Ph.D. Thesis

ESSAYS ON INTERNATIONAL FINANCE

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Abstract

This thesis consists of three essays on international finance.

In the first study, we examine the properties of carry trade and momentum returns in the interwar period currency markets. We find that these active currency trading strategies earn an annualized average excess return of about 7%, consistent with estimates from modern samples. On the grounds that the interwar period represents rare events better than modern samples, we provide evidence unfavorable to the rare disaster based explanation for the returns to the carry trade and momentum. Global FX volatility risk, however, turns out to account for the carry trade return in the interwar sample as well as in modern samples.

In the second study, we provide a scientific account for the risk-off phenomenon which refers to a change in risk preferences and the effect on asset prices of the associated portfolio rebalancing. We identify risk-off episodes as a switch to a polarized correlation regime of currency returns. These risk-off transitions are relatively infrequent but noticeably increasing over time. They are persistent and associated with geopolitical events. Finally, risk-off switches are unrelated to changes in macroeconomic fundamentals and to other shocks. Risk-off switches have very significant spill-over to the returns of broad asset classes and trading strategies and are associated with significant changes in the positions of professional investors across different financial markets.

In the third study, we explore the broader implications of the present value relations for return predictability. More specifically, we estimate global risk premium factors in international stock markets, international bond markets, and the currency markets from the whole cross-section of present value measures (the price-dividend ratio, bond yields, and the real exchange rate, respectively for the abovementioned three asset classes). We find that the global risk premium factors: substantially improve the predictability of returns relative to the asset-specific present value measures; are intimately linked with macroeconomic fundamentals; and imply strong and consistent exchange rate predictability.

Chapter 1

Introduction

My PhD thesis studies topics in international finance. It consists of three chapters:

My working paper, "Off the Golden Fetters: Examining Interwar Carry Trade and Momentum" (joint work with Ian Marsh), forms **Chapter 1** of my PhD thesis. In this paper, we study the properties of currency carry trade and momentum returns in the interwar period (1921-1936).

We find that (i) currencies with higher interest rates outperform currencies with lower interest rates by about 7% per annum, consistent with estimates from modern samples, while a momentum strategy that is long past winner and short past loser currencies rewards an average annual excess return of around 7% in the interwar sample, slightly larger than its modern counterparts; (ii) global FX volatility risk premium accounts for the carry trade returns in the interwar sample as well as in modern samples; (iii) unlike findings from modern samples, the volatility risk premium is also a key contributor to currency momentum returns in the interwar sample; (iv) we also provide evidence unfavorable to the Peso problem explanation and the rare disaster based explanation for the returns to currency trading strategies.

My working paper, "Switching Risk Off: FX Correlations and Risk Premia" (joint work with Alessandro Beber and Michael W. Brandt) is included as **Chapter 2** my PhD thesis. This paper provides a scientific account of risk-off episodes: their detection, their relation with economic conditions and other risk measures, and their consequences on the financial landscape.

We start by defining risk-off as a change in risk preferences and the effect on asset prices of the resulting portfolio rebalancing. We identify risk-off episodes as switches to a polarized correlation regime of currency returns. We find that (i) risk-off transitions are relatively infrequent but become increasingly frequent over time; (ii) they are persistent and associated with geopolitical events; (iii) risk-off switches are unrelated to changes in microeconomic fundamentals and volatility or average implied correlation shocks; (iv) risk-off shifts impact broad asset classes and active trading strategies, with risky and safe asset returns being penalized and favored, respectively; (v) risk-off switches are also associated with significant changes in the positions of institutional investors, suggesting the return dynamics come from price pressure induced by portfolio rebalancing.

My working paper "Global Risk Premiums in the Cross Section of Present Values" completes my PhD thesis as **Chapter 3**. This paper is motivated by the present value approach to forecasting returns which builds on that asset price incorporates information on future cash flows and expected returns. We explore the broader implications of the present value identities for return predictability. More specifically, we estimate global risk premiums in international stock markets, international bond markets, and the currency markets using the whole cross-section of present value measures (the price-dividend ratio, bond yields, and the real exchange rate, respectively for the abovementioned three asset classes).

Our findings are (i) global risk premiums substantially improve the predictability of returns relative to standard present value based predictors; ii) global risk premiums are intimately linked with past and future economic prospects; and iii) global risk premiums imply strong and consistent exchange rate predictability with more than doubled R-squared relative to standard exchange rate predictors, such as interest differentials and real exchange rates.

Chapter 2

Off the Golden Fetters: Examining Interwar Carry Trade and Momentum

2.1 Introduction

In this paper, we study returns to two types of popular currency speculation in the context of the interwar period from 1921:1 to 1936:12. We consider the carry trade, in which an investor borrows a basket of currencies with lower interest rates and invests in a basket of currencies with higher interest rates, and the momentum strategy, in which an investor holds a long position in currencies with superior past returns and a short position in currencies with poor past performance. Both of these strategies have proved profitable to follow over prolonged periods during the recent float (post 1973). Explaining these positive returns has been more difficult, and competing explanations each have merit and have found some support from data from the recent period.

Our contribution is two-fold. First, we document the returns to currency strategies in the interwar period. Note that we do not assume these strategies were being followed by investors in the interwar period. Rather, we examine the performance of the strategies viewing the interwar sample period as a hitherto unexplored test period. Second, we evaluate two competing explanations for currency returns, global FX volatility risk [Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)] and the rare disaster explanation [Farhi and Gabaix (2011)], using evidence from the interwar sample.

We find that forward discounts, or equivalently interest rate differentials, and past returns continue to be strong predictors for future currency returns in the interwar sample. Both the carry trade and momentum strategies are profitable in the interwar period. Further, the average payoffs are virtually the same as their modern sample counterparts. In particular, an US investor would have been rewarded with a 7% annual excess return on average in the interwar period, had she followed either the carry trade or the momentum strategy. The magnitude of these profits is similar in the modern samples, except that momentum effect seems absent in the post Euro sample 1999:1-2013:3. Although the interwar carry trade and momentum may not seem impressive given their Sharpe ratios of 0.3∼0.4, the US stock market also provides a Sharpe ratio of similar magnitude in the interwar period.

We highlight that the interwar carry trade and momentum strategies resemble each other in terms of their source of profitability. The interwar carry trade is profitable not only due to the interest rate spread between high-yielding countries and low-yielding countries but also because the appreciation of high-interest-rate currencies relative to low-interest rate currencies contributes 21 percent of the total profits. For interwar momentum, currencies with positive past returns are those with high interest rates and currencies with negative past returns are those with low interest rates; hence, 14 percent of momentum profits are produced by interest rate differential. This contrasts with the modern data where momentum and carry strategies typically invest in different currencies and gain returns from different sources - carry from the interest differential and momentun from exchange rate changes.

Another key contribution of our paper is that we examine the validity of competing explanations for profitable currency speculation using interwar evidence. It is of interest to examine the interwar period since it contained many 'rare' events, while these are arguably absent or at least under-represented in modern samples. To be specific, we evaluate two streams of explanations that have proved successful in modern data: the rare disaster based explanation and the importance of global FX volatility risk.

We start by evaluating whether a rare disaster distribution for currency returns can account for the average carry trade and momentum returns. We estimate the empirical likelihood of each return observation under the null hypothesis that the true mean return is zero. We find that if one maintains that carry trade or momentum returns are generated from a "special" distribution such that the true mean returns are zero, then we also have to accept (i) that it is extremely unlikely that empiricists would observe the sizable average returns to currency speculation documented in the interwar and modern periods, and/or (ii) that this "special" distribution features more negative skewness which implies, we feel, an unrealistically high frequency of disastrous events, and (iii) that such a "special" distribution is in any case unable to reconcile carry trade returns and momentum returns simultaneously. Consequently, our evidence is unfavorable to the pure rare disaster based explanation.

We then explore the robustness the global FX volatility risk explanation in the interwar data. We find that global FX volatility risk explains the majority of both the carry trade and momentum strategies in the interwar sample. In modern samples, volatility risk can only account for carry trade returns. In the interwar sample, financing currencies, either those with lower interest rates or those with poorer past performance, hedge volatility risk while investment currencies, either those with higher interest rates or those with superior past performance, incur losses when global FX volatility is unexpectedly high. Even though the spread in volatility beta, or the covariation of portfolio returns to the global FX volatility innovations, is smaller in the interwar sample than in the modern period, the interwar price of volatility risk is double that of the post Bretton Woods sample (1976:1-1998:12) and is six times that of the post Euro sample. Therefore, around 6%

(5%) out of the 7% annual average returns of the carry trade (momentum) is accounted for by compensation for global FX volatility risk.

Related literature. We build on a growing literature that addresses the risk-return nexus in foreign exchange market speculation, focusing in particular on the carry trade and momentum.

This literature starts from the empirical documentation of violations of uncovered interest parity or the forward premium puzzle in the seminal papers by Hansen and Hodrick (1980a) and Fama (1984a) and has made progress due to the work by Lustig and Verdelhan (2007) who apply standard asset pricing techniques to examine risk-return relationships based on currency portfolios. Although their claim that consumption risk can explain carry trade returns is controversial, [see Burnside (2011) and Lustig and Verdelhan (2011)] their finance-oriented approach to understanding the foreign exchange market has led to a resurgence in the literature seeking to explain exchange rates. For example, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) provide a comprehensive empirical documentation on the return to a variety of currency momentum strategies.

We follow this literature and make our first contribution by documenting carry trade and momentum returns in the interwar period. This is a period that has been widely examined in the time-series/economic literature, especially with regard to covered interest parity [e.g. Peel and Taylor (2002)] and regime credibility [e.g. Hallwood, MacDonald, and Marsh (1997a,b, 2000)]. However, data from this period have not been used to consider the new cross-section/finance explanations of exchange rate behaviour. We consider the examination of the interwar period as an 'out of sample' test of competing theories hitherto tested only on data from the modern era.

An important aspect of the new branch of the literature is to account for currency returns by various types of risk.[1] Lustig, Roussanov, and Verdelhan (2011) conduct

[1] Lustig and Verdelhan (2012) provide a detailed exposition of risk-based analysis of exchange rates and currency returns in the stochastic discount factor framework.

principal component analysis of the cross section of currency portfolios sorted on interest rates (or, equivalently, forward discounts) and derive two factors, a "level" or dollar factor and a "slope" or carry factor, to explain carry trade returns. Using a similar approach, Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) attribute carry trade returns to compensation for global FX volatility risk. Recent progress in considering higher-order moment risks has been made by Mueller, Stathopoulos, and Vedolin (2012) who show that carry trade returns also reflect compensation for global FX correlation risk, while Della Corte, Riddiough, and Sarno (2013) establish global imbalances as a macroeconomic risk factor to explain currency premia.

In addition to the risk-based explanations, many papers explore non-risk-based frameworks, including the peso problem explanation. This is investigated by Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010) who argue that carry trade returns reflect some peso states featuring large stochastic discount factors but modestly large carry trade losses. Related to this, the rare disaster based explanation[2] argues that the observed recent float sample under-represents some rare disastrous events [see Farhi and Gabaix (2011), Farhi, Fraiberger, Ranciere, and Verdelhan (2013), Brunnermeier, Nagel, and Pedersen (2008b).] A common feature of empirical papers in this field is that they use currency options data to infer the properties of the unknown rare events.

We make our second contribution by exploring the interwar data to re-examine the power of these explanations. In order to make our analysis clear and parsimonious, we only make the case for global FX volatility risk explanation and the peso/rare disaster based explanations. The distinction of our paper is that although options data are not available in the interwar period, we are able to evaluate rare disaster/peso based explanations on the grounds that rare events are better represented in the interwar sample. We find evidence unfavourable for non-risk based explanations.[3]

[2]The rare disaster based theory was initially proposed by Rietz (1988) as a solution to the equity premium puzzle [see Mehra and Prescott (1985)], and was revived by Barro (2006) who calibrates rare disaster probabilities using international data in the twentieth century.

[3]Our results resonate with Jurek (2014) who compares the returns to hedged and unhedged carry trades and points out that peso problem can account for only one-third of average carry trade return.

This literature has focused on explaining carry trade returns, whereas currency momentum returns are left virtually unexplained. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) test whether global FX volatility risk can explain momentum returns without success. On the other hand, rare disaster based explanations are not promising in explaining carry trade and momentum returns simultaneously because in modern data, during carry trade crashes, momentum strategies tend to profit [see Burnside, Eichenbaum, and Rebelo (2011)].

With unique evidence from interwar data, we push forward the joint explanation of returns to the carry trade and momentum. Our results suggest that global FX risk does appear to acount for a significant part of interwar currency portfolio returns.

The rest of this paper is organized as follows. Section 3.2 describes our data including both interwar and modern period forward and spot exchange rates. Section 2.3 demonstrates the profitability of the carry trade and currency momentum strategies in the interwar period, and compares performance to the modern sample evidence. Section 2.4 uses the interwar data to re-evaluate risk-based and non-risk based explanations for the returns to carry trade and momentum. Section 2.5 concludes.

2.2 Data Description

This section describes the data used in our empirical analysis, namely spot and forward exchange rates in the interwar period from 1921:1 to 1936:12 and in the modern period from 1976:1 to 2013:3.

2.2.1 Interwar Spot and Forward Rates

We use weekly spot and one-month forward exchange rates from the interwar sample period, November 1921 to December 1936. We use exchange rates for the following seven countries: Belgium (BEF), France (FRF), Germany (DEM), Italian (ITL), Netherlands (NLG), Switzerland (CHF), United States (USD). The data initially use the British pound (GBP) as the base currency.

The data are sourced by Enzig (1937) from the weekly publication by the Anglo-Portuguese Colonial and Overseas Bank, Ltd. (Originally the London branch of the Banco Nacional Ultramarina of Lisbon). The rates are for the Saturday of each week, except when the market was closed on the Saturday or there were no rates available; in these cases, the latest rates available prior to that Saturday was used. Note that Saturday was an active trading day during this period. The raw exchange rates are quotes against the British Pounds. However, we change the reference currency to the US dollar through the assumption of a lack of triangukar arbitrage in order to be consistent with studies using modern data. We transform the weekly data into monthly data by selecting the end-of-month observations since this literature typically analyses data at the monthly frequency.

A major concern with regard to the implementability of currency speculation in the interwar period is the German hyperinflation and German mark's devaluation at an exponential rate in the early 1920s. We argue that our results are not impacted for the following reasons. First and foremost, Panel a. in Table 2.1 indicates that the German mark is neither a primary financing currency nor is it a major investment currency. Second, the forward exchange rate data are not available from 1923:9 to 1924:11, the most severe phase of the German hyperinflation. Finally, our implementation of currency strategies are based on a cut-off rule for the interest rate spread such that we do not consider countries whose interest rates are 22% per annum higher than the US interest rate. According to Bansal and Dahlquist (2000), the forward premium puzzle is more prominent in countries with hyperinflation and thereby spurious nominal interest rates.

For the purpose of constructing a foreign exchange market volatility index (detailed below), we also gather daily spot rates of the US dollar against the British pound, French franc, Deutsch mark, and Swiss franc for the interwar period from the Global Financial Database.

The interwar foreign exchange market saw considerable exchange rate variations at least in the case of the developed european economies we study. For instance, as Figure 2.1 illustrates, in the early 1920s, major economies faced heightened pressure to adjust the value of their currencies to a new parity in line with their relative post World War I price levels. This induced an ideal speculative environment for betting on whether countries with already high cost of debt would devalue their currencies and caused substantial exchange rate fluctuations until 1927 when all major european countries returned to the gold standard. The interwar gold standard was shortlived and any stability ended soon after the Wall Street Crash of 1929. Figure 2.2 shows that currencies followed a series of large valuation changes in the subsequent years.

It is important to stress that the FX markets were active during the interwar period. Enzig (1937) notes that the forward market developed in London soon after the end of World War I, and both spot and forward foreign exchange was actively traded, especially in the 1920s. He also specifically reports that the foreign exchange markets were actively ued for hedging trade or investment ransactions and for arbitrage and speculation. Initially, trading was dominated by professional investors but considerable retail activity was recorded as the decade progressed. Trading was greatly reduced during the fixed fixed rate period (late 1920s) but recovered once the managed float period began, although the global depression limited volumes relative to the boom years of the early 1920s.

2.2.2 Post Bretton Woods and the Euro Era

We follow Menkhoff et al. (2012) by complementing BBI data on spot and one-month forward rates quoted against the US dollar with Reuters data converted to quotations against the US dollar. This extended sample starts from January 1976 and ends in March 2013. We further divide the sample into two categories: 1) the Post Bretton Wood Period from January 1976 to December 1998, and 2) the euro-era from January 1999 to March 2013. This partition of the modern sample is not arbitrary because it gives us three samples (one interwar and two modern) with approximately equal length and within each sample, the cross section is relatively fixed and therefore it helps us make more sensible historical comparisons.

The cross section of our modern sample consists of 15 developed countries, namely, Australia, Belgium, Canada, Denmark, Euro Zone, France, Germany, Italy, Japan, the Netherlands, Norway, New Zealand, Sweden, Switzerland, and the UK.

It is a concern that our comparative analysis is based on different sets of currencies in different historical samples. One solution might be to just use the seven currencies that are common across the three historical samples. However, we argue that fixing the cross sectional dimension for our historical comparison ignores the fact that the financial markets and in particular, the foreign exchange markets, have expanded through time. The group of seven european countries which used to be large enough to be counted as global in the 1920s, is not global in the modern era. Further, if we limit analysis to the seven european currencies (against the dollar) there will be only four currencies in the post Euro era due to the introduction of euro. Finally, keeping a common cross section through the modern era would exclude three of the four currencies most closely associated with the carry trade - the yen as a funding currency and the Australian and New Zealand dollars as investment currencies.

On the other hand, one may be concerned that limiting analysis to developed countries is too narrow to well represent currency speculation, especially for the modern era. As Burnside, Eichenbaum, and Rebelo (2008) document, diversification can significantly boost the Sharpe ratio of the carry trade and Menkhoff et al. (2012b) show that the inclusion of both developed and emerging countries is important to generate large positive average momentum returns. Nonetheless, the findings by Burnside, Eichenbaum, and Rebelo (2007) suggest a significant effect of transactions costs on emerging country carry trades given that spreads are two to four times larger in emerging markets than in developed countries. The focus on developed countries is also supported by the evidence in Bansal and Dahlquist (2000) who find violation of the uncovered interest parity is more prevalent for developed countries than emerging economies.

Therefore, we believe that our choice of the cross section is the best tradeoff between comparability across samples and the representativeness of the currency market.

2.3 Profitability of the Carry Trade and Momentum Strategies

This section examines the robustness and pervasiveness of the profitability of the carry trade and currency momentum strategies in the interwar period, as compared to the modern period. We begin by briefly outlining the implementation of the key foreign exchange strategies and the measurement of returns.[4]

2.3.1 Decomposition of Currency Returns

Following the notation of Burnside (2012) and Koijen, Moskowitz, Pedersen, and Vrugt (2013a), we denote the time t spot and forward rates of a country against the US dollar as S_t and F_t respectively, in terms of the dollar price of one foreign currency unit. As is standard in the literature, we implement currency investments via the forward markets. Accordingly, a long position in a currency is carried out by buying forward currency.

[4] Koijen, Moskowitz, Pedersen, and Vrugt (2013a) provides detailed explanation and comprehensive empirical analysis to show the 'carry everywhere' phenomenon. We recast their intuition back into the currency context in order to provide the basic intuition underlying the predictability of carry and momentum for currency returns.

Under the assumption of full collateralization, the payoff or excess return is

$$
\begin{aligned}
Z_{t+1} &= \frac{S_{t+1} - F_t}{F_t} && (2.1)\\
&= C_t + \mathbf{E}_t\left[\frac{\Delta S_{t+1}}{F_t}\right] + u_{t+1} && (2.2)
\end{aligned}
$$

where

$$
C_t = \frac{S_t - F_t}{F_t} \qquad (2.3)
$$

Eq. 2.2 presents an explicit decomposition of currency return into three components: 1) the carry component of the expected return, C_t, 2) the expected appreciation component of the expected return, and 3) the return innovation. Given that the carry is observable at time t and is a key element of the currency return, we would expect other return predictors to have predictive powers for exchange rate appreciation. It is worth noting, however, that the carry arguably predicts the appreciation rate; on the other hand, potential forecasting variables for the appreciation rate are in general not independent of the carry.

In complete markets the depreciation rate of the home currency is equal to the relative (foreign v.s. domestic) marginal utility growth rates,

$$
\frac{S_{t+1}}{S_t} = \frac{M^*_{t+1}}{M_{t+1}} \qquad (2.4)
$$

The expected foreign currency appreciation rate can therefore be written as

$$
\begin{aligned}
\mathbf{E}_t\left[\frac{\Delta S_{t+1}}{F_t}\right] &= \mathbf{E}_t\left[\frac{\Delta S_{t+1}}{S_t}\frac{S_t}{F_t}\right] && (2.5)\\
&= \mathbf{E}_t\left[\frac{M^*_{t+1}/\mathbf{E}_t[M^*_{t+1}]}{M_{t+1}/\mathbf{E}_t[M_{t+1}]} - 1\right] - C_t && (2.6)\\
&\approx \frac{1}{2}(\lambda_t^2 - \lambda_t^{*2}) - C_t && (2.7)
\end{aligned}
$$

where the third Eq. holds approximately by log-linerization and under the assumption of a Gaussian one-factor model for stochastic discount factors shown below with $\lambda_t^{(*)}$

denoting the domestic (foreign) price of risk, and $r_t^{(*)}$ denoting the domestic (foreign) short rate:

$$M_{t+1}^{(*)} = \exp\left\{-r_t^{(*)} - \frac{1}{2}\lambda_t^{(*)2} - \lambda_t^{(*)}\epsilon_{t+1}\right\} \tag{2.8}$$

Combining Eq. (2) and Eq. (7), we see that no matter how we decompose the return, a variable predicts the currency return if and only if it reflects the relative price of risk between the domestic country and the foreign country. A foreign currency with 1% higher carry is supposed to deliver 1% higher return in excess of the domestic currency. However, unless the carry contains information about the relative price of risk or put differently, as long as the uncovered interest parity holds, the foreign currency is expected to depreciate by exactly 1%, thereby wiping out gains from higher carry and resulting in zero net profit.

Despite the fact that the essence of predictability of currency return lies in time varying relative price of risk across countries, it is worth emphasizing that the decomposition of return into a carry component and an appreciation component is intuitive for three reasons. First, a currency investment is risky only to the extent that the exchange rate fluctuates. Second, the literature has provided plenty of empirical evidence that the change in the exchange rate is largely unpredictable, at least in the one-month horizon. It makes sense to partition the return into the carry which involves no uncertainty at all and is directly observable from the market data without any time series model, and the appreciation whose forecast is far from being stable and reliable. Third, from the perspective of investors in the foreign exchange market, the carry offers a natural benchmark for performance evaluation as investors do not need to have any econometric skills or fund management experience to obtain it. By contrast, the hard-to-capture currency appreciation is likely to benefit from investment experience, model stability, talent, or pure luck.

We next outline two major currency return predictors, carry (for the carry trade) and past excess return (for currency momentum), that have been extensively studied in the literature and briefly discuss their relationship with returns. Ang and Chen (2010) extends this idea by documenting the predictability due to the link between risk premia and yield curve predictors including the short interest rate, the long-term interest rate, the term spread, and the change in interest rate. In untabulated results, we show that the carry (interest rate differential) is the only robust predictor for currency returns across different subsamples, controlling for other predictors.

2.3.2 Currency Return Predictors

Carry. It is well known that the short term interest rate moves in the opposite direction to the risk premium. This can easily be seen within a simple consumption based model within which the risk premium is high when uncertainty goes up, and at the same time the short rate drops due to precautionary saving motives.

On the empirical front, the well documented failure of uncovered interest parity suggests the foreign currency with higher interest rate tends not to depreciate enough to erase the deterministic interest profits. In fact, exchange rate movements are likely to enhance gains from the carry.

To sum up, the currency with higher carry C_t earns higher returns.

Momentum. In spite of the voluminous literature documenting various types of momentum phenomena in different asset markets, there is no unified theory explaining why high past returns forecast high future returns.

Nonetheless, a decomposition of the momentum predictor, the past return Z_t, into past carry C_{t-1} and past spot appreciation $Q_t^S \equiv \Delta S_t / F_{t-1}$ may shed some light on the intuition behind momentum. Interest rates are highly persistent and therefore high interest rates are followed by high subsequent interest rates. Further, auto-correlation of exchange rate changes is arguably weakly positive and hence the bull market for a currency tends to continue and investors expect to earn higher returns.

In sum, the return momentum, or the past return is a combined signal which seeks the tradeoff between the carry component and the appreciation component of the currency return.

2.3.3 Evidence from Individual Currencies

We start with currency speculation exploiting individual bilateral exchange rates before considering portfolio-based stategies in the following sub-section. Table 2.1 presents key statistics for the interwar sample versus the modern samples. We find, on average, that the interest rate differential or carry is not as dispersed in the cross section of interwar currencies as in the cross section of modern currencies. This is partly because we have a relatively small set of solely european countries during the interwar period. However, the dispersion of average appreciation is much larger in the interwar sample than in modern samples, indicating the potential attractiveness of currency momentum in the interwar period, and potentially a large appreciation component in the carry trade.

We also find that interwar exchange rate returns feature substantially larger standard deviations, more negative skewness, and heavier tail distributions than modern exchange rate returns. These higher moments highlights the our basic idea that the interwar sample accommodates more disastrous events that are rarely seen in the modern samples.

The second and the fourth columns indicates the positive carry-mean excess return relationship in the cross section for the interwar sample as well as the two modern samples.

Turning to the last two columns of table 2.1, we show that in the time series individual currency carry trade and momentum are mostly profitable in the interwar period as well as in the modern periods. This is especially true for the momentum strategy. This interwar evidence provides an out-of-sample verification of the profitability of not only the equally-weighted carry trade [see Burnside et al. (2010)] which is essentially the cross sectional average of our individual currency carry trades , but also the time-series momentum strategy proposed by Moskowitz, Ooi, and Pedersen (2012). In the interwar sample, an equally-weighted carry trade, which may not cancel out dollar effect, turns out delivers a mean excess return of much smaller size than a zero-cost carry trade that cancels out the dollar effect. Profits of equally-weighted time series momentum, however, is virtually as profitable as zero-cost momentum in the interwar period.

2.3.4 Evidence from Currency Portfolios

We form sets of portfolios on the basis of each predictor in the interwar period, the post Bretton Woods period, and the Eurozone period respectively. We aim to make sensible comparisons of portfolios across these three historical samples. For the interwar sample, we sort the seven european currencies into three portfolios at the end of each month based on the end-of-month observations of the predictor. In detail, we allocate currencies with carry in the bottom 33% into portfolio 'L', the middle 34% into portfolio 'M', and the top 33% into portfolio 'H'. We follow the same procedure for the two modern samples except that we can exploit the larger dimensions of this data set and in line with the literature form five portfolios.

To get more sense from our portfolio allocation, we show in Table **??** that the size of our portfolios is similar over the three samples. Corner portfolios, either 'L' and 'H' or '1' and '5', typically contains two to three currencies, though there are a few cases in which intermediate portfolios may contain currencies of varying numbers.

We discuss in detail below summary statistics of the currency strategies which are long the portfolio with the highest value of the predictors and short the portfolio with the lowest value of the predictor. Perhaps the key finding from the comparative analysis across three different historical environments is that carry is not only a robust predictor of currency returns, but also has fairly stable predictive power.

Mean Return and Sharpe Ratio. Table 2.2 reports key statistics of currencies portfolios sorted according to carry and momentum, respectively. The first row in each panel shows the average annualized excess return of currency investments against the US dollar. It is evident that for the interwar sample that carry predicts currency excess returns. Currencies at larger forward discounts or with higher interest rates perform better than those with forward premia or with lower interest rates. These observations from the interwar era are consistent with modern sample evidence as shown in Panels b and c. Past return is also a strong predictor for currency excess returns in the interwar period and in the post Bretton Woods era; past winners continue to outperform past losers. However, momentum is absent in the post Euro era, at least for our set of developed countries.

The second row of each panel presents mean excess returns of the zero-cost *carry* and *momentum* strategies. For the carry strategy, for example, this means being long a portfolio with a large forward discount (portfolio 'j') while short the portfolio with the lowest forward discounts (portfolio '1'). The t-statistics of mean returns are given in the third row. It is evident that both carry and momentum strategies yield economically sizable and statistically significant excess returns in the interwar era as well as in the post Bretton Woods era. The largest return spread is always given by the long/short strategy involving the two extreme portfolios (which we denote high-minus-low or HML). It is notable that the HML carry strategy on average delivers around 7% per annum in all three historical samples while average returns to the HML momentum strategy is around 6% per annum interwar and post Bretton Woods. The outlier case is momentum in the post Euro sample where statistically significant returns are absent.

Turning to the annualized Sharpe ratios (row four), we find that the both carry and momentum strategies deliver decent risk-return tradeoffs in most historical samples. In the interwar era, the annualized Sharpe ratio of 37% for the carry strategy and 31% for the momentum strategy may seem less impressive. However, we argue that the risk-return tradeoffs of the strategies are reasonably good in that exchange rate movements are of substantially larger magnitude in the interwar sample than in the modern sample. As a result, the standard deviation of the excess return is most likely to be overestimated. It is also worth noting that the nominal mean excess return may have underestimated the numerator of the Sharpe ratio given the deflation of the reference currency (USD) in the interwar period and its inflation in the modern era. Furthermore, the Sharpe ratio of the US stock market was also around 40% in the interwar period, of similar magnitude to the currency strategies.

Carry vs Appreciation. We then take an in-depth look at the sources of currency strategy profits by decomposing the mean excess return into a (ex ante known) carry component and the (ex ante unknown) exchange rate appreciation component highlighted in Eq.2.2.The decomposition suggested by Eq.2.2 reflects a simple idea: the excess return of any currency strategy should be earned from either the interest rate difference between the investment and funding currencies or the relative change in spot exchange rates. There is no other source of profit. Consequently, the decomposition of excess return into a carry component and a price appreciation component helps us understand the information the various predictors exploit to forecast future returns.

Our results in Table 2.3 suggest that the *carry* trade derives the majority of its profits from the interest rate difference whereas the momentum strategy's main source of profits is price change or appreciation of investment currencies relative to the financing currencies. In the interwar period, more than one-fifth of the 7% annual return of the carry strategy is contributed by appreciation. The share of profits is similar in the post Euro sample. The post Bretton Woods period features a substantial average depreciation of the high interest rate currencies relative to low interest rate currencies, partially eroding the gain from interest differentials. However, this still suggests that spot rate changes play an important role in carry strategy profits. In spite of the dominance of the appreciation component for the momentum strategy, the interest differential contributes non-negligible shares of profits to the average returns of the momentum strategy - 15% in the interwar sample and 43% post Bretton Woods.

Dynamics of carry trade and momentum. In order to understand how the profit/loss of the carry trade and momentum strategies are accumulated through time, we present the simple cumulative excess returns along with the corresponding cumulation of carry component and appreciation component for each currency strategy in each historical sample in Figure 2.3. The interwar carry trade and momentum are quite similar: they both benefit from interest rate spread and appreciation of the investment currencies relative to the financing currencies. In contrast, modern carry trade and momentum returns display rather different composition.

Another aspect worth discussion is the return cumulation dynamics. Interwar carry trade and momentum displays unparalleled variation during the post-WWI floating exchange rate regime from the beginning of 1921 till about 1928 when all major economies returned to the gold standard, and carry trade stopped generating profits. Following the collapse of interwar gold standard, marked by the departure of UK from gold, the carry trade initially crashes and then starts to accumulate gradual profits in the managed floating regime of the early 1930s. Different from the interwar period, the modern era subsequent to the collapse of the Bretton-Woods system has never seen such large scale foreign exchange regime transitions. As a result, the cumulative returns look smoother in the modern era in spite of several notorious carry trade crashes during the Asian financial crisis and the 2008/9 financial crisis.

2.4 Competing Explanations

In this section, we examine the risk profile of the carry and momentum strategies in order to re-evaluate a number of explanations proposed in the literature. In particular, we consider two key explanations of carry and momentum profits: 1) rare disasters, and 2) global FX volatility risk. These explanations have proved successful to some extent in rationalizing the average return of the carry trade in the recent floating rate period. We extend our understanding by adding the interwar float data.

2.4.1 Rare Disasters

We start with the rare-disasters-based explanation that assumes all states are present in the sample but that the true probability density is not well represented by the sample.

We examine what the most likely rare disaster distribution for payoffs under the null of a zero mean would imply for our actual observation of sizable carry trade and momentum returns in-sample.[5] We estimate the rare disaster distribution via the empirical likelihood method (EL) according to Ghosh and Julliard (2013) who adopt the EL method to investigate the implication of rare disaster models for the equity risk premium.[6]

To be precise, we estimate the probability of each sample observation by maximizing the empirical likelihood function under the constraint that the mean excess return of the estimated probability is zero, i.e.

$$\{\hat{p}_t\}_{i=1}^{T} = arg \max_{\{p_t\}_{t=1}^{T}} \sum_{t=1}^{T} \log(p_t) \tag{2.9}$$

$$s.t. \sum_{t=1}^{T} p_t = 1 \tag{2.10}$$

$$\sum_{t=1}^{T} p_t Z_t = 0 \tag{2.11}$$

where Z_t denotes the excess return of the trading strategy and p_t is the probability of observing Z_t in the sample under the rare disaster distribution with zero mean. Our estimation is conducted separately for carry trade and momentum strategies and over the three historical samples.

Given the estimated empirical likelihood $\{\hat{p}_t\}_{t=1}^{T}$ such that $\mathbf{E}_T^{\hat{p}}[Z] = \sum_{t=1}^{T} \hat{p}_t Z_t = 0$, we resample the return data $\{Z_t\}_{t=1}^{T}$ with replacement and generate 10,000 artificial samples

[5] In the online appendix to Menkhoff et al. (2012a), the authors report their asset pricing results based on empirical likelihood estimation and verify that global FX volatility risk is priced in the cross section of carry trade portfolios in the sample from 1983:12 to 2009:8. In this paper, however, we do not verify whether the FX volatility risk model is robust to empirical likelihood estimation.

[6] For detailed reference, see Kitamura (2006) and Owen (2001).

of the same size as the actual sample (T). We compute the average return for each bootstrap sample: $\overline{Z}^{(r)} = \sum_{t=1}^{T} Z_t^{(r)}$, where $r = 1, 2, \cdots, 10,000$ indexes the bootstrap samples. As a result, the EL-implied distribution for the **average excess return** can be constructed using the sequence $\left\{\overline{Z}^{(r)}\right\}_{r=1}^{10,000}$.

Figure 2.4 gives the distribution of **average excess returns** (blue shade) along with the actual sample average return (red vertical line). The distribution is obviously centered around zero due to the null hypothesis that the average return should be zero. The plots in the second and third row suggest that the probability of observing the sizable average carry trade and momentum payoff that have actually been seen in the modern periods is close to zero given the (sample specific) rare disaster distribution of payoffs with zero mean. For the carry trade, for example, the probability of observing an average return $6 - 7\%$ per annum is 0.01% in the post-Bretton Woods sample, as shown in panel a1 of Table 2.4. The probability of experiencing carry trade returns as high as observed during the post-Euro era under a rare disaster distribution is slightly higher, but is still only 1.74%. Panel b2 shows that the momentum profits in the post Bretton Woods sample are also highly unlikely under the null.

Under rare disaster distributions, the chance to observe the large positive carry trade return is slightly higher in the interwar sample than in the modern samples, though it is still only about eight percent. However, we argue that disastrous states tend to be over-represented in the interwar sample: supposedly rare events are actually quite regular in this period. Table 2.5 shows that in order to generate the rare disaster distribution with zero mean, the empirical likelihood method has to substantially reduce the skewness of the data[7] by weighing more on bad states with drastic losses to currency speculation and thereby making what we consider to be already unusually frequent disastrous events even more frequent.

The final row of each block in Table 2.4 pools all three samples and results are based on a single generated rare disaster distribution (one each for carry and momentum). The

[7]Other moments, however, remain at similar levels.

probability of observing a mean return in excess of of 6.61% from the carry trade is just 0.05% under the null. The full sample mean momentum return is more likely - 2.2% - driven by the post-euro failure of this strategy.

We now ask whether rare disaster-based explanations can rationalize returns to the carry trade and momentum in a consistent way. To this end, we examine the distribution of average *carry trade* returns implied from empirical likelihood estimates based on *momentum* returns under the null hypothesis that the mean return to the momentum is zero. As Table 2.4, Panel b1 shows, momentum-based EL cannot rationalize the average return to the carry trade because even if the true mean of momentum return is zero, the average return to the carry trade is still at the level of 6∼7 % per annum. Turning to Panel a2, the results indicate it is impossible to explain momentum return by carry trade-based EL. Even if the carry trade produces zero average return, the momentum is as profitable as the simple sample average suggests. As Figure 2.5 demonstrates, zero mean carry trade return implies large positive average momentum returns of virtually the same magnitude as the simple sample average; likewise, zero mean momentum return implies large positive average carry trade returns similar to the sample average.

To summarize our findings for rare disaster-based explanations, we claim that it is always possible to construct a rare disaster distribution in favor of zero-profit carry trade or momentum. However, if one is to believe this rare disaster-based explanation, one has also to believe that (i) it is almost impossible to observe the currency investment strategy profits we have actually witnessed; and (ii) it is unrealistically likely to see so-called “rare” disasters. Because neither of these two beliefs sounds convincing, our evidence is therefore unfavorable to the rare disaster-based explanation for profitable carry trade and momentum strategies. Furthermore, our results show that either the carry trade or currency momentum is profitable since returns to the carry trade and momentum cannot be explained simultaneously by rare disasters.

