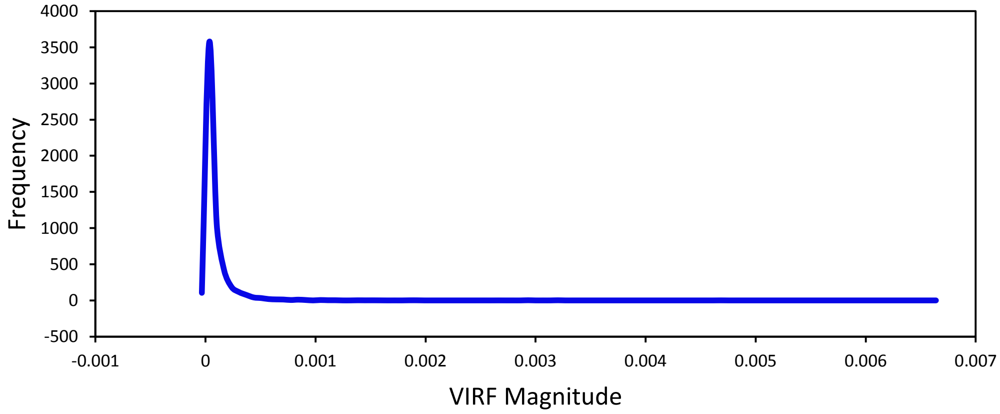


Fig. 5.5 Volatility impulse responses distribution (VIRFD) for WTI crude oil variances with a forecast time horizon h=1(top), h= 5 (middle) and h=20 (down) on September 15, 2008 (Lehman Brother Bankruptcy).

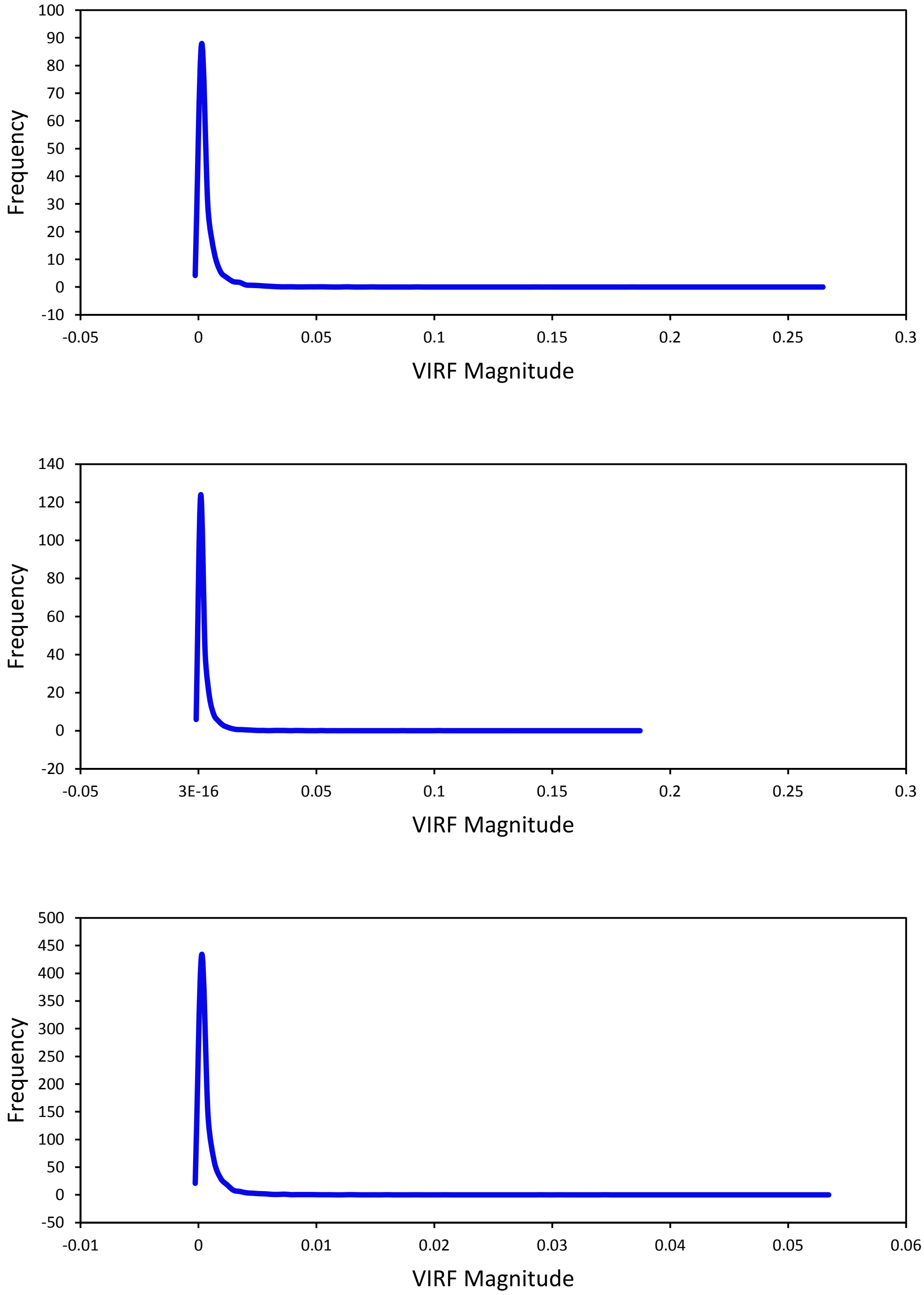


Fig. 5.6 Volatility impulse responses distribution (VIRFD) for Dubai crude oil variances with a forecast time horizon h=1(top), h= 5 (middle) and h=20 (down) on September 15, 2008 (Lehman Brother Bankruptcy).

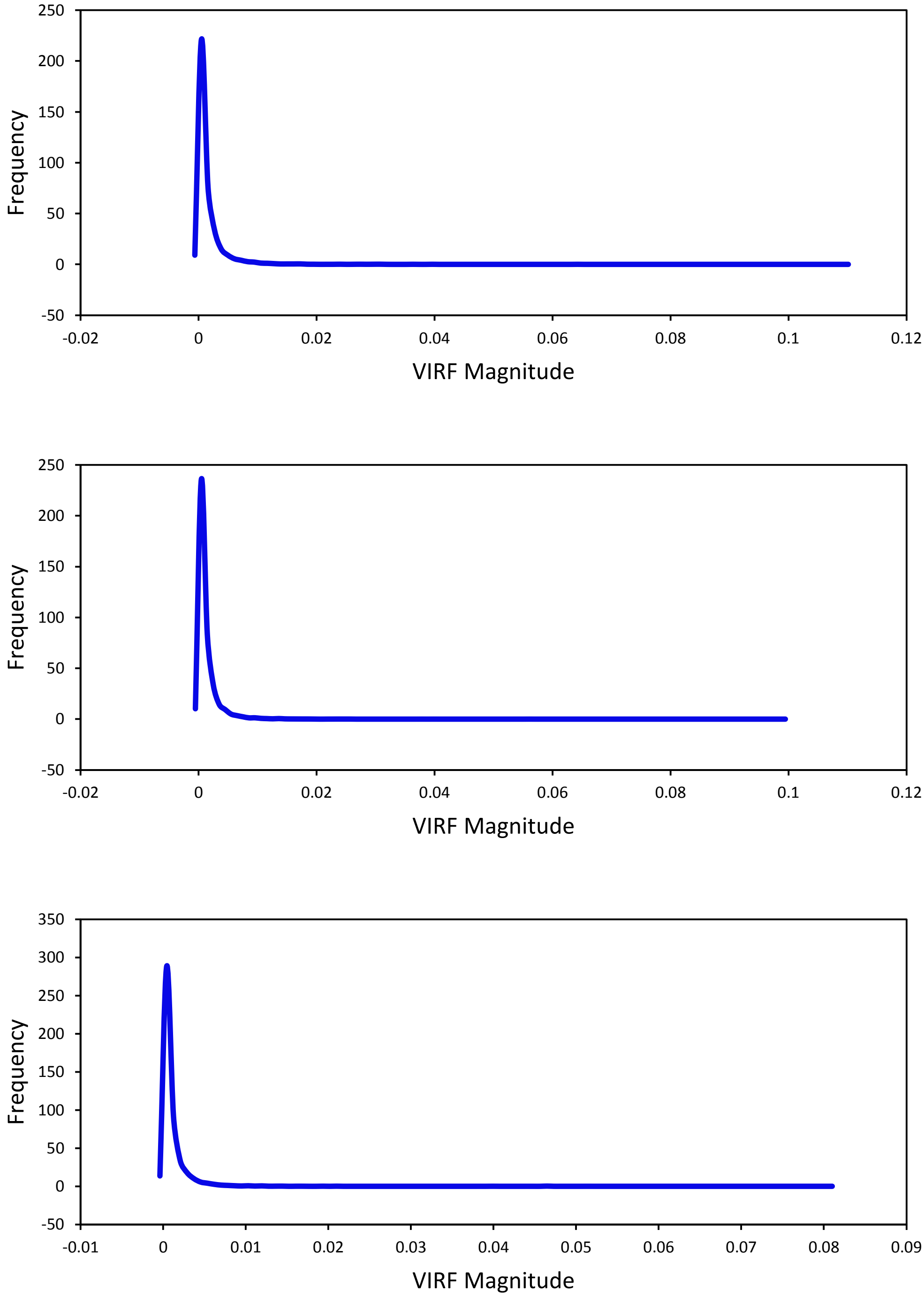


Fig. 5.7 Volatility impulse responses distribution (VIRFD) for Brent crude oil variances with a forecast time horizon h=1(top), h= 5 (middle) and h=20 (down) on September 15, 2008 (Lehman Brother Bankruptcy).