2.4.2 Global FX volatility risk

Global FX volatility measure. We initially follow Menkhoff et al. (2012a) and measure global FX volatility in the following way. First, we compute absolute daily log exchange rate returns for each currency. Next we average over all currencies available on any day. Finally we calculate within-month averages of daily values to give our monthly measure of global FX volatility. To be consistent with our portfolio construction, we only use developed countries' currencies to construct our global FX volatility measure.

In the case of the interwar sample, the daily data for only five currencies are available, namely, the British pounds, Deutsche mark, French franc, Italian lira, and Swiss franc against the US dollar. In order to investigate whether this relatively small cross section is able to measure the global FX volatility effectively, we compare, in the modern samples, FX volatility measured using 15 developed countries and that using only the five currencies. The lower panel of Figure 2.6 exhibits the comparison of these two volatility measures and their corresponding AR(1)-innovations. It is clear that the two volatility levels and their corresponding innovations closely track each other. The correlation between both pairs is more than 90%. [8]

Exposure to global FX volatility risk. In Table 2.6, we present the global FX volatility beta of each of the carry and momentum portfolios and the corresponding zero-cost HML strategies. In detail, we run time-series regressions of portfolio returns on the global FX volatility risk factor and the dollar factor in each of the three historical samples. The dollar factor is a simple cross-sectional average excess return of developed countries (seven european countries for the interwar sample) and it is used to control the "level" effect, i.e. the common time series variation across currencies or currency portfolios. Accordingly, the global FX volatility risk factor captures the "slope" effect in some sense.

The left panel shows that portfolios of currencies with the lower forward discounts

[8] We also calculate the global FX volatility index using all countries data and find that its correlation with that based on five european countries is 87%.

hedge volatility risk, whereas portfolios of currencies with higher forward discounts are subject to devaluation when volatility is unexpectedly high. Importantly, this pattern holds for the interwar sample as well as the two modern samples.

Interestingly, exposure to volatility risk, consistently measured, varies over the three samples. Volatility risk of the post Bretton Woods carry trade doubles that of the interwar carry trade while the post euro carry trade is exposed to volatility risk three times as large as the interwar carry trade. In spite of the extremely large volatility spikes in the interwar period, this should not happen in a world with constant currency volatility risk exposure. Given that over the three samples, volatility risk varies whereas returns to the carry trade or momentum are of similar magnitude, we conjecture and empirically verify that the volatility risk price estimates must be varying in the opposite way over the three samples in order to account for the similar mean excess returns.

Momentum, on the other hand, displays an even more puzzling risk profile over the three samples. The volatility beta is tiny in the post Bretton Woods sample and takes a large positive value in the post euro sample, consistent with what the extant literature has documented. However, in the interwar sample, momentum bears negative loadings on volatility shocks in the same way as the carry trade, i.e. their volatility betas are both -2.38, pointing toward the potential for volatility risk to account for returns to the carry trade and momentum at the same time.

Price of global FX volatility risk. We follow the standard Fama-McBeth procedure [see Fama and MacBeth (1973) and Cochrane (2005)] to estimate the market price of global FX volatility risk, along with the dollar risk price, as reported in Table 2.7. The key messages from these results are, first, that the price of global FX volatility risk is negative and, second, that the level of the price of risk varies over different historical samples.

The left panel shows estimates of the price of risk for the cross section of portfolios sorted by forward discounts. In line with our intuition from volatility betas, the price of global FX volatility risk is substantially higher in the interwar period than in the two modern periods. In fact, the absolute magnitude of the volatility risk price in the interwar period is twice as large as that in the post Bretton Woods era, and six times that in the post Euro era. Given these volatility betas and volatility risk prices, we find that volatility risk premium amounts to nearly 6% per annum in the interwar sample and the post Bretton Woods sample, leaving only about 1% out of the 7% average excess return of the carry strategy unexplained by the global FX volatility risk. The volatility risk premium explains about 4% out of the 6% annual mean excess return in the post Euro sample. Overall, a significant proportion of excess returns from the carry trade can be explained by compensation for global FX volatility risk.

Risk price estimates for momentum portfolios are shown in the right panel. Similar to results for the carry portfolios, global FX volatility risk price varies considerably over the three historical samples. Around 5% out of the 7% return from momentum is attributed to a volatility risk premium in the interwar sample but this falls to less than 1% out of the 5% momentum return in the post Bretton Woods sample. Recall that there is no excess return from momentum in the post-Euro sample.

In terms of the χ^2 statistics, we cannot reject the null hypothesis that pricing errors are jointly zero for the carry trade in the interwar sample. Interestingly, the null hypothesis is also rejected for currency momentum in the interwar sample, which lends considerable support to the global FX volatility risk model for both carry trade and momentum returns in this period.

Statistical Significance. We note that the standard errors suggest that the volatility beta estimates and the volatility risk price estimates are not statistically significant. This is in spite of the economic (and statistical) significance of the risk premium which is able to account for the majority of average excess returns to the carry trade and momentum. Given the extremely volatile interwar sample, it is not surprising to see noisy estimates from time series regressions. The relatively smaller interwar cross section of currency portfolios may also impact the statistical power of our cross sectional tests. Another key reason for the statistically weakly results is that the global FX volatility and its innovations are likely to be poorly estimated following the procedure in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) given the much smaller cross section for the daily interwar exchange rates.

To address this issue, we consider a GARCH-based proxy for global FX volatility that better incorporates information about exchange rate volatility from the time series. Specifically, we estimate a univariate GARCH(1, 1) model for demeaned monthly spot exchange rate returns at the monthly frequency and obtain an aggregate FX volatility measure from the cross-sectional average of the square roots of each individual variance forecast $\widehat{\sigma}^2_{i,t|t-1}$. The GARCH-based FX volatility innovation is then computed as the difference between realized volatility and forecasted volatility, represented by $dFXVOL = \frac{1}{22}\left(|\Delta s_t| - \frac{1}{N}\sum_{i=1}^{N}\widehat{\sigma}_{i,t|t-1}\right)$. We scale the measure by 22 in order to compare volatility derived from daily exchange rate changes.

We then repeat the above asset pricing tests with this new proxy for global FX risk. The results, shown in Table 2.8 for the carry trade portfolios in the interwar period, demonstrate the ability of volatility risk to account for the average excess return to the carry trade. High interest-rate currencies tend to load negatively on volatility risks (i.e., lose when volatility is heightened) while low interest-rate currencies turn out to be a hedge for volatility risks. The zero-cost carry strategy has a statistically significantly negative volatility beta of -13.11 and the compensation for volatility risk amounts to a statistically significant 6.11% per annum. [9]

Overall, the foreign exchange volatility risk explanation of carry trade returns appears to have some power according to interwar evidence, as well as from evidence relating to the modern era.

[9]We note that untabulated results sugest that the GARCH-based volatility measure does not seem to improve the explanatory power of volatility risk for average excess returns to the momentum strategy.

2.5 Concluding Remarks

Putting a spotlight on the interwar foreign exchange market, we document that returns to two popular currency trading strategies, namely the carry trade and momentum, were both profitable. Further, average returns to the carry trade and momentum were of virtually the same magnitude in the interwar sample as in the modern samples.

We examine two competing explanations that have been proposed in the literature to rationalize the returns to currency speculation. Our interwar evidence implies that global FX volatility risk remains an economically sensible explanation for both the carry trade and, to a lesser extent, momentum. Because both the carry trade and momentum are exposed to volatility risk and since the average investor dislikes volatility risk and so requires compensation for taking on volatility risk, the carry trade and momentum have to earn sizable average returns.

On the other hand we show that non-risk based explanations such as rare disasters lead to economically implausible and unrealistic inference. We show that believing the average return to the carry trade is in reality zero is difficult because it follows that either the sizable in-sample average returns observed in each of three distinct samples are themselves rare events, or that disasters are not rare at all. A further implication is that zero mean returns to carry (momentum) imply that momentum (carry trade) produces a large positive mean return. We argue that our evidence is unfavorable to the pure rare disaster-based explanations, although we do not claim that non-risk based explanations are completely unappealing.

Table 2.1

Descriptive Statistics of Individual Currencies.

This table reports summary statistics of individual bilateral exchange rates including the number of observations, the mean forward discount or carry, the average exchange rate return "ΔS", the average excess return "rx" and its standard deviation "StD" , skewness, and excess kurtosis "KurtX". The last two columns reports the mean return of the carry trade and momentum based on individual currencies. Panel a. presents the above statistics calculated by interwar data from 1921:1 to 1936:12, while Panel b. and c. present these statistics calculated by modern sample data from 1976:1 to1998:12, and from 1999:1 to 2013:3, respectively. The mean and standard deviation are expressed in terms of percentage per annum.

a. 1921:1-1936:12

	obs	Carry	ΔS	rx	StD	Skew	KurtX	sign(carry)*rx	sign(mom)*rx
AUD	—	—	—	—	—	—	—	—	—
BEF	190	-0.14	-2.85	-2.89	18.65	0.39	5.90	3.05	-1.07
CAD	—	—	—	—	—	—	—	—	—
CHF	180	0.33	1.61	2.02	9.84	-5.09	60.30	-0.99	3.84
DEM	103	0.48	-17.75	-17.26	42.60	-0.83	14.73	-0.73	11.74
DKK	—	—	—	—	—	—	—	—	—
EUR	—	—	—	—	—	—	—	—	—
FRF	189	1.72	0.24	2.01	18.13	1.03	6.42	0.87	2.10
GBP	192	-0.45	2.10	1.65	9.25	-2.62	29.24	-2.01	2.28
ITL	178	2.60	5.01	7.42	16.37	0.87	5.87	6.92	11.45
JPY	—	—	—	—	—	—	—	—	—
NLG	192	0.76	3.45	4.22	8.44	-1.46	23.84	0.41	3.96
NOK	—	—	—	—	—	—	—	—	—
NZD	—	—	—	—	—	—	—	—	—
SEK	—	—	—	—	—	—	—	—	—

b. 1976:1-1998:12

	obs	Carry	ΔS	rx	StD	Skew	KurtX	sign(carry)*rx	sign(mom)*rx
AUD	168	3.97	-1.54	2.43	10.81	-0.68	2.13	5.82	6.92
BEF	275	1.10	1.26	2.36	11.66	-0.03	0.90	8.18	5.80
CAD	275	1.20	-1.76	-0.55	4.74	-0.45	1.18	3.37	0.36
CHF	275	-3.73	3.61	-0.12	12.99	-0.04	0.53	1.55	5.04
DEM	275	-2.03	2.58	0.55	11.56	-0.10	0.48	0.82	5.69
DKK	275	2.85	0.49	3.34	11.47	0.03	0.52	10.46	5.94
EUR	—	—	—	—	—	—	—	—	—
FRF	275	2.05	-0.36	1.70	11.11	-0.14	0.44	5.87	3.61
GBP	275	2.57	-0.21	2.36	11.55	0.01	1.38	7.03	4.38
ITL	275	5.76	-2.82	2.94	10.83	-0.38	1.27	3.53	7.50
JPY	246	-3.58	3.74	0.15	13.25	0.62	1.34	4.68	6.74
NLG	275	-1.25	2.19	0.94	11.59	-0.01	0.61	3.97	6.32
NOK	275	2.76	-0.90	1.86	9.98	-0.19	1.26	4.77	5.89
NZD	168	6.10	1.34	7.43	11.10	0.21	2.39	6.69	5.08
SEK	275	3.17	-2.13	1.04	10.60	-0.90	3.38	6.34	6.85

c. 1999:1-2013:3

	obs	Carry	ΔS	rx	StD	Skew	KurtX	sign(carry)*rx	sign(mom)*rx
AUD	171	2.63	4.58	7.21	12.90	-0.60	1.88	8.45	3.28
BEF	—	—	—	—	—	—	—	—	—
CAD	171	0.32	3.26	3.58	8.92	-0.41	2.99	-0.28	-1.08
CHF	171	-1.54	3.24	1.69	11.25	0.29	1.51	-0.07	3.99
DEM	—	—	—	—	—	—	—	—	—
DKK	171	0.02	1.21	1.23	10.57	0.01	0.79	5.92	5.67
EUR	170	-0.23	1.43	1.20	10.67	-0.06	0.72	5.43	5.61
FRF	—	—	—	—	—	—	—	—	—
GBP	171	0.93	-0.26	0.67	8.80	-0.21	1.34	2.66	1.03
ITL	—	—	—	—	—	—	—	—	—
JPY	171	-2.62	1.77	-0.86	9.74	-0.19	0.01	0.52	0.49
NLG	—	—	—	—	—	—	—	—	—
NOK	171	1.41	2.50	3.91	11.30	-0.31	0.88	2.69	-1.37
NZD	171	2.89	4.14	7.04	13.62	-0.32	1.42	10.38	5.67
SEK	171	-0.02	2.23	2.21	11.90	0.01	0.17	9.25	5.89

Table 2.2

Descriptive Statistics of Portfolios.

This table reports mean portfolio returns to the carry trade and currency momentum strategies, categorized according to the subsample: Panel a. for the interwar sample from 1921:1 to 1936:12, Panel b. for the post-Bretton-Woods sample from 1976:1 to 1998:12, and Panel c. for the post-euro sample from 1999:1 to 2013:3. In each panel, the first row reports mean returns to currency portfolios indexed by $j = 1, 2, \cdots, 5$, with higher j indicates higher interest rate for the carry trade portfolios and higher past excess return for the momentum portfolios; the second row reports mean returns to the zero-cost currency strategies long $j = 2, 3, \cdots, 5$-short $j = 1$; the third row reports the t-ratio for the above zero cost strategies based on Newey-West standard errors with optimal number of lags [see Newey and West (1987) and Andrews (1991).]; and the last row reports the annualized Sharpe ratio of these zero-cost currency strategies. The mean return and standard deviation are expressed in terms of percentage per annum. The Sharpe ratio is annualized.

	Carry					Momentum				
	1L	2	3M	4	5H	1L	2	3M	4	5H
	a. 1921:1-1936:12					a. 1921:1-1936:12				
j	-2.16	—	0.29	—	4.50	-3.93	—	-0.56	—	3.52
j-1	—	—	2.46	—	6.66	—	—	3.37	—	7.45
tstat	—	—	0.76	—	1.98	—	—	1.19	—	1.28
S.R.	—	—	0.17	—	0.37	—	—	0.19	—	0.31
	b. 1976:1-1998:12					b. 1976:1-1998:12				
j	-1.72	0.76	0.68	2.66	5.03	-2.27	1.06	3.10	2.57	3.11
j-1	—	2.62	2.40	4.39	6.75	—	3.34	5.38	4.85	5.39
tstat	—	2.46	1.85	2.48	4.01	—	2.20	3.46	3.70	3.66
S.R.	—	0.52	0.39	0.53	0.79	—	0.52	0.76	0.60	0.61
	c. 1999:1-2013:3					c. 1999:1-2013:3				
j	0.65	0.35	2.16	3.36	6.98	2.34	2.30	2.52	4.75	1.99
j-1	—	-0.30	1.51	2.72	6.34	—	-0.04	0.18	2.42	-0.35
tstat	—	-0.13	0.67	1.22	2.80	—	-0.05	0.14	1.16	-0.23
S.R.	—	-0.04	0.19	0.31	0.60	—	-0.01	0.02	0.29	-0.04
	d. Full sample					d. Full sample				
j	-1.21	—	0.96	—	5.39	-1.53	—	1.84	—	2.93
j-1	—	—	2.18	—	6.61	—	—	3.38	—	4.46
tstat	—	—	1.71	—	5.21	—	—	2.93	—	2.26
S.R.	—	—	0.23	—	0.52	—	—	0.30	—	0.30

Table 2.3

Carry vs Appreciation.

This table presents the Carry Component and the Appreciation Component in the Mean Excess Return of long-short Carry (upper panel) and Momentum Strategies (lower panel). Column "Z" denote the mean excess return (% per annum), column "C" denotes the mean interest rate differential or carry component (% per annum), and column "A" denotes the mean spot exchange rate return or appreciation (% per annum). The columns "C/Z" and "A/Z" reports the portions of the carry component and the appreciation component in the mean excess return respectively.

	Carry				
	Z	C	A	C/Z	A/Z
Interwar	6.66	5.41	1.38	81%	21%
Post Bretton Woods	6.75	9.98	-3.24	148%	-48%
Euro Era	6.34	5.44	0.90	86%	14%

	Momentum				
	Z	C	A	C/Z	A/Z
Interwar	7.45	1.11	6.24	15%	84%
Post Bretton Woods	5.39	2.34	3.04	43%	57%
Euro Era	-0.35	0.81	-1.16	-231%	331%

Table 2.4

Distribution of **Average Excess Returns.** Implied from Empirical Likelihoods.

This table reports key statistics of the distribution of average excess returns to the carry trade and momentum based on empirical likelihood estimates under the null hypothesis that the true mean return to the carry trade or momentum is zero. The distribution of average returns are obtained by resampling the actual data with replacement to generate bootstrap sample of the same size as the actual sample and compute the average in each bootstrap sample. The numbers reported in this table include the actual sample average return, and the mean, median, 2.5% percentile, 97.5% percentile, the probability that the average return is no smaller than of the distribution for the average return, and the probability that the average return is no larger than zero. Panel a1 presents the distribution for average carry trade returns based on empirical likelihood such that mean carry trade return is zero; Panel a2 presents the distribution for average momentum returns based on the same EL as in Panel a1. Separately, Panel b1 presents the distribution for average carry trade returns based on empirical likelihood such that mean momentum return is zero while Panel b2 presents the distribution for average momentum returns based on the same EL as in Panel b1. In each panel, we report results for each of the three subsamples and the full sample.

	Data	EL implied Distribution for Average Carry Return						Data	EL implied Distribution for Average Mom. Return					
	$\overline{Z}$	Mean	Med	2.5%	97.5%	P[$\geq \overline{Z}$]	P[≤ 0]	$\overline{Z}$	Mean	Med	2.5%	97.5%	P[$\geq \overline{Z}$]	P[≤ 0]
	a1. $Distr(\overline{Z}^{carry})$ implied from $\overline{Z}^{carry} = 0$							a2. $Distr(\overline{Z}^{mom})$ implied from $\overline{Z}^{carry} = 0$						
1921:1-1936:12	6.66	-0.02	0.04	-9.78	9.50	8.09	49.69	7.45	7.15	7.22	-5.84	20.02	48.38	14.24
1976:1-1998:12	6.75	-0.02	0.01	-4.17	4.07	0.01	49.82	5.39	5.00	5.02	0.78	9.18	42.92	1.07
1999:1-2013:3	6.34	-0.08	-0.03	-6.41	5.90	1.74	50.52	-0.35	0.85	0.84	-4.61	6.47	66.54	37.84
Full Sample	**6.61**	**0.00**	**0.02**	**-4.07**	**3.88**	**0.05**	**49.51**	**4.46**	**4.46**	**4.46**	**0.44**	**8.50**	**49.85**	**1.53**
	b1. $Distr(\overline{Z}^{carry})$ implied from $\overline{Z}^{mom.} = 0$							b2. $Distr(\overline{Z}^{mom.})$ implied from $\overline{Z}^{mom} = 0$						
1921:1-1936:12	6.66	6.54	6.60	-2.33	15.41	49.35	7.52	7.45	0.02	0.18	-12.31	11.71	10.90	48.68
1976:1-1998:12	6.75	5.45	5.46	1.80	9.06	24.35	0.21	5.39	0.01	0.03	-3.90	3.87	0.33	49.45
1999:1-2013:3	6.34	6.31	6.32	0.87	11.77	49.72	1.26	-0.35	-0.02	-0.02	-5.01	5.00	54.98	50.37
Full Sample	**6.61**	**6.12**	**6.12**	**2.59**	**9.56**	**32.67**	**0.04**	**4.46**	**0.01**	**0.02**	**-4.38**	**4.33**	**2.17**	**49.65**

Table 2.5

Sample v.s. Rare Disaster Moments for the **Realized Excess Return**.

This table contrasts sample moments with the moments implied from a rare disaster distribution of excess returns. The rare disaster distribution is estimated using Empirical Likelihood methods under the null that the true mean excess return is zero.

	Carry					
	1921:1-1936:12		1976:1-1998:12		1999:1-2013:3	
	Sample	EL	Sample	EL	Sample	EL
Mean	6.66	0.92	6.75	0.17	6.34	-0.22
Median	2.84	2.29	8.85	4.98	9.11	4.43
StD	18.14	18.76	8.52	9.86	10.51	11.76
Skew	-0.58	-1.24	-0.90	-1.15	-0.73	-1.07
KurtX	9.11	9.00	2.62	2.48	2.68	2.91

	Momentum					
	1921:1-1936:12		1976:1-1998:12		1999:1-2013:3	
	Sample	EL	Sample	EL	Sample	EL
Mean	7.45	-1.50	5.39	0.37	-0.35	-0.68
Median	1.10	0.42	5.61	2.76	0.35	-0.22
StD	23.66	24.40	8.89	9.26	9.52	9.47
Skew	0.25	-0.91	0.01	-0.49	0.28	0.18
KurtX	10.36	10.23	2.62	2.48	1.90	1.62

Table 2.6

Volatility Beta.

This table reports volatility beta's of Portfolios sorted by carry and momentum respectively, i.e. the exposure of portfolio excess return to the innovations to foreign exchange market volatility measure as in Menkoff et al. (2012) while the exposure to dollar risk is controlled. Newey-West standard errors with optimally chosen lags are presented in parentheses [see Newey and West (1987) and Andrews (1991)]. We also report the time series R-squared.

	Carry						Momentum					
	1L	2	3M	4	5H	HML	1L	2	3M	4	5H	HML
	a. 1921:1-1936:12						a. 1921:1-1936:12					
β_{vol}	0.85	—	0.69	—	-1.53	-2.38	0.03	—	0.47	—	-2.35	-2.38
s.e.	(1.05)	—	(0.97)	—	(1.30)	(2.17)	(1.78)	—	(0.81)	—	(2.91)	(4.48)
R^2	0.62	—	0.63	—	0.68	0.03	0.74	—	0.70	—	0.36	0.20
	b. 1976:1-1998:12						b. 1976:1-1998:12					
β_{vol}	2.92	0.28	0.04	-1.66	-1.60	-4.53	0.82	-1.00	1.60	-0.53	-0.43	-1.25
s.e.	(0.71)	(0.60)	(0.56)	(0.94)	(0.88)	(1.30)	(0.94)	(0.70)	(0.61)	(1.06)	(0.82)	(1.66)
R^2	0.82	0.86	0.89	0.75	0.73	0.06	0.72	0.86	0.90	0.81	0.68	0.01
	c. 1999:1-2013:3						c. 1999:1-2013:3					
β_{vol}	6.20	0.02	-0.05	-2.73	-3.44	-9.65	-2.94	-0.35	0.58	-0.33	3.14	6.07
s.e.	(2.31)	(2.11)	(0.74)	(1.03)	(1.42)	(3.04)	(1.59)	(0.95)	(2.24)	(1.48)	(3.12)	(4.57)
R^2	0.60	0.80	0.84	0.83	0.81	0.28	0.74	0.82	0.79	0.79	0.69	0.05
	d. Full sample						d. Full sample					
β_{vol}	2.13	—	0.21	—	-1.67	-3.80	0.55	—	0.35	—	-1.42	-1.97
s.e.	(1.00)	—	(0.69)	—	(1.01)	(1.81)	(1.03)	—	(0.58)	—	(1.90)	(2.72)
R^2	0.67	—	0.76	—	0.72	0.06	0.68	—	0.78	—	0.51	0.09

Table 2.7

Fama-McBeth Estimates of Risk Prices.

This table reports prices of the dollar risk and the volatility risk estimated via the Fama-McBeth procedure. Standard errors with Shanken's adjustment [see Shanken (1992)], and Newey-West standard errors with optimally chosen lags [see Newey and West (1987) and Andrews (1991)] are presented in the parentheses. We also report the dollar risk premium and volatility risk premium respectively in the row "$\lambda\beta_{HML}$". The column "χ^2_{SH}" reports the χ^2 statistics based on Shanken's adjustment and the column "χ^2_{NW}" reports the χ^2 statistics based on Newey-West procedure with optimal number of lags according to Andrews (1991). The statistic $||\,\alpha\,||$, expressed in terms of percentage per annum, is calculated as the cross-sectional standard deviation of pricing errors under the null of zero mean. Panel a. reports results for the interwar sample from 1921:1 to 1936:12, Panel b. for the post-Bretton-Woods sample from 1976:1-1998:12, Panel c. for the post-euro sample from 1999:1 to 2013:3, and Panel d. for the full sample combining all the time series. The cross section analysis for the full sample only includes three portfolios $j = 1, 3, 5$ in the period from 1976:1 to 2013:3.

	Carry				Momentum			
a. 1921:1-1936:12								
	DOL	VOL	χ^2_{SH}	χ^2_{NW}	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.80	-2.31	0.79	0.43	-1.86	-1.93	1.12	0.70
(SH)	(3.02)	(2.22)	[0.37]	[0.51]	(3.21)	(1.77)	[0.29]	[0.40]
(NW)	(3.36)	(1.68)			(3.40)	(1.35)		
			$\|\|\,\alpha\,\|\|$				$\|\|\,\alpha\,\|\|$	
$\lambda\beta_{HML}$	0.18	5.49	0.91		1.65	4.61	1.10	
b. 1976:1-1998:12								
	DOL	VOL	χ^2_{SH}	χ^2_{NW}	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	1.47	-1.28	9.40	4.29	1.57	-0.33	14.02	12.03
(SH)	(1.83)	(0.49)	[0.02]	[0.23]	(1.84)	(0.40)	[0.00]	[0.01]
(NW)	(1.87)	(0.37)			(1.89)	(0.39)		
			$\|\|\,\alpha\,\|\|$				$\|\|\,\alpha\,\|\|$	
$\lambda\beta_{HML}$	-0.22	5.75	0.91		-0.13	0.41	1.98	
c. 1999:1-2013:3								
	DOL	VOL	χ^2_{SH}	χ^2_{NW}	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	2.75	-0.41	7.14	7.06	2.78	-0.09	2.78	2.59
(SH)	(2.30)	(0.25)	[0.07]	[0.07]	(2.30)	(0.41)	[0.43]	[0.46]
(NW)	(2.38)	(0.25)			(2.38)	(0.38)		
			$\|\|\,\alpha\,\|\|$				$\|\|\,\alpha\,\|\|$	
$\lambda\beta_{HML}$	1.18	3.92	1.58		-0.02	-0.56	0.98	
d. Full Sample								
	DOL	VOL	χ^2_{SH}	χ^2_{NW}	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	2.11	-1.65	1.38	0.76	0.63	-1.75	—	5.35
(SH)	(1.38)	(0.61)	[0.24]	[0.38]	(1.38)	(1.15)	—	[0.02]
(NW)	(1.53)	(0.47)			(1.51)	(0.76)		
			$\|\|\,\alpha\,\|\|$				$\|\|\,\alpha\,\|\|$	
$\lambda\beta_{HML}$	0.33	6.29	0.42		-0.27	3.45	1.33	

Table 2.8

GARCH-based FX Volatility Risk Premium in the Interwar Period.

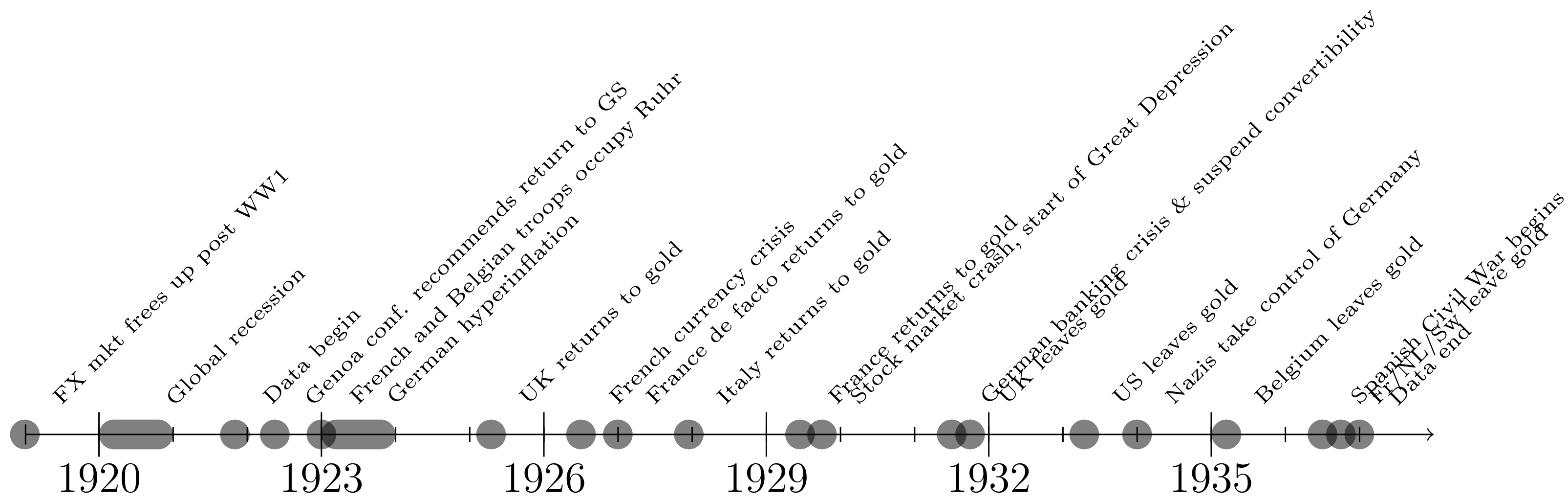
This table presents Fama-MacBeth two-stage estimates for the GARCH-based FX volatility risk beta and the corresponding risk premium for the interwar sample spanning from 1921:1 to 1936:12. The standard errors, reported in parentheses, are computed based on the Newey-West procedure for the beta and lambda estimates and are based on bootstrapping for the risk premium estimates.

a. GARCH-based FX Volatility Beta

	1L	2	3	4	5H
β_{VOL}	7.23	—	-1.35	—	-5.88
s.e.	(3.19)	—	(2.52)	—	(2.79)
R2	0.65	—	0.63	—	0.69

b. Risk Premium for Carry HML

β_{DOL}	λ_{DOL}	rp_{DOL}	β_{VOL}	λ_{VOL}	rp_{VOL}
0.24	0.98	0.24	-13.11	-0.47	6.11
(0.30)	(3.02)	(1.11)	(5.35)	(0.35)	(3.88)



1

Three regimes of Interwar period:

- Free float: 1920 - December 1927 (73 observations in sample)
- Interwar Gold Standard: January 1928 - August 1931 (39 observations)
- Managed float: September 1931 - 1936 (63 observations)

Figure 2.1. Chronology of the Interwar Period.

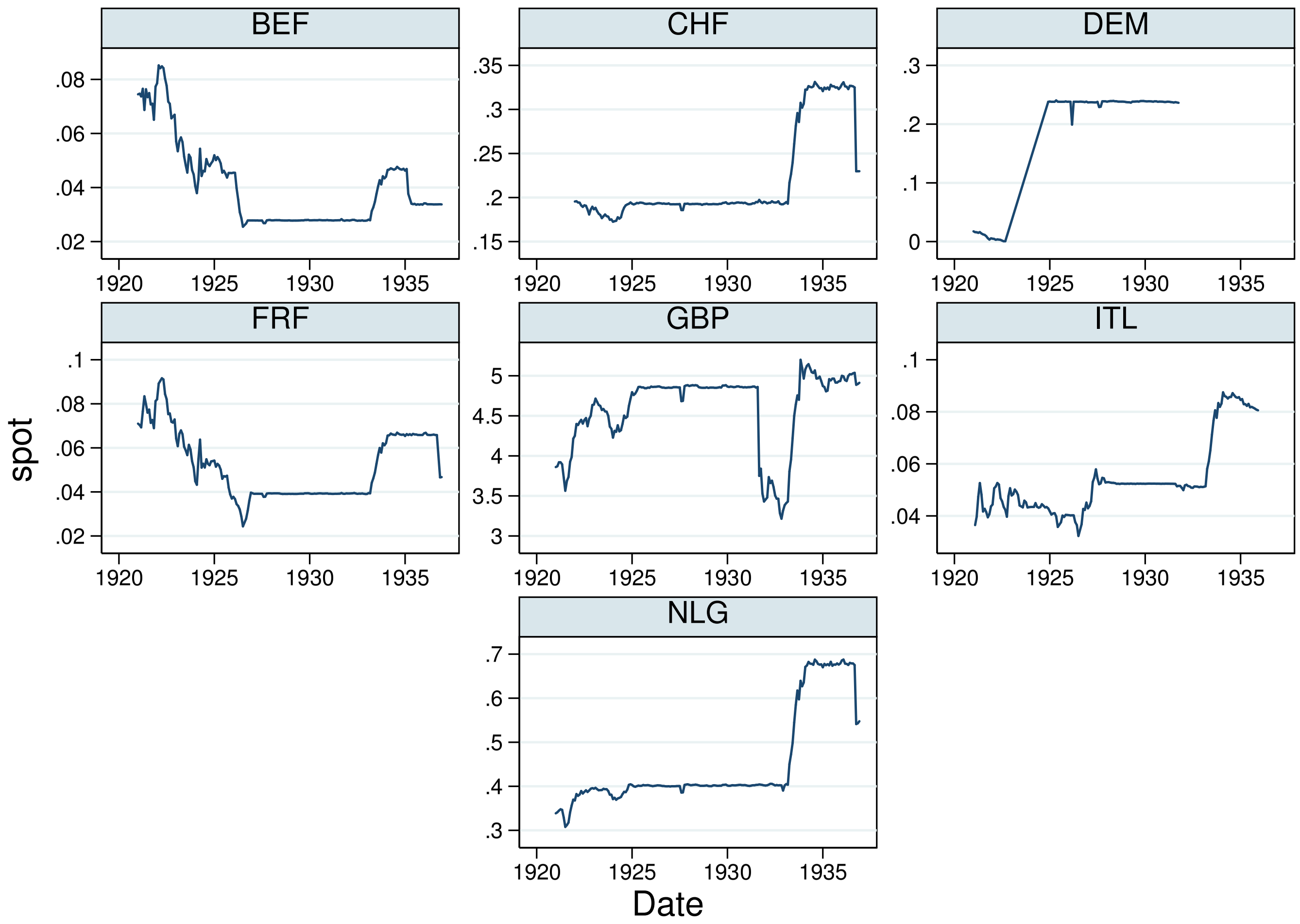


Figure 2.2. Interwar Exchange Rates against the US dollar.
The figure shows the dynamics of the spot exchange rate, in terms of the US dollar price of one foreign currency unit, of the seven european currencies in the interwar era, i.e. 1921:1-1936:12.