The estimated densities of the impact of a stochastic shock date t=15/09/08 are depicted on Fig.5.5 to Fig. 5.7 with forecast time horizons h=1 (top) day, h=5 (middle) days and h=20 (down) days for crude oil WTI, Dubai and Brent, respectively. The VIRF distributions are highly skewed to the right-hand side, indicating that the probability of observing a large positive impact of a shock is very low while the probability of a relatively smaller positive impact is much higher. In comparison with the other two crude oils, the VIRF distributions for Dubai crude (Fig. 5.6) show that they have the highest probability of observing a very large positive impact. However, as the time horizon increases the VIRF become more and more centred around zero, indicating the gradual fading of the impact of the shock.[21]

5.5.5 Forecasted volatility impulse response analysis for a given random shock (Value-at-Risk analyses)

We now proceed to forecast the change in future volatility in terms of volatility impulse response analysis for a given possibility of a random shock from an innovation distribution. This setting will correspond to a situation where we can observe the current state of volatility and forecast the change in future volatility given the known probability of the possible, still unobserved, shock (e.g. economic downturn). We use shock z_0 from independent, standardized Student's t distribution with degrees of freedom $\nu = 4.02$ and we assign to the occurrence of the random shock as $p = \{0.01, 0.025, 0.05, 0.1, 0.2, 0.25, 0.3, 0.4, 0.45\}$. We estimate the VIRF up to five hundred steps ahead for expected conditional variance in crude oil returns within the WTI, Dubai and Brent markets. We estimate VIRF for the date t=30/06/11, which is the last date in our sample period.

[21] Similar results are observed for other dates. Given the similarity among the VIRF fitted distribution on other random dates, it seems that the change in the initial condition H_0 does not have a significant effect on the VIRF distributions.

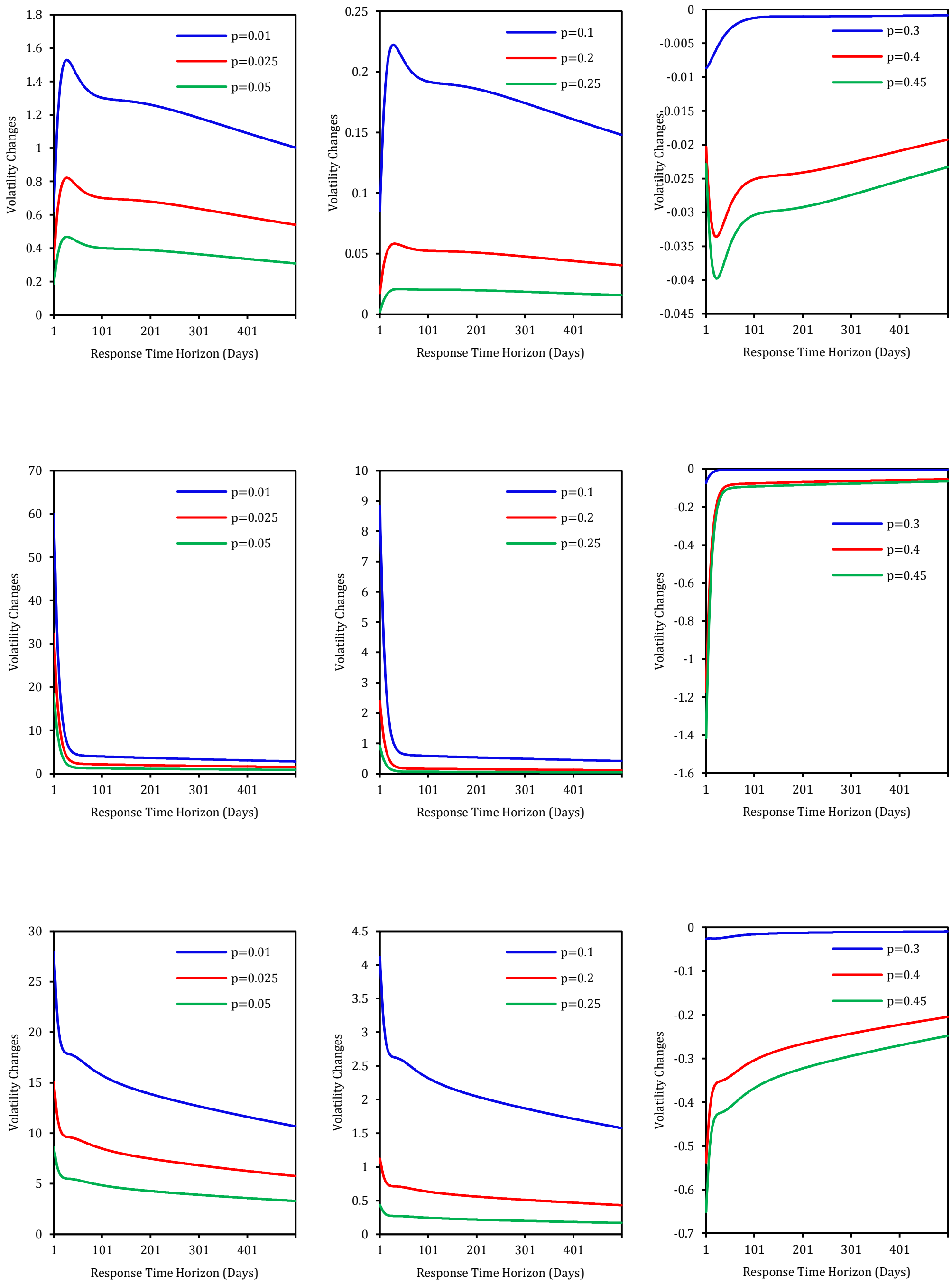


Fig. 5.8 Volatility impulse responses functions for a given possibility of a random shock on June 30, 2011. From top to down: WTI, Dubai and Brent crude oil variance.

The estimated time profiles of the impulse response of volatilities are depicted in Fig. 5.8. The first columns of Fig. 5.8 plot the impulse response of volatilities corresponding to a random shock with a probability of $p = 0.01$ (blue lines), $p = 0.025$ (red lines), and $p = 0.05$ (green lines); the second columns of Fig. 5.8 plot the impulse response of volatilities corresponding to a random shock with a probability of $p = 0.1$ (blue lines), $p = 0.2$ (red lines), and $p = 0.25$ (green lines), which indicate that there is a positive impact of the shock on all three expected conditional variances. The size of this specific impact for a given probability is however not the same for all crude oil markets and the size of the positive impact of the shock on a specific crude oil market gradually declines following the increase of the probability of the shock.

The third columns of Fig. 5.8 plot the impulse response of volatilities corresponding to a random shock with a probability of $p = 0.3$ (blue lines), $p = 0.4$ (red lines), and $p = 0.45$ (green lines), which indicate there is a small negative impact of the shock on all three expected conditional variances in crude oil returns within the WTI, Dubai and Brent markets. The size of this specific impact for a given possibility is however not the same for all crude oil markets and the size of the negative impact of the shock on a specific crude oil market is gradually increased following the increase of the probability of the shock.

The VIRF presented here shows us at least three results. Firstly, only a “large” shock (with smaller probability of occurrence) will result in increased expected conditional volatilities. For example, in the Dubai market with graphs illustrated in Fig. 5.8, a large shock may increase its expected conditional variance by 600% even though the probability of the shock is as small as 0.01(or 1%). By contrast, its one-step ahead expected conditional variance is only increased by 100% when the probability of the shock is equal to 0.25(or 25%). Secondly, the probability of $p = 0.3$ seems to be the critical transition point for the impact of the shocks. A probability higher than 0.3 indicates a “small” shock and normal market conditions, where the expected conditional variance tends to gradually reduce. Therefore, the impact of a given shock will be reversed to be negative following the increase of the possibility of the shock over the critical transition point.

Thirdly, the size and the dynamics of the impact of a given shock are largely market specific as Dubai crude is the most sensitive and information-efficient, which is reflected by the relatively large response from the given shock in comparison with other two markets. This finding may implicate the position of Brent a leading price benchmark, followed by Dubai, both of which push WTI into third place and making it more of domestic US crude oil.

This VIRF illustrated above can be used as a risk warning method that gives us the entire probability distribution of the risk that is still unidentified. It could help the development of risk matrix among risk professionals. This is a powerful risk prediction method that can find its use for investors, traders and other market participants.

5.6 Conclusion

We analyze the volatility transmission effects among three crude oil markets using a VAR-BEKK model. The results demonstrate that Brent crude is highly responsive to market shocks, which is concomitant with its position as a leading benchmark for crude oil pricing. Our findings also suggest that Dubai crude demonstrates similar, but scaled down, properties to that of Brent. Probably the most interesting result is that WTI shows the least responsiveness of the three benchmarks, which adds evidence to the recent developments in WTI prices, which have seen its relationship with Brent prices reverse and its position to be viewed increasingly as that of a dominant US domestic crude, rather than as an international benchmark. We also quantify the size and persistence of volatility connections of the three oil benchmarks through VIRF analyses. We analyse three historical shocks, namely the 2008 Financial Crisis, the BP Deepwater Horizon oil spill and the OPEC Announcements, and observe that the first two events have large and positive impacts on expected conditional variance, whereas the last event has relatively small and negative impact on expected conditional variance. We then simulate random shocks drawn from the estimated data generating process to fit the VIRF distributions and show the estimated VIRF distributions are asymmetric and highly skewed to the right, indicating the probability of observing a large positive impact of a shock is very low while the probability of a relatively smaller positive impact is much higher. In comparison with the other two crude oils, the VIRF distribution for Dubai crude shows that it has the highest probability of observing a very large positive impact. Furthermore, we simulate the VIRF for a given possibility of a random shock which can be used as risk measure to be applied by investors and risk professionals. Again Dubai crude is the most sensitive in this measure.