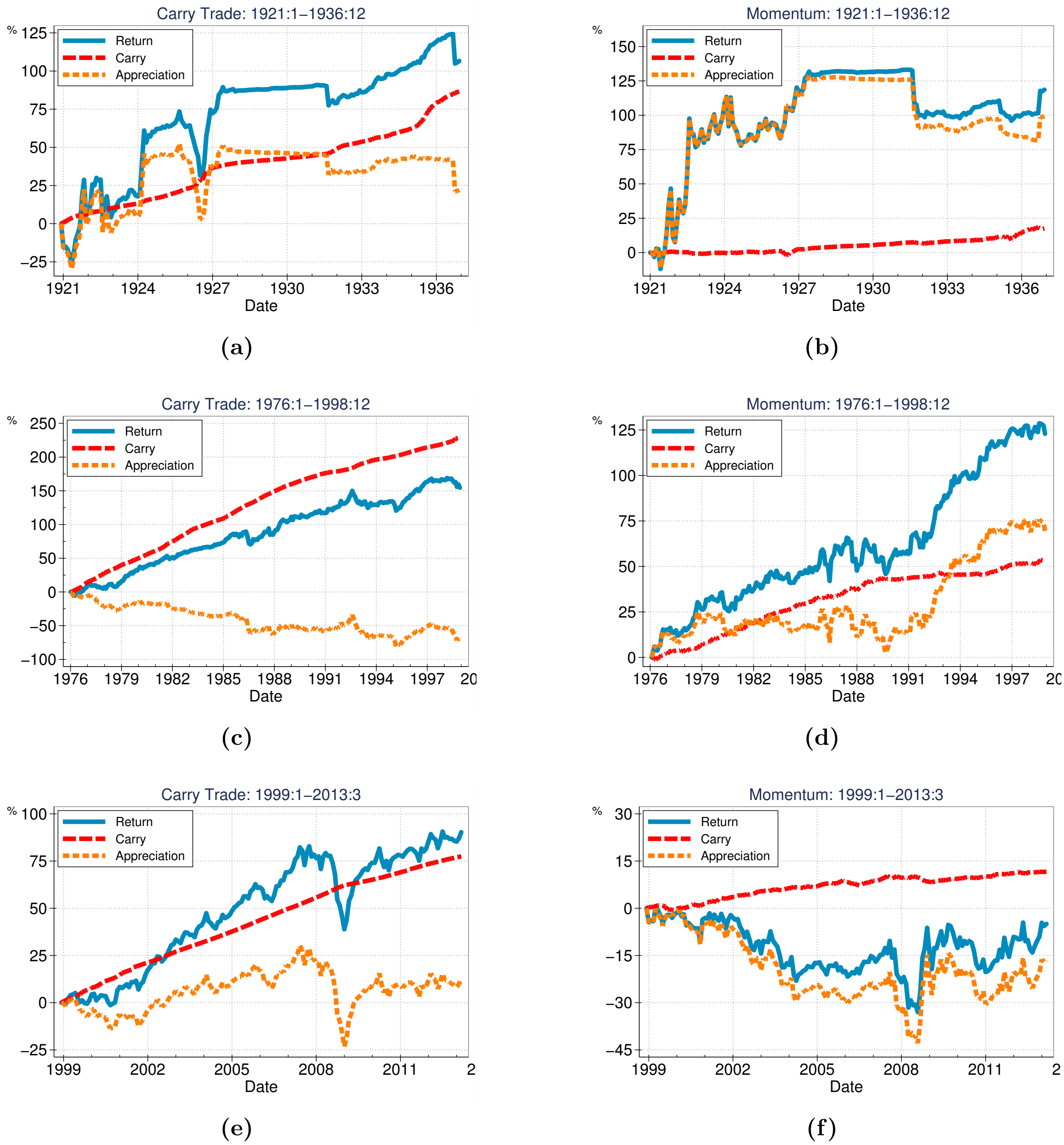
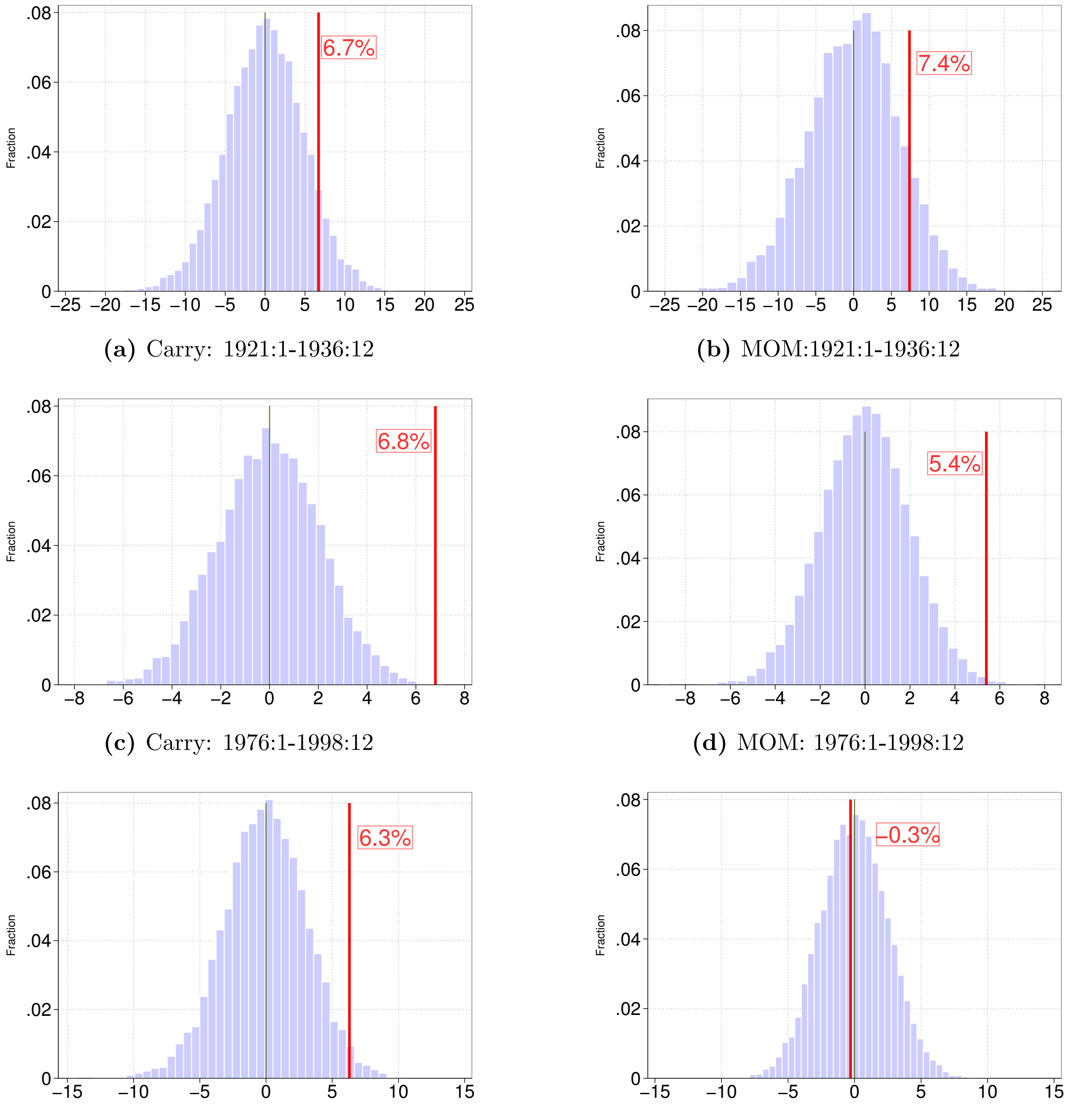


Figure 2.3. Cumulative Returns of the Carry and Momentum Strategies. This figure shows the simple cumulative excess returns of the long-short carry strategy and the long-short momentum strategy, along with the simple interest cumulations and simple cumulative exchange rate returns.



(a) Carry: 1921:1-1936:12

(b) MOM:1921:1-1936:12

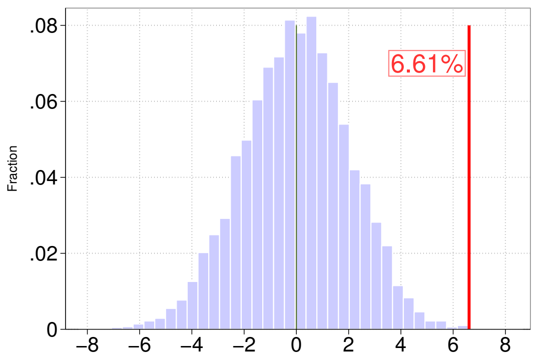
(c) Carry: 1976:1-1998:12

(d) MOM: 1976:1-1998:12

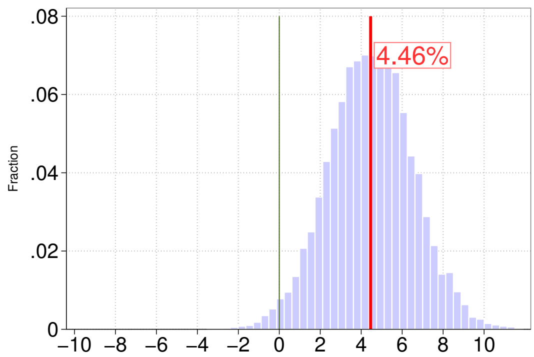
(e) Carry: 1999:1-2013:3

(f) MOM: 1999:1-2013:3

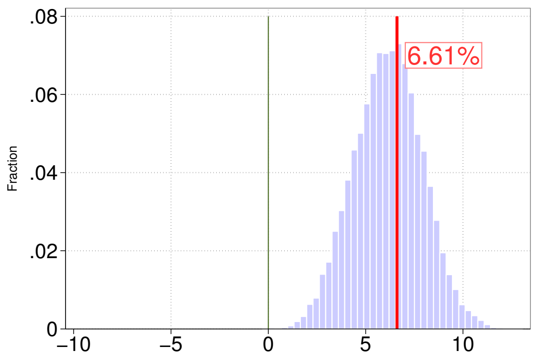
Figure 2.4. Distribution for the Average Excess Return given zero true mean.



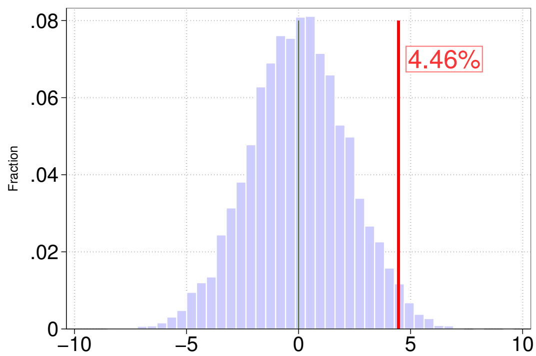
(a) Distr($\overline{Z}^{carry}$) under H_0 : $\overline{Z}^{carry} = 0$



(b) Distr($\overline{Z}^{mom}$) under H_0 : $\overline{Z}^{carry} = 0$

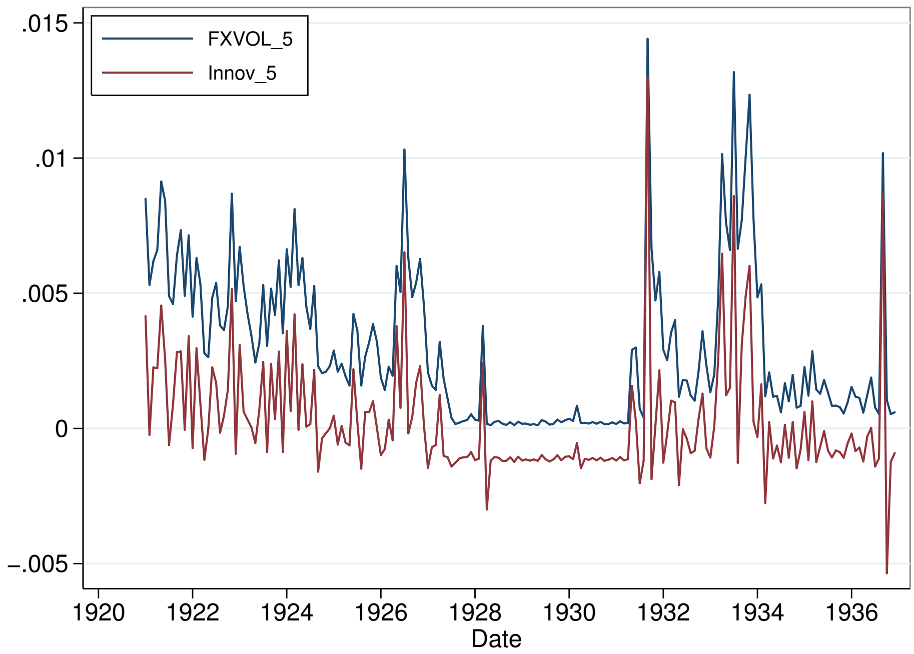


(c) Distr($\overline{Z}^{carry}$) under H_0 : $\overline{Z}^{mom} = 0$

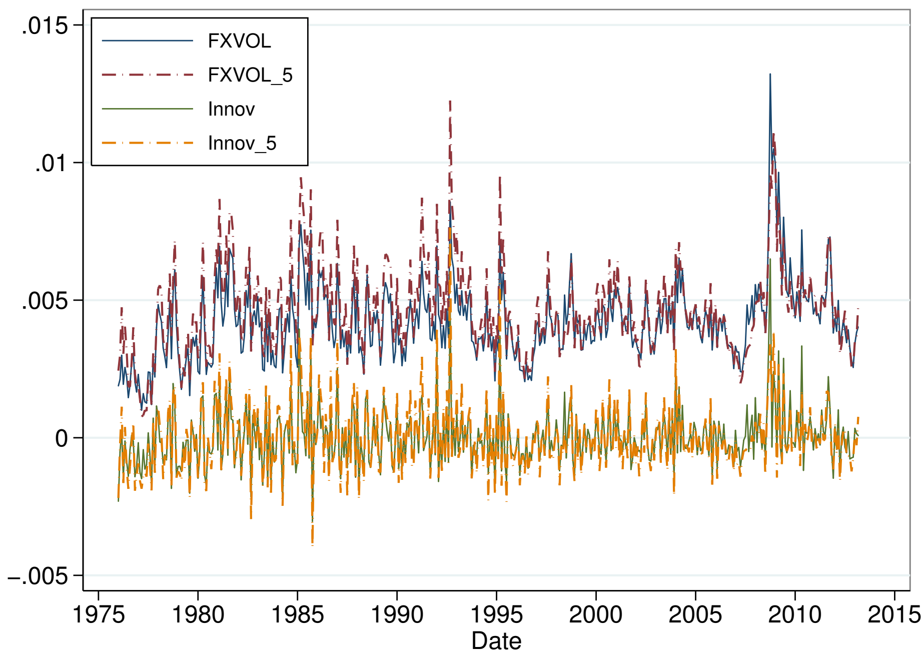


(d) Distr($\overline{Z}^{mom}$) under H_0 : $\overline{Z}^{mom} = 0$

Figure 2.5. Full-sample implied Distribution for the Average Excess Return given zero true mean of either carry trade or momentum.



(a) Interwar Sample



(b) Modern Sample

Figure 2.6. Global FX Volatility and its Innovations.
This upper panel shows the Global FX volatility measure using daily exchange rate returns of only five major currencies (CHF, DEM, GBP, FRF, ITL) and its innovations implied by an AR(1) model. The lower panel contrasts the Global FX volatility measure using daily exchange rate returns of only five major currencies (CHF, DEM, GBP, FRF, ITL) and that using daily exchange rate returns of all developed countries.

Chapter 3

Switching Risk Off: FX Correlations and Risk Premium

3.1 Introduction

> Who flipped a switch? Which god-like overlord of financial markets decided that, verily, today is a "risk-off day"? Someone did. Early Tuesday in Europe, for no real reason, the financial markets leapt feet-first into a blind panic. The yen – rightly or wrongly a bellwether of the market's general nerves – suddenly shot to major highs against a range of other currencies, in a classic "risk-off" (or "run for your lives") shift.
>
> *The Wall Street Journal*, 24 Aug 2010.

Asset prices are determined by beliefs and preferences. In recent years, financial markets have experienced relatively frequent cases of abrupt changes in investors' attitude towards risk, with dramatic effects on asset prices, such as the episode described in the opening quote. This common rhetoric, with little scientific basis, suggests that these events, dubbed "risk-off" episodes, are not driven by changes in economic fundamentals. Risk-off is thus hard to predict and can have devastating consequences on investors' portfolios, as diversification benefits are eroded by increasing correlations among risky assets.

In the asset pricing literature, models are often conditioned on persistent variables that are correlated with *levels* of risk preferences, like the VIX index. However, risk-off refers to a *change* in risk preferences and the associated portfolio rebalancing. We exploit this basic facet in our methodology. Specifically, we capture the simultaneous price impact induced by arbitrageurs using similar trading strategies triggered by a change in preferences. We focus on correlated returns in currency markets of G10 countries, where we believe preference-induced trades are more likely to be identified, given the less significant role of macroeconomic fundamentals for currencies (e.g., Meese and Rogoff (1983)), the negligible influence of private information, and the small number of relatively homogeneous assets.

Our empirical approach is straightforward. We detect a change in risk attitudes through a concurrent change in the correlation structure of G10 currency returns, which reflects the crowded arbitrageurs trades in risk-off episodes. More specifically, we estimate a model with regime-switching correlations for G10 exchange rates, hypothesizing that switches to a polarized correlation regime should endogenously identify risk-off events. We then study the pattern of correlation regime probabilities to provide a more scientific account of the classic risk-off shifts, including how they play out across the financial landscape beyond currencies.

The empirical results are intriguing. We start by identifying two foreign-exchange correlation regimes. The first regime, which we refer to as high or polarized correlations, features large correlations among most currencies, with the notable exceptions of the Japanese yen and the Swiss Franc. The second regime exhibits moderate correlations across the board, except again for the Japanese yen and the Swiss Franc that tend to be relatively more correlated with the other currencies here than in the first regime. We associate risk-off events with the switch of correlation from the moderate to the polarized regime and document that these events tend to be relatively infrequent, but noticeably increasingly frequent over time. Furthermore, we observe that these regime switches are persistent and tend to be associated with relevant geopolitical events.

We perform a battery of empirical analyses to understand better the driving forces of the risk-off shifts. We show that the switches in correlations tend to be unrelated to changes in real-time macroeconomic fundamentals. Risk-off events do not have a clear-cut association with volatility shocks, suggesting that the transition in the correlation structure is not just the result of a simple increase in risk and is different from a variance risk premium interpretation. Interestingly, the detected risk-off shifts cannot be picked up by innovations in average implied correlations either, indicating that the standard correlation risk premium explanation does not apply.

We also look at the relation between correlation regime switches and the prices of currency risk reversals and find that after risk-off shifts, the price of insuring tail events significantly increases for *growth* currencies and decreases for *safe-haven* currencies, consistent with a change in investors' risk preferences. Finally, we compare our method with alternative ways of detecting risk-off events and find only weak similarities, which emphasizes the original insights obtained by the use of our methodology in the foreign-exchange market.

After establishing the nature and characteristics of the risk-off shifts, we analyze their effects on the financial landscape beyond currencies. We find that the probability of a switch from the moderate to the high polarized correlation regime has a strong negative impact on the returns of a large number of risky underlyings and trading strategies in different asset classes: G10 foreign-exchange returns, emerging market currencies, commodities, and international stock markets. Consistent with the implications of a risk-off event, safe-haven asset returns benefit dramatically, in both foreign exchange and international bond markets.

We study the robustness of these results on asset returns to volatility innovations, to average implied correlation shocks, and to innovations in alternative risk-off indices. All of the original findings are unchanged, confirming our earlier evidence that regime switches to polarized currency correlations contain different information than innovations in other risk measures. For example, while it is often the case that the moderate-to-polarized correlation regime switch is associated with positive volatility shocks, the same is true for the switch from the polarized to moderate correlation regime, with quite different asset return implications.

We attempt to rationalize this impact on asset returns with an analysis of professional investor positions across different financial markets. Given the explicit link of our identification method to the simultaneous trades of arbitrageurs or speculators hit by a risk preference shock, the effect on asset returns could simply be the outcome of the price pressure exerted by crowded portfolio rebalancing towards safer assets. Consistent with this conjecture, we find that the probability of switching to the polarized correlation regime is associated with a significant reduction in the net speculator positions for futures contracts on relatively more risky assets and a significant increase in net positions for safer assets.

Related literature

Our paper contributes to the literature that has examined the asset pricing effects of changes in preferences and the ensuing movements of arbitrage capital. Incidentally, given the focus of our methodology on currency returns, it also contributes to research in foreign-exchange.

The analysis of co-movement to infer the effects of shifts of arbitrage capital on asset prices is inspired by the seminal work of Barberis, Shleifer, and Wurgler (2005), who document that stock returns co-move in excess of what is implied by their fundamentals because of institutional features.[1] These ideas motivate the study of asset return correlations generated by the simultaneous price impact of the trades of arbitrageurs or speculators taking similar positions in more or less risky assets. The contribution of our paper is to come up with a reasonable empirical measure of these shifts in aggregate trading activity and to document their asset pricing effects across financial markets.

[1]More recently, Greenwood and Thesmar (2011), Lou (2012), and Anton and Polk (2014) find that flow-induced trading by mutual funds can lead to excess co-movement among stocks collectively held by mutual funds.

Similar to our paper, Lou and Polk (2013) use a novel approach to measuring arbitrage activity in stock markets by co-momentum (i.e., average pairwise correlations within equity momentum portfolios). The risk-off episodes that we identify in our paper are the results of shifts in arbitrage capital. Like Lou and Polk (2013), our identification strategy uses correlation dynamics. However, we do not focus on the stock market but on the foreign-exchange market, where the effect of fundamentals is much less clear-cut. Furthermore, we do not rely on a specific trading strategy, but on the more basic link between changes in attitude toward risks, foreign exchange market correlations, and returns to currency speculation. Xing Hu, Pan, and Wang (2012) use a different approach and obtain a measure of shortage of arbitrage capital using deviations of U.S. Treasury market yields from a smooth yield curve. In our setting, we are not after shortages of arbitrage capital and their potential asset pricing effects, but more specifically we aim to capture shifts of arbitrage or speculative capital away from risky assets.

Our focus on risk-off events is related to recent work by Baele, Bekaert, Inghelbrecht, and Wei (2013), who characterize empirically flight-to-safety episodes using data on international bond and stock returns. The purpose of their analysis is very different though. We do not focus on *local* episodes that feature a specific pattern of returns, correlations, and volatility between stocks and bonds, but instead use foreign-exchange market dynamics to identify *global* episodes and *global* shifts of risk capital. In fact, less than 25% of the events detected in Baele, Bekaert, Inghelbrecht, and Wei (2013) are global and these global flight-to-safety episodes are not significantly correlated with our risk-off events.[2]

Finally, given the focus of our methodology on currencies and the asset pricing implications, our work is related to a large number of papers in foreign-exchange, especially research on risk-based explanations for currency trading strategies (e.g., Lustig and Verdelhan (2007); Lustig, Roussanov, and Verdelhan (2011)). For example, recently Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) attribute the returns of carry trade

[2]We thank Lieven Baele and Geert Bekaert for providing us with their data on global flight-to-safety episodes.

strategies to compensation for global FX volatility risk. Our findings enrich this explanation and suggest that higher volatility is a rewarded risk for carry trades only when it is associated with correlation switches to the polarized regime. In a similar vein, Mueller, Stathopoulos, and Vedolin (2012) show that the profits of a carry trade strategy are compensation for an average correlation risk premium. We show that our findings cannot be interpreted with the same model, because our polarized correlation regime tends to have, if anything, a lower average implied correlation than the moderate correlation regime.

The rest of our paper is organized as follows. Section 3.2 describes our data. In Section 3.3, we introduce the regime-switching model that we use to estimate correlation regimes and characterize their key properties. We study potential explanations for the switch in correlations in Section 3.4. We present our empirical results on the relation between asset returns and switches of correlation regimes in Section 3.5, where we also conduct the analysis of net speculator positions. Section 3.6 concludes with a summary of our results.

3.2 Data

Our sample period spans from January, 1995 to December, 2013. We collect all asset prices at the daily frequency and we compute daily logarithmic returns. Our primary data source are the exchange rate returns of G10 countries. Specifically, we obtain currency returns for Australia (AUD), Canada (CAD), Switzerland (CHF), the Eurozone (EUR), the United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), using the U.S. dollar (USD) as the reference currency.[3] We follow the literature and obtain daily spot exchange rates from BBI and Reuters via Datastream.

The major advantage of using G10 exchange rates is that they are readily available at the daily frequency for a long time period. This will be important in our empirical analysis

[3]Prior to the introduction of the Euro on January 1, 1999, we use the Deutsche Mark as the representative currency for the Eurozone.

later, because we can use a fixed cross-section to estimate the correlation matrices. Another advantage of using G10 countries is that their exchange rates are less subject to transaction cost and other liquidity concerns. While we identify correlation regimes using exclusively G10 currency returns, we also use returns on a number of trading strategies and different asset classes in the rest of our empirical analysis:

- We construct popular currency trading strategies return series, namely, the carry trade strategy and the momentum strategy, both formed by G10 currencies. Specifically, we obtain 1-month forward exchange rates also from BBI and Reuters via Datastream. We then calculate the carry trade returns by going long the three currencies with the largest forward discounts and going short the three currencies with the smallest forward discounts. Similarly, we form the momentum strategy by going long the three most profitable currencies over the previous three months and going short the three least profitable currencies over the previous three months. Both strategies are rebalanced every month.

- Our dataset also covers spot exchange rates of 16 emerging economies: Bulgaria (BGN), Brazil (BRL), Czech Republic (CZK), Egypt (EGP), Croatia (HRK), Hungary (HUF), Israel (ILS), India (INR), Mexico (MXN), Malaysia (MYR), Phillipine (PHP), Poland (PLN), Russia (RUB), Singapore (SGD), Thailand (THB), and South Africa (ZAR), obtained from Datastream using again the USD as a numeraire.

- We collect data for global equity markets that include 16 equity market indices obtained from Bloomberg. Five indices are North-American (S&P 500, Dow Jones Industrial Average, NASDAQ 100, Russell 2000, and S&P TSE 60), eight are in Europe (Euro STOXX 50, CAC 40, DAX, AEX, IBEX, OMX, SMI, and FTSE 100), and the remaining three indices are in Asia and Pacific (Nikkei 225, HSI, and S&P/ASX 200).

- We use global government bond data, namely the 10-year zero-coupon yields for the United States, Australia, Canada, Switzerland, Germany, the United Kingdom, Japan, New Zealand, and Sweden, all obtained from Bloomberg.

- We consider 12 commodities return series, including three energy commodities (WTI crude, gasoline, and heating oil), two precious metals (gold and silver), four industrial metals (aluminum, copper, nickel, and zinc), and three agricultural commodities (coffee, cocoa, and sugar), all obtained from Bloomberg.

Besides using data on a wide range of asset returns, we also collect data on the futures positions of speculators from the Commodity Futures Trading Commission (CFTC). Our selected data consist of the long and short positions of non-commercial traders, which are traditionally labeled speculators in the literature, and the open interest of futures contracts on the U.S. dollar price of AUD, CAD, CHF, EUR, GBP, JPY, NZD, S&P 500, 10-year US Treasury Notes, Gold and Crude Oil. We also use the corresponding positions data for the U.S. dollar index futures.[4] From these futures positions, we compute *net speculator positions*, defined as the net (i.e., long minus short) positions of non-commercial traders divided by the open interest, to proxy for trading activity (Brunnermeier, Nagel, and Pedersen (2008a); Moskowitz, Ooi, and Pedersen (2012)). This dataset is available at the weekly frequency.

Finally, we complement the underlying exchange rates with FX option implied volatilities of the same G10 currencies from Reuters (via Datastream). We also obtain daily time series of the VIX index from the Chicago Board of Options Exchange (CBOE).

Table 3.1 reports the mean, standard deviations and the first order autocorrelation coefficients of returns, net speculator positions, implied volatilities, and currency forward discounts. All assets in our daily sample have tiny average mean return, sizable standard deviation, and negligible autocorrelation. More specifically, Panel A shows that all G10 currencies and currency trading strategies earn essentially zero average returns from exchange rate appreciation, consistent with exchange rates that tend to follow a random

[4] The US dollar index (USDX) tracks the value of the U.S. dollar against six major currencies (weights): EUR (57.6%), JPY (13.6%), GBP (11.9%), CAD (9.1%), SEK (4.2%), and CHF (3.6%).

walk. The unconditional average return earned by carry trades are attributed to interest rate differentials. The same pattern generally holds for emerging-country currencies (Panel B) and 10-year government bonds of G10 countries (Panel D). In contrast, the average capital gain in global equities (Panel C) and commodities (Panel E) tend to be positive, but there is significant heterogeneity and standard deviations are roughly twice as large as standard deviations in currency and bond markets.

Panel F of Table 3.1 shows summary statistics for net speculator positions. Traditional funding currencies, such as the Japanese yen and the Swiss franc, are in net short positions, while investment currencies such as the Australian dollar and the New Zealand dollar tend to be in net long positions. Net speculator positions tend to be very persistent (even at the weekly frequency) and therefore our empirical analysis will focus on changes rather than levels.

The extreme persistence of volatility is evident from the autocorrelation coefficients reported in Panel G. Moreover, foreign exchange rate implied volatilities are in general of different magnitude than the VIX index. For these reasons, in our empirical analysis of volatility, we use standardized first differences of the volatility series.

Finally, Panel H shows that popular investment currencies (AUD and NZD) are on average at significant forward discounts, while funding currencies (JPY and CHF) earn on average lower interest rates. Major commodity currencies, such as the Canadian dollar and the Norwegian krone, are on average at moderate forward discounts.

3.3 Methodology

In this section, we first describe the simple regime-switching dynamic correlation (RSDC) model that we use to identify two foreign-exchange correlation regimes from G10 currency returns. We then illustrate the empirical properties of these two regimes. Specifically, we analyze regime persistence, we compare model estimates with simpler correlation models, and then relate correlation regime switches to notable events in our sample.

3.3.1 The RSDC model

We estimate a regime-switching dynamic correlation (RSDC) model as in Pelletier (2006). Assume we have K underlying returns and N regimes. Specifically, let y_t denote the $K \times 1$ vector of demeaned exchange rate returns, σ_t the $K \times 1$ vector of dynamic volatilities or standard deviations, H_t the $K \times K$ covariance matrix of y_t, Γ_t the correlation matrix of y_t, ϵ_t the $K \times 1$ vector of independent random variables with zero mean. The model for currency returns is then:

$$y_t = H_t^{1/2} \epsilon_t \tag{3.1}$$

$$H_t = (\sigma_t \sigma_t') \otimes \Gamma_t \tag{3.2}$$

$$\Gamma_t = \sum_{n=1}^{N} \Gamma_n \mathbf{1}_{\Delta_t = n} \tag{3.3}$$

$$\epsilon_t \sim \text{IID}\,(0, I)\ , \tag{3.4}$$

where $\otimes$ is the element-by-element product operator, and $\Delta_t \in \{1, 2, \cdots, N\}$ indicates the correlation regime at time t. The probability of switching to regime j conditional on currently being in regime i is $\pi_{ij} \equiv \text{Prob}(\Delta_t = j \,|\, \Delta_{t-1} = i)$.

Standardizing the demeaned returns y_t by their corresponding volatility forecasts based on K univariate GARCH(1,1) models, we obtain the RSDC model for the standardized returns u_t:

$$u_t = \Gamma_t^{1/2} \epsilon_t \tag{3.5}$$

$$\Gamma_t = \sum_{n=1}^{N} \Gamma_n \mathbf{1}_{\Delta_t = n} \tag{3.6}$$

$$\epsilon_t \sim \text{IID}\,(0, I)\ . \tag{3.7}$$

We estimate the RSDC model of equations (3.5)-(3.7) using the EM algorithm. This procedure effectively generates quasi-maximum likelihood estimates of the regime-dependent correlation matrices and the corresponding regime-switching probabilities. Specifically, let θ be the vector that stacks all the parameters in our RSDC model, i.e., $\theta = (vec(\Pi)', vec(\Gamma_1)', \cdots, vec(\Gamma_N)', \text{Prob}(\Delta_1 = 1), \cdots, \text{Prob}(\Delta_1 = N))'$. In the $(m+1)$-th iteration, given the parameter estimates obtained in the m-th iteration, $\hat{\theta}^{(m)}$, and the full sample observation of standardized returns $\underline{u_T} = \{u_1, u_2, \cdots, u_T\}$, we update the parameter estimates, $\hat{\theta}^{(m+1)}$, according to the following equations:

$$\hat{\Gamma}_n^{(m+1)} = \frac{\sum_{t=1}^{T} u_t u_t' \,\text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})}{\sum_{t=1}^{T} \text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})} \tag{3.8}$$

$$\hat{\pi}_{ij}^{(m+1)} = \frac{\sum_{t=2}^{T} \text{Prob}(\Delta_t = j,\, \Delta_{t-1} = i \,|\, \underline{u_T}; \hat{\theta}^{(m)})}{\sum_{t=2}^{T} \text{Prob}(\Delta_{t-1} = i \,|\, \underline{u_T}; \hat{\theta}^{(m)})} \tag{3.9}$$

$$\text{Prob}^{(m+1)}(\Delta_1 = n) = \text{Prob}(\Delta_1 = n \,|\, \underline{u_T}; \hat{\theta}^{(m)}) \quad , \tag{3.10}$$

where $n, i, j = 1, 2, \cdots, N$. We continue updating parameter estimates according to this iteration until the parameter estimates converge, that is, $\| \hat{\theta}^{(m+1)} - \hat{\theta}^{(m)} \| < \delta$, for some small $\delta > 0$.

The probabilities in equations (3.8)-(3.10) can be computed according to the standard recursive procedure specified in Hamilton (1994). In brief, given model parameters θ and observations $\underline{u_t} = \{u_1, \cdots, u_t\}$, $\forall t = 1, 2, \cdots, T$, the filtered and forecasted probabilities can be computed recursively as:

$$\text{Prob}(\Delta_t = n \,|\, \underline{u_t}; \theta) = \frac{\text{Prob}(\Delta_t = n \,|\, \underline{u_{t-1}}; \theta) \times f(u_t | \underline{u_{t-1}}; \Delta_t = n; \theta)}{\sum_{i=1}^{N} \text{Prob}(\Delta_t = i \,|\, \underline{u_{t-1}}; \theta) \times f(u_t | \underline{u_{t-1}}; \Delta_t = i; \theta)} \tag{3.11}$$

$$\text{Prob}(\Delta_{t+1} = n \,|\, \underline{u_t}; \theta) = \sum_{i=1}^{N} \text{Prob}(\Delta_t = i \,|\, \underline{u_t}; \theta) \times \pi_{in} \quad , \tag{3.12}$$

for $n = 1, 2, \cdots, N$, where $f(\cdot)$ is the standard normal density function.

Next, the smoothed probabilities for regime n can be derived using the backward recursion from period T according to the following equation:

$$\text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \theta) = \sum_{j=1}^{N} \text{Prob}(\Delta_{t+1} = j,\, \Delta_t = n \,|\, \underline{u_T}; \theta). \tag{3.13}$$

The bivariate probability of regimes at period t and period $t-1$ is given by:

$$\begin{aligned} P_t^{i \to j} &:= \text{Prob}(\Delta_t = j,\, \Delta_{t-1} = i \,|\, \underline{u_T}; \theta) \\ &= \frac{\pi_{ij} \times \text{Prob}(\Delta_t = j \,|\, \underline{u_T}; \theta) \times \text{Prob}(\Delta_{t-1} = i \,|\, \underline{u_{t-1}}; \theta)}{\text{Prob}(\Delta_t = j \,|\, \underline{u_{t-1}}; \theta)} \quad \text{, for } i, j = 1, 2, \cdots, N \end{aligned} \tag{3.14}$$

Note that the smoothed probability of regime switching defined in equation (3.14) will be the key explanatory variable in our empirical analysis in Section 3.5.

3.3.2 RSDC estimates and preliminaries

Correlation regimes

We estimate the RSDC model of the previous section using two correlation regimes ($N = 2$). We use the identity matrix as the starting value for the first regime's correlation matrix and the unconditional correlation matrix for the second regime's correlations. Table 3.2, Panel A shows the estimated correlations for the two regimes in the upper right and lower left triangular matrices, respectively. It turns out that correlations in the first regime are generally higher than those in the second regime. For convenience, we label the first regime the *high* correlation regime ($n = 1$), and the second regime the *low* correlation regime ($n = 2$). The few exceptions to this regularity appear in blue color in the upper right part of Table 3.2, Panel A. Interestingly, it is the Japanese yen that covaries uniformly and significantly less with all the other currencies in the high correlation regime. The Swiss franc also exhibits lower correlation for all but three currency pairs.

Both regimes display strong persistence and a switch of regime is infrequent in our sample. As Panel B of Table 3.2 shows, the conditional probability of staying in the high (low) correlation regime is 0.9688 (0.9910). The expected regime durations are 33 days for the high correlation regime and 112 days for the low correlation regime. In contrast, the conditional probability of a switch to the high (low) regime from the low (high) regime is only 0.0090 (0.0312).

To further understand the implications of the RSDC model, we use insights from Principal Component Analysis (PCA). The high (low) correlation regime features a polarized (moderate) pattern of currency co-movement. We thus expect that in the high correlation regime a larger portion of total currency variation is driven by the first principal component of currency returns than in the low correlation regime. In order to see how regime-dependent correlations help improve our understanding of currency co-movement relative to constant correlations, we compute, for each time period t, the eigenvalues of three types of covariance matrices: the RSDC-implied covariance matrix, $\sum_{n=1}^{2}(\sigma_t\sigma_t') \otimes \Gamma_n \times \text{Prob}(\Delta_t = n|\underline{u_T})$, the constant conditional correlation (CCC) model implied covariance matrix, $(\sigma_t\sigma_t') \otimes \Gamma_0$, and the constant covariance matrix, $(\sigma_0\sigma_0') \otimes \Gamma_0$, where Γ_0 is the unconditional correlation matrix and σ_0 is the unconditional volatility. We then construct the variance ratio of the first principal component for each type of covariance matrix as:

$$\text{VR}_t^{(1)} = \frac{\lambda_t^{(1)}}{\sum_{k=1}^{K}\lambda_t^{(k)}} , \tag{3.15}$$

where $\lambda_t^{(k)}$ is the k-th largest eigenvalue of the corresponding covariance matrix.

Figure 3.1 illustrates the dynamics of the variance ratios of equation (3.15) based on the three types of covariance matrices. The time-variation of currency return co-movement implied by the RSDC model is remarkably different from that implied by the CCC model and the constant covariance matrix, especially in the more recent part of the sample. For example, during the 2007-09 financial crisis, the RSDC model-based variance ratio reaches as high as 75%, suggesting that the first principal component explains a large portion of total currency return variations. In contrast, the variance ratio implied by the CCC model is generally below 60%.

Correlation regime transitions

The estimated RSDC model allows us to identify two persistent regimes and two regime transitions when we observe a change in regime from $t-1$ to t on a daily time scale. Since we aim to explore the implications of the change in risk preferences, we focus on transitions and specifically on the cases when correlation switches from one regime at $t-1$ to the other regime at time t.

In particular, we are interested in the low-to-high regime transitions, which we use to identify risk-off episodes. To illustrate the link between this specific switch of regime and risk-off episodes, Figure 3.2 shows 25 risk-off events identified in our 19-year sample period when the probability of a low-to-high transition is relatively high.[5] We find that these risk-off episodes correspond to major market disruptions or economic crisis events such as the Asian financial crisis, the Russian default, the burst of the Dotcom bubble, the subprime crisis, the European debt crisis, etc.

Interestingly, many of the risk-off episodes identified in Figure 3.2 do not seem directly related to macroeconomic fundamentals or at least do not involve immediate shift in fundamentals, suggesting that changes in global risk-aversion tend to occur quite independently.

To understand more formally the time pattern of transitions from the low to the high correlation regime, we estimate the following regression specification:

$$P_{t+h}^{2\to 1} = \theta_{11}(h)P_t^{1\to 1} + \theta_{12}(h)P_t^{1\to 2} + \theta_{21}(h)P_t^{2\to 1} + \theta_{22}(h)P_t^{2\to 2} + \epsilon_{t+h}, \quad \text{for } h = -10, \cdots, 10, \tag{3.16}$$

[5] We set the threshold for the low-to-high probability to identify risk-off events at 0.20. There are 39 risk-off events in total identified by this criterion, amongst which we select the 25 most noteworthy for the figure.

where we regress the probability of a low-to-high transition at different points in time on the current probabilities of the two persistent regimes and the two regime transitions. We plot the coefficient $\theta_{21}(h)$ as a function of the horizon h in Figure 3.3, to get a sense of the time dependence of the probability of switching from low to high. For a risk-off event occurring for sure on $h = 0$ (i.e., $P_t^{i\rightarrow j} = 1$), any day within the $[-5, 5]$ window around the event turns out to contain a sizable probability of regime switch. Hence, risk-off episodes can be better described as a short period from about five days prior to about five days after the low-to-high transition.