A number of shortcomings and research opportunities could be followed to improve this study. Our empirical results may be sensitive to the data frequency. Thus, it would be interesting to consider other data frequencies, for example, high frequency data (tick-by-tick) and weekly data, which will provide an opportunity to examine the robustness of this study to data frequency. This study could be extended into describing the impact of shocks on conditional covariances and then correlations, which will be of practical importance to financial practitioners in making optimal portfolio allocation decisions. Furthermore, the VIRF methodology could be extended in two ways: to incorporate asymmetric effect in conditional volatility, which could be captured by the asymmetric BEKK model and to analyze the impacts of shocks on third and higher moments of a distribution, which has been pioneered by Jondeau and Rockinger (2009). Both these extensions will be the object of our future work.

In the following chapter, which is the closing chapter, we will summarize the main empirical findings of this thesis, discuss the implications, and suggest potential interesting paths of future research as directed by the findings of this thesis.

Appendix 5.A

The derivation of the unique equivalent Vec-representation of a BEKK model is straightforward. For a vector stochastic process $\{r_t\}$ of dimension $3*1$ as the returns series of crude oil prices, the BEKK (1, 1) is given by:

$$H_t = C_0 * C_0' + A * \varepsilon_{t-1} * \varepsilon_{t-1}' * A' + G * H_{t-1} * G' \qquad (5.A.1)$$

In which:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix}, C_0 = \begin{bmatrix} \omega_{11} & 0 & 0 \\ \omega_{21} & \omega_{22} & 0 \\ \omega_{31} & \omega_{32} & \omega_{33} \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, G = \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix}, \varepsilon_{t-1} = \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{bmatrix}$$

Therefore, the Vec-representation of the BEKK (1, 1) model is given by:

$$vech\ (H_t) = vech(C) + R * vech(\varepsilon_{t-1} * \varepsilon_{t-1}') + F * vech(H_{t-1}) \qquad (5.A.2)$$

In which:

$$vech\ (H_t) = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{13,t} \\ h_{22,t} \\ h_{23,t} \\ h_{33,t} \end{bmatrix}, vech(C) = \begin{bmatrix} \omega_{11}^2 \\ \omega_{11}\omega_{21} \\ \omega_{11}\omega_{31} \\ \omega_{21}^2 + \omega_{22}^2 \\ \omega_{21}\omega_{31} + \omega_{22}\omega_{32} \\ \omega_{31}^2 + \omega_{32}^2 + \omega_{33}^2 \end{bmatrix}, vech(\varepsilon_{t-1} * \varepsilon_{t-1}') = \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}^2 \\ \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}^2 \end{bmatrix}, vech\ (H_{t-1}) = \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{13,t-1} \\ h_{22,t-1} \\ h_{23,t-1} \\ h_{33,t-1} \end{bmatrix}$$

And

$$R = \begin{bmatrix} a_{11}^2 & 2a_{11}a_{12} & 2a_{11}a_{13} & a_{12}^2 & 2a_{12}a_{13} & a_{13}^2 \\ a_{11}a_{21} & a_{12}a_{21} + a_{11}a_{22} & a_{13}a_{21} + a_{11}a_{23} & a_{12}a_{22} & a_{13}a_{22} + a_{12}a_{23} & a_{13}a_{23} \\ a_{11}a_{31} & a_{12}a_{31} + a_{11}a_{32} & a_{13}a_{31} + a_{11}a_{33} & a_{12}a_{32} & a_{13}a_{32} + a_{12}a_{33} & a_{13}a_{33} \\ a_{21}^2 & 2a_{21}a_{22} & 2a_{21}a_{23} & a_{22}^2 & 2a_{22}a_{23} & a_{23}^2 \\ a_{21}a_{31} & a_{22}a_{31} + a_{21}a_{32} & a_{23}a_{31} + a_{21}a_{33} & a_{22}a_{32} & a_{23}a_{32} + a_{22}a_{33} & a_{23}a_{33} \\ a_{31}^2 & 2a_{31}a_{32} & 2a_{31}a_{33} & a_{32}^2 & 2a_{32}a_{33} & a_{33}^2 \end{bmatrix}$$

$$P = \begin{bmatrix} g_{11}^2 & 2g_{11}g_{12} & 2g_{11}g_{13} & g_{12}^2 & 2g_{12}g_{13} & g_{13}^2 \\ g_{11}g_{21} & g_{12}g_{21} + g_{11}g_{22} & g_{13}g_{21} + g_{11}g_{23} & g_{12}g_{22} & g_{13}g_{22} + g_{12}g_{23} & g_{13}g_{23} \\ g_{11}g_{31} & g_{12}g_{31} + g_{11}g_{32} & g_{13}g_{31} + g_{11}g_{33} & g_{12}g_{32} & g_{13}g_{32} + g_{12}g_{33} & g_{13}g_{33} \\ g_{21}^2 & 2g_{21}g_{22} & 2g_{21}g_{23} & g_{22}^2 & 2g_{22}g_{23} & g_{23}^2 \\ g_{21}g_{31} & g_{22}g_{31} + g_{21}g_{32} & g_{23}g_{31} + g_{21}g_{33} & g_{22}g_{32} & g_{23}g_{32} + g_{22}g_{33} & g_{23}g_{33} \\ g_{31}^2 & 2g_{31}g_{32} & 2g_{31}g_{33} & g_{32}^2 & 2g_{32}g_{33} & g_{33}^2 \end{bmatrix}$$

In general, any given BEKK model has a unique equivalent Vec-representation (Engle and Kroner, 1995), while the reverse is not true. It is possible that a Vec-model has no equivalent BEKK representation.

Chapter 6

Summary, Discussion, and Further Research

6.1 Introduction

Crude oil markets around the world are undergoing rapid financialization and integration, leading to more competition, increased volatility in crude oil prices and exposing participants to potentially much greater risks. The financialization of crude oil markets impacts both consumers and producers and has led to a heightened awareness of the need for identifying, quantifying and then managing the risks. The increasing integration of crude oil markets all over the world has generated a good deal of interest in understanding the volatility spillover effects from one market to another. As a result, it is of considerable interest to energy economists to understand, model oil price volatility and promote applications in risk management in a multivariate framework. Therefore, the objective of this thesis will be on explaining the dynamic interdependencies in petroleum markets and further demonstrate whether the existence of such interdependencies prompt for the need to assess risk differently, which has been explored in three aspects in three cohesive and related chapters: the investigation of optimal hedging strategy in petroleum markets (Chapter 3), the discussion of the theory and applications of multivariate GARCH models to oil and stock markets in China (Chapter 4), and the application of the volatility impulse response function (VIRF) to crude oil futures markets (Chapter 5).

In the literature, although volatility modeling and hedging strategies in a multivariate framework have been widely documented in crude oil markets, few studies have analyzed in depth the nature of volatility spillovers and asymmetric effects of spot and futures prices in gasoline and heating oil markets. Therefore, it is within the context of previous limited empirical work that Chapter 3 is conducted to fill this gap by modeling volatility spillovers and asymmetric effects in crude oil (WTI), gasoline and heating oil markets and then constructing an optimal hedging strategy. The growing significance of crude oil markets to investors and portfolio managers in Chinese stock market, coupled with a lack of sufficient research to characterize volatility dynamics, paint the background of Chapter 4. Our reported evidence of volatility transmission between crude oil markets and stock market in China has in turn led us to construct an optimal oil-stock portfolio with the aim to exploit optimal portfolio management signals. Finally, Chapter 5 is firstly inspired by a novel methodology designed to test market integration in terms of volatility transmission and thus market efficiency, and secondly, by the lack of attention in the existing literature to the distribution of volatility that could be used to determine the cost of capital, for assessing investment and leverage decisions, and for computing the optimal hedge ratio and portfolio weights as many financial instruments, especially options[1], are priced according to the entire price distribution as well as the distribution of volatility[2].

6.2 Summary of the findings and conclusions

In this thesis we have examined many empirical issues relating to the modelling and exploitation of information contents in petroleum markets from three different perspectives, elaborated upon in three self-contained chapters. The topics studied in this thesis range from risk quantification, volatility/correlation modeling, futures hedging as well as identification of risk factors. All essays have many things in common. First, they all focus on time series properties of petroleum prices. Second, they all explicitly model the return volatilities and correlations of these assets in a multivariate framework. Third, they all aim on accurate risk assessment and enhanced forecasting ability. The balance of this thesis explores the importance of volatility spillovers and asymmetry in petroleum markets and their influence on optimal hedging strategy, the volatility transmission mechanisms between crude oil and Chinese stock market which provide insight into means of building accurate valuation models and accurate forecasts of the volatility of both

[1] For example, put options for negative skewed assets are more expensive thus indicating that volatility is not a sufficient criterion to price derivatives.
[2] Hull and White (1987) suggest that this is of much concern for option pricing using stochastic volatility.

markets, and discovering the impact of historical innovations on conditional volatility which is helpful for the successful implementation of hedging strategies as well as the evaluation of risk measures and investment policies. Therefore, the whole research of this thesis is a cohesive and continuous process to comprehend the evolution of prices, volatilities, correlations and economic relationship among economic variables. It will help market participants (i.e. crude oil producers and consumers, refiners, portfolio managers, commodity traders etc.) develop efficient risk measurement schemes and devise sound risk management strategies.