3.4 Why do correlations switch?

In this section, we relate the probabilities of switching correlation regime to a number of potential explanations. First, we study whether correlation regime transitions occur because of changes in macroeconomic fundamentals. Second, we examine the relation between correlation switching probabilities and innovations in volatility or innovations in average implied correlations. We then look at measures of implied skewness, as proxied by the prices of currency option risk-reversals. Finally, we compare our probabilities of switching FX correlation regime to alternative methodologies that aim to capture risk-off episodes.

3.4.1 Risk-off and macroeconomic fundamentals

We measure economic fundamentals using the macroeconomic growth indices constructed by Beber, Brandt, and Luisi (2014), which are available for the four largest economies: U.S., U.K., Eurozone, and Japan. These indices are measured in real-time, are free of look-ahead biases induced by data restatements, track very closely the national GDP and, most importantly, are available at the daily frequency. These features give the best chance for macroeconomic fundamentals to explain the probabilities of switching correlation regimes.

We regress the probabilities of switching from the moderate to the polarized correlation regime on the changes in real-time economic growth over the previous week, month, or quarter. More formally, we estimate

$$P_t^{i \to j} = \kappa_0 + \kappa_{ij} \left(Growth_{t-1} - Growth_{t-1-L} \right) + \epsilon_t \, , \; L = 5, 22, 65, \tag{3.17}$$

where $P_t^{i \to j}$ is the probability of a moderate-to-polarized regime switch from $t-1$ to t, $Growth$ is the real-time macroeconomic growth index, and time is measured in trading days.

Table 3.3 shows the results. As can be readily seen, only very few coefficients are significantly different from zero using different lags to measure innovations to macroeconomic fundamentals and using economic conditions of different countries. Furthermore, the signs of the significant coefficients tend to be inconsistent. For example, a drop in Eurozone growth over the previous week reduces the probability of both transitions, from the moderate to the polarized regime and the opposite direction.

3.4.2 Risk-off, volatility, and implied correlations

The portfolio rebalancing activities associated with the risk-off events could simply be the outcome of volatility shocks. For example, Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) show the significant effects of currency volatility innovations on foreign-exchange returns. Furthermore, innovations in VIX are often associated with a change in investors' risk attitude.

We consider three volatility measures: a global FX realized volatility index (FXRV), a global FX implied volatility index (FXIV), and the CBOE volatility index (VIX). The FXRV index captures the concept of the foreign exchange market volatility proposed in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and is measured as an equally-weighted cross-sectional average of individual G10 exchange rate return realized volatilities, computed as the exponentially-weighted moving average of squared daily returns (similar to Moskowitz, Ooi, and Pedersen (2012) and Clarida, Davis, and Pedersen (2009)). For currency pair i, the realized volatility is:

$$\mathrm{FXRV}_{t,i} = \sqrt{261 \times \sum_{j=0}^{\infty}(1-\rho)\rho^{j}(r_{t-j,\,i} - \bar{r}_i)^2}\,, \quad \text{for } i = 1, \cdots, 9\,, \tag{3.18}$$

where $r_{t,i}$ is the daily logarithm exchange rate return, $\bar{r}_i$ is the sample mean return. We choose the exponential weighting parameter $\rho = 0.98$, and we annualize the volatility measure by assuming that there are 261 trading days in one calendar year. The global FX realized volatility is thus an average across all nine pairs of G10 currencies, i.e., $\mathrm{FXRV}_t = \frac{1}{9}\sum_{i=1}^{9}\mathrm{FXRV}_{t,i}$. Similarly, we measure FXIV index as the equally-weighted cross-sectional average of individual G10 currency implied volatilities for the one-month horizon, $\mathrm{FXIV}_t = \frac{1}{9}\sum_{i=1}^{9}\mathrm{FXIV}_{t,i}$.

We now examine directly the relationship between correlation regime switching and volatility dynamics, at different leads and lags. Specifically, we estimate:

$$\frac{V_{t+h} - V_{t-1}}{\sigma_{\Delta V}} = \omega_{11}(h)P_t^{1\to1} + \omega_{12}(h)P_t^{1\to2} + \omega_{21}(h)P_t^{2\to1} + \omega_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,, \tag{3.19}$$

where V_t is volatility level, and $\sigma_{\Delta V}$ is the unconditional standard deviation of volatility innovations $\Delta V_t = V_t - V_{t-1}$.

Figure 3.4 shows $\omega_{12}(h)$ and $\omega_{21}(h)$ as functions of h in the left and right panels, respectively. Each row of panels corresponds to a different volatility measure. If our correlation regime-switching dynamics were merely a manifestation of volatility dynamics, we would expect to see the left panel be the mirror image to the right panel for each row of panels. However, we find that volatility dynamics look similar in the case of either the low-to-high or the high-to-low correlation regime switches. For example, global FX realized volatility tends to increase by two standard deviations during both low-to-high and high-to-low switches of correlation regimes (see Figure 3.4, Panel (a) and (b)). Therefore, the correlation regime-switching dynamics are significantly different from volatility dynamics and cannot simply be explained by volatility shifts.

Another important relation to explore is the connection between the correlation regime transitions and a more basic innovation in average correlations. Given that the two regimes we identify do not necessarily correspond to average low or high correlations, this is not a trivial point and further analysis can shed light on the link between our findings and the results that the recent foreign exchange literature has attributed to an international correlation risk-premium (e.g., Mueller, Stathopoulos, and Vedolin (2012)).

We construct global FX implied correlation as an equally-weighted average of implied correlations across G10 currency pairs, subject to data availability.[6] The implied correlation for each individual currency pair is computed using option-implied volatilities of the corresponding currencies:

$$IC_{ij,t} = \frac{IV_{i,t}^2 + IV_{j,t}^2 - IV_{ij,t}^2}{2\, IV_{i,t}\, IV_{j,t}}\,, \tag{3.20}$$

where $IV_{i,t}$ denotes the option implied volatility of the dollar exchange rate of currency i, and $IV_{ij,t}$ the implied volatility of the exchange rate of currency i to currency j.

We start by computing the correlation between the risk-off transition probability (i.e., the probability of a correlation regime switch from moderate to polarized) and the first differences in our measures of average implied correlation from equation (3.20). We find that this correlation is not significantly different from zero in the full sample or in the two halves of the sample, suggesting that our risk-off episodes cannot be captured by innovations in average correlations.

To have a better sense of the potential lead and lag relations between average implied correlations and risk-off events, we estimate the analogue of equation (3.19), replacing volatility innovations with average implied correlation innovations. Figure 3.5 shows the

[6] Our measure of average implied correlation is very similar to Mueller, Stathopoulos, and Vedolin (2012), except for the slightly longer sample period and the larger cross-section of implied volatilities that we consider. In any case, the results are invariant to these alternative measures.

loadings on the regime switching probabilities as a function of h. We note that global FX average implied correlation tends to decrease, but only significantly so in the right Panel (b) representing the risk-off transition. This is mainly driven by the fact that six of the ten pairs of implied correlations in our dataset involve either JPY or CHF, and these two currencies tend to correlate less with other currencies in the polarized regime than in the moderate regime.[7]

Finally, we investigate whether there are potential differences between the dynamics of pairwise realized FX correlation that we model with our regime-switching framework and the corresponding pairwise *implied* correlations. This is a reality check to understand whether our empirical findings could depend on the risk-measure of correlation. Figure 3.6 shows that the pairwise implied correlations respond in a consistent manner to risk-off transitions. Specifically, all implied correlations on currency pairs involving the JPY and CHF tend to decrease significantly after the switch to the polarized regime.

3.4.3 Risk-off and risk reversals

We construct a measure of global FX risk reversals as an equally-weighted average of risk reversals across all G10 currencies obtained from Bloomberg. We adjust the sign of the risk reversal data for AUD, EUR, GBP, and NZD such that the US dollar is consistently the base currency and therefore, large positive risk reversals correspond to more positively skewed returns for the US dollar and more negatively skewed returns for the quoted currency.

Figure 3.7 summarizes the dynamics of the global risk reversal measure around correlation regime switches. More specifically, we represent $\omega_{12}(h)$ and $\omega_{21}(h)$ as functions of h in the left and right panels, using equation (3.19) with innovations in global risk reversal as the dependent variable. In Panel (a), we show that switches from polarized to moderate correlations are not associated with any pattern for global risk reversals.

[7]The ten pairs are (CAD, EUR); (CHF, EUR); (GBP, EUR); (JPY, EUR); (NOK, EUR); (SEK, EUR); (AUD, JPY); (CHF, JPY); (CHF, GBP). All currencies are quoted against the US dollar.

In contrast, Panel (b) illustrates very clearly that a risk-off transition is associated with significantly increasing risk reversals, implying more negatively skewed returns of foreign currencies and more positively skewed returns of the US dollar.

We further analyze this pattern in Figure 3.8, where we break down the dynamic relation between the risk-off transition and bilateral FX risk reversals for each of the G10 currencies. For all but the safe-haven currencies, we observe a very significant increase in risk reversals. In unreported analysis, we also estimate a similar specification using simply the level of risk reversal prices as the dependent variable, rather than the standardized changes. Interestingly, risk reversal prices are not significantly different from zero before the risk-off shift, but become significantly positive for all currencies except for the JPY afterward, suggesting that investors start paying a positive premium to insure against negative tail events. We do not find any corresponding significant pattern for the polarized-to-moderate transition, consistent with the previous empirical evidence in Panel (a) of Figure 3.7.

In summary, risk-off shifts tend to coincide with an increase in the price of insuring against crash risk for growth currencies. This empirical evidence is consistent with the motivation of our identification strategy that the switch to a polarized correlation structure is induced by a change in the attitude towards risk and the associated portfolio rebalancing. Investors are attaching a larger price to the risk of negative tail events for risky assets.

3.4.4 Alternative identification methodologies

We compare our method with an alternative that has in recent years become popular in the industry, called the Risk-on-Risk-off (RoRo) index (e.g., Economist (2014)). The RoRo index is the ratio of the variance of the first principal component to the total variance using the daily returns of a large number of asset classes. In this section, we use the whole range of assets in our dataset, including G10 and emerging-country currencies, international stock and bond markets, and commodities. We compute the variance ratio based on a rolling one-year window.

Figure 3.9 plots the RoRo index along with the variance ratio implied by our RSDC model for G10 currency returns. We notice some similarities, especially at the peaks of the index, but overall there seem to be a lot of independent dynamics. In fact, the simple linear correlation between the risk-off probabilities from our RSDC model and first differences in the RoRo index is 0.01 over the full sample and not significantly different from zero in either half of the sample.

To get a better sense of the potential lead-lag relations between risk-off events and the RoRo index, we estimate the analogue of equation (3.19), replacing volatility innovations this time with RoRo index innovations. Figure 3.10 shows the loadings on the regime switching probabilities as a function of h. We can clearly see that the innovation in the RoRo index do not have a statistically significant impact on both the correlation regime transitions. If anything, the RoRo index tends to exhibit quite inconsistent negative innovations with risk-off events.

Part of the problem with the RoRo index approach is that it becomes arbitrary to define what is the level or the change in the index that would trigger a risk-off episode. For example, a big positive shock to the index on a specific day could be irrelevant for risk-off dynamics because the level of the index is still reasonable. In contrast, a small positive shock could be relevant just because it follows a number of innovations with the same sign. An advantage of our FX RSDC model is the direct availability of a probability measure for the switch of regime that perfectly characterizes the risk-off episode and associated portfolio rebalancing we are interested in.

Another related approach to identifying risk-off episodes is the short-run correlation between bond and stock markets (e.g., Baele, Bekaert, Inghelbrecht, and Wei (2013)). We examine this possibility in our context in two ways. First, we estimate the RSDC model using returns of all G10 equity indices and bonds [8]. Second, we compare the

[8] Norway and New Zealand are excluded due to data unavailability.

flight-to-safety events identified in Baele, Bekaert, Inghelbrecht, and Wei (2013) with the risk-off shifts identified in our framework.[9]

Table 3.4 reports estimates of the RSDC model using all G10 equities and bonds. The model implies two equity-bond correlation regimes: one features a uniformly negative correlation pattern between equities and bonds while the other features moderate (and largely positive) correlations between equities and bonds. Interestingly, the first regime is also associated with higher positive correlations within international stock markets and international bond markets, respectively. Both regimes are persistent and a switch of regime is relatively infrequent. However, the conditional transition probabilities are substantially larger than the probabilities of G10 currency correlation regime transitions. Furthermore, the correlation between our risk-off transition probability and the positive-to-negative transition probability in equities and bonds is nearly zero.

Figure 3.11 illustrates the lead-lag correlation between our FX correlation regime transition probability and the probability of equity-bond correlation regime-switching (from positive to negative). We find that both the moderate-to-polarized transition (risk-off) and the polarized-to-moderate transition are followed by weakly significantly positive probabilities of equity-bond correlation regime switching from positive to negative.

We now perform a direct comparison to the Baele, Bekaert, Inghelbrecht, and Wei (2013) events. They identify local flight-to-safety (FTS) events using equity and bond returns and define a global FTS as the case in which more than two-third of the local markets are experiencing local FTS events. We examine lead-lag correlations between a transition to global FTS, more specifically $\Delta GFTS_t = \mathbf{I}_{\{GFTS_t=1, GFTS_{t-1}=0\}}$, and our risk-off shifts. The two sets of events are only weakly contemporaneously correlated, with a correlation of about 0.1. If we examine different horizons, Figure 3.12 shows that global FTS do not present a distinct pattern between moderate-to-polarized or polarized-to-moderate correlation regime switches. It is also hard to detect a specific pattern with the horizon h.

[9] We thank Lieven Baele and Geert Bekaert for providing us with their data on global flight-to-safety episodes.

To further understand the relation between global FTS and our risk-off shifts, we take a closer look at the surrounding geopolitical events. We first oberve that risk-off days and global FTS days generally do not overlap. Further, we find that the risk-off indicator tends to lead the global FTS indicator in both of the two largest crises in our sample period, i.e., the 1997-1998 Asian Financial Crisis and the 2007-2008 Global Financial Crisis. The risk-off transition coincides with the infamous warning messages of Alan Greenspan. Another notable example is during the recent European sovereign debt crisis. Our risk-off indicator identifies relevant geopolitical events (e.g. Greece strike in protest ofausterity measures turn violent; and Greece is downgraded by all three major credit rating agencies) from the end of 2009 to early 2010. However, the global FTS indicators only identifies financial market events in May, 2010 when the Greek crisis sends world stock markets sharply down.[10] Finally, we also note that no local FTS event occurs on risk-off days unless that local event is also part of a global FTS event.

In summary, alternative methodologies are only weakly related to our method for identifying risk-off episodes. As a result, we expect the effects of our regime-switching correlation probabilities on the broader financial landscape to be different from what the existing literature has documented. We investigate these issues in the next sections of the paper.

3.5 Effects on the broader financial landscape

This section presents our empirical results on the impact of risk-off regime switches that we identify. We first show the effects of risk-off probabilities on asset prices across different asset classes. Then, we investigate whether our findings on asset returns are consistent with a price pressure story and examine the effect of correlation regime switches on net speculator positions. Finally, we study the robustness of our correlation regime switching

[10] A similar and more recent example pertains to the risk-off episodes in early 2011, when the European debt crisis intensified sharply with the European Central Bank warnings of interest rate increases and the European Union warnings of the spill-over effect of the EU debt crisis. In contrast, the global FTS only occurs when the European stock markets fell heavily later in August, 2011.

findings to a number of different shocks, including innovations to volatility and other risk-off indicators.

3.5.1 Risk-off effects on asset prices

We use the probability of low-to-high regime switching as an indicator of risk-off events and study the behavior of asset prices during these risk-off episodes. Specifically, we regress the log returns for different assets on the probabilities of remaining in the two persistent regimes or transitioning between regimes:

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to 1} + \alpha_{12}(h)P_t^{1\to 2} + \alpha_{21}(h)P_t^{2\to 1} + \alpha_{22}(h)P_t^{2\to 2} + \epsilon_{t-1\to t+h}\,, \tag{3.21}$$

where S_t is the price or index level and the horizon h ranges from -20 to 20 days. We focus on the coefficient $\alpha_{21}(h)$ which corresponds to the low-to-high transition regime. Given a risk-off event day from $t-1$ to t (with $P_t^{2\to 1} = 1$), the coefficient $\alpha_{21}(0)$ can be interpreted as the average return earned by the corresponding asset on the risk-off event day ($h = 0$). Accordingly, for $h > 0$, $\alpha_{21}(h)$ corresponds to the average return from $t-1$ to $t+h$, and for $h < 0$, $-\alpha_{21}(h)$ corresponds to the pre-event average return from $t+h$ to $t-1$.

We estimate equation (3.21) for each asset separately and plot the coefficient $\alpha_{21}(h)$ as a function of h and associated confidence bands in figures 3.13 to 3.17 for each asset class.[11] The results are generally consistent with our basic intuition that risk-off episodes, resulting from increases in risk aversion, exert markedly strong downward pressure on risky assets prices but tend to induce positive returns of relatively safe assets. However, we find significant heterogeneity of risk-off impacts within and across different asset classes.

[11] We also report simulation-based confidence bands to account for the concerns that our explanatory variables, the regime-switching probabilities, are generated from G10 currency returns, and that our dependent variables, cumulative returns, are overlapping observations. Specifically, we generate simulated G10 currency returns using the estimated RSDC model. For each simulation, we re-estimate the RSDC model and equation (3.21). Figure 3.13 confirms that the confidence bands obtained with this procedure are very similar to the standard ones.

Figure 3.13 shows the effect on G10 currencies. We find that popular high-yielding currencies such as the Australian dollar and the New Zealand dollar incur dramatic losses when correlation switches from low to high, whereas low-yielding currencies such as the Japanese yen and the Swiss franc make significant profits or only lose slightly. Interestingly, commodity currencies with intermediate-yields such as the Canadian dollar and the Norwegian krone also experience substantial devaluation in the low-to-high switching regime. In spite of the relatively short duration of the low-to-high transition regime, the impact on asset prices turns out to be long-lasting. For example, the Australian dollar depreciates by nearly 80 basis points on the risk-off event day and the depreciation continues over the following 20 days to reach about 300 basis points. In addition, if we include the 5 days before the risk-off event to take into account the time dependence of the risk-off probability (see Figure 3.3), then the Australian dollar has depreciated by an additional 300 basis points, taking the total depreciation to as much as 600 basis points, or about 6% in one month.

Furthermore, the U.S. dollar plays an important role in driving the risk-off asset price dynamics. As Panel (l) of Figure 3.13 illustrates, the U.S. dollar, represented by the Dollar factor which is measured as the equally-weighted average return of nine G10 currency pairs times a minus sign, tends to appreciate during risk-off episodes. This observation is consistent with the safe haven status of the U.S. dollar. However, this provides only a partial explanation for the risk-off impact on currencies because risk-off episodes are also associated with large drawdowns of currency trading strategies such as the carry trade strategy and the momentum strategy shown in Panel (j) and (k) of Figure 3.13 respectively, which are neutral to U.S. dollar risk.

Figure 3.14 shows a significant impact of the risk-off probability on emerging-country exchange rates. Currencies of emerging economies tend to depreciate when risk-off is triggered, with a weaker effect for emerging currencies that are pegged to the U.S. dollar. The economic magnitudes are large. For example, the Russian ruble falls by almost 400 basis points on the risk-off event day and incurs a total loss of over 1000 basis points, or

10% in a one-month horizon.

Besides currency markets, the impact of risk-off events can also be observed in global equity markets, as Figure 3.15 illustrates. All major equity markets drop by 100 to 200 basis points on the risk-off event day and the decline leads to a capital loss of as much as 5-10% within a month. Although the risk-off effect on major equity markets seem to be relatively short-lived, all major equity markets tend to anticipate somewhat, and start dropping from about 5 days prior to the risk-off event day, generating losses of about 2-3%. The pre-event decline is more significant for North American and European equity markets than for Asian and Pacific equity markets.

Figure 3.16 illustrates return patterns of government bond of G10 economies. We find a strong global flight-to-safety phenomenon in that all 10-year government bonds earn large positive returns in risk-off episodes, with the most significant profits exhibited by U.S. Treasuries, in stark contrast to the pattern observed in global equity markets.

Finally, Figure 3.17 proceeds to show the behavior of commodity prices in risk-off episodes. It is evident that the energy and agricultural sectors tend to incur a large loss in general, while the precious and industrial metal sectors lose by a relatively moderate magnitude.

3.5.2 Risk-off effects on speculator positions

Our hypothesis is that risk-off episodes are driven by an increase in risk aversion and should thus be associated with portfolio rebalancing toward safer assets. The widespread risk-off effects on asset returns documented in the previous section is consistent with the price pressure exerted by this portfolio rebalancing. If this is the case, we should observe the effect of risk-off transitions on the position of institutional investors. In this section, we study the dynamics of net speculator futures positions predicted by our correlation regime switching model. More specifically, we regress the change of net speculator position at different horizons on the probabilities of the two persistent regimes and the two regime transitions:

$$\text{NSP}_{t+h} - \text{NSP}_{t-1} = \psi_{11}(h)P_t^{1\to 1} + \psi_{12}(h)P_t^{1\to 2} + \psi_{21}(h)P_t^{2\to 1} + \psi_{22}(h)P_t^{2\to 2} + \epsilon_{t-1\to t+h}\,, \tag{3.22}$$

where NSP_t is the net speculator position at time t and the horizon h ranges from -20 to 20 days. We focus on the coefficient $\psi_{21}(h)$ which corresponds to the low-to-high transition regime.

We estimate equation (3.22) separately for a number of futures contracts and plot the coefficient $\alpha_{21}(h)$ as a function of h in Figure 3.18. Consistent with our intuition on risk-off transitions and our evidence from asset prices, higher probabilities of low-to-high switches are associated with speculators unwinding their positions in risky assets and increasing their exposure to safer assets. All these changes in net speculator position around risk-off episodes are generally statistically significant and economically relevant. For example, during the 20 days following the risk-off event, net speculator positions in high-yielding currencies such as the Australian dollar and the New Zealand dollar decline by about 15% and 25%, respectively, and net speculator positions in intermediate-yielding commodity currencies such as the Canadian dollar decline by more than 20%. In contrast, net speculator positions in the Japanese yen increase by more than 13% during the ten days following the risk-off event day, while the Swiss franc positioning increases by nearly 10% during the five days following the risk-off event day. Interestingly, the increase in the net positions of the U.S. dollar is of similar magnitude.

Consistent with the evidence on equity and bond returns in the previous section, net speculator positions in equity and bond markets are also in line with a flight-to-safety pattern during risk-off episodes, with a reduction in the net speculator positions in the S&P 500 index futures and a rise in the net speculator positions in the 10-year U.S. Treasury note futures (see Figure 3.18, Panel (i) and (j)). Commodities, on the other hand, tend to have reduced net speculator positions during risk-off episodes, as panels (k) and (l) illustrate for gold and crude oil.

3.5.3 Robustness

We already showed that a number of alternative risk measures do not fully explain the switch in correlations underlying the risk-off events. In this section, we extend that analysis and investigate whether the effects of correlation switching probabilities on asset returns are robust to controls for volatility and other risk indicator shocks. We also study the relation between the full sample smoothed transition probabilities and real-time counterparts obtained from rolling samples.

Volatility

We consider the robustness of the return findings to volatility shocks using the three volatility measures introduced in Section 3.4.2. We first measure volatility shocks as standardized volatility innovations, that is, the daily first difference of volatility standardized using the sample mean and standard deviation. To understand the impact of risk-off controlling for volatility innovations, we regress asset returns on both standardized volatility innovations dV_t and regime-switching probabilities:

$$\log S_{t+h} - \log S_{t-1} = \sum_{i,j \in \{1,2\}} \widetilde{\alpha}_{ij}(h)\, P_t^{i \to j} + \widetilde{\beta}_0(h)\, dV_t + \epsilon_{t-1 \to t+h}\,, \text{for } h = 0, 5, 10, 20. \quad (3.23)$$

We standardize volatility innovations to normalize their units, so that $\widetilde{\beta}_0$ represents the average return associated with one standard deviation increase in volatility. Table 3.5 shows our estimates for $\widetilde{\alpha}_{21}(h)$ corresponding to the low-to-high transition regime. In general, risk-off episodes have large and statistically significant price impact in excess of the effect of different types of volatility innovations, across different asset classes, and over different horizons, implying that correlation regime transitions are quite different from volatility innovations and that the low-to-high transition regime of FX correlations is a robust risk-off indicator.

We extend this analysis using alternative ways of constructing volatility shocks. Simple volatility innovations tend to capture small and frequent variations, while risk-off episodes are more likely to be associated with large and infrequent shifts in volatility.[12] To better represent this feature, we construct a dummy variable to indicate a volatility transitions from below to above the 75th percentile.[13] We thus regress asset returns on the volatility transition indicator $\mathbf{I}_{\{V_t > V_{75\%}, V_{t-1} \leq V_{75\%}\}}$, in additional to regime-switching probabilities:

$$\log S_{t+h} - \log S_{t-1} = \sum_{i,j \in \{1,2\}} \widetilde{\alpha}_{ij}(h) P_t^{i \to j} + \widetilde{\beta}_0(h) \, \mathbf{I}_{\{V_t > V_{75\%}, V_{t-1} \leq V_{75\%}\}} + \epsilon_{t-1 \to t+h} \text{ , for } h = 0, 5, 10, 20 \, . \quad (3.24)$$

Table 3.6 shows our estimates for $\widetilde{\alpha}_{21}(h)$ corresponding to the low-to-high transition regime. We find again that risk-off episodes have large and significant price impact beyond the effect of different types of volatility transitions, across different asset classes, and over different horizons, confirming the previous evidence that correlation regime transitions are quite different from volatility transitions.

As a final investigation in the relation between risk-off shifts and volatility shocks, we study some conditional asset pricing implications. The literature documents the negative price of volatility risk unconditionally (e.g., Ang, Hodrick, Xing, and Zhang (2006), Lustig, Roussanov, and Verdelhan (2011), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)). These findings could be different conditional on different correlation regimes, as our previous results seem to imply. We thus compare the exposure of asset returns to volatility innovations conditional on correlation regime transitions and the exposure of asset returns to unconditional volatility innovations. Specifically, we estimate

[12] Volatility regimes have strong economic implications. For example, Baillie and Chang (2011), Christiansen, Ranaldo, and Söderlind (2011), and Clarida, Davis, and Pedersen (2009) study the implication of volatility regimes in the foreign exchange markets for the uncovered interest rate parity or for the forward anomaly.

[13] We explore different percentile thresholds and find the robustness of our results is not sensitive to this choice.

the following two specifications:

$$\text{Unconditional volatility innovation: } r_{t-1\to t} = \alpha_0 + \beta_0\, dV_t + \epsilon_{t-1\to t}\,, \tag{3.25}$$

$$\text{Conditional volatility innovation: } r_{t-1\to t} = \alpha_0 + \sum_{i,j\in\{1,2\}} \beta_{ij}\, \left(P_t^{i\to j} \times dV_t\right) + \epsilon_{t-1\to t}\,, \tag{3.26}$$

where $r_{t-1\to t}$ is the logarithm return on the risk-off event day, and dV_t is the standardized volatility innovations. Table 3.7 presents the results of estimating equations (3.25) and (3.26) using global FX implied volatility and the VIX index for returns in different asset classes.[14] The left block of each panel corresponds to global FX implied volatility innovations and the right block corresponds to VIX innovations. The first column of each block reports β_0 from equation (3.25), while the rest four columns report β_{ij}'s from equation (3.26). Positive volatility shocks in the low-to-high risk-off transition is strong bad news for risky assets and good news for safe assets. In contrast, volatility shocks in the high-to-low transition are good news for risky assets and bad news for the safest assets such as U.S. Treasuries, the U.S. dollar, and the Japanese yen.

Other risk indicators

We examine whether the impact of risk-off shifts on asset returns is subsumed by shocks to other risk indicators. More specifically, we look at average implied correlation shocks, at risk reversal shocks, and at RoRo index shocks, using the measures introduced in Section 3.4.2. Formally, we estimate the following specification:

$$r_{t-1\to t+h} = \sum_{i,j\in\{1,2\}} \alpha_{ij}(h) P_t^{i\to j} + \beta_0(h) d\text{Other}_t + \epsilon_{t-1\to t+h}\,,\ \ h = 0, 5, 20, \tag{3.27}$$

where $r_{t-1\to t+h}$ is the return from $t-1$ to $t+h$, $P_{i\to j}$ is the probability of a i-to-j correlation regime switch, and $d\text{Other}_t$ denotes the standardized innovations to other market stress

[14]We do not report the results using global FX realized volatility to save space. However, they are very similar to the other two measures of volatility and are available on request.

indicators, including the average implied correlation, global FX risk reversal, and RoRo index.

Table 3.8 reports the results for $\alpha_{21}(h)$, the average return associated with the risk-off transition over the horizon of h days, and $\beta_0(0)$, the contemporaneous impact of the corresponding market stress indicator. We only show the contemporaneous impact because the effect of these market stress indicators are typically short-lived so that the total response over longer horizons are of similar magnitude to the instantaneous response. Panel A-E are dedicated to G10 currencies and currency trading strategies, emerging country currencies, equities, government bonds, and commodities, respectively. We find that the risk-off impact on returns remains economically and statically significant in the presence of other market stress indicators, especially over longer horizons. Moreover, although other market stress indicators generally have statistically significant impact on returns, the magnitude is smaller relative to the risk-off impact.

Full-sample and real-time probabilities

We have shown ample evidence on the strong impact of risk-off shifts on the financial landscape. In this section, we explore the possibility of forecasting risk-off transitions via a real-time estimation of the RSDC model using G10 currency returns using a rolling 10-year estimation window. Table 3.9, Panel A, lists all the days featuring either a real-time or a full-sample probability estimate of a risk-off shift probability that is greater than 0.20, from the beginning of 2007 onwards. Although the real-time transition probability generally does not match the smoothed full-sample probability, we observe that it tends to anticipate future full-sample risk-off events.

To explore this observation more formally, we define a risk-off indicator that equals to one if the corresponding risk-off transition probability is above 0.20 and equals to 0 otherwise. We then regress the full-sample risk-off indicator on day $t+h$, $h = 0, 1, \cdots, 60$, onto the real-time risk-off indicator on day t. Table 3.9, Panel B, reports the results for horizons at which the coefficients are significantly different from zero. We find that the real-time indication of a risk-off event tends to predict a realized risk-off event with the probability of 5% contemporaneously and in one month, and of 10% in two and three months, a statistically significant increase relative to the unconditional mean realized risk-off probability of 1%.

3.6 Conclusions

Risk-off shifts are important events for financial markets in recent years, because they can have devastating consequences on investors' portfolios, with diversification benefits eroded by increasing correlations among risky assets. In this paper, we provide a scientific account of risk-off episodes: their detection, their relation with economic conditions and other risk indicators, and their consequences on the financial landscape.

- Risk-off refers to a *change* in risk preferences and the associated effect on asset prices due to portfolio rebalancing. We exploit this basic facet in our methodology and focus on a change in the correlation structure of G10 currency returns. Specifically, we identify risk-off shifts with the switch to a polarized correlation regime that features large correlations among most currencies except the safe haven ones.

- Risk-off transitions are relatively infrequent but noticeably increasing over time, are persistent and tend to be associated with geopolitical events, and seem unrelated to changes in macroeconomic fundamentals and to volatility or average correlation shocks. We do not find much overlapping with events identified with different methodologies based on stock and bond market returns, such as the so-called *RoRo* indices or the *flight-to-safety* of Baele, Bekaert, Inghelbrecht, and Wei (2013). This evidence suggests that the foreign-exchange market is ideally suited for our purposes, as it is arguably less subject to idiosyncratic events and more prone to dynamics induced by changes in global risk preferences.

- Risk-off shifts have very significant effects on the returns of a large number of asset classes and trading strategies, with risky and safe asset returns being penalized and favored, respectively. These results are robust to controls for innovations in other risk measures, such as volatility or average correlation shocks. This overwhelming evidence on different asset classes returns is consistent empirically with a price pressure story induced by portfolio rebalancing, as we document that risk-off transitions are associated with significant changes in the positions of professional investors across different futures markets.

Table 3.1

Summary Statistics.

This table describes our dataset and reports summary statistics on the mean and standard deviation and the first order autocorrelation coefficient for asset returns (basis points per day), net speculator positions, implied 1-month volatilities (% per annum), and currency forward discounts (% per annum). Sample is January 1995 to December 2013.

	Mean	**StDev**	**AC(1)**
PANEL A: G10 EXCHANGE RATE RETURNS: BPS PER DAY			
AUD	0.28	78.41	-0.02
CAD	0.56	52.23	0.00
CHF	0.78	69.25	-0.02
EUR	0.17	62.43	0.00
GBP	0.11	55.27	0.02
JPY	-0.11	70.07	0.00
NOK	0.22	73.37	-0.02
NZD	0.50	80.60	0.01
SEK	0.30	73.75	-0.03
Dollar factor	-0.31	50.05	-0.01
CarryHML	-0.04	58.33	0.01
MOM3HML	0.22	57.76	-0.01
PANEL B: EMERGING-COUNTRY EXCHANGE RATE RETURNS: BPS PER DAY			
BGN	0.42	62.61	0.01
BRL	-2.07	95.85	0.06
CZK	0.69	76.13	0.03
EGP	-1.44	33.18	-0.09
HRK	0.20	64.54	0.01
HUF	-1.30	83.83	0.03
ILS	-0.28	46.44	0.04
INR	-1.37	37.94	0.07
MXN	-1.97	84.99	-0.08
MYR	-0.50	76.89	0.04
PHP	-1.21	53.94	0.09
PLN	-0.42	81.09	0.04
RUB	-4.45	155.15	0.12
SGD	0.29	37.13	-0.04
THB	-0.54	57.43	0.11
ZAR	-2.19	98.93	0.02
PANEL C: GLOBAL EQUITY MARKET RETURNS: BPS PER DAY			
US: S&P 500	2.81	121.9	-0.07
US:DJIA	2.95	114.82	-0.06
US:NASDAQ100	4.44	188.7	-0.06
US:Russell2000	3.10	144.88	-0.05
CA:S&P/TSX60	2.56	118.56	-0.03
EU:STOXX50	1.74	144.74	-0.01
FR:CAC40	1.66	145.17	-0.02
DE:DAX	3.08	150.24	-0.01
NE:AEX	1.52	144.03	0.00
ES:IBEX	2.35	146.95	0.02
SE:OMX	3.10	151.44	-0.01
CH:SMI	2.31	119.75	0.03
UK:FTSE100	1.59	117.75	-0.02
JP:Nikkei225	-0.38	150.2	-0.03
HK:HIS	2.20	165.6	-0.01
AU:S&P/ASX200	2.14	97.21	-0.02
PANEL D: 10-YEAR GOVERNMENT BOND RETURNS: BPS PER DAY			
US	0.92	64.74	-0.06
Australia	1.10	74.48	-0.05
Canada	1.22	50.17	0.02
Switzerland	0.78	39.18	0.01
Germany	1.09	43.58	0.02
UK	1.10	52.79	0.02
Japan	0.75	38.27	-0.09
New Zealand	0.67	54.27	0.02
Sweden	1.59	50.62	0.08
PANEL E: COMMODITY RETURNS: BPS PER DAY			
WTI Crude	3.49	213.61	-0.02
Gasoline	3.30	216.80	0.00
Heating Oil	3.66	203.31	-0.02
Gold	2.32	107.98	0.00
Silver	2.83	191.74	-0.02
Copper	1.84	165.65	-0.04
Aluminum	-0.26	130.00	-0.03
Nikel	0.88	222.39	0.00
Zinc	1.16	177.17	-0.02
Coffee	1.49	184.06	0.01
Cocca	-0.84	225.17	-0.01
Sugar	0.13	200.50	0.01
PANEL F: NET SPECULATOR POSITIONS			
AUD	0.16	0.29	0.95
CAD	0.06	0.25	0.94
CHF	-0.09	0.28	0.91
EUR	0.05	0.23	0.96
GBP	0	0.26	0.91
JPY	-0.09	0.26	0.94
NZD	0.39	0.28	0.94
USD	0.07	0.31	0.94
S&P 500	0.04	0.08	0.96
TNote10yr	0.01	0.08	0.95
Gold	0.23	0.29	0.97
Crude Oil	0.04	0.07	0.96
PANEL G: IMPLIED VOLATILITIES: % PER ANNUM			
AUD	11.38	4.27	0.99
CAD	8.09	3.43	0.99
CHF	10.84	2.53	0.98
EUR	10.48	3.02	0.99
GBP	8.89	2.84	0.99
JPY	11.14	3.32	0.98
NOK	12.37	3.87	0.99
NZD	13.05	3.91	0.99
SEK	12.08	3.55	0.99
VIX	21.11	8.49	0.98
PANEL H: FORWARD DISCOUNTS: % PER ANNUM			
AUD	2.20	1.97	0.61
CAD	0.14	1.36	0.45
CHF	-1.96	1.86	0.68
EUR	-0.59	1.51	0.69
GBP	0.92	1.29	0.52
JPY	-3.09	3.47	0.23
NOK	0.76	3.13	0.42
NZD	2.86	2.04	0.46
SEK	0.15	2.56	0.45

Table 3.2
Correlation matrix of G10 exchange rate returns.

This table presents correlation coefficients of G10 exchange rate returns. Panel A reports the correlation matrices estimated by the regime switching dynamic correlation (RSDC) model, where the upper right triangular matrix (in red shade) corresponds to the *high* correlation regime with polarized correlation patterns and the lower left triangular matrix (in green shade) corresponds to the *low* correlation regime with moderate correlation patterns. Numbers in bold blue indicates cases in which correlation coefficients tend to be smaller in the high regime than in the low regime, and numbers in bold red indicates cases in which correlation coefficients tend to be larger in the high regime than in the low regime. Panel B reports the conditional transition probability matrix, with the element in row i, column j showing the probability of regime j at time t conditional on regime i at time $t-1$. Panel C reports the correlation matrix estimated by the constant conditional correlation model (CCC) with conditional volatilities and constant correlations.

Panel A. Correlation matrices in regime 1 (high) and regime 2 (low)

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
AUD	1.00	**0.70**	**0.36**	**0.64**	**0.58**	**-0.20**	**0.74**	**0.86**	**0.69**
CAD	0.40	1.00	**0.28**	**0.55**	**0.53**	**-0.20**	**0.64**	**0.63**	**0.61**
CHF	0.33	0.18	1.00	**0.69**	**0.40**	**0.37**	**0.53**	**0.34**	**0.56**
EUR	0.36	0.21	0.94	1.00	**0.64**	**0.11**	**0.82**	**0.60**	**0.87**
GBP	0.36	0.20	0.64	0.65	1.00	**-0.07**	**0.60**	**0.55**	**0.60**
JPY	0.24	0.12	0.43	0.41	0.31	1.00	**-0.04**	**-0.20**	**-0.02**
NOK	0.36	0.23	0.78	0.83	0.57	0.35	1.00	**0.67**	**0.86**
NZD	0.71	0.34	0.35	0.38	0.36	0.26	0.38	1.00	**0.63**
SEK	0.38	0.25	0.73	0.78	0.54	0.32	0.77	0.36	1.00

Panel B. Transition probability matrix

	$s_t = 1$ (Polarized)	$s_t = 2$ (Moderate)
$s_{t-1} = 1$ (Polarized)	0.9688	0.0312
$s_{t-1} = 2$ (Moderate)	0.0090	0.9910

Panel C. Constant correlation matrix

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
AUD	1.00	0.48	0.33	0.43	0.41	0.13	0.46	0.75	0.46
CAD	0.48	1.00	0.20	0.29	0.28	0.05	0.33	0.41	0.34
CHF	0.33	0.20	1.00	0.88	0.58	0.42	0.72	0.34	0.69
EUR	0.43	0.29	0.88	1.00	0.64	0.33	0.83	0.43	0.80
GBP	0.41	0.28	0.58	0.64	1.00	0.22	0.58	0.41	0.55
JPY	0.13	0.05	0.42	0.33	0.22	1.00	0.26	0.15	0.24
NOK	0.46	0.33	0.72	0.83	0.58	0.26	1.00	0.45	0.79
NZD	0.75	0.41	0.34	0.43	0.41	0.15	0.45	1.00	0.43
SEK	0.46	0.34	0.69	0.80	0.55	0.24	0.79	0.43	1.00

Table 3.3
Risk-off and Macroeconomic Fundamentals.

We show whether macroeconomic fundamentals can predict correlation regime switching. We estimate the following univariate predictive regression:

$$P_t^{i \to j} = \kappa_0 + \kappa_{ij} \left(Growth_{t-1} - Growth_{t-1-L} \right) + \epsilon_t \,, \;\; L = 5, 22, 65,$$

where $P_t^{i \to j}$ is the probability of a low-to-high (or high-to-low) regime switch from $t-1$ to t, and $Growth$ is the real-time macroeconomic growth index for U.S., U.K., Eurozone, and Japan, as in Beber, Brandt, and Luisi (2014). We report the coefficients κ_{12} and κ_{21}, corresponding to high-to-low and low-to-high regime switch respectively, using real-time growth factors. We standardize the independent variable using its unconditional standard deviation. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10%, respectively.

	$L = 5$		$L = 22$		$L = 65$	
	$hi \to lo$	$lo \to hi$	$hi \to lo$	$lo \to hi$	$hi \to lo$	$lo \to hi$
US	−0.0002	0.0002	−0.0000	0.0000	0.0003	0.0004
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)
EU	−0.0014**	−0.0014**	0.0004	−0.0011*	0.0001	−0.0006
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)
JP	0.0006	−0.0004	−0.0004	−0.0000	0.0008	0.0012*
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)
UK	−0.0009	−0.0008	0.0014**	0.0003	0.0005	−0.0000
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)

Table 3.4
Correlation matrix of All G10 stock and bond returns.

This table presents correlation coefficients of G10 stock and bond returns. Panel A reports the correlation matrices estimated by the regime switching dynamic correlation (RSDC) model, where the upper right triangular matrix (in red shade) corresponds to the *negative equity-bond* correlation regime and the lower left triangular matrix (in green shade) corresponds to the *normal* correlation regime. Panel B reports the conditional transition probabilities.

Panel A. Correlation matrices in regime 1 (negative corr) and regime 2 (normal)

	US^e	AU^e	CA^e	CH^e	EU^e	UK^e	JP^e	SE^e	US^b	AU^b	CA^b	CH^b	EU^b	UK^b	JP^b	SE^b
US^e	1.00	0.12	**0.71**	**0.49**	**0.60**	**0.55**	**0.12**	**0.51**	**-0.38**	**-0.07**	**-0.35**	**-0.22**	**-0.28**	**-0.26**	**-0.06**	**-0.23**
AU^e	0.14	1.00	0.18	**0.29**	0.26	**0.31**	**0.56**	0.28	**-0.07**	**-0.30**	**-0.08**	**-0.17**	**-0.15**	**-0.16**	**-0.22**	**-0.19**
CA^e	0.63	0.23	1.00	**0.43**	**0.52**	**0.51**	**0.16**	**0.46**	**-0.30**	**-0.07**	**-0.28**	**-0.21**	**-0.24**	**-0.23**	**-0.06**	**-0.21**
CH^e	0.30	0.27	0.35	1.00	**0.79**	**0.80**	**0.30**	**0.74**	**-0.25**	**-0.21**	**-0.27**	**-0.34**	**-0.40**	**-0.38**	**-0.14**	**-0.37**
EU^e	0.32	0.34	0.39	0.62	1.00	**0.83**	**0.26**	**0.81**	**-0.32**	**-0.16**	**-0.32**	**-0.34**	**-0.42**	**-0.39**	**-0.11**	**-0.38**
UK^e	0.36	0.27	0.39	0.59	0.61	1.00	**0.28**	**0.78**	**-0.28**	**-0.18**	**-0.29**	**-0.33**	**-0.39**	**-0.36**	**-0.12**	**-0.35**
JP^e	0.09	0.35	0.16	0.21	0.24	0.21	1.00	**0.27**	**-0.07**	**-0.37**	**-0.10**	**-0.20**	**-0.17**	**-0.18**	**-0.33**	**-0.22**
SE^e	0.31	0.29	0.38	0.59	0.59	0.59	0.20	1.00	**-0.27**	**-0.17**	**-0.28**	**-0.34**	**-0.39**	**-0.36**	**-0.12**	**-0.36**
US^b	0.22	0.02	0.14	0.07	0.05	0.11	-0.01	0.10	1.00	0.06	**0.78**	**0.39**	**0.54**	**0.49**	0.06	**0.42**
AU^b	0.05	0.19	0.10	0.11	0.10	0.07	0.03	0.04	0.09	1.00	0.13	**0.29**	**0.25**	**0.24**	**0.33**	**0.34**
CA^b	0.12	0.19	0.15	0.06	0.11	0.07	0.08	0.04	0.28	0.33	1.00	**0.40**	**0.55**	**0.51**	**0.10**	**0.45**
CH^b	0.04	0.05	0.05	0.06	0.06	0.06	0.02	0.06	0.16	0.25	0.14	1.00	**0.73**	**0.64**	0.16	**0.67**
EU^b	0.10	0.07	0.11	0.15	0.19	0.14	0.02	0.10	0.32	0.19	0.28	0.39	1.00	**0.82**	**0.16**	**0.81**
UK^b	0.10	0.10	0.11	0.14	0.18	0.19	0.02	0.10	0.28	0.23	0.29	0.32	0.55	1.00	**0.16**	**0.70**
JP^b	-0.03	-0.03	-0.02	-0.06	-0.06	-0.03	-0.15	-0.07	0.08	0.17	0.07	0.17	0.06	0.09	1.00	**0.19**
SE^b	0.12	0.12	0.11	0.14	0.20	0.14	0.05	0.14	0.15	0.25	0.26	0.25	0.39	0.38	0.03	1.00

Panel B. Transition probability matrix

s_t	1(neg. equity-bond corr)	2(normal)
s_{t-1}		
1(neg. equity-bond corr)	0.9697	0.0303
2(normal)	0.0662	0.9338

Table 3.5

Risk-off effects on returns controlling for volatility innovations.

This table presents the effects of correlation regime-switching on exchange rate returns, controlling for volatility innovations, according to the regression:

$$\log S_{t+h} - \log S_{t-1} = \sum_{i,j\in\{1,2\}} \alpha_{ij}(h) P_t^{i\to j} + \beta_0(h) dV_t + \epsilon_{t-1\to t+h}\,,\ h = 0, 5, 10, 20,$$

where S_t is the price or index level, $P_{i\to j}$ is the probability of a i-to-j correlation regime switch, and dV_t is the standardized volatility innovation. The table reports $\alpha_{21}(h)$, the coefficient associated with the low-to-high regime switch, expressed as basis points over the horizon h. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10%, respectively. The sample runs from January 1995 through December, 2013. Panel A-E are dedicated to G10 currencies and currency trading strategies, emerging country currencies, equities, government bonds, and commodities, respectively.

Panel A. G10 currencies and currency trading strategies

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
AUD	−67**	−136**	−172*	−259**	−32	−111*	−152*	−236*	−63**	−130*	−170*	−270**
CAD	−69***	−93**	−105*	−68	−48***	−82*	−99*	−56	−63***	−85*	−105*	−71
CHF	−27	−121**	−101	−137	−26	−125**	−109	−140	−25	−124**	−103	−146
EUR	−52**	−112**	−64	−154	−38*	−105*	−63	−151	−46**	−111**	−62	−160
GBP	−13	−96**	−34	−0	5	−89*	−35	1	−9	−98**	−44	−17
JPY	13	41	148*	52	−6	28	138*	39	19	45	160**	65
NOK	−104***	−215***	−187**	−229**	−80***	−206***	−181**	−226**	−99***	−218***	−193**	−244**
NZD	−50*	−128*	−164*	−266**	−19	−106	−150	−253**	−44	−119*	−161*	−280**
SEK	−106***	−114*	−75	−205*	−81***	−104*	−69	−203*	−97***	−109*	−72	−218*
DOL	53***	108**	84	141*	36**	100**	80	136*	48***	105**	83	149*
CarryHML	−39*	−91*	−167**	−171*	−11	−70	−150**	−157*	−41**	−91*	−173***	−189**
MOM3HML	−35*	−99**	−88	−110	−52**	−104**	−90	−112	−45**	−110**	−96	−115

Table 3.5
Risk-off effects on returns controlling for volatility innovations (cont.)

Panel B. Emerging country currencies

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
BGN	−66***	−158***	−123	−272**	−44*	−146**	−121	−267**	−59**	−155**	−126	−282**
BRL	−52	−94	−187	−336*	−22	−77	−182	−316*	−52	−83	−193	−341*
CZK	−91***	−91	68	−101	−66**	−87	65	−100	−78***	−87	68	−103
EGP	−17	−37	−48	−135**	−16	−36	−47	−133**	−17	−38	−47	−134**
HRK	−39*	−106*	−59	−150	−19	−92	−53	−144	−31	−102*	−59	−155
HUF	−111***	−168**	−94	−161	−76***	−157**	−88	−152	−100***	−165**	−100	−174
ILS	−52***	−133***	−90	−100	−41**	−130***	−90	−95	−50***	−136***	−94*	−106
INR	−22	−108***	−128**	−153**	−8	−90**	−118**	−142*	−20	−104***	−127**	−156**
MXN	−55*	−107*	−133	−84	−30	−95	−118	−68	−52*	−101	−137	−88
MYR	6	84	−5	−16	19	99	2	−15	12	97	3	−31
PHP	25	15	−54	−224**	34*	26	−46	−215**	26	17	−56	−228**
PLN	−63**	−221***	−119	−247*	−25	−206***	−113	−230*	−54*	−214***	−123	−253*
RUB	−320***	−691***	−917***	−984***	−305***	−693***	−913***	−984***	−323***	−712***	−933***	−1004***
SGD	−14	−45	−89**	−108*	−2	−37	−82*	−101*	−8	−39	−83**	−108*
THB	−6	50	−16	−142	−1	57	−9	−136	−2	56	−7	−136
ZAR	−82**	−325***	−414***	−405**	−43	−313***	−401***	−386**	−70**	−314***	−410***	−408***

Table 3.5
Risk-off effects on returns controlling for volatility innovations (cont.)

Panel C. Global equity market indices

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
US:S&P500	−105**	−143	−121	21	−65	−126	−107	33	−47	−93	−78	51
US:DJIA	−99**	−162*	−113	−39	−63	−148	−101	−29	−46	−119	−76	−12
US:NASDAQ100	−148**	−397***	−315	−275	−111*	−375**	−301	−257	−74	−327**	−258	−226
US:Russell2000	−125**	−135	−159	33	−80	−118	−147	54	−58	−73	−106	70
CA:S&P/TSX60	−125***	−72	5	−99	−83**	−46	27	−72	−89**	−38	39	−79
EU:STOXX50	−165***	−119	−319**	−560***	−95**	−76	−275*	−520**	−136***	−69	−275*	−535**
FR:CAC40	−187***	−99	−286*	−495**	−118**	−56	−243	−456**	−158***	−50	−243	−473**
DE:DAX	−138***	−167	−290*	−362	−75	−132	−249	−323	−111**	−120	−250	−336
NE:AEX	−157***	−85	−230	−339	−92*	−45	−188	−296	−130***	−41	−192	−314
ES:IBEX	−180***	−186	−373**	−676***	−111**	−139	−326**	−624***	−153***	−141	−331**	−644***
SE:OMX	−124**	−123	−249	−299	−60	−78	−205	−247	−93*	−71	−200	−264
CH:SMI	−170***	34	−90	−117	−117***	68	−48	−84	−150***	77	−44	−87
UK:FTSE100	−129***	−95	−224*	−303*	−72*	−64	−186	−265	−104***	−56	−181	−274*
JP:Nikkei225	−99*	−146	−318*	−564**	−43	−69	−254	−497**	−96*	−119	−285*	−562**
HK:HSI	−123**	−474***	−782***	−929***	−62	−399***	−714***	−860***	−118**	−430***	−735***	−908***
AU:S&P/ASX200	−119***	−220***	−266**	−136	−81**	−168**	−225**	−89	−119***	−188**	−233**	−117

Table 3.5
Risk-off effects on returns controlling for volatility innovations (cont.)

Panel D. Ten-year government bonds (zero-coupon)

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
US	33	179***	235***	358***	19	177***	235***	364***	20	167***	230***	357***
Australia	−5	43	154**	242**	−16	36	150**	245**	−3	37	154**	252**
Canada	−31*	53	94*	176**	−41**	50	94	179**	−39**	44	90	175**
Switerland	−9	9	50	97*	−18	1	44	96	−12	1	43	94
Germany	5	39	138***	259***	−6	35	137***	264***	0	32	136***	262***
UK	26	97**	171***	241***	12	90**	168***	245***	20	86*	165***	241***
Japan	−4	10	62	141**	−6	7	62	142**	−4	7	63	146**
New Zealand	−4	23	43	150	−11	15	41	155	−4	15	41	157*
Sweden	−23	19	78	159*	−33*	9	73	161*	−26	9	73	159*

Table 3.5
Risk-off effects on returns controlling for volatility innovations (cont.)

Panel E. Commodities

	FXRV				FXIV				VIX			
	$h = 0$	$h = 5$	$h = 10$	$h = 20$	$h = 0$	$h = 5$	$h = 10$	$h = 20$	$h = 0$	$h = 5$	$h = 10$	$h = 20$
WTI Crude	−87	−292*	−595**	−923***	−38	−272	−589**	−918***	−70	−295*	−619***	−964***
Gasoline	−97	−477**	−604**	−849**	−49	−452**	−602**	−839**	−79	−487**	−640**	−899**
Heating Oil	−28	−286*	−461**	−726**	10	−266	−464**	−729**	−14	−283	−480**	−756**
Gold	−32	−85	−10	−40	−22	−78	−19	−37	−33	−93	−26	−51
Silver	−129*	−300*	−367*	−782***	−89	−272*	−356	−757**	−125*	−303*	−379*	−805***
Copper	−15	−49	110	66	39	−46	109	61	2	−51	89	19
Aluminum	−45	−245**	−313**	−516**	−8	−231**	−303**	−505**	−34	−233**	−314**	−535***
Nikel	−117	−358*	−49	−299	−67	−364*	−44	−306	−95	−353*	−71	−338
Zinc	−105*	−371**	−273	−628**	−55	−361**	−266	−622**	−87	−367**	−289	−668**
Coffee	−18	−391**	−331	−521*	7	−374**	−313	−510*	−11	−390**	−343	−558**
Cocca	115	−80	−634**	−1496***	129	−56	−623**	−1473***	117	−71	−633**	−1501***
Sugar	−215***	−679***	−769***	−1137***	−191***	−658***	−743***	−1112***	−206***	−664***	−768***	−1135***

Table 3.6
Risk-off effects on returns controlling for volatility transitions.

This table presents the effects of correlation regime-switching on exchange rate returns, controlling for transition in volatility, according to the regression:

$$\log S_{t+h} - \log S_{t-1} = \sum_{i,j \in \{1,2\}} \alpha_{ij}(h) P_t^{i \to j} + \beta_0 h \mathbf{I}_{\{V_t > V_{75\%}, V_{t-1} \leq V_{75\%}\}} + \epsilon_{t-1 \to t+h}\ ,\ h = 0, 5, 10, 20,$$

where S_t is the price or index level, $P_{i \to j}$ is the probability of a i-to-j correlation regime switch, and $\mathbf{I}_{\{V_t > V_{75\%}, V_{t-1} \leq V_{75\%}\}}$ is a dummy variable if volatility (level) surpasses the 75th percentile from day $t-1$ to t. The table reports α_{21}, the coefficient associated with low-to-high correlation regime switch, expressed as basis points over the horizon h. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10% respectively. The sample runs from January 1995 through December, 2013.

Panel A. G10 currencies and currency trading strategies

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
AUD	−76***	−148**	−188**	−292**	−76***	−148**	−189**	−293**	−76***	−148**	−189**	−294**
CAD	−70***	−97**	−116*	−86	−71***	−97**	−116*	−87	−70***	−97**	−116*	−87
CHF	−21	−118**	−99	−141	−21	−119**	−99	−142	−21	−118**	−99	−141
EUR	−47**	−111**	−64	−163	−48**	−112**	−65	−163	−48**	−112**	−64	−163
GBP	−11	−100**	−45	−22	−11	−100**	−45	−23	−11	−100**	−45	−23
JPY	26	53	166**	74	25	53	166**	75	26	53	166**	75
NOK	−104***	−225***	−202**	−252**	−104***	−225***	−202**	−253**	−104***	−225***	−202**	−253**
NZD	−56*	−134*	−176*	−299**	−56**	−135*	−176*	−300**	−56**	−135*	−176*	−300**
SEK	−102***	−117*	−81	−227**	−103***	−117*	−82	−228**	−103***	−117*	−81	−228**
DOL	51***	111***	90	157*	52***	111***	90	157*	52***	111***	90	157*
CarryHML	−52**	−106**	−188***	−206**	−52**	−106**	−189***	−207**	−52**	−107**	−189***	−208**
MOM3HML	−41**	−107**	−94	−109	−41**	−107**	−94	−110	−41**	−107**	−94	−110

Table 3.6
Risk-off effects on returns controlling for volatility transitions (cont.)

Panel B. Emerging country currencies

	FXRV				FXIV				VIX			
	$h = 0$	$h = 5$	$h = 10$	$h = 20$	$h = 0$	$h = 5$	$h = 10$	$h = 20$	$h = 0$	$h = 5$	$h = 10$	$h = 20$
BGN	−62**	−159***	−130	−287**	−62**	−159***	−130	−288**	−62**	−159***	−130	−288**
BRL	−64*	−104	−212*	−365**	−64*	−105	−212*	−366**	−64*	−105	−213*	−367**
CZK	−85***	−88	64	−108	−85***	−88	64	−109	−85***	−88	65	−108
EGP	−17	−39	−48	−136**	−17	−39	−48	−136**	−17	−39	−49	−136**
HRK	−34	−104*	−62	−159	−34	−104*	−62	−160	−34	−104*	−61	−159
HUF	−109***	−173**	−109	−186	−109***	−173**	−110	−187	−109***	−173**	−109	−187
ILS	−54***	−141***	−101*	−114	−54***	−141***	−101*	−114	−54***	−141***	−101*	−114
INR	−24*	−111***	−134***	−164**	−24*	−111***	−134***	−164**	−24*	−111***	−134***	−164**
MXN	−65**	−118*	−155*	−109	−65**	−119*	−155*	−110	−65**	−119*	−155*	−110
MYR	8	92	1	−37	8	92	1	−37	8	92	1	−37
PHP	23	10	−62	−236***	23	10	−62	−237***	23	9	−63	−237***
PLN	−65**	−225***	−134	−269**	−65**	−226***	−134	−269**	−65**	−225***	−134	−269**
RUB	−327***	−720***	−935***	−1012***	−327***	−721***	−934***	−1013***	−327***	−721***	−934***	−1013***
SGD	−13	−43	−87**	−113*	−13	−43	−88**	−113*	−13	−43	−88**	−113*
THB	−4	51	−12	−141	−5	51	−12	−141	−5	51	−12	−141
ZAR	−84**	−329***	−429***	−425***	−85**	−329***	−429***	−426***	−85**	−329***	−430***	−426***

Table 3.6
Risk-off effects on returns controlling for volatility transitions (cont.)

Panel C. Global equity market indices

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
US:S&P500	−117***	−149	−136	−8	−117***	−149	−137	−9	−118***	−150	−138	−10
US:DJIA	−110***	−169*	−129	−64	−110***	−169*	−130	−66	−111***	−170*	−131	−67
US:NASDAQ100	−159**	−397***	−329*	−299	−160**	−398***	−331*	−301	−161**	−399***	−333*	−303
US:Russell2000	−134***	−136	−173	−2	−134***	−137	−174	−4	−135***	−138	−175	−5
CA:S&P/TSX60	−138***	−87	−10	−130	−139***	−87	−11	−132	−139***	−88	−12	−133
EU:STOXX50	−182***	−127	−331**	−590***	−182***	−128	−332**	−593***	−183***	−129	−333**	−594***
FR:CAC40	−203***	−106	−296*	−526**	−203***	−107	−297**	−529**	−203***	−108	−298**	−530**
DE:DAX	−157***	−180	−309*	−396*	−158***	−181	−310*	−399*	−158***	−182	−311*	−400*
NE:AEX	−174***	−102	−254	−377*	−174***	−103	−255	−380*	−175***	−104	−257	−382*
ES:IBEX	−196***	−195	−383**	−697***	−197***	−196	−384**	−699***	−197***	−197	−386**	−700***
SE:OMX	−137**	−130	−258	−322	−138***	−131	−260	−324	−138***	−132	−261	−325
CH:SMI	−183***	28	−90	−133	−183***	27	−91	−135	−183***	26	−92	−135
UK:FTSE100	−142***	−106	−229*	−319*	−142***	−106	−230*	−321**	−143***	−107	−231*	−322**
JP:Nikkei225	−110**	−168	−336**	−614***	−110**	−168	−336**	−616***	−110**	−169	−337**	−617***
HK:HSI	−138**	−482***	−788***	−966***	−138**	−483***	−789***	−968***	−139**	−484***	−790***	−970***
AU:S&P/ASX200	−130***	−226***	−271**	−154	−131***	−227***	−272**	−155	−131***	−227***	−273**	−156

Table 3.6
Risk-off effects on returns controlling for volatility transitions (cont.)

Panel D. Ten-year government bonds (zero-coupon)

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
US	31	174***	237***	363***	31	174***	237***	364***	31	175***	237***	364***
Australia	−1	42	159**	257***	−1	42	159**	257***	−1	42	159**	258***
Canada	−32*	48	93	177**	−32*	48	93	177**	−32*	48	93	177**
Switerland	−9	5	46	97*	−9	5	46	97*	−9	5	46	97*
Germany	6	37	140***	266***	6	37	140***	266***	6	37	140***	266***
UK	24	90**	168***	245***	24	90**	168***	245***	24	90**	168***	246***
Japan	−3	11	65	147***	−3	11	65	147***	−3	11	66	147***
New Zealand	−4	20	45	161*	−4	20	45	161*	−4	20	45	161*
Sweden	−22	14	77	163*	−22	14	77	164*	−22	14	77	164*

Table 3.6
Risk-off effects on returns controlling for volatility transitions (cont.)

Panel E. Commodities

	FXRV				FXIV				VIX			
	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$	$h=0$	$h=5$	$h=10$	$h=20$
WTI Crude	−96	−325*	−649***	−1004***	−96	−326*	−650***	−1006***	−97	−326*	−650***	−1006***
Gasoline	−106	−518***	−673***	−946***	−106	−519***	−673***	−948***	−106	−519***	−674***	−948***
Heating Oil	−35	−310*	−506**	−793**	−36	−311*	−508**	−795**	−36	−311*	−507**	−795**
Gold	−32	−97	−27	−61	−33	−98	−27	−60	−33	−97	−26	−59
Silver	−136**	−324**	−399*	−834***	−137**	−324**	−399*	−834***	−137**	−324**	−399*	−833***
Copper	−24	−78	52	−28	−25	−79	51	−30	−25	−79	51	−30
Aluminum	−51	−251**	−337**	−565***	−51	−251**	−337**	−567***	−51	−252**	−337**	−567***
Nikel	−123	−387**	−115	−392	−123	−388**	−117	−395	−123	−389**	−117	−395
Zinc	−109*	−395***	−327*	−714***	−110*	−395***	−328*	−717***	−110*	−396***	−328*	−717***
Coffee	−23	−403**	−357	−574**	−23	−403**	−357	−574**	−23	−403**	−356	−573**
Cocca	103	−92	−654***	−1521***	103	−92	−654***	−1521***	103	−93	−654***	−1522***
Sugar	−220***	−678***	−783***	−1156***	−220***	−678***	−783***	−1156***	−220***	−677***	−782***	−1156***

Table 3.7

Response of Returns to Volatility shocks conditioned on correlation regime switching.

This table presents the effects of volatility shocks conditioned on transitional regimes according to the following regressions:

$$\text{Unconditional Volatility Shock:} \quad r_{t-1\to t} = \alpha_0 + \beta_0\, dV_t + \epsilon_{t-1\to t}$$

$$\text{Conditional Volatility Shock:} \quad r_{t-1\to t} = \alpha_0 + \sum_{i,j\in\{1,2\}} \beta_{ij}\, \left(P_t^{i\to j} \times dV_t\right) + \epsilon_{t-1\to t}$$

where $r_{t-1\to t}$ is daily logarithm asset return. $\left(P_t^{i\to j} \times dV_t\right)$ is the standardized volatility innovation, dV_t, conditioned on regime transition from i to j. The coefficients, β_0, and β_{ij}'s are expressed as basis points per day. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10% respectively. The sample runs from January 1995 through December, 2013.

Panel A. G10 currencies and currency trading strategies

	FXIV					VIX				
	β_0	β_{11}	β_{12}	β_{21}	β_{22}	β_0	β_{11}	β_{12}	β_{21}	β_{22}
AUD	−26***	−36***	77***	−59***	−10***	−14***	−25***	187***	−64***	−6***
CAD	−14***	−17***	48***	−43***	−7***	−8***	−15***	65***	−46***	−2**
CHF	3***	−2	66***	0	11***	4***	−2	110***	28	7***
EUR	−6***	−13***	59***	−33***	7***	−2*	−10***	127***	−14	5***
GBP	−10***	−16***	52***	−10	1	−2***	−9***	90***	−8	3***
JPY	19***	17***	3	18	22***	7***	13***	85***	56***	1
NOK	−14***	−23***	138***	−53***	−0	−6***	−17***	222***	−57***	2*
NZD	−22***	−31***	97***	−24	−8***	−13***	−23***	201***	−37*	−6***
SEK	−13***	−19***	104***	−44***	−3*	−6***	−17***	162***	−18	1
DOL	9***	16***	−72***	27***	−1	4***	12***	−139***	18	−1
CarryHML	−24***	−28***	57***	−36***	−18***	−12***	−20***	87***	−66***	−5***
MOM3HML	6***	8***	38***	−22*	3**	4***	7***	−36	−4	3***

Table 3.7
Volatility shocks conditioned on correlation regime switching (cont.)

Panel B. Emerging-country currencies

	FXIV					VIX				
	β_0	β_{11}	β_{12}	β_{21}	β_{22}	β_0	β_{11}	β_{12}	β_{21}	β_{22}
BGN	−9***	−14***	97***	−27**	1	−3***	−10***	135***	−12	4**
BRL	−25***	−34***	16	−1	−11***	−13***	−26***	155***	−7	−4**
CZK	−11***	−20***	89***	−32**	3	−7***	−17***	145***	−15	−0
EGP	−1	−1	−10	−10	0	−0	−0	3	−8	0
HRK	−9***	−15***	54***	−27**	3**	−3***	−11***	141***	−9	4***
HUF	−20***	−29***	78***	−46***	−5***	−10***	−25***	146***	−14	1
ILS	−8***	−8***	−22*	−15	−6***	−5***	−9***	43**	−7	−1
INR	−10***	−12***	14	−5	−7***	−4***	−8***	56***	−8	−2***
MXN	−21***	−23***	−20	−32*	−17***	−15***	−18***	75**	−34	−12***
MYR	−7***	−8***	13	−4	−4**	−4***	−5***	33	4	−4**
PHP	−6***	−8***	−26**	−8	−3**	−3***	−4***	18	2	−2*
PLN	−24***	−32***	28	−39**	−10***	−12***	−23***	103***	−20	−4***
RUB	−13***	−14***	481***	−221***	−13***	−4**	−9***	309***	−508***	7**
SGD	−6***	−10***	0	−2	0	−5***	−9***	37**	12	−3***
THB	−2***	−3**	−9	−4	−1	−2***	−2*	31	−2	−3**
ZAR	−25***	−32***	69***	−45**	−14***	−16***	−25***	120***	−100***	−8***

Table 3.7
Volatility shocks conditioned on correlation regime switching (cont.)

PANEL C. GLOBAL EQUITY MARKET INDICES

	FXIV					VIX				
	β_0	β_{11}	β_{12}	β_{21}	β_{22}	β_0	β_{11}	β_{12}	β_{21}	β_{22}
US:S&P500	−31***	−38***	−30	−37	−18***	−75***	−89***	−58	−106***	−64***
US:DJIA	−28***	−34***	−30	−36	−16***	−68***	−79***	−53	−104***	−58***
US:NASDAQ100	−29***	−34***	−74	−49	−19***	−92***	−86***	23	−77*	−99***
US:Russell2000	−32***	−38***	−42	−8	−22***	−81***	−102***	−104**	−127***	−63***
CA:S&P/TSX60	−33***	−40***	8	−43*	−22***	−53***	−63***	3	−100***	−44***
EU:STOXX50	−52***	−56***	−5	−64**	−45***	−50***	−60***	32	−89**	−41***
FR:CAC40	−51***	−56***	1	−65**	−43***	−49***	−60***	26	−93***	−40***
DE:DAX	−49***	−51***	9	−32	−48***	−51***	−58***	29	−93**	−44***
NE:AEX	−49***	−53***	3	−58**	−43***	−48***	−59***	54	−96***	−39***
ES:IBEX	−51***	−55***	−31	−96***	−42***	−47***	−57***	−31	−102***	−38***
SE:OMX	−47***	−52***	3	−54*	−38***	−48***	−58***	107*	−101***	−40***
CH:SMI	−40***	−42***	−12	−72***	−34***	−36***	−41***	17	−100***	−31***
UK:FTSE100	−42***	−47***	−23	−74***	−32***	−41***	−50***	4	−83***	−33***
JP:Nikkei225	−40***	−49***	−55	−64**	−23***	−15***	−16***	7	−125***	−13***
HK:HSI	−46***	−54***	−15	−9	−35***	−23***	−31***	54	−57	−15***
AU:S&P/ASX200	−30***	−35***	−24	−74***	−18***	−12***	−17***	−2	−125***	−7***

Table 3.7
Volatility shocks conditioned on correlation regime switching (cont.)

Panel D. Ten-year government bonds (zero-coupon)

	FXIV					VIX				
	β_0	β_{11}	β_{12}	β_{21}	β_{22}	β_0	β_{11}	β_{12}	β_{21}	β_{22}
US	7***	11***	−15	18	−1	12***	20***	−97***	59***	4***
Australia	9***	13***	−31*	−25	4**	2**	5***	5	−43**	1
Canada	5***	9***	−1	−16	−0	8***	14***	−11	2	3***
Switerland	5***	8***	12	−14*	1	4***	6***	12	7	1
Germany	7***	11***	6	−5	−1	6***	9***	17	21*	2***
UK	7***	12***	−2	−9	−0	5***	9***	−25	15	2
Japan	2***	3***	15	−7	0	1*	0	−18	−12	2**
New Zealand	4***	6***	−23*	−9	2	0	3**	−1	−9	−2
Sweden	6***	12***	16	−21**	−3**	4***	7***	−11	10	2

Table 3.7
Volatility shocks conditioned on correlation regime switching (cont.)

PANEL E. COMMODITIES

	FXIV					VIX				
	β_0	β_{11}	β_{12}	β_{21}	β_{22}	β_0	β_{11}	β_{12}	β_{21}	β_{22}
WTI Crude	−35***	−46***	97*	−137***	−11**	−29***	−58***	252***	−151***	−5
Gasoline	−34***	−44***	83	−143***	−12**	−29***	−55***	311***	−100*	−8*
Heating Oil	−27***	−36***	78	−119***	−8	−23***	−45***	315***	−122**	−6
Gold	−6***	−9***	31	13	−3	−0	−4*	131***	30	1
Silver	−29***	−38***	−19	−54	−11**	−13***	−27***	253***	−24	−4
Copper	−38***	−50***	38	−47	−16***	−28***	−46***	172**	−64	−15***
Aluminum	−26***	−34***	69**	−16	−14***	−18***	−31***	205***	−23	−10***
Nikel	−34***	−43***	39	−88*	−16***	−30***	−48***	117	−130**	−14***
Zinc	−33***	−42***	15	−35	−17***	−25***	−41***	215***	−124***	−12***
Coffee	−18***	−25***	41	−24	−6	−13***	−28***	101	−5	−2
Cocca	−15***	−25***	69	5	−1	−14***	−24***	2	−49	−6
Sugar	−18***	−24***	98**	−144***	−2	−15***	−28***	120	−84	−5

Table 3.8
Risk-off effects on returns controlling for other risk indicators.

This table presents the effects of correlation regime-switching on exchange rate returns, controlling for innovations to other risk indicators, according to the following regression:

$$r_{t-1\to t+h} = \sum_{i,j\in\{1,2\}} \alpha_{ij}(h)P_t^{i\to j} + \beta_0(h)d\text{Other}_t + \epsilon_{t-1\to t+h}\,,\ \ h = 0, 5, 20,$$

where $r_{t-1\to t+h}$ is cumulative return from day $t-1$ to day $t+h$, $P_{i\to j}$ is the probability of a i-to-j correlation regime switch, $d\text{Other}_t$ denotes the standardized innovations to other market stress indicators including global FX implied correlation, global FX risk reversal (as a proxy for skewness with large positive values associated with more positively skewed return of USD and more negatively skewed return of other currencies), and the Risk on-Risk off (RoRo) index. The table reports $\alpha_{21}(h)$, the coefficient associated with the low-to-high regime switch, expressed as basis points over the horizon h, and $\beta_0(h)$, the contemporaneous impact of a one standard deviation increase in other market stress indicators. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10% respectively. Panel A-E are dedicated to G10 currencies and currency trading strategies, emerging country currencies, equities, government bonds, and commodities, respectively.

Panel A. G10 currencies and currency trading strategies

	FX Implied Correlation				FX Risk Reversal (USD)				RoRo Index			
	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$
AUD	-76^{***}	-148^{**}	-294^{**}	-2^{*}	-71^{*}	-272^{**}	-457^{**}	-37^{***}	-76^{***}	-148^{**}	-295^{**}	-5^{***}
CAD	-70^{***}	-97^{**}	-87	-0	-70^{**}	-154^{**}	-122	-20^{***}	-70^{***}	-96^{**}	-84	-1
CHF	-21	-119^{**}	-142	5^{***}	28	-254^{***}	-429^{***}	-25^{***}	-20	-114^{**}	-132	-3^{**}
EUR	-48^{**}	-112^{**}	-163	3^{***}	-8	-242^{***}	-505^{***}	-26^{***}	-47^{**}	-109^{**}	-158	-3^{***}
GBP	-11	-100^{**}	-23	1	11	-273^{***}	-371^{***}	-21^{***}	-11	-100^{**}	-26	-2^{**}
JPY	25	53	74	11^{***}	54	105	385^{***}	-9^{***}	25	53	71	1
NOK	-104^{***}	-225^{***}	-253^{**}	2^{*}	-36	-384^{***}	-636^{***}	-33^{***}	-104^{***}	-222^{***}	-248^{**}	-4^{***}
NZD	-56^{*}	-135^{*}	-300^{**}	-1	-68	-244^{**}	-468^{**}	-36^{***}	-56^{*}	-133^{*}	-296^{**}	-3^{**}
SEK	-103^{***}	-117^{*}	-228^{**}	1	-30	-256^{***}	-547^{***}	-33^{***}	-102^{***}	-112^{*}	-215^{*}	-3^{***}
DOL	52^{***}	111^{***}	157^{*}	-2^{***}	21	219^{***}	350^{***}	27^{***}	51^{***}	109^{**}	154^{*}	3^{***}
CarryHML	-52^{**}	-106^{**}	-207^{**}	-6^{***}	-74^{**}	-174^{**}	-338^{**}	-15^{***}	-52^{**}	-106^{**}	-204^{**}	-2^{***}
MOM3HML	-41^{**}	-107^{**}	-110	2^{**}	-49	-258^{***}	-423^{***}	1	-41^{**}	-105^{**}	-101	0

Table 3.8
Risk-off effects on returns controlling for other risk indicators (cont.)