6.2.1 Chapter 3: Optimal hedging strategies in petroleum markets

While the risks faced by petroleum industry are various and differ throughout the sectors of the industry, -from upstream to downstream- price risk is universal to all. Chapter 3 addressed the concept of hedging oil price risk. Oil price risk management has always been a vital part of the successful operation of oil-related business. A key parameter in devising effective futures hedging strategies is the hedge ratio. Traditionally, hedge ratios are estimated to minimise the variance of the hedged portfolio. To allow for time-dependency in the hedging decision, GARCH models have been widely used (Kroner and Sultan, 1993). After considering the evidence of volatility spillovers and asymmetric effects in petroleum markets, this chapter presented the VARMA-AGARCH model of McAleer et al. (2009) with DCC structure to investigate the hedging effectiveness of petroleum futures.

Results indicate that, for the WTI crude oil and gasoline market, the optimal portfolio weights obtained from all multivariate volatility models suggest holding spot in larger proportion than futures. On the contrary, for the heating oil market, the optimal portfolio weights obtained from all multivariate volatility models suggest holding futures in larger proportion than spot. In the case of minimizing risk by using a hedge, a long position of one dollar in the petroleum spot markets should be shorted by a large cents in the petroleum futures markets. The hedging effectiveness indices indicate that the VARMA-AGARCH model with DCC structure is the best for

OHR calculation in terms of the variance of portfolio reduction and the BEKK model is the worst for OHR calculation in terms of the variance of portfolio reduction. Overall, the results indicated that volatility spillovers and asymmetry may be able to offer superior gains to market agents, measured in terms of both variance reduction and increase in utility. These findings held even when we examined the downside risk and Value-at-Risk analysis.

6.2.2 Chapter 4: Oil market and Chinese stock market

Chapter 4 addressed the concept of volatility interdependencies between crude oil market and Chinese stock market with implication to optimal portfolio management. As there is an increasing trend of financial globalization throughout the world, dynamic links through volatility transmission across capital markets are of greater interest to the financial community. This issue has been extensively investigated in the context of international asset markets and has been expanded to the context of crude oil and stock markets following the financialization of crude oil markets.[3] For a robust estimation of the volatility interdependencies between crude oil market and Chinese stock market, the asymmetric version of BEKK model proposed by Grier et al. (2004) was employed. By considering the volatility spillovers and asymmetries between crude oil and Chinese stock markets, the optimal portfolio management was more efficient.

Results indicate that oil price fluctuations constitute a systematic asset price risk at the sector level. This implies that the knowledge of the relative sensitivities of sector stock returns to changes in oil prices would be of benefit for risk management purposes and it is important for investors to fully account for the differences in sectoral oil sensitivities when implementing sector-based investment strategies. Moreover, we find that the correlations between oil and stock markets (sectors) are time-varying and must be modelled as such. Finally, our investigation of optimal portfolio weights and hedge ratios indicates that optimal portfolios should have more stocks than oil assets and that the stock investment risk can be hedged with relatively low

[3] Please see Syriopoulos (2007) for stock markets, Wang et al. (2007) for monetary markets, and Johansson (2008) for bond markets. These studies generally find evidence of significant volatility transmissions across markets, and the degree of volatility transmissions is highly dependent on economic and financial integration.

hedging costs by taking a short position in the oil futures markets. Overall, our analysis suggests that oil assets can be treated as a dynamic and valuable asset class that helps improve the risk-adjusted performance of a well-diversified portfolio of sector stocks and serves to hedge oil risk more effectively.

6.2.3 Chapter 5: Volatility impulse response function in oil markets

The last empirical part of this thesis, Chapter 5, deals with an important issue in crude oil market dynamics, volatility impulse response functions (VIRFs).[4] Although some research has been conducted to investigate the volatility transmission effect in crude oil markets (see Chang et al., 2010; Kang et al., 2011), little is known about how a shock to one market influences the dynamic adjustment of volatility to another market and the persistence of these transmission effects. Following a shock (in a given market), the entire price distribution as well as the distribution of volatility has been a cause of great concern for market participants. When a shock is expected to have a low and/or a non-persistent impact on volatility, then portfolio rebalancing may be postponed to limit transaction costs. Option pricing will be more accurate with the help of forecasting the distribution of volatility. This chapter exploits the information content of historical events on expected conditional volatility and describes the dynamic volatility interdependencies among three benchmark oil markets, i.e. WTI, Dubai, and Brent. By employing the VIRF methodology, we are able to obtain this distribution at any desired horizon and then build several scenarios, using the "stress testing" methodology, to evaluate the riskiness of a derivative asset.