Panel B. Emerging country currencies

	FX Implied Correlation				FX Risk Reversal (USD)				RoRo Index			
	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$
BGN	-62^{**}	-159^{***}	-288^{**}	2	-10	-230^{***}	-501^{***}	-28^{***}	-60^{**}	-155^{**}	-285^{**}	-3^{***}
BRL	-64^{*}	-105	-366^{**}	-3^{**}	-78^{*}	-283^{**}	-701^{***}	-26^{***}	-64^{*}	-107	-373^{**}	-5^{***}
CZK	-85^{***}	-88	-109	1	-42	-218^{**}	-433^{**}	-33^{***}	-85^{***}	-86	-106	-3^{***}
EGP	-17	-39	-136^{**}	-0	-12	-57^{***}	-209^{***}	-1^{*}	-17	-38	-131^{**}	0
HRK	-34	-104^{*}	-160	3^{**}	-20	-222^{***}	-463^{***}	-29^{***}	-34	-103^{*}	-159	-4^{***}
HUF	-109^{***}	-173^{**}	-187	1	-86^{*}	-360^{***}	-474^{**}	-40^{***}	-110^{***}	-177^{**}	-205	-4^{***}
ILS	-54^{***}	-141^{***}	-114	-1^{*}	-38	-150^{**}	27	-15^{***}	-54^{***}	-142^{***}	-115	-0
INR	-24^{*}	-111^{***}	-164^{**}	-0	-28	-159^{***}	-248^{**}	-13^{***}	-25^{*}	-114^{***}	-176^{**}	-2^{***}
MXN	-66^{**}	-119^{*}	-111	-4^{***}	-88^{***}	-108	-1	-20^{***}	-68^{***}	-128^{**}	-138	-2^{**}
MYR	8	92	-36	0	-33^{*}	-44	-261^{***}	-12^{***}	8	94	-34	-1
PHP	23	10	-236^{***}	1	-27	-140^{***}	-377^{***}	-9^{***}	23	9	-238^{***}	-0
PLN	-65^{**}	-225^{***}	-269^{**}	-2^{*}	-81^{*}	-438^{***}	-565^{**}	-40^{***}	-65^{**}	-225^{***}	-272^{*}	-4^{***}
RUB	-327^{***}	-721^{***}	-1013^{***}	-2	-46^{*}	-233^{***}	-555^{***}	-20^{***}	-329^{***}	-724^{***}	-1017^{***}	12^{***}
SGD	-13	-44	-113^{*}	2^{***}	-28^{*}	-87^{**}	-147^{*}	-15^{***}	-13	-42	-110^{*}	-2^{***}
THB	-5	51	-141	-0	11	61	-108	-9^{***}	-4	52	-140	-1
ZAR	-85^{**}	-329^{***}	-426^{***}	-2^{*}	-116^{**}	-588^{***}	-622^{**}	-34^{***}	-84^{**}	-327^{***}	-421^{***}	-5^{***}

Table 3.8
Risk-off effects on returns controlling for other risk indicators (cont.)

Panel C. Global equity market indices

	FX Implied Correlation				FX Risk Reversal (USD)				RoRo Index			
	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$
US:S&P500	-116^{***}	-149	-8	-15^{***}	-118^{*}	-22	8	-8^{***}	-116^{***}	-144	12	-2
US:DJIA	-109^{***}	-169^{*}	-65	-15^{***}	-88	6	60	-7^{***}	-109^{***}	-164^{*}	-44	-1
US:NASDAQ100	-159^{**}	-397^{***}	-300	-15^{***}	-106	-7	-231	-6^{**}	-159^{**}	-392^{***}	-278	0
US:Russell2000	-133^{***}	-136	-3	-14^{***}	-145^{*}	-10	137	-10^{***}	-133^{**}	-133	12	-1
CA:S&P/TSX60	-138^{***}	-87	-132	-11^{***}	-97	-26	-103	-13^{***}	-138^{***}	-84	-121	-6^{***}
EU:STOXX50	-182^{***}	-128	-592^{***}	-16^{***}	-149^{**}	-290^{*}	-810^{***}	-28^{***}	-182^{***}	-126	-583^{***}	-1
FR:CAC40	-202^{***}	-106	-529^{**}	-15^{***}	-139^{**}	-207	-724^{***}	-28^{***}	-204^{***}	-108	-532^{**}	-1
DE:DAX	-157^{***}	-180	-398^{*}	-18^{***}	-163^{**}	-362^{**}	-658^{**}	-25^{***}	-158^{***}	-181	-394^{*}	-1
NE:AEX	-173^{***}	-102	-379^{*}	-15^{***}	-156^{**}	-257	-336	-22^{***}	-174^{***}	-99	-365	-2
ES:IBEX	-196^{***}	-196	-699^{***}	-14^{***}	-154^{**}	-227	-1017^{***}	-29^{***}	-197^{***}	-194	-688^{***}	0
SE:OMX	-137^{**}	-131	-323	-14^{***}	-117	-80	35	-23^{***}	-138^{**}	-130	-320	-1
CH:SMI	-183^{***}	28	-134	-12^{***}	-124^{**}	-0	-159	-14^{***}	-183^{***}	32	-117	-1
UK:FTSE100	-142^{***}	-106	-320^{*}	-12^{***}	-139^{**}	-127	-388^{*}	-22^{***}	-142^{***}	-102	-304^{*}	-3^{*}
JP:Nikkei225	-110^{**}	-168	-616^{***}	-0	-64	-373^{**}	-1131^{***}	-31^{***}	-110^{**}	-167	-608^{***}	-6^{***}
HK:HSI	-138^{**}	-483^{***}	-969^{***}	-9^{***}	-93	-541^{***}	-864^{***}	-36^{***}	-137^{**}	-477^{***}	-940^{***}	-4^{*}
AU:S&P/ASX200	-131^{***}	-227^{***}	-155	-0	-134^{**}	-263^{**}	-289	-29^{***}	-130^{***}	-224^{***}	-144	-2

Table 3.8
Risk-off effects on returns controlling for other risk indicators (cont.)

Panel D. Ten-year government bonds (zero-coupon)

	FX Implied Correlation				FX Risk Reversal (USD)				RoRo Index			
	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$
US	31	175***	364***	1	49	224***	379***	0	32	180***	384***	2**
Australia	−1	42	257***	−3***	63**	161**	258**	4***	−0	46	275***	1
Canada	−32*	48	177**	1*	2	116**	138	−0	−31*	52	194**	2***
Switerland	−9	4	97*	−0	6	27	122	0	−8	8	108*	−0
Germany	6	37	267***	−1	25	108*	291***	1*	6	40	278***	1
UK	24	90**	246***	1	37	214***	302***	1	25	92**	253***	1*
Japan	−3	11	147***	−1	−4	35	150***	−0	−2	15	161***	1
New Zealand	−4	20	161*	−1	48**	74	111	2**	−3	23	174*	−0
Sweden	−22	14	164*	−1	−3	94	291***	4***	−22	19	185**	1

Table 3.8
Risk-off effects on returns controlling for other risk indicators (cont.)

Panel E. Commodities

	FX Implied Correlation				FX Risk Reversal (USD)				RoRo Index			
	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$	$\alpha_{21}(0)$	$\alpha_{21}(5)$	$\alpha_{21}(20)$	$\beta_0(0)$
WTI Crude	−96	−326*	−1005***	−0	−116	−372	−1357***	−28***	−96	−324*	−1006***	−12***
Gasoline	−106	−518***	−946***	−1	−89	−528*	−972*	−28***	−105	−517***	−948**	−12***
Heating Oil	−36	−312*	−796**	1	−85	−418*	−1051**	−26***	−35	−307*	−785**	−9***
Gold	−33	−97	−60	1	8	−82	55	−30***	−32	−95	−56	−5***
Silver	−137**	−324**	−834***	−2	−84	−387	−1176**	−62***	−136**	−319*	−820***	−14***
Copper	−24	−78	−30	−6**	−76	−297	−259	−44***	−24	−80	−46	−9***
Aluminum	−51	−251**	−566***	−3	−107	−510***	−991***	−33***	−52	−256**	−592***	−7***
Nikel	−123	−387**	−393	2	−171	−604*	−414	−38***	−123	−391**	−416	−7**
Zinc	−110*	−395***	−717***	−2	−156	−666**	−1272***	−38***	−110*	−399***	−734***	−10***
Coffee	−23	−403**	−573**	2	27	−758***	−971**	−34***	−23	−406**	−585**	−7**
Cocca	103	−93	−1522***	−1	−26	−67	−1032**	−22***	101	−109	−1574***	−9***
Sugar	−220***	−678***	−1157***	−1	−212**	−799***	−1810***	−20***	−221***	−685***	−1177***	−7**

Table 3.9
Real-time filtered risk-off probabilities.

This table presents the date, full-sample smoothed probability of the risk-off transition, and the real-time probability of the risk-off transition when either probability is above 0.2 (Panel A) and the predictive power of real-time risk-off indicator for risk-off events (Panel B). Specifically, we regress the full-sample risk-off indicator on day $t+h$, $h = 0, 1, \cdots, 60$, onto the real-time risk-off indicator on day t. A risk-off indicator equals to 1 if the corresponding transition probability is above 0.2 and equals to 0 otherwise.

Panel A: risk-off transition probability			Panel B: Real-time forecasts of risk-off		
Date	Full-sample	Real-time	horizon h	coefficient $i(h)$	$t - statistic$
24-Jan-2007	0.00	**0.32**	0	5.00%	1.95
22-Feb-2007	**0.23**	0.01	21	5.00%	1.94
27-Feb-2007	0.11	**0.22**	24	5.00%	1.94
8-May-2007	0.00	**0.30**	33	5.00%	1.94
29-May-2007	0.00	**0.32**	34	5.00%	1.93
26-Jul-2007	**0.23**	0.00	42	10.00%	3.96
31-Jul-2007	**0.39**	0.00	45	5.26%	2.02
7-Sep-2007	0.00	**0.22**	48	5.26%	2.02
8-Nov-2007	0.00	**0.40**	49	5.26%	2.02
28-Feb-2008	0.01	**0.44**	52	5.26%	2.02
2-Jun-2008	0.01	**0.34**	57	5.26%	2.01
7-Aug-2008	**0.61**	0.03	60	10.53%	4.04
8-Aug-2008	**0.20**	0.08			
26-Aug-2008	0.02	**0.64**			
10-Oct-2008	**0.23**	0.04			
22-Jan-2009	0.01	**0.24**			
23-Mar-2009	**0.33**	0.01			
15-Jun-2009	**0.20**	0.03			
18-Jun-2009	**0.25**	0.05			
24-Sep-2009	0.01	**0.24**			
28-Oct-2009	**0.39**	0.06			
31-Dec-2009	**0.25**	0.04			
12-Mar-2010	**0.24**	0.02			
19-Mar-2010	0.02	**0.26**			
6-May-2010	**0.32**	0.04			
16-Sep-2010	0.00	**0.98**			
12-Oct-2010	0.03	**0.29**			
22-Oct-2010	0.00	**0.20**			
1-Nov-2010	0.03	**0.69**			
9-Dec-2010	0.04	**0.23**			
3-Mar-2011	**0.65**	0.16			
5-Aug-2011	**0.64**	0.03			
8-Aug-2011	**0.34**	**0.27**			
6-Mar-2012	0.15	**0.25**			
17-May-2012	**0.22**	0.02			
9-Jan-2013	**0.20**	0.01			
11-Jan-2013	**0.28**	0.09			
14-Jan-2013	**0.21**	0.01			
25-Feb-2013	**0.31**	0.01			
26-Feb-2013	**0.54**	0.17			
17-May-2013	**0.25**	0.01			
21-May-2013	**0.26**	0.10			
31-Oct-2013	0.00	**0.45**			

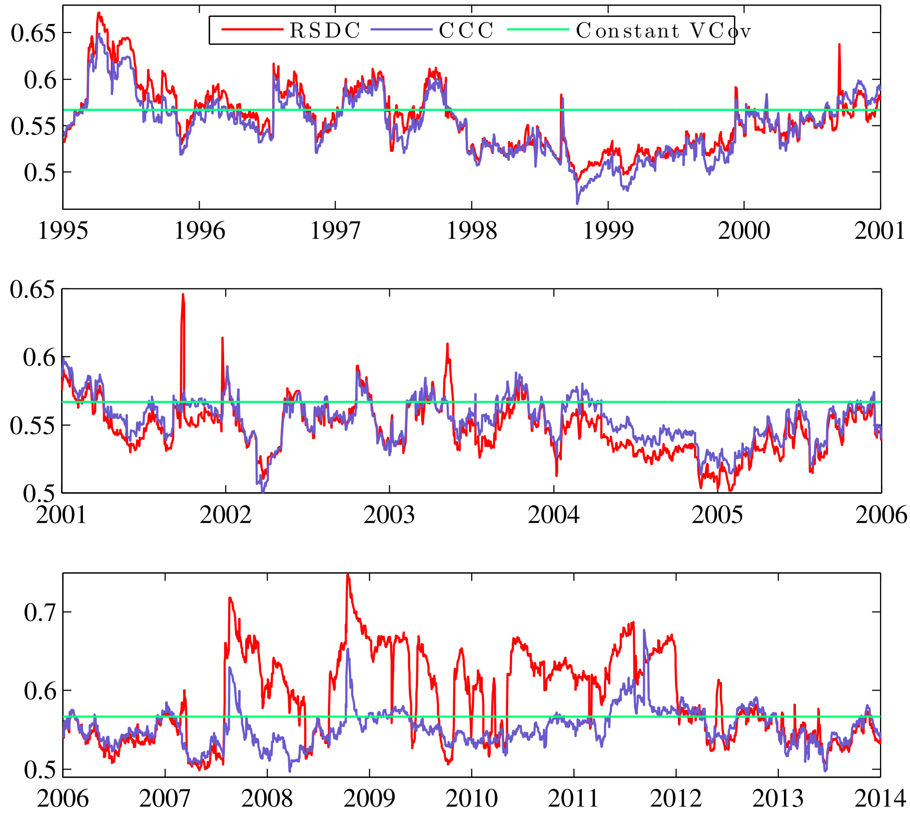


Figure 3.1. Variance ratio of the first principal component. This figure shows the ratio of the variance of the first principal component of G10 exchange rate returns to the total variance of all principal components, which measures the portion of total G10 exchange rate variation that can be explained by the first principal component. The principal component analysis is based on three different types of variance-covariance matrices for G10 exchange rate returns : 1) the regime-dependent dynamic correlations (RSDC) model; 2) the constant conditional correlation (CCC) model; and 3) the unconditional variance-covariance matrix. Sample is January 1995 to December 2013.

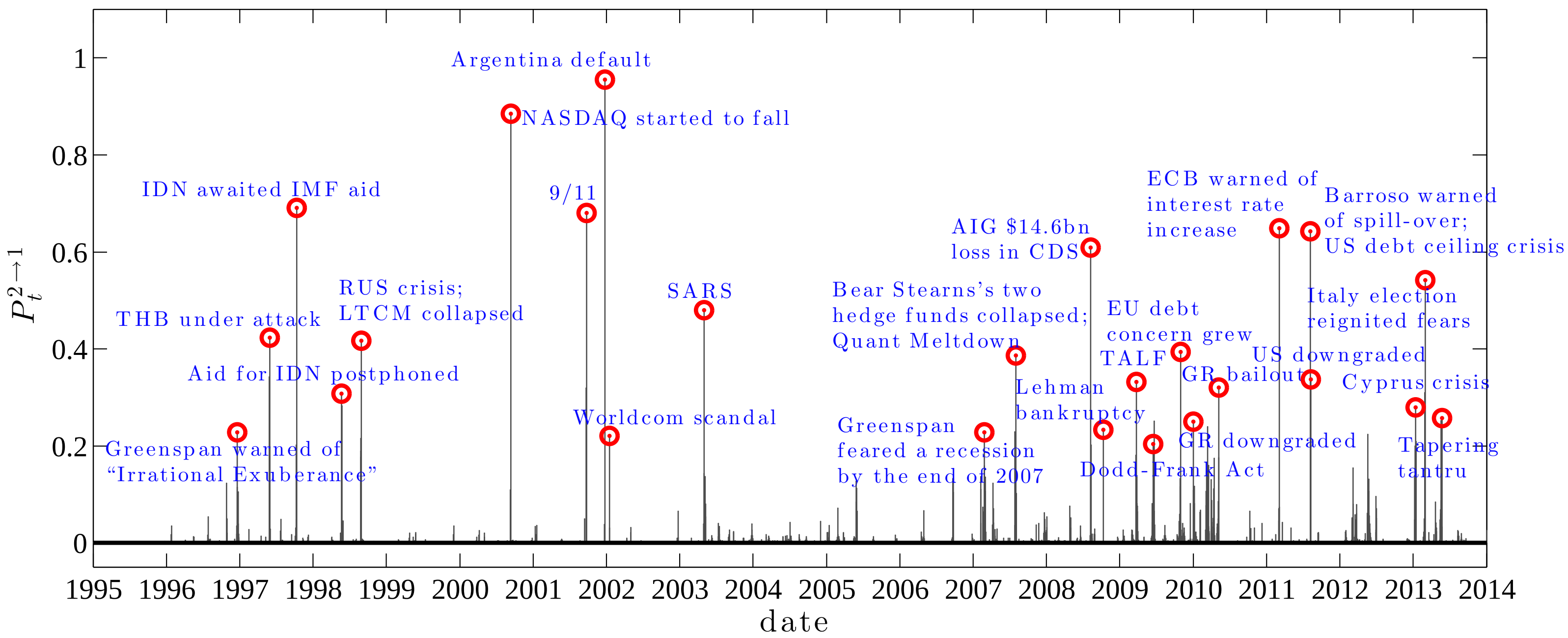


Figure 3.2. Risk-off episodes associated with low-to-high correlation regime switch. This figure shows noteworthy risk-off events (marked by red circle and described by blue texts) with the the low-to-high correlation regime switching probability (plotted as gray lines) in excess of 0.2. Sample is January 1995 to December 2013.

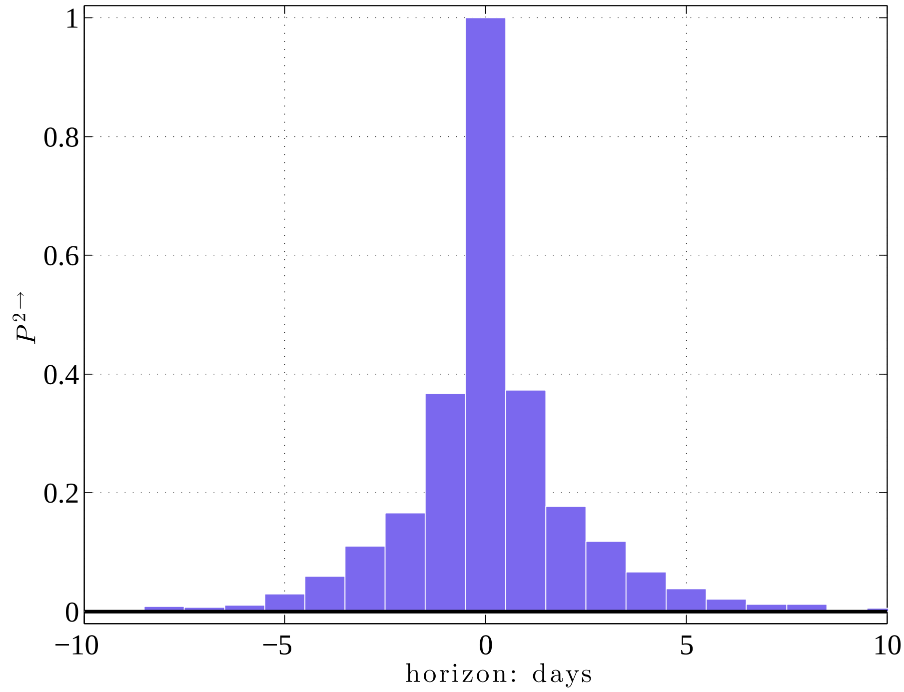
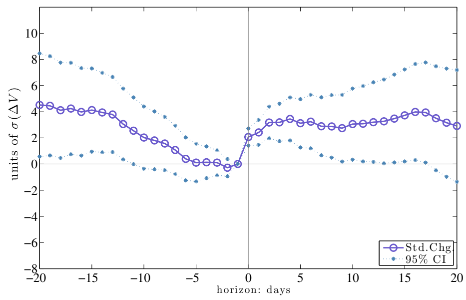
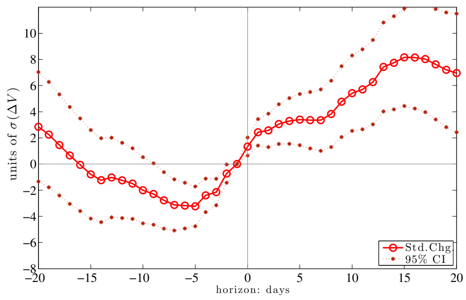


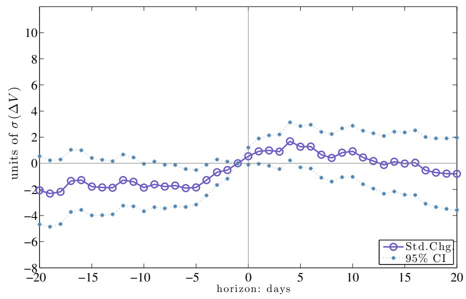
Figure 3.3. Low-to-high switching probability during the risk-off event. We plot the coefficient $\theta_{21}(h)$ estimated from equation (3.16) for $h \in [-10, 10]$. Given a risk-off event for $h = 0$, the graph shows that the build-up in the probability before the event, and the gradual reduction afterwards.



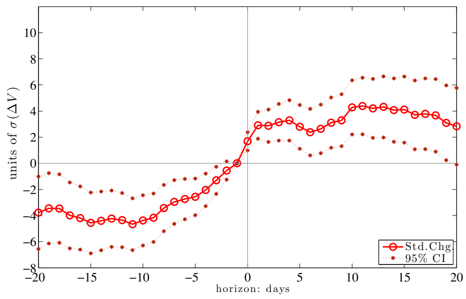
(a) FXRV: 1(*high*) → 2(*low*)



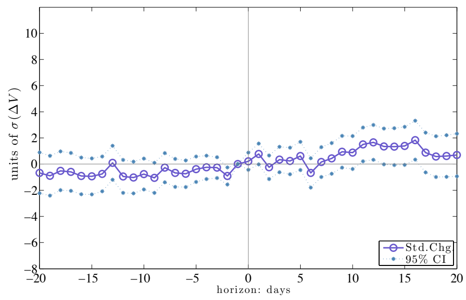
(b) FXRV: 2(*low*) → 1(*high*)



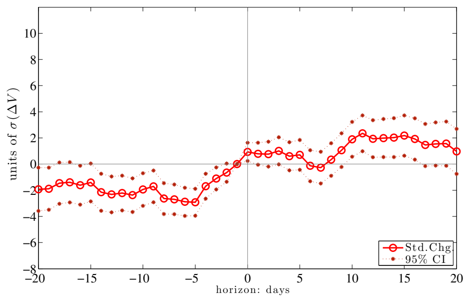
(c) FXIV: 1(*high*) → 2(*low*)



(d) FXIV: 2(*low*) → 1(*high*)



(e) VIX: 1(*high*) → 2(*low*)

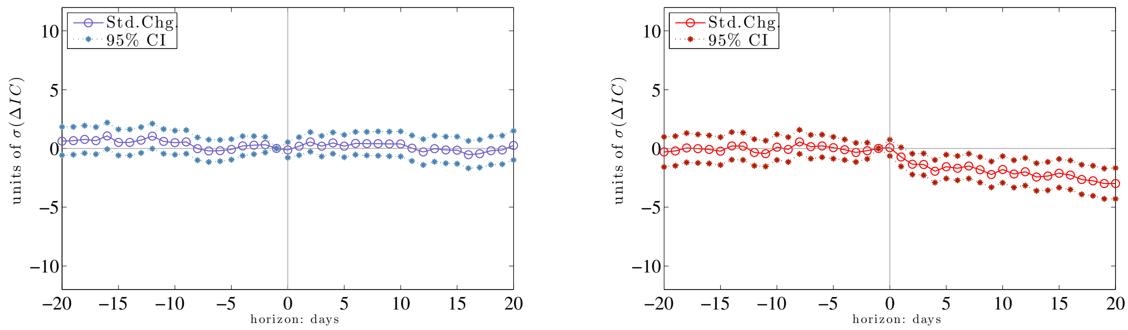


(f) VIX: 2(*low*) → 1(*high*)

Figure 3.4. Volatility dynamics and correlation regime switching. We estimate

$$\frac{V_{t+h} - V_{t-1}}{\sigma_{\Delta V}} = \omega_{11}(h)P_t^{1\to1} + \omega_{12}(h)P_t^{1\to2} + \omega_{21}(h)P_t^{2\to1} + \omega_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,,$$

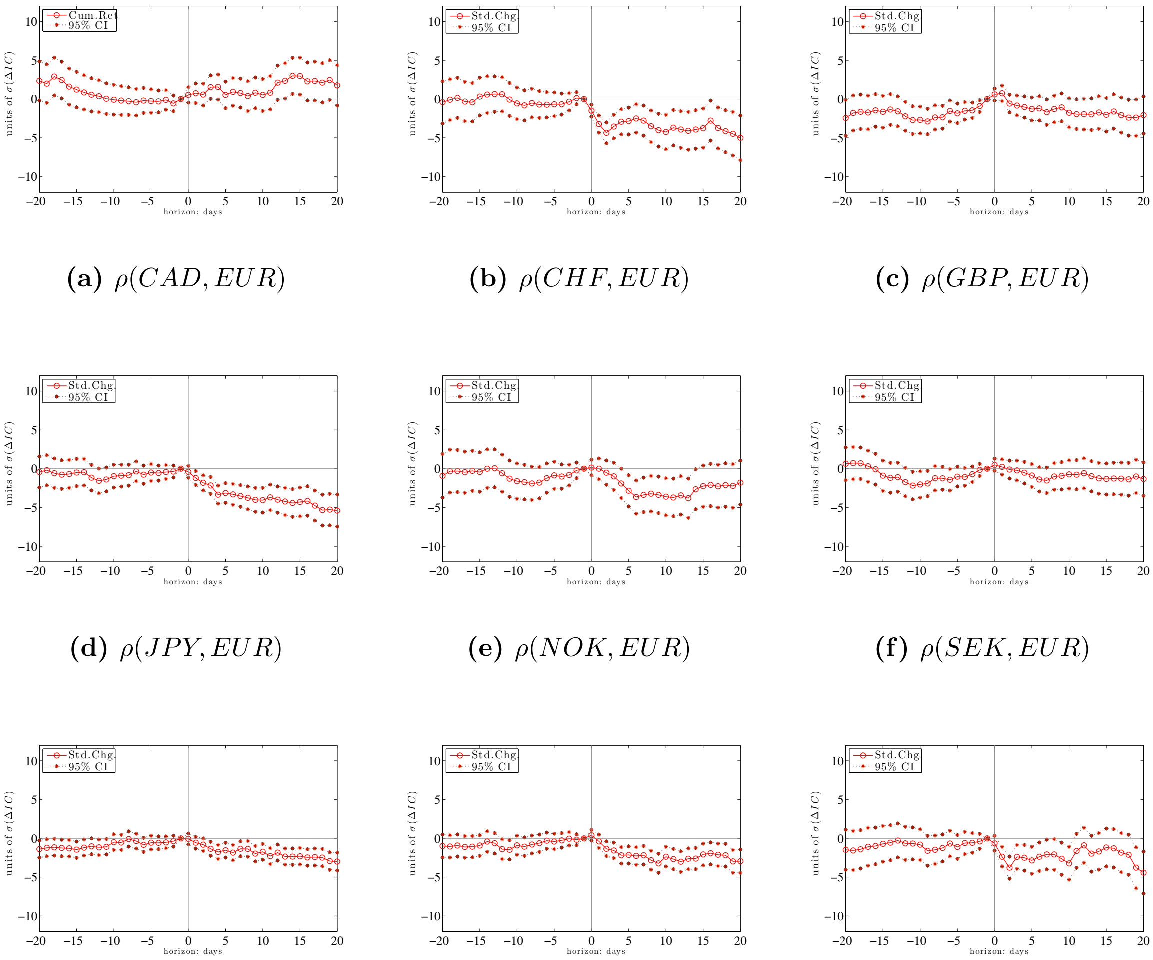
where V_t is volatility level, and $\sigma_{\Delta V}$ is unconditional standard deviation of volatility innovations $\Delta V_t = V_t - V_{t-1}$. The figure plots $\omega_{12}(h)$ and $\omega_{21}(h)$ as functions of h, along with 95% confidence bands.



(a) FXIC: 1(*polarized*) $\rightarrow$ 2(*moderate*)

(b) FXIC: 2(*moderate*) $\rightarrow$ 1(*polarized*)

Figure 3.5. Dynamics of average implied global correlations surrounding the FX correlation regime transitions.

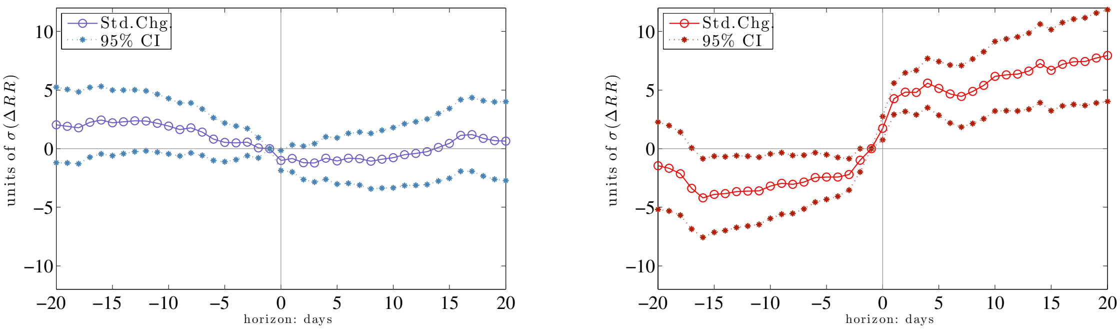


(a) $\rho(CAD, EUR)$ **(b)** $\rho(CHF, EUR)$ **(c)** $\rho(GBP, EUR)$

(d) $\rho(JPY, EUR)$ **(e)** $\rho(NOK, EUR)$ **(f)** $\rho(SEK, EUR)$

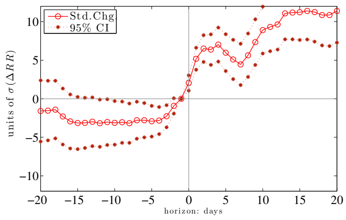
(g) $\rho(AUD, JPY)$ **(h)** $\rho(CHF, JPY)$ **(i)** $\rho(CHF, GBP)$

Figure 3.6. Dynamics of pairwise implied correlations surrounding the risk-off transition. All currencies are quoted against the US dollar.

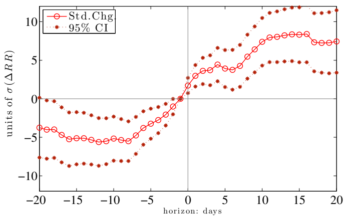


(a) FXRR: $1(polarized) \rightarrow 2(moderate)$ **(b)** FXRR: $2(moderate) \rightarrow 1(polarized)$

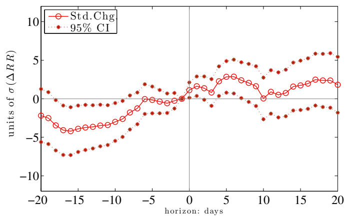
Figure 3.7. Dynamics of risk reversals surrounding FX correlation regime transitions.



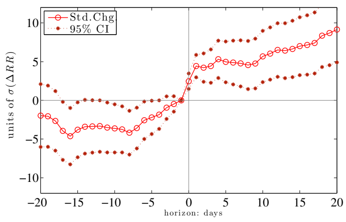
(a) AUD



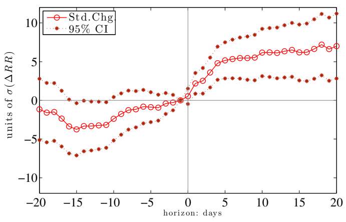
(b) CAD



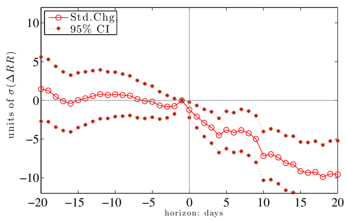
(c) CHF



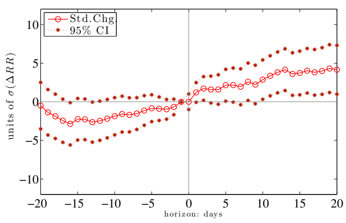
(d) EUR



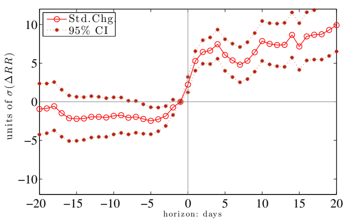
(e) GBP



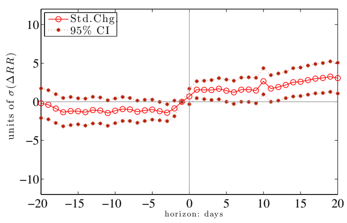
(f) JPY



(g) NOK



(h) NZD



(i) SEK

Figure 3.8. Dynamics of bilateral FX risk reversals (against USD) surrounding the risk-off transition. All currencies are quoted against the US dollar such that an increase of value corresponds to more negatively skewed returns of the quoted currency and more positively skewed returns of the US dollar.

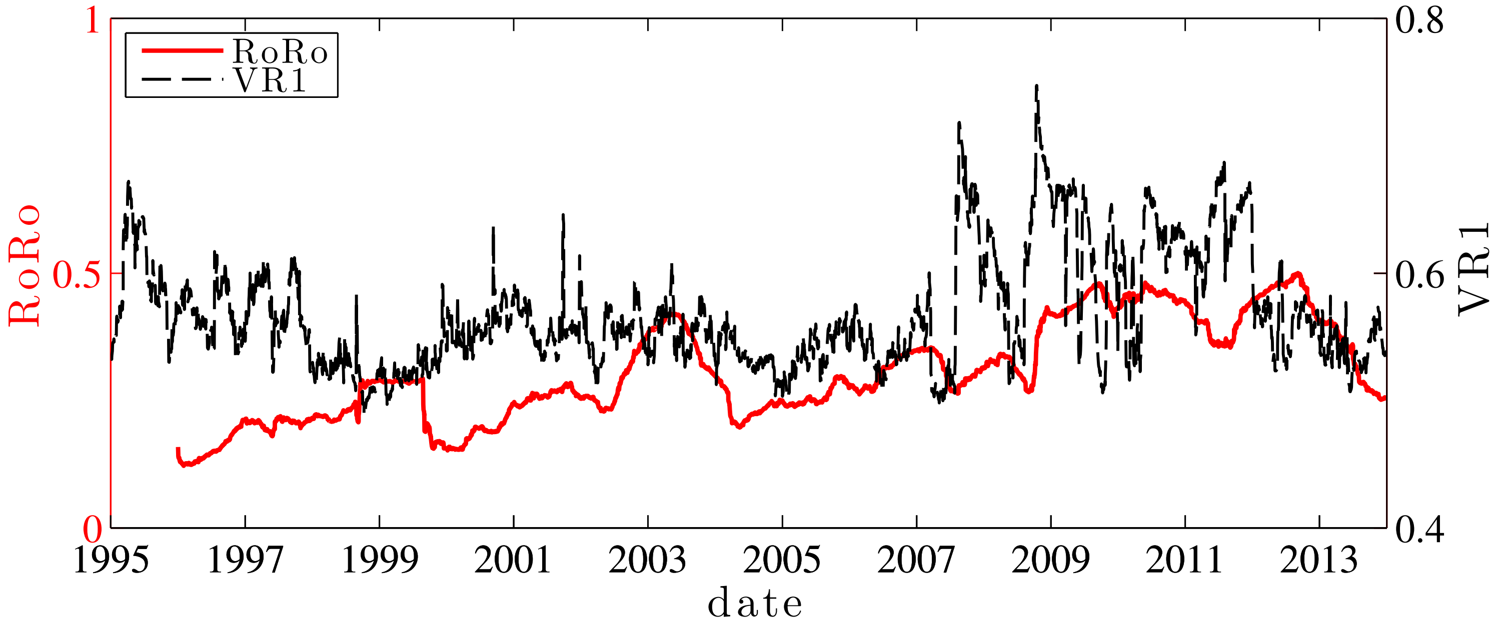
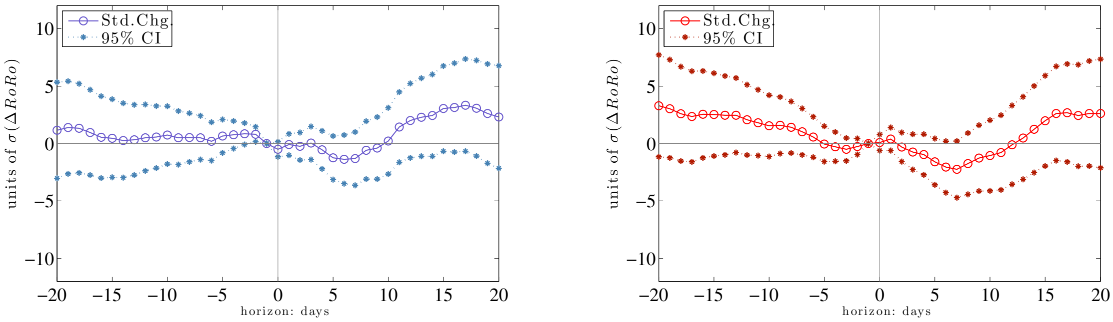


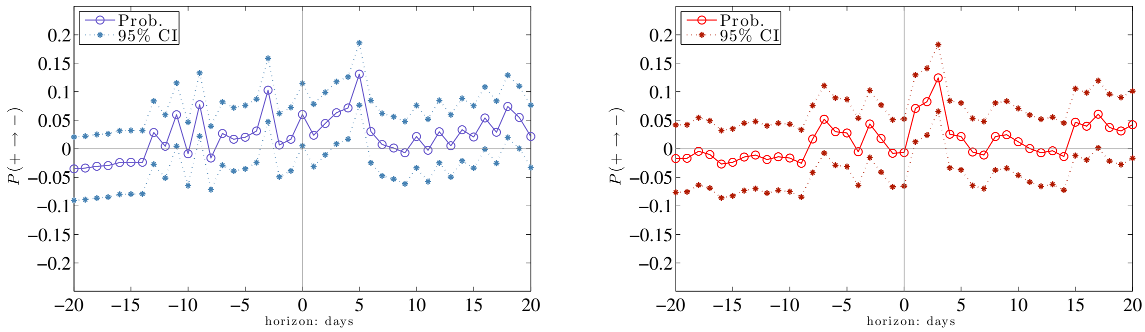
Figure 3.9. Risk on-Risk off (RoRo) index and Variance Ratio of the first PC implied by our RSDC model on G10 FX. We compute the risk-on risk-off RoRo index based on a one-year rolling window using returns of all assets including G10 currencies, emerging-country currencies, international equity market indices, international 10-year government bonds, and commodities.



(a) RoRo: 1(*polarized*) $\rightarrow$ 2(*moderate*)

(b) RoRo: 2(*moderate*) $\rightarrow$ 1(*polarized*)

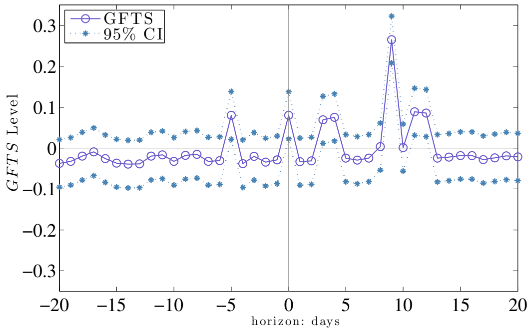
Figure 3.10. Dynamics of the RoRo surrounding the FX correlation regime transitions.



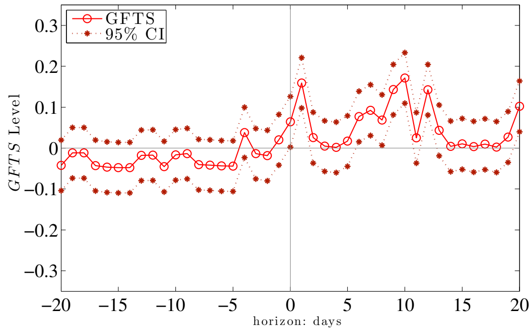
(a) $P^{+\rightarrow -}$: 1(*polarized*) $\rightarrow$ 2(*moderate*)

(b) $P^{+\rightarrow -}$: 2(*moderate*) $\rightarrow$ 1(*polarized*)

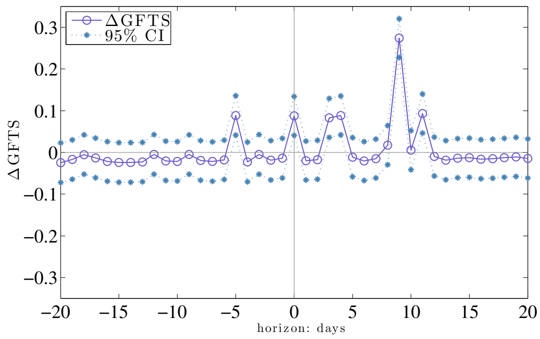
Figure 3.11. Dynamics of equity-bond correlation regime switch surrounding FX correlation regime transitions.



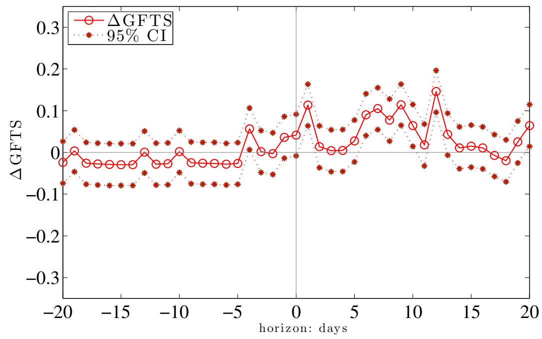
(a) GFTS and high-to-low



(b) GFTS and low-to-high

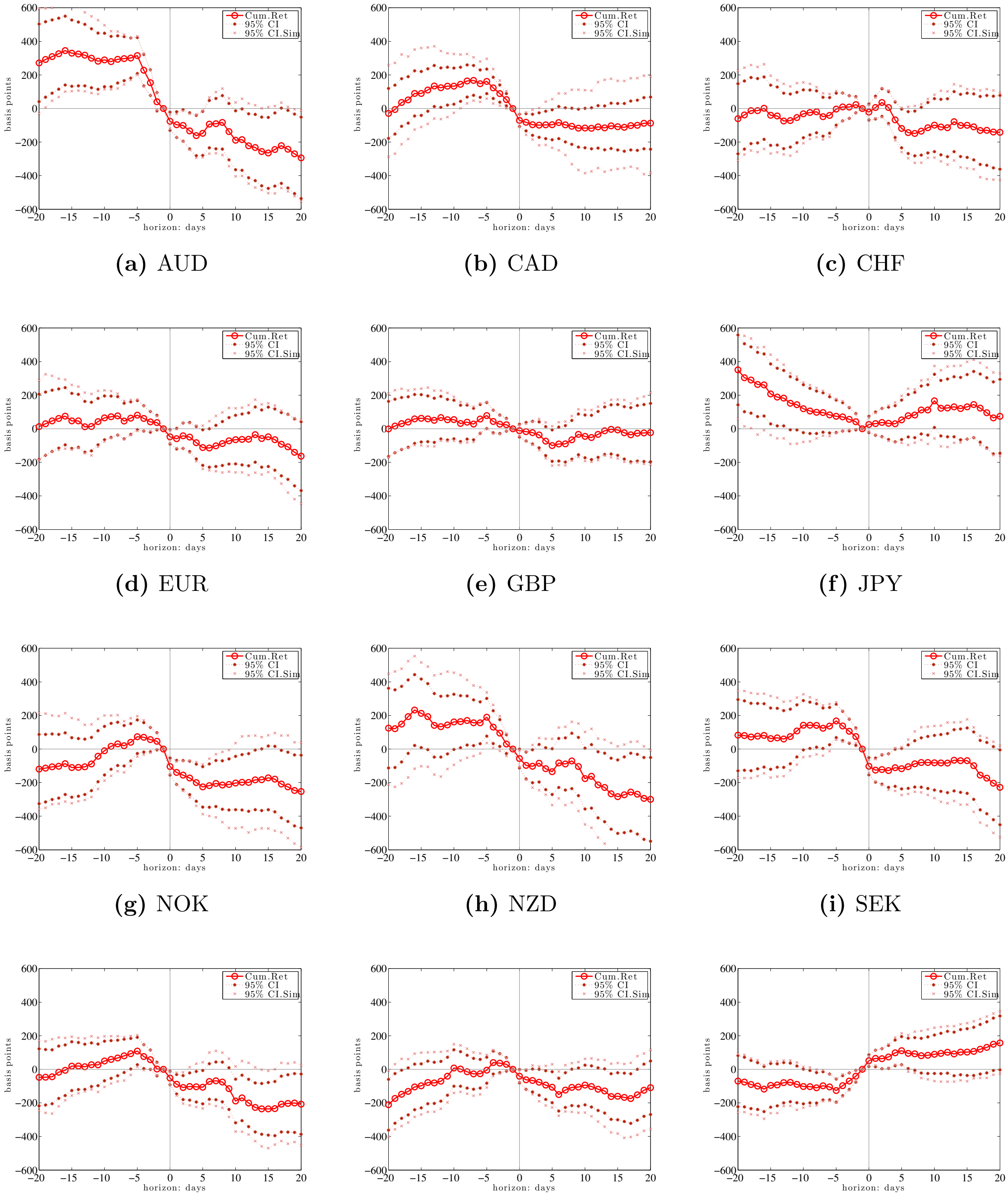


(c) ΔGFTS and high-to-low



(d) ΔGFTS and low-to-high

Figure 3.12. Global flight-to-safety and correlation regime switching. We regress the global flight-to-safety indicator (GFTS) and the global flight-to-safety transition indicator (ΔGFTS) on correlation regime transition probabilities and plot the coefficients associated with the high-to-low (low-to-high) switch as a function of the horizon in the left (right) column. GFTS=1 if more than 2/3 local markets are experiencing local FTS events and 0 otherwise. $\Delta GFTS = \mathbf{I}_{\{GFTS_t=1, GFTS_{t-1}=0\}}$.



(a) AUD **(b)** CAD **(c)** CHF

(d) EUR **(e)** GBP **(f)** JPY

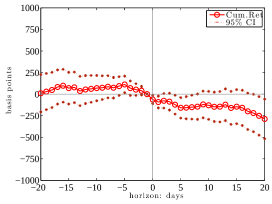
(g) NOK **(h)** NZD **(i)** SEK

(j) CarryHML **(k)** MOM3HML **(l)** Dollar Factor

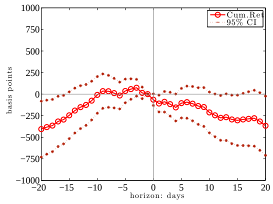
Figure 3.13. Risk-off impact on G10 currencies and currency trading strategies. We estimate

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to1} + \alpha_{12}(h)P_t^{1\to2} + \alpha_{21}(h)P_t^{2\to1} + \alpha_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,,$$

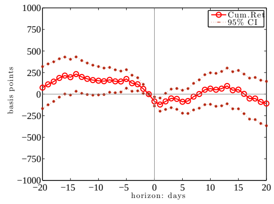
where S_t is the spot exchange rate and the horizon h ranges from -20 to 20 days. The figure plots $\alpha_{21}(h)$ in the unit of basis points as a function of h along with 95% confidence bands based on OLS standard errors and simulation-based standard errors.



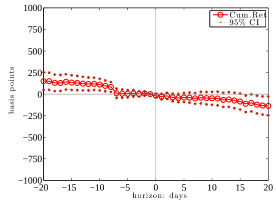
(a) BGN



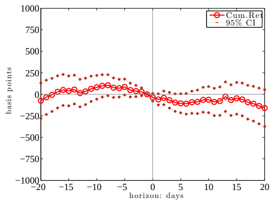
(b) BRL



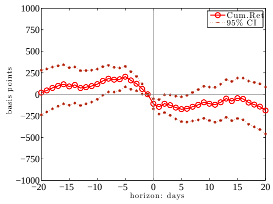
(c) CZK



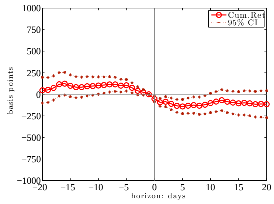
(d) EGP



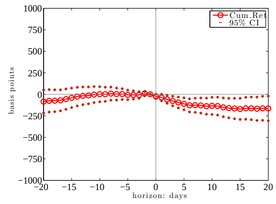
(e) HRK



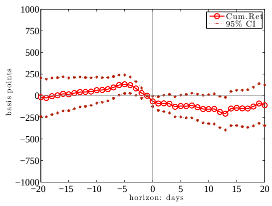
(f) HUF



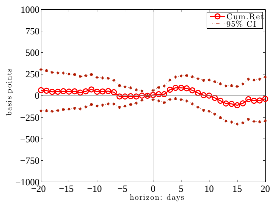
(g) ILS



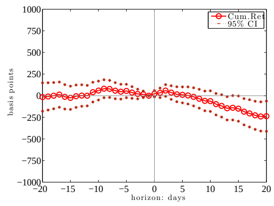
(h) INR



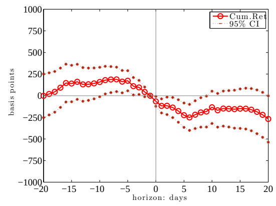
(i) MXN



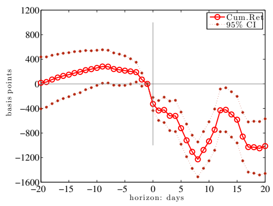
(j) MYR



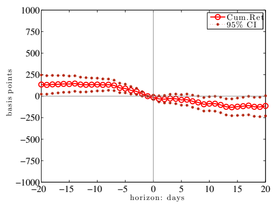
(k) PHP



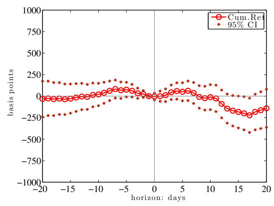
(l) PLN



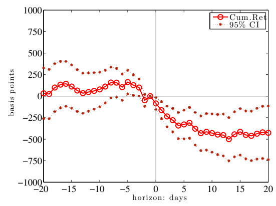
(m) RUB



(n) SGD



(o) THB

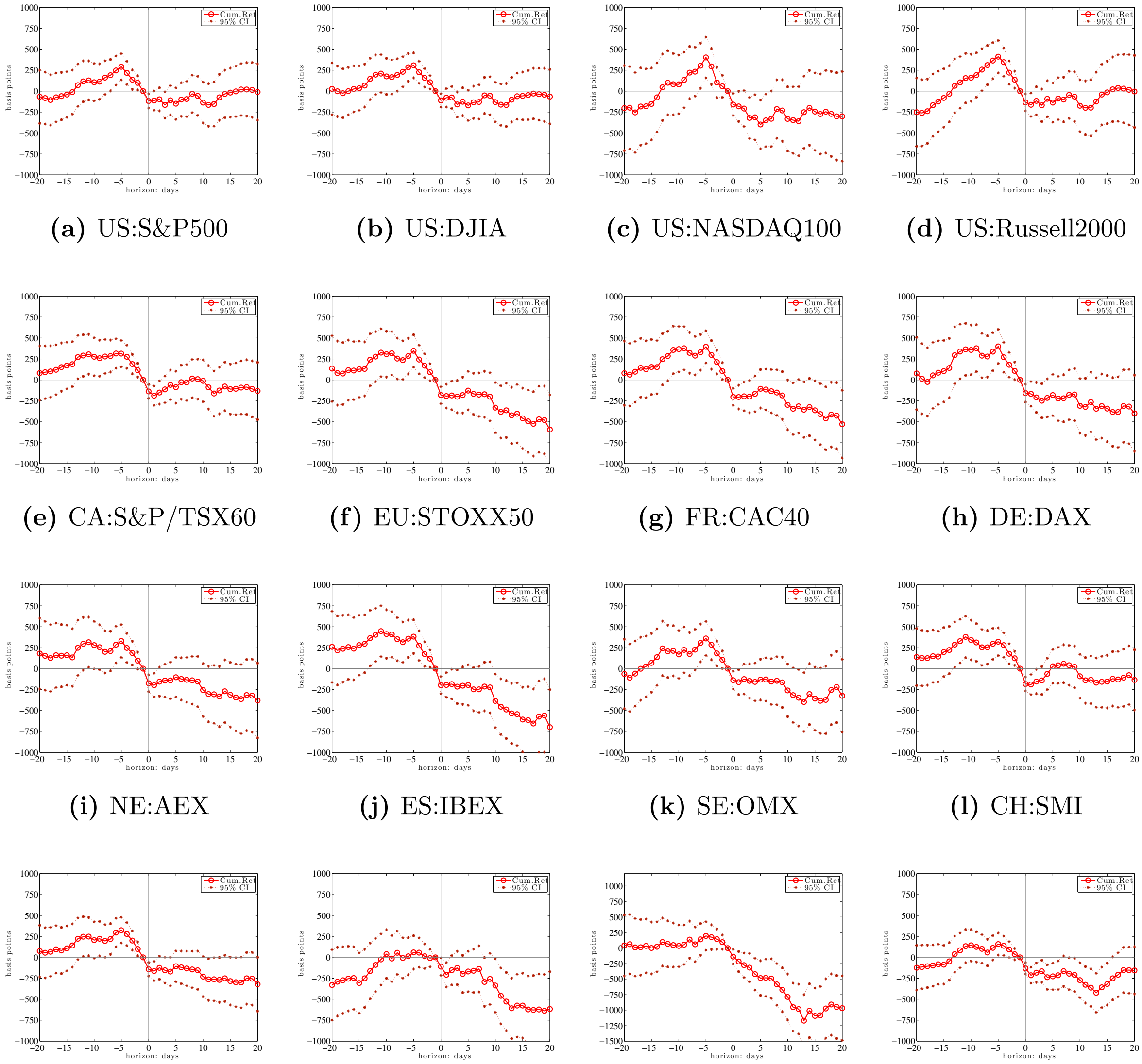


(p) ZAR

Figure 3.14. Risk-off impact on emerging-country currencies. We estimate

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to 1} + \alpha_{12}(h)P_t^{1\to 2} + \alpha_{21}(h)P_t^{2\to 1} + \alpha_{22}(h)P_t^{2\to 2} + \epsilon_{t-1\to t+h}\,,$$

where S_t is the spot exchange rate and the horizon h ranges from -20 to 20 days. The figure plots $\alpha_{21}(h)$ in the unit of basis points as a function of h along with 95% confidence bands.



(a) US:S&P500 **(b)** US:DJIA **(c)** US:NASDAQ100 **(d)** US:Russell2000

(e) CA:S&P/TSX60 **(f)** EU:STOXX50 **(g)** FR:CAC40 **(h)** DE:DAX

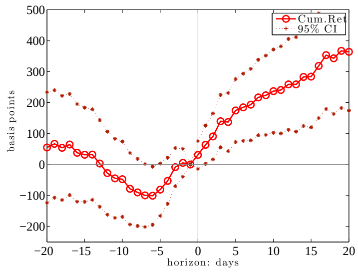
(i) NE:AEX **(j)** ES:IBEX **(k)** SE:OMX **(l)** CH:SMI

(m) UK:FTSE100 **(n)** JP:Nikkei225 **(o)** HK:HSI **(p)** AU:S&P/ASX200

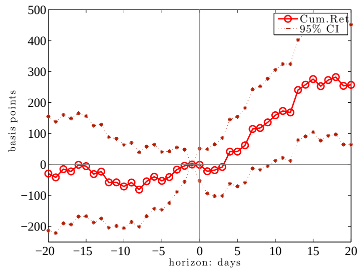
Figure 3.15. Risk-off impact on global equity markets. We estimate

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to1} + \alpha_{12}(h)P_t^{1\to2} + \alpha_{21}(h)P_t^{2\to1} + \alpha_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,,$$

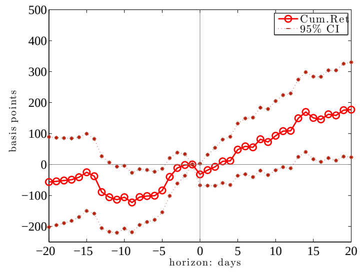
where S_t is the index level and the horizon h ranges from -20 to 20 days. The figure plots $\alpha_{21}(h)$ in the unit of basis points as a function of h along with 95% confidence bands.



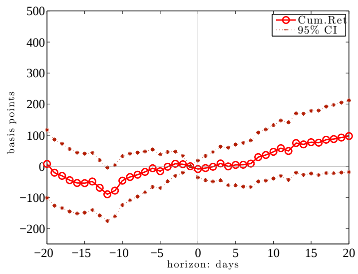
(a) US



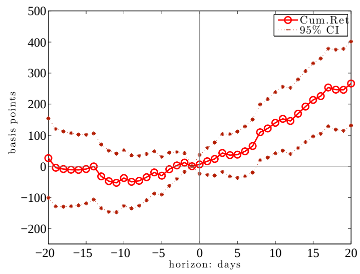
(b) Australia



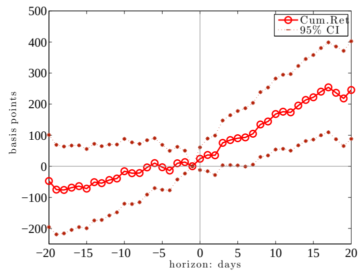
(c) Canada



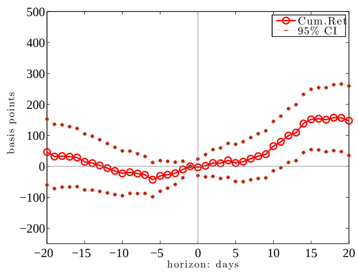
(d) Switzerland



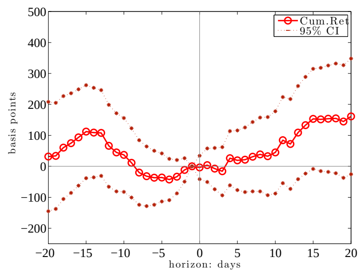
(e) Germany



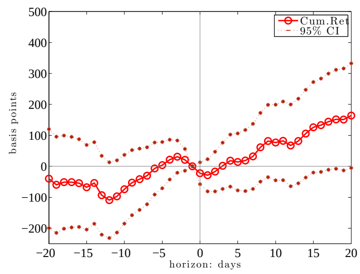
(f) UK



(g) Japan



(h) New Zealand

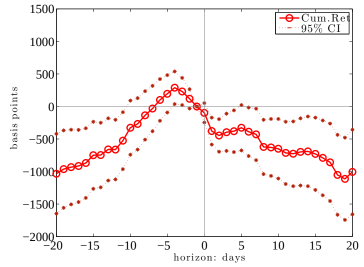


(i) Sweden

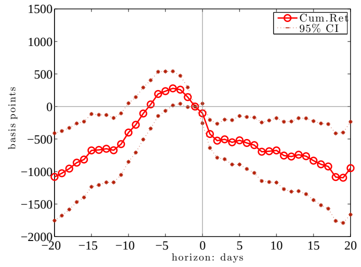
Figure 3.16. Risk-off impact on 10-year government bonds of G10 countries. We estimate

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to1} + \alpha_{12}(h)P_t^{1\to2} + \alpha_{21}(h)P_t^{2\to1} + \alpha_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,,$$

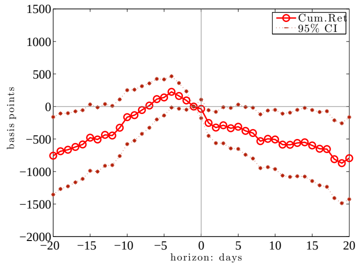
where S_t is the price of 10-year zero coupon bonds and the horizon h ranges from -20 to 20 days. The figure plots $\alpha_{21}(h)$ in the unit of basis points as a function of h along with 95% confidence bands.



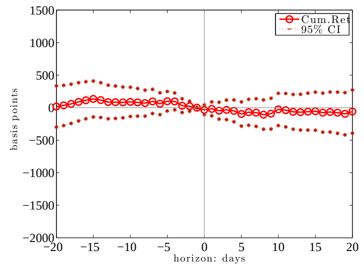
(a) WTI Crude



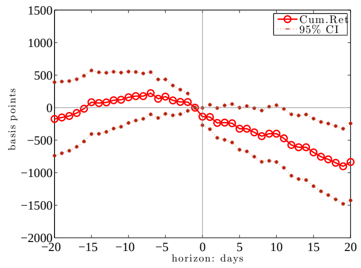
(b) Gasoline



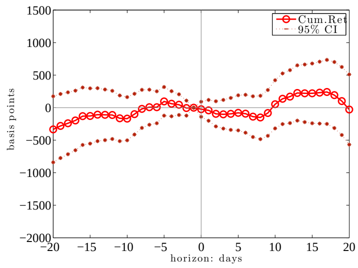
(c) Heating Oil



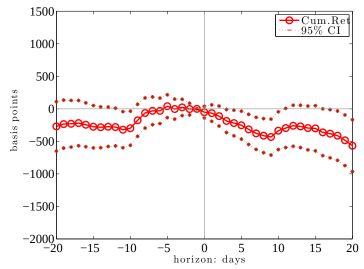
(d) Gold



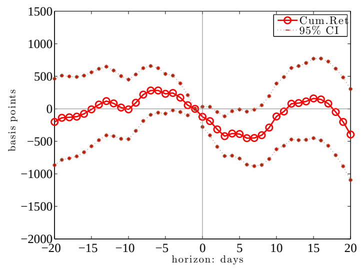
(e) Silver



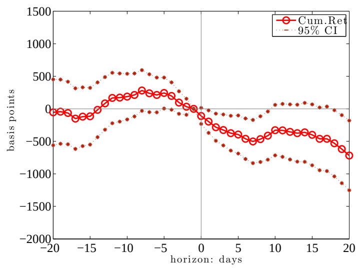
(f) Copper



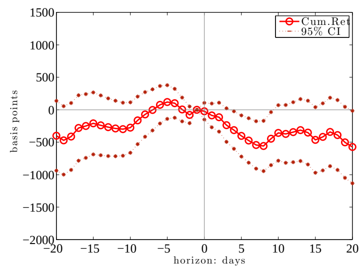
(g) Aluminum



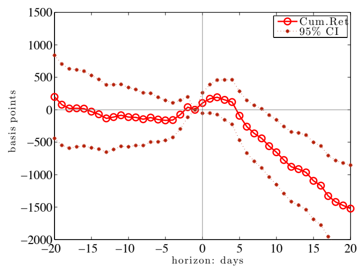
(h) Nickel



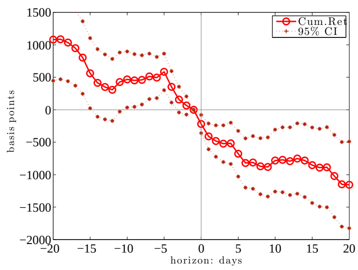
(i) Zinc



(j) Cocca



(k) Coffee

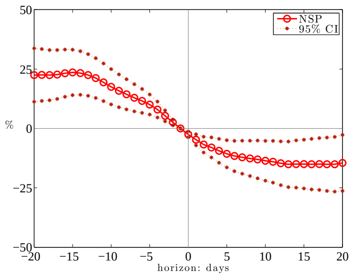


(l) Sugar

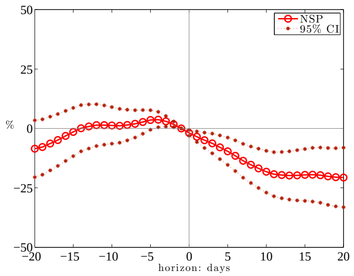
Figure 3.17. Risk-off impact on commodities. We estimate

$$\log S_{t+h} - \log S_{t-1} = \alpha_{11}(h)P_t^{1\to 1} + \alpha_{12}(h)P_t^{1\to 2} + \alpha_{21}(h)P_t^{2\to 1} + \alpha_{22}(h)P_t^{2\to 2} + \epsilon_{t-1\to t+h}\,,$$

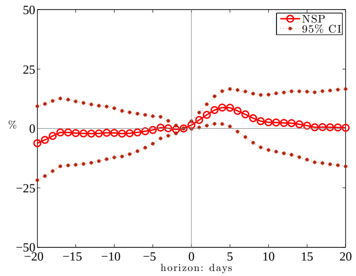
where S_t is the index level and the horizon h ranges from -20 to 20 days. The figure plots $\alpha_{21}(h)$ as a function of h in the unit of basis points along with 95% confidence bands.



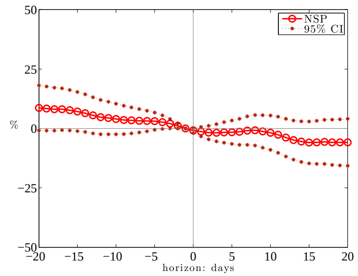
(a) AUD



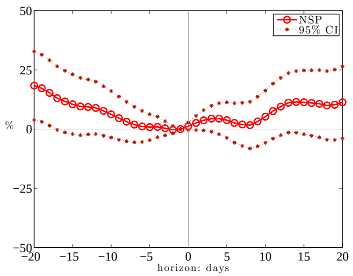
(b) CAD



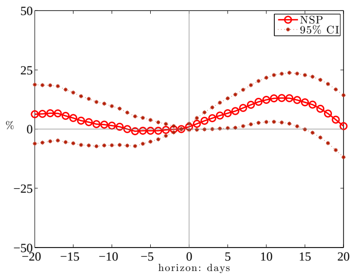
(c) CHF



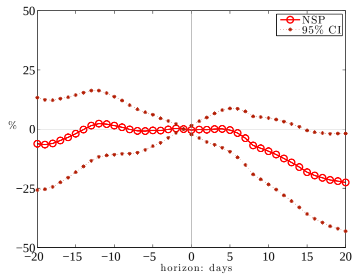
(d) EUR



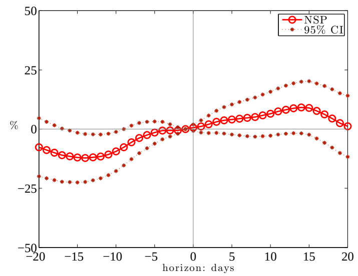
(e) GBP



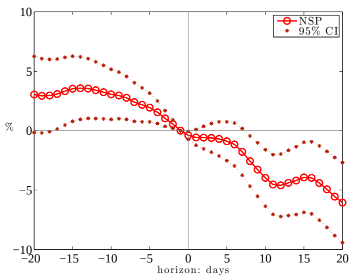
(f) JPY



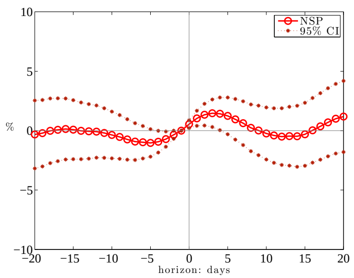
(g) NZD



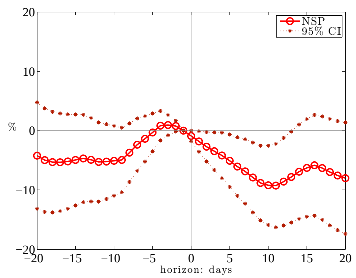
(h) USD



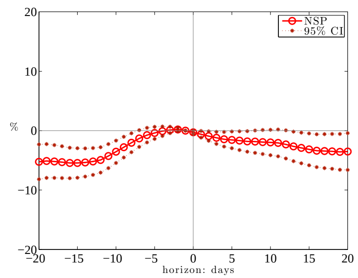
(i) SPX



(j) US 10-year Treasury Note



(k) Gold



(l) Crude Oil

Figure 3.18. Net Speculator Positions (%) around the Risk-off event. we estimate

$$\mathrm{NSP}_{t+h} - \mathrm{NSP}_{t-1} = \psi_{11}(h)P_t^{1\to1} + \psi_{12}(h)P_t^{1\to2} + \psi_{21}(h)P_t^{2\to1} + \psi_{22}(h)P_t^{2\to2} + \epsilon_{t-1\to t+h}\,,$$

where NSP_t is the net speculator position at time t and the horizon h ranges from -20 to 20 days. The figure plots $\psi_{21}(h)$ in the unit of % as a function of h, along with 95% confidence bands.

Chapter 4

Global Risk Premiums in the Cross Section of Present Values

4.1 Introduction

In this paper, we study the time variation of risk premium from a global perspective. We provide supportive evidence for return predictability in international stock markets, bond markets, and currency markets. We build on the present value relationship which describes the fact that the price of an asset reflects not only its expected future cash flows but also the expectation of future discount rates. The implication of this relationship for return predictability is that undervalued stocks are expected to earn higher future returns. However, dividend yield is a noisy return predictor of stock returns due to the presence of expected future cash flows, future real interest rates and possibly multiple components of expected returns that varies at different frequencies.

We propose a novel extension of the present value approach to return forecasting by conjecturing that there is a potentially large common component of expected returns of assets across countries. To see the intuition underlying this assumption, suppose that the marginal investor is a global portfolio manager investing in the international equity markets. The expected returns of equities across countries should be associated with the price of risk demanded by the global investor, which is common to all assets, in equilibrium. Therefore, it may help to better uncover predictable components of asset returns from the whole cross section of dividend yields across countries.

Similarly, bond yields and real exchange rates are noisy return predictors. Combining information of the whole cross section of bond yields (real exchange rates) may improve bond (currency) return predictability.

Our empirical strategy involves three steps. We first estimate local risk premiums for each country each asset class using the asset specific present value measures. We then estimate global risk premiums for each asset class as combinations of lobal risk premiums. The last step is to predict asset returns using the estimated globel risk premiums.

Our empirical results show economically and statistically significant predictive power of global risk premiums for international asset returns. This return predictability implied by global risk premiums appears substantially stronger than implied by traditional present value based predictors, and local risk premiums which are estimated by removing noisy component in present values, such as trend inflation, trend economic growth, real interest rates.

Our estimated global risk premiums are intimately associated with past and future economic prospects. Higher global risk premiums tend to be accompanied with lower than average economic prospects while higher past and future economic prospects.

Noting that currency excess return consists of the predetermined interest rate differential and the realized foreign currency appreciation, we also find global risk premiums imply strong and consistent exchange rate predictability with more than doubled R-squared relative to standard exchange rate predictors, such as real exchange rates and interest rate differentials.

Related Literature

Return predictability is a classic topic in asset pricing and the literature has grown voluminous, with the present value approach as a starting point (e.g., Campbell and Shiller (1988), Fama and French (1988), Fama (1984b, 1986), Hansen and Hodrick (1980b)).

The empirical success of the present value approach to forecasting returns, however, is rather limited because present value based predictors tend to lose power when we examine multiple asset classes[1], choose more robust standard errors (e.g., Hansen and Hodrick (1980b) and Wei and Wright (2013)), and turn to international asset returns (e.g., Ang and Bekaert (2007))[2].

Our empirical strategy of combining the cross section of present value based predictors is in the similar spirit to the idea in Cochrane and Piazzesi (2005, 2008) who propose a single factor (the CP factor), which is a combination of forward interest rates, to forecast one-year US government bond returns[3]. Our paper, on the other hand, aim to find global risk premiums as combinations of present value based predictors across countries.

The idea of extracting predictive information from the cross-section of asset present values is also explored in an innovative way in Kelly and Pruitt (2013). They estimate the expect market return using the cross section of US stocks, applying the three-pass regression filter detailed in Kelly and Pruitt (2015). The goal of our paper, however, is to find global risk premiums to predict all individual asset returns (in each country each asset class).

Our paper is also related to the large body of literature on exchange rate predictability, with the seminal papers by Meese and Rogoff (1983) who establish the puzzle that exchange rates seem to be disconnected with macroeconomic fundamentals, and by Fama

[1]Koijen, Moskowitz, Pedersen, and Vrugt (2013b) provides supporting evidence for (asset-specific) carry to forecast international returns in all asset classes in a panel regression and portfolio based framework. Our paper, however, aims to study return predictability in a traditional time-series framework using a novel extension of the present value approach.

[2]Cochrane (2007) critically re-examines the literature and provides economics-based evidence in support of stock return predictability.

[3]Dahlquist and Hasseltoft (2013) extend the Cochrane-Piazzesi results to international bond returns.

(1984b) as an early attempt to document and explain the forward premium puzzle [4]. In spite of continuing efforts in predicting exchange rates, the empirical success is also limited given that empirical evidence typically depends on many empirical choices, such as the sample period, the inference method, the data, the panel of currencies (See Rossi (2013) for a detailed survey.)[5] Our paper shows that global risk premiums, in particular, the global currency risk premium, help to predict future exchange rates.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 we explains our methodology of estimating the global risk premiums. We present our empirical results in Section 4, where we first carry out some preliminary analyses of the properties of global risk premiums and proceed to show results for the predict power of global risk premiums, their dynamic relationship with economic prospects, and their implication for exchange rate predictability. Section 5 concludes.

4.2 Data

Our sample period spans from January, 1970 to March, 2014. We collect all our data at the monthly frequency and we aim to predict the one-year excess return of stocks, bonds, and currencies. We focus on a panel of G10 countries, including Australia, Canada, Switzerland, Denmark, Germany, the United Kingdom, Japan, Norway, Sweden, and the United States. In order to build the longest time-series for the G10-panel in all three asset classes, we use Global Financial Data as our primary data source.

More specifically, our dataset for asset returns includes for each country in our G10-panel, a country-specific stock market total return index, a 10-year government bond total return index, a Treasury-bill total return index, all denominated in the corresponding local currency. Besides, the dataset also includes spot exchange rates of G10 countries, with the US dollar as the base currency.

[4]For extensive surveys of the literature, see Engel, Mark, and West (2007), and Lewis (1995).