Whereas impulse response analysis has mainly focused on the impact of shocks on the conditional mean of returns, we are more interested in their impact on conditional variance as measured by the VIRFs. In comparison with Lin's (1997) model, the VIRFs depend on both the volatility state and the unexpected returns vector when the shock occurs, which indicates that a

[4] The concept of volatility impulse response function is recently developed by Hafner and Herwartz (2006).

given shock will not always increase expected conditional volatility. Results indicate that Brent and Dubai crude are highly responsive to market shocks, whereas WTI crude shows the least responsiveness of the three benchmarks, which creates questions about its predominance as a benchmark crude oil. While the VIRF methodology is primarily used to aid our understanding of the market responsiveness to historical events, the methodology is also found useful when forecasting the distribution of volatility at any desired horizon as well as in risk measures such as Value-at-Risk. Results from these simulated random shocks indicate that the probability of observing a large impact of a shock is lower whereas the probability of a relatively smaller impact is much higher, as well as only a "large" shock (derived from a smaller probability) will result in an increase in expected conditional volatilities. These features denote good market efficiency and a good reaction to shocks from market participants. Overall, the VIRFs methodology is very promising, providing a very practical policy analysis tool to market participants for forecasting the entire probability distribution of the risk that is still unidentified, as well as helping the development of a risk matrix for investors, traders and other market participants.

6.3 Suggestions for further research

The theme of the research in this thesis is to explicitly model petroleum price volatility in a multivariate framework and to analyze the relative merits of multivariate models to describe change in the context of petroleum markets risk. The main motivation of this thesis is to build on modern quantitative techniques with a view to address several issues of oil price modelling and risk management which are very relevant topics in the industry. The driving force for developing such models of oil markets is the desire, by market participants, to ensure accurate estimation of risk measures, successful implementation of hedging strategies as well as thorough evaluation of investment policies.

The empirical investigation presented in Chapter 3 to 5 of this thesis, although quite comprehensive, is subjected to certain limitations due to space and time constraints and availability of data. Therefore, the aim of this section is to suggest a number of potential directions in which fruitful future research can be undertaken to complement to some degree the study and consequently shed some light on the issues not covered in this thesis.

First, the findings of Chapter 3 offer several avenues for future research. Our empirical results are available for only in-sample time horizon. So it would be interesting to assess the optimal hedging strategy for the out-of-sample time horizon which in turn may provide more information about petroleum markets risk to central governments and businesses. As our results may be sensitive to the choice of the return innovation's distribution, it would be interesting to consider the distributions of other innovations. Furthermore, it would be interesting to expand the current study to cover a wider spectrum of the energy markets, such as natural gas and electricity.

Second, given the results of Chapter 4, an interesting extension would be to focus on simulation and analysis of government intervention regarding how to alleviate the impact of oil price fluctuations on equity markets. For example, how could governments of oil-importing countries benefit from increasing their strategic oil reserves, and thus protect themselves from the risk of supply disruptions?[5] Oil-saving measures may be considered by governments of oil-importing countries. Oil-saving measures, especially renewable energy or other technological developments (e.g. improved fuel efficiency), will have significant impacts on specific stock sectors. Additional insight may also be gained by exploring regime changes in the role of oil price fluctuations in explaining the equity market behaviour as well as employing the spillover index from the Diebold and Yilmaz (2009) framework (DY 2009). The multivariate regime switching framework could shed light on the information content of regimes in risk measures and optimal portfolio management. Another advantage of this framework is its ability to deal with fat-tails for more details beyond normal distribution assumption. The DY 2009 framework has several advantages

[5] The Chinese government began to prepare for the establishment of strategic petroleum reserve in March 2004. Chinese reserves would consist of a government-controlled strategic reserve complemented by mandated commercial reserves. The government-controlled reserves are being completed in three phases. Phase one consisted of a 101.9 million barrel reserve, mostly completed by the end of 2008. The second phase of the government-controlled reserves with an additional 170 million barrels will be completed by 2011. The third phase that will expand reserves by 204 million barrels will be completed by 2020.

over common econometric methodologies measuring volatility spillover, such as the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH), Regime Switching (RS) and Stochastic Volatility (SV) models. The DY 2009 can be used to gauge the magnitude of the volatility spillover as well as to indicate the direction of the spillover.

Third, given the results of Chapter 5, a number of research opportunities could be followed to improve this study. Our empirical results may be sensitive to the data frequency. Thus, it would be interesting to consider other data frequencies, for example, high-frequency data (tick-by-tick) and weekly data, which will provide an opportunity to examine the robustness of this study to data frequency. As the findings in this study indicate the presence of beneficial strategies for market participants, it could be useful to evaluate these strategies. This study could be extended into describing the impact of shocks on conditional covariances and then correlations, which will be of practical importance to financial practitioners in making optimal portfolio allocation decisions. Furthermore, a challenging extension would be to apply the VIRF methodology in two directions: to incorporate the asymmetric effect in conditional volatility, which could be captured by the asymmetric BEKK model and to analyse the impacts of shocks on third and higher moments of a distribution which has recently been opened by Jondeau and Rockinger (2006). As options are known to be priced in reference to the skewness (and also higher moments), a better understanding of the impact of a shock on the conditional skewness of crude oil markets might be able to improve the pricing and hedging performances.

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