[5]More recently, Verdelhan (2015) finds substantial systematic variation in bilateral exchange rates in the dollar risk factor.

To construct present value based predictors, we obtain data on the dividend yield, 10-year long term government bond yield, the short-term (Treasury bill) yield, also from Global Financial Data.

In addition to data on asset returns and present values, we collect data on macroeconomic variables, including the consumer price indices (CPI), and the industrial production indices (IP) of G10 countries, again from Global Financial Data. These variables are used to construct trends in inflation and economic growth. The sample for these macroeconomic variables runs from January, 1950 to March, 2014.

Finally, in order to study the relationship between global risk premiums and economic prospects, we obtain the aggregate leading economic indicators from OECD via Datastream.

4.3 Methodology

Our methodology builds on the present value relationship which describes the fact that the price of an asset reflects not only its expected future cash flows but also the expectation of future discount rates. This macro-finance nexus can be illustrated by the following variant of the Campbell-Shiller (1988) approximate present value identity,

$$dp_t = -\mathbf{E}_t \sum_{j=1}^{\infty} \kappa^{j-1} \Delta d_{t+j} + \mathbf{E}_t \sum_{j=1}^{\infty} \kappa^{j-1} r_{t+j-1} + \mathbf{E}_t \sum_{j=1}^{\infty} \kappa^{j-1} rx^M_{t+j}\,, \tag{4.1}$$

where dp_t is the dividend yield, Δd_t the growth rate of aggregate dividends, r_t the real interest rate, and rx_t^M the excess return of the stock market. All variables are expressed in logarithm and κ is the discount rate resulting from the log-linearization of the present value formula. The intuition underlying this present value identity is that variations in the dividend yield are due to either time-varying future dividend growth or time-varying risk premiums, or both. The implication for return predictability is that undervalued stocks are expected to earn higher future returns. However, dividend yield is a noisy return predictor due to the presence of cash flow, real interest rates and possibly multiple components of expected returns that varies at different frequencies.

We make the novel point that there is a potentially large common component of future discount rates pricing assets across countries. To see the intuition underlying this assumption, suppose that the marginal investor is a global portfolio manager investing in the international equity markets. The expected returns of equities across countries should be associated with the price of risk demanded by the global investor, which is common to all assets, in equilibrium. Therefore, it may help to better uncover predictable components of asset returns from the whole cross section of dividend yields across countries.

Similarly, we can obtain present value identities for bonds and currencies as follows

$$y_t^{(n)} = \frac{1}{n}\mathbf{E}_t \sum_{j=1}^{n} \pi_{t+j} + \frac{1}{n}\mathbf{E}_t \sum_{j=1}^{n} r_{t+j-1} + \frac{1}{n}\mathbf{E}_t \sum_{j=1}^{n-1} rx_{t+j}^{(n-j+1)}, \tag{4.2}$$

$$-q_t = -\mathbf{E}_t \sum_{j=1}^{\infty} r_{t+j-1}^{*} + \mathbf{E}_t \sum_{j=1}^{\infty} r_{t+j-1} + \mathbf{E}_t \sum_{j=1}^{\infty} rx_{t+j}^{FX}, \tag{4.3}$$

where $y_t^{(n)}$ is the long-term (n-year) bond yield, π_t is the year-on-year inflation, r_t is the domestic (US) real short-term interest rate, r_t^* is the foreign real short-term interest rate, q_t is the real exchange rate, rx_{t+1} is the excess return from t to $t+1$.

The implication for return predictability is also similar to that of the international stock markets: undervalued bonds (currencies), with higher yields (log inverse real exchange rate), tend to earn higher future returns. However, bond yields and real exchange rates are noisy return predictors. Combining information of the whole cross section of bond yields (real exchange rates) may improve bond (currency) return predictability.

Our empirical strategy involves three steps. For comparison and pedagogical purposes, we do not pursue the estimation of global risk premiums directly from present value predictors. Instead, we first estimate local risk premiums for each country each asset class using the asset specific present value measures. In detail, we follow the procedure:

- We take the residual ρ_t from the following regression as an estimate of the real interest rates

$$y_t^{(tbill)} = \eta\tau_t + \rho_t\,, \tag{4.4}$$

where $\tau_t = \frac{\sum_{j=0}^{\infty}\phi^j\pi_{t-j}}{\sum_{j=0}^{\infty}\phi^j}$, and $\phi = 0.98$. This operation is similar to Cieslak and Povala (2015).

- We estimate local bond risk premium $\widehat{RP}_t^B$ as the residual of the regression of the 10-year bond yield on the trend inflation τ_t, and the real interest rate ρ_t.

- We estimate local equity risk premium $\widehat{RP}_t^M$ as the residual of the regression of the log dividend yield on the real interest rate ρ_t, and the trend growth rate $x_t = \frac{\sum_{j=0}^{\infty}\phi^j g_{t-j}}{\sum_{j=0}^{\infty}\phi^j}$, where $\phi = 0.98$, and g_t, the year-on-year change of log industrial production.

- We estimate local currency risk premium $\widehat{RP}_t^{FX}$ as the residual of the regression of the log inverse real exchange rate on foreign and domestic real interest rates (ρ_t^* and ρ_t^{US}).

The second step is then to estimate global risk premiums for each asset class. For simplicity, we pursue a straightforward procedure, and aim to find a combination of local risk premiums that best forecast the asset return averaged across countries. To be specific, we estimate the following multivariate regression

$$\frac{1}{N}\sum_{i=1}^{N} rx_{i,\,t+12} = \alpha + \sum_{i=1}^{N}\lambda_i\,\widehat{RP}_{i,\,t} + \varepsilon_{t+12}\,, \tag{4.5}$$

for international stocks, bonds, and currencies. In the above equation $rx_{i,t+12}$ is the one-year (12-month) excess return for the stock, bond, or the currency, respectively for each country i. $\widehat{RP}_{i,t}$ denotes the "local" risk premium for country i in a given asset class.

We take the fitted values of the above regressions (equation (4.5)) as our estimates of global risk premiums. Note that it is not necessary to use equally-weighted average return as the left-hand side variable in the above regressions. One can use alternatives such as a value-weighted average, GDP-weighted average, or the first principle component. The choice of average return denominated in respective local currencies is not necessary for forecasting, but it is important for our purpose because we want to isolate the contribution from currency movements.

The final step is to predict the return of each asset using global risk premiums, which we show in detail in the next section.

4.4 Empirical Results

4.4.1 Preliminaries

In this section, we provide a preliminary description of the properties of the estimated global risk premium factors in the three asset classes, namely the international stocks, bonds, and currencies. We begin with presenting the estimates of the regression equation (4.5) in Table 4.2. The regression is estimated separately for each asset class using "local" market-specific risk premiums of all G10 countries and the fitted value of the regression is taken as the estimated global risk premium. It turns out that the loadings of global risk premiums on "local" risk premiums vary substantially across countries. For example, while the "local" bond risk premium in the United States contributes to the global bond risk premium significantly positively with the weight being 2.97, the "local" bond risk premium in Canada has significantly negative contribution to the global bond risk premium.

The heterogeneous loadings across countries cannot be interpreted as an indication of the riskiness of each country. Instead, it should be noted that like the standard present value based predictors, the estimated "local" risk premiums are still noisy proxies for expected returns. Regression equation (4.5) aims to find the combination of noisy "local" risk premiums that has the highest explanatory power for the average return across countries.

We now look at the time-series of global risk premiums. Figure 4.1 plots the time-series of the global equity risk premium, the global bond risk premium, and the global currency risk premium, all estimated as a combination of the "local" risk premiums of all countries, according to equation (4.5).

To have preliminary understanding of the relationship between global risk premiums and the business cycles, we also indicate the NBER recession periods by grey shades. We notice that the global risk premium factors in all three asset classes tend to be higher in recessions, most notably for example the most recent Great Recession following the 2008-2009 Financial Crisis, consistent with the intuition that investors demand larger compensation for risk and therefore expect to earn higher returns in bad times such as economic downturns.

Taking a closer look at the dynamics of global risk premium factors, we find that global risk premiums display different variations through time. For example, although global risk premiums in all three asset classes tend to move upward during the 2008-2009 Financial Crisis, the timing and dynamics seems different, suggesting multiple components in investors' required returns.

The above observations are further analyzed by computing the serial correlations of global risk premiums as shown in Figure 4.2, where sample autocorrelations are plotted as a function of the horizon h. To compare the time-series property of global risk premiums with standard present value based predictors, we show the autocorrelation functions of the former in Panel (b) of Figure 4.2 and the latter in Panel (a) of Figure 4.2. It appears that among the three global risk premiums, the global bond risk premium varies at the highest frequency with the half life of about 6 months, slightly shorter than that of the global equity risk premium. However, the global currency risk premium seems to vary at the lowest frequency with the half life of about 12 months, roughly the same as that of the average real interest rate of G10 countries.

By contrast, the frequency at which standard present value based return predictors seem to be generally lower than the global risk premiums in all three asset classes, with the half life ranging from the shortest for the term spread (12 months) to the longest for the log dividend yield (more than 4 years). Hence, global risk premiums capture generally higher-frequency components of expected returns in all asset classes.

4.4.2 Return predictability based on global risk premiums

This section presents our empirical results on the predictive power of global risk premiums for asset returns in international stocks, bonds, and currencies. We first perform univariate analysis of return predictability, comparing the predictive power of standard present value based predictors, "local" risk premiums, and global risk premiums. Then we proceed with multivariate analysis on the cross-market predictability, investigating whether asset returns in a given asset classes can be predicted by global risk premiums in other asset classes beyond the predict power of the global risk premium specific to the given asset class.

Univariate Analysis

We employ a univariate predictive regression specification to forecast one-year asset returns. Specifically, we regress the log one-year excess return for a given asset on the corresponding standard present value based predictor, the "local" risk premium specific to the given asset, and the global risk premium in the given asset class:

$$rx_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12} \, , \tag{4.6}$$

where rx_{t+12} is log excess return of international stocks, bonds, or currencies, and x_t is the predictor, including the standard present value based predictors, the asset-specific "local" risk premium $\widehat{RP}_t$, and the global risk premium $\widehat{GRP}_t$ corresponding to the asset class in consideration.

First, we look at international stock returns. In this case, the left-hand side variable in equation (4.6) is the one-year log excess return of a given country, and the right-hand side variable is the log dividend yield, the "local" equity risk premium specific to the given country, and the global equity risk premium, respectively. Figure 4.3 plots the R-squared of the regression for each predictor and each asset in Panel (a) and the corresponding t-statistic for the estimate of the coefficient β based on the reverse regression approach (See Wei and Wright (2013)) in Panel (b).

The results reveal strong evidence for return predictability using the global equity risk premium. First of all, the predictable variation in international stock returns, as implied by the global equity risk premium, ranges from about 10% to more than 30%, in stark contrast to the standard predictor, the log dividend yield, which implied nearly zero predictable variation in stock returns in all countries except for the United Kingdom.

Second, the predictive power of the global equity risk premium for international stock returns is statistically significant for all countries, except that the t-statistic for Norway lies on the borderline of the 5% level of significance.

Finally, we find that the estimated "local" equity risk premiums achieve basically no improvement in predictive power either in terms of the R-squared or the robust t-ratios. This finding suggests that the "local" equity risk premiums, estimated by isolating out components in present values unrelated to discount rates, are still noisy proxies for expected returns.

We now turn to the evidence in international bond markets, shown in Figure 4.4. The pattern is generally consistent with our findings in international stock markets. The global bond risk premium raises substantially the predictable portion of bond returns in all countries, with the R-squared ranging from 12% for Sweden to nearly 50% for Canada. In addition, the predictive power of the global bond risk premium is statistically significant for all countries, given that the t-statistics are far above the level of 5% significance.

An observation from international bond markets at odds with findings in the international stock markets is that "local" bond risk premiums do have higher predictive power than standard predictors such as the term spread. However, we note that "local" risk premiums have remarkably different implications for bond return predictability in the case of different countries. For instance, although "local" bond risk premiums significantly predict bond returns in the United States, Australia, Canada, Norway, and Sweden, they do not have significant predictive power in Switzerland, Denmark, Germany, the United Kingdom, and Japan.

Last, Figure 4.5 provides evidence supporting the strong predictive power of the global currency risk premium for currency excess returns. The predictable variation in currency excess returns implied by the global currency risk premium is at the level of about 20% while the predictable variation implied by the real exchange rate or "local" currency risk premiums is only about 10%. Similarly, the global currency risk premium suggests that currency excess returns are significantly predictable whereas the real exchange rate and "local" currency risk premiums only achieve borderline significance.

Multivariate Analysis

We have shown that global risk premium in a given asset classes can significantly predict returns in the given asset classes in all countries. We now further investigate whether the global risk premiums have any cross-market predictive power. Specifically, we perform a multivariate analysis and forecast one-year log excess returns in a given asset class by global risk premiums in all three asset classes:

$$rx_{t+12} = \alpha + \sum_{k \in \{M,B,FX\}} \beta_k \widehat{GRP}_t^k + \varepsilon_{t+12}\,,$$

where $rx_{i,t+12}$ is the one-year (12-month) excess return for the stock, bond, or the currency, respectively for each country. $\widehat{GRP}_t^k$ denotes the global risk premium for stocks ($k = M$), bonds ($k = B$) and for currencies ($k = FX$). The results are presented in Table 4.3, where Panel A, B and C show results for international stock markets, international bond markets, and currency markets, respectively. Each panel reports point estimates, adjusted R-squared, and the increase of R-square relative to the univariate case.

We find that global bond risk premium helps to predict international stock returns to some extent. The cross-market evidence is significant for the United States, Switzerland, and the United Kingdom. It implies that stock returns are expected to be higher when either global equity risk premium is higher or global bond risk premium is higher, or both. Adjusted R-squared increases by 6%-8% relative to the univariate case.

However, the global equity risk premium has weaker predictive power for international bond returns. Global equity risk premium can only significantly predict stock returns in Switzerland and the United Kingdom with weaker significance.

In contrast, neither global equity risk premium nor global bond risk premium significantly predict excess returns of any currency.

4.4.3 Global risk premiums and economic prospects

We have derived global risk premiums from the cross section of present values and shown their significant predictive power for international asset returns. We have also explored briefly the cyclical properties of global risk premiums. To further understand the economic content of global risk premiums, in this section, we examine the dynamic relationship between global risk premiums and economic prospects. Specifically, we estimate

$$\frac{LEI_{t+L}}{\sigma(LEI)} = \omega_0 + \omega_1(h)\,\frac{GRP_t}{\sigma(GRP)} + \varepsilon_{t+L}\,,$$

where LEI is the OECD leading economic indictor led by $L > 0$ or lagged by $L < 0$, and GRP denotes the global risk premium for the stock, bond, and currency markets, respectively. The dependent variable and the independent variables are standardized by the corresponding unconditional standard deviations $\sigma(LEI)$, and $\sigma(GRP)$.

Figure 4.6 plots the estimate of the coefficient $\omega_1(h)$ as a function of the lead $L > 0$ or the lag $L < 0$ for the global equity risk premium in Panel (a), the global bond risk premium in Panel (b), and the global currency risk premium in Panel (c). We find that higher global risk premiums tend to be associated with lower economic prospects, although this evidence is only statistically significant for global equity risk premium, at borderline significance for global bond risk premium, and statistically insignificant for global currency risk premium.

We also find strong evidence that lower global risk premiums tend to be followed by brighter future economic prospects in one- to three-year horizons. Moreover, lower global equity and bond risk premiums tend to be associated with higher previous economic prospects.

4.4.4 Global risk premiums and exchange rate predictability

We have documented the strong predictive power of our estimated global currency risk premium for currency excess returns. Because currency excess returns can be decomposed into a realized exchange rate return (foreign currency appreciation) component and a pre-determined interest rate differential component, it seems an intriguing question to investigate whether the currency return predictability revealed by global currency risk premium implies stronger exchange rate predictability, relative to traditional exchange rate predictors, such as the interest rate differential and the real exchange rate. This section devotes to answering this question.

We start with a univariate regression specification which forecast one-year exchange rate changes using global currency risk premium, and in comparison, traditional exchange rate predictors (e.g., interest rate differentials, and real exchange rates). More specifically, we estimate

$$\Delta s_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12} \,,$$

where ds_{t+12} is the one-year (12-month) exchange rate return. X_t denotes the exchange rate predictor, namely, the interest rate differential $y_t^{tbill,*} - y_t^{tbill,US}$, the real exchange rate q_t, and the global currency risk premium factor $\widehat{GRP}_t^{FX}$. For each predictor, the first column reports the point estimates of the regression coefficient β, and the second column reports the R-squared.

Consistent with the literature, interest rate differentials have very weak predictive power for future exchange rates. The regression coefficients are generally insignificant and have alternating signs, and the R-squared tends to be near zero for all currencies except for the Japanese yen.

Real exchange rates, on the other hand, predict future exchange rates with statistically significant coefficient. Furthermore, the regression coefficients are consistently positive and the magnitude are generally homogeneous across countries. The finding of exchange rate predictability by real exchange rates is consistent with the intuition of the mean-reverting property of currency values which states that undervalued currencies tend to appreciate.

By contrast, we find that global currency risk premium predicts future exchange rates with statistically significantly positive coefficients and substantially larger R-squared, relative to interest rate differentials and real exchange rates. The finding suggests that higher global currency risk premium leads to currency appreciation.

We proceed with multivariate analyses to investigate whether the global equity risk premium and the global bond risk premium can help predict exchange rates beyond the predictive power of the global currency risk premium. More specifically, we estimate

$$\Delta s_{t+12} = \alpha + \sum_{k \in \{M,B,FX\}} \beta_k \widehat{GRP}_t^k + \varepsilon_{t+12} \,, \tag{4.7}$$

where ds_{t+12} is the one-year (12-month) exchange rate return. $\widehat{GRP}_t^k$ denotes the global risk premium for stocks ($k = M$), bonds ($k = B$) and for currencies ($k = FX$). Table 4.5 presents the results. For each predictor, we report the point estimates of the regression coefficients β_k and the R-squared. For comparison purposes, we report the results for the univariate case in Panel a, and the results for the multivariate case in Panel b.

We find that global bond risk premium helps to predict all exchange rates except for the Canadian dollar. The predictability is statistically significantly negative for all currencies except for the Janpanese yen. The negative sign suggests that higher global bond risk premium predicts foreign currency depreication. This observation is consistent with Lustig, Stathopoulos, and Verdelhan (2015) who find that bond risk premium tend to be negatively correlated with currency risk premium. The adjusted R-squared also increase remarkably relative to the univariate case, particularly for the Australian dollar.

4.5 Conclusions

This paper study time-varying risk premiums from a global perspective. We provide ample evidence for remarkably strong return predictability in international stock markets, international bond markets, and currency markets, using global risk premiums estimated as combinations of "local" risk premiums, or essentially the whole cross section of present value predictors.

We show that global risk premiums, summarizing predictive information in the whole cross section of present values into one variable, have consistently strong predictive power for international asset returns in all three asset classes, with substantially higher R-squared and stronger statistical significance.

Furthermore, our estimated global risk premiums are dynamically associated with past and future economic prospects. And finally, exchange rates tend to be highly predictable using our global risk premiums, with consistent and intuitive sign of predictive regression coefficients, and more than doubled R-squared.

Table 4.1
Predictive Regressions Using Standard Present Value Measures.

This table presents results for predictive regressions for asset returns using standard present value measures, according to the following specification:

$$rx_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12} \,,$$

where rx_{t+12} is the one-year (12-month) excess return for the stock, bond, or the currency, respectively. X_t denotes the standard present value predictor corresponding to each market, namely, the log dividend yield dp_t for international stock markets, the term spread $y^{10yr} - y^{tbill}$ for international bond markets, and the real exchange rate q_t for currency markets. For each asset class in each country, the first column reports the point estimates of the regression coefficient β, the second column reports the corresponding t-statistic based on the reverse regression approach (See Wei and Wright (2013)), and the third column reports the R-squared. All regressions are based on monthly observations running from January, 1970 to March, 2014.

	Bond			Equity			Currency		
	β	t_{RR}	$\bar{R}^2$	β	t_{RR}	$\bar{R}^2$	β	t_{RR}	$\bar{R}^2$
US	2.49	2.96	0.13	0.06	1.01	0.02			
AU	0.60	0.95	0.01	0.08	0.85	0.01	0.20	1.90	0.09
CA	1.31	1.86	0.07	0.02	0.25	0.00	0.12	1.32	0.05
CH	0.85	1.73	0.05	0.04	0.45	0.00	0.19	1.87	0.09
DK	0.48	0.86	0.01	0.05	0.70	0.01	0.25	1.93	0.13
DE	0.81	0.90	0.02	0.06	0.64	0.01	0.27	1.75	0.12
UK	0.56	1.30	0.03	0.28	2.85	0.17	0.35	1.85	0.14
JP	1.23	0.93	0.02	0.11	1.42	0.07	0.17	2.03	0.10
NO	0.58	1.05	0.03	0.23	1.97	0.09	0.26	1.75	0.10
SE	0.44	0.73	0.01	0.14	1.42	0.05	0.23	1.92	0.11

Table 4.2
Loadings of Global Risk Premiums on "Local" Risk Premiums.

This table presents results for predictive regressions for asset returns using standard present value measures, according to the following specification:

$$\frac{1}{N}\sum_{i=1}^{N} rx_{i,\,t+12} = \alpha + \sum_{i=1}^{N} \lambda_i \,\widehat{RP}_{i,\,t} + \varepsilon_{t+12}\,,$$

where $rx_{i,t+12}$ is the one-year (12-month) excess return for the stock, bond, or the currency, respectively for each country i. $\widehat{RP}_{i,t}$ denotes the "local" risk premium for country i in a given asset class. For each asset class in each country, the first column reports the point estimates of the regression coefficient β, the second column reports the corresponding t-statistic based on the reverse regression approach (See Wei and Wright (2013)), and the third column reports the R-squared. All regressions are based on monthly observations running from January, 1970 to March, 2014.

	Bond	Equity	Currency
US	2.97***	−3.36	
AU	0.57	4.81	4.17***
CA	−2.01*	−2.79	−1.75
CH	0.24	−11.68***	5.79**
DK	1.05**	4.75	−8.56
DE	−0.80	5.24	5.27
UK	1.89***	8.07**	4.56***
JP	−0.73**	3.80	−1.88
NO	1.93***	5.64***	−3.91
SE	−0.53	−6.76*	0.72

Table 4.3
Multivariate Predictive Regressions Using Global Risk Premiums.

This table presents results for predictive regressions for asset returns using standard present value measures, according to the following specification:

$$rx_{t+12} = \alpha + \sum_{k \in \{M,B,FX\}} \beta_k \widehat{GRP}_t^k + \varepsilon_{t+12}\,,$$

where $rx_{i,t+12}$ is the one-year (12-month) excess return for the stock, bond, or the currency, respectively for each country i. $\widehat{GRP}_t^k$ denotes the global risk premium for stocks ($k = M$), bonds ($k = B$) and for currencies ($k = FX$). Panel A, B and C show results for international stock markets, international bond markets, and currency markets, respectively. Each panel reports point estimates, adjusted R-squared, and the increase of R-square relative to the univariate case. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10%, respectively, based on the reverse regression standard error in Wei and Wright (2013). All regressions are based on monthly observations running from January, 1970 to March, 2014.

PANEL A. INTERNATIONAL STOCK MARKETS

	β_B	β_M	β_{FX}	$\bar{R}^2$	$\Delta\bar{R}^2$
US	1.17**	0.85***	0.04	0.24	0.06
AU	−0.06	0.98***	0.24	0.16	0.00
CA	0.02	0.79**	0.29	0.11	0.00
CH	1.45**	0.79***	0.05	0.20	0.08
DK	0.44	1.03**	−0.48	0.14	0.01
DE	1.16*	0.83***	0.03	0.13	0.03
UK	1.39***	1.38***	0.38	0.39	0.08
JP	−0.85	1.25***	0.43	0.21	0.02
NO	−0.27	0.99*	0.45	0.07	0.00
SE	1.16	1.15***	−1.05	0.21	0.05

Table 4.3
Multivariate Predictive Regressions Using Global Risk Premiums (cont.).

Panel B. International Bond Markets

	β_B	β_M	β_{FX}	$\bar{R}^2$	$\Delta\bar{R}^2$
US	1.54***	−0.16	0.22	0.48	0.05
AU	1.00***	−0.13	−0.03	0.21	0.01
CA	1.46***	−0.06	0.18	0.50	0.02
CH	0.58***	0.14**	0.10	0.27	0.06
DK	1.45***	0.11	−0.09	0.32	0.01
DE	0.95***	0.13	0.13	0.29	0.02
UK	0.82***	0.18*	0.05	0.36	0.07
JP	0.68***	0.16	−0.01	0.18	0.04
NO	0.80***	0.02	−0.07	0.22	0.00
SE	0.64**	−0.01	0.13	0.13	0.01

Table 4.3
Multivariate Predictive Regressions Using Global Risk Premiums (cont.).

Panel C. Currency Markets

	β_B	β_M	β_{FX}	$\bar{R}^2$	$\Delta\bar{R}^2$
AU	-0.52	0.20	1.06***	0.20	0.04
CA	0.04	0.17	0.31*	0.08	0.05
CH	-0.21	-0.13	1.38***	0.30	0.01
DK	-0.16	0.00	1.26***	0.27	-0.00
DE	-0.27	-0.07	1.34***	0.31	0.01
UK	-0.55	0.10	1.17***	0.28	0.03
JP	0.22	0.07	1.04***	0.15	0.00
NO	-0.35	-0.10	1.33***	0.36	0.01
SE	-0.29	0.07	1.35***	0.28	0.01

Table 4.4
Univariate Predictive Regressions of Exchange Rates.

This table presents results for predictive regressions for asset returns using standard present value measures, according to the following specification:

$$\Delta s_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12} ,$$

where ds_{t+12} is the one-year (12-month) exchange rate return. X_t denotes the exchange rate predictor, namely, the interest rate differential $y_t^{tbill,*} - y_t^{tbill,US}$, the real exchange rate q_t, and the global currency risk premium factor $\widehat{GRP}_t^{FX}$. For each predictor, the first column reports the point estimates of the regression coefficient β, and the second column reports the R-squared. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10%, respectively, based on the reverse regression standard error in Wei and Wright (2013). All regressions are based on monthly observations running from January, 1970 to March, 2014.

	I.R. Diff.		Real FX		FX GRP	
	β	$\bar{R}^2$	β	$\bar{R}^2$	β	$\bar{R}^2$
AU	0.27	0.00	0.19*	0.08	0.78**	0.11
CA	−0.25	0.00	0.14*	0.08	0.26*	0.04
CH	1.15*	0.06	0.20**	0.12	1.22***	0.24
DK	−0.23	0.00	0.21*	0.10	1.25***	0.29
DE	0.39	0.00	0.27*	0.13	1.24***	0.27
UK	0.14	-0.00	0.35**	0.15	1.02***	0.23
JP	1.74***	0.12	0.15*	0.09	0.82**	0.11
NO	0.31	0.01	0.25*	0.12	1.06***	0.25
SE	−0.34	0.00	0.24**	0.12	1.19***	0.23

Table 4.5
Multivariate Predictive Regressions of Exchange Rates.

This table presents results for predictive regressions for asset returns using standard present value measures, according to the following specification:

$$\Delta s_{t+12} = \alpha + \sum_{k \in \{M,B,FX\}} \beta_k \widehat{GRP}_t^k + \varepsilon_{t+12} \,,$$

where ds_{t+12} is the one-year (12-month) exchange rate return. $\widehat{GRP}_t^k$ denotes the global risk premium for stocks ($k = M$), bonds ($k = B$) and for currencies ($k = FX$). For each predictor, we report the point estimates of the regression coefficients β_k and the R-squared. For comparison purposes, we report the results for the univariate case in Panel a, and the results for the multivariate case in Panel b. "$***$", "$**$", and "$*$" indicate statistical significance level of 1%, 5%, and 10%, respectively, based on the reverse regression standard error in Wei and Wright (2013). All regressions are based on monthly observations running from January, 1970 to March, 2014.

	a. Univariate		**b.** Multivariate			
	β_{FX}	$\bar{R}^2$	β_B	β_M	β_{FX}	$\bar{R}^2$
AU	0.78**	0.11	−0.68***	0.20	0.90***	0.18
CA	0.26*	0.04	−0.00	0.16	0.32***	0.08
CH	1.22***	0.24	−0.32***	−0.00	1.24***	0.25
DK	1.25***	0.29	−0.24***	−0.08	1.23***	0.29
DE	1.24***	0.27	−0.38***	0.01	1.26***	0.28
UK	1.02***	0.23	−0.56***	0.14	1.11***	0.27
JP	0.82**	0.11	0.19***	0.11	0.85***	0.12
NO	1.06***	0.25	−0.48***	−0.04	1.07***	0.28
SE	1.19***	0.23	−0.59***	0.10	1.26***	0.27

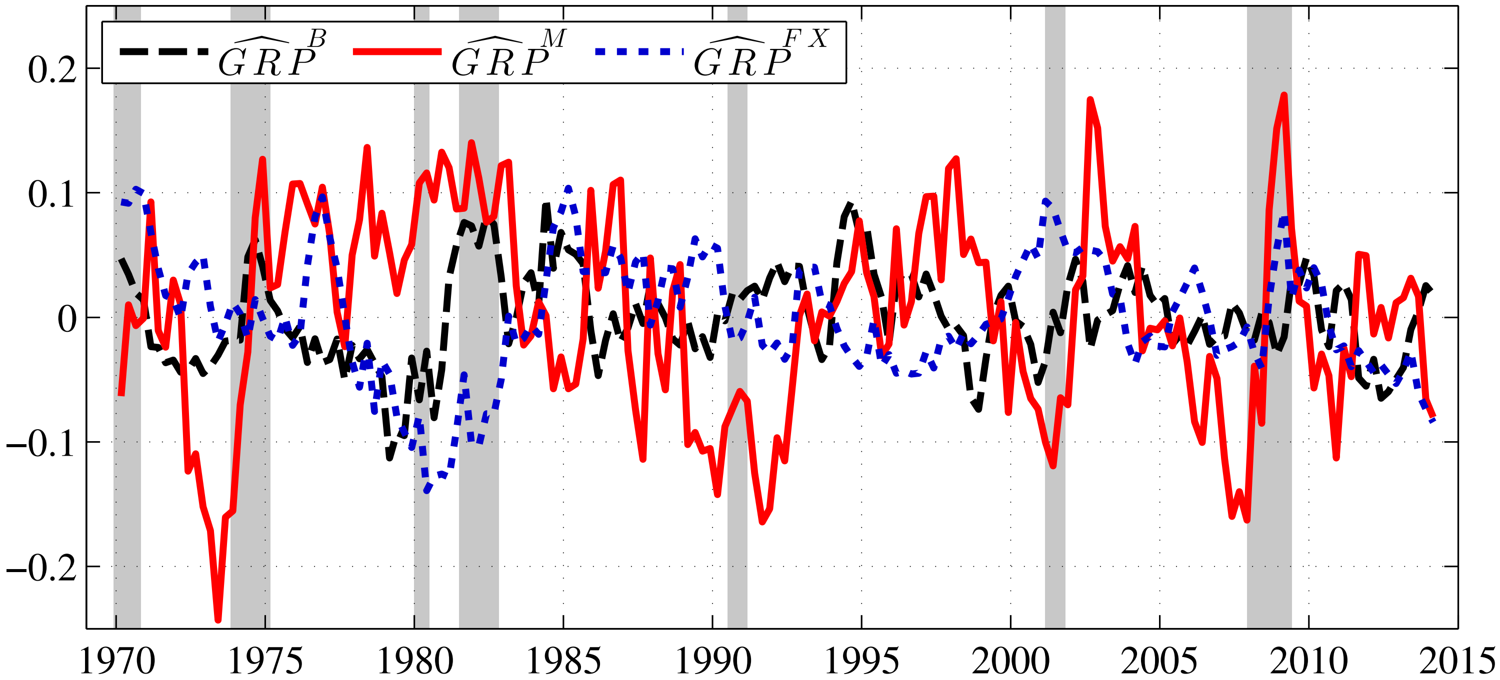
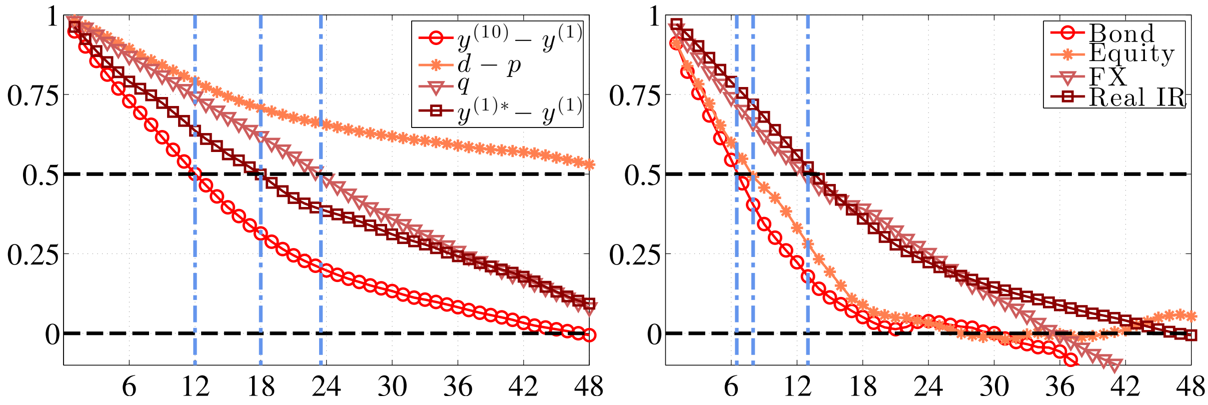
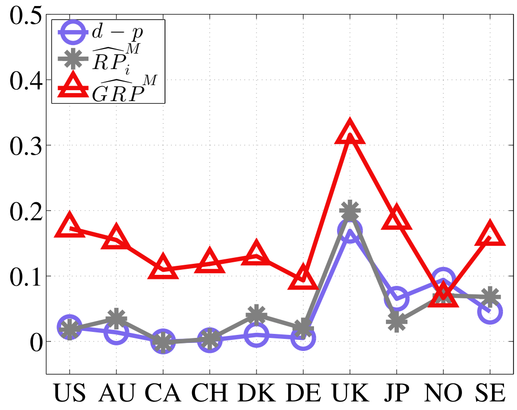


Figure 4.1. The Time-series of Global Risk Premiums. This figure plots the global risk premium factors for the equity (GRP^{M}), bond (GRP^{B}), and currency (GRP^{FX}) markets, respectively. The grey shaded regions indicate ex-post dated NBER recessions.

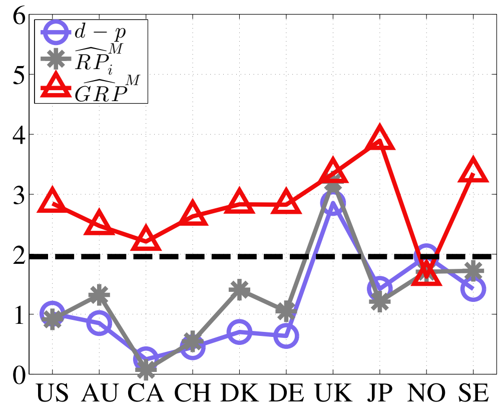


(a) ACF of PV's **(b)** ACF of GRP's

Figure 4.2. Autocorrelations of Risk Premiums. The figure plots the autocorrelations (as a function of the horizon h) of traditional return predictors in Panel (a) versus the global risk premium factors in Panel (b).



(a) R^2

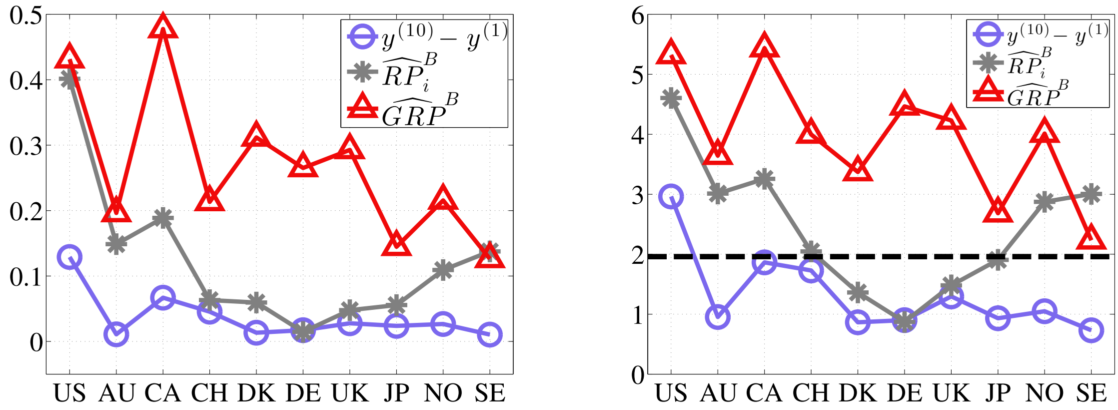


(b) t-stat of β

Figure 4.3. Univariate Predictive Regressions of International Stock Returns. We estimate the following return-forecasting model

$$rx^M_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12} \, ,$$

where rx^M_{t+12} is log excess return of international stock markets, and x_t denotes the predictor, including the log dividend yield dp_t, the "local" risk premium factor $\widehat{RP}_t^M$ for the corresponding stock market, and the global equity risk premium factor $\widehat{GRP}_t^M$, respectively. The figure plots the R-squared of the regression for each specification and each country in Panel (a) and the corresponding t-statistic for the estimate of the coefficient β based on the reverse regression approach (See Wei and Wright (2013)) in Panel (b). All regressions are based on monthly observations running from January, 1970 to March, 2014.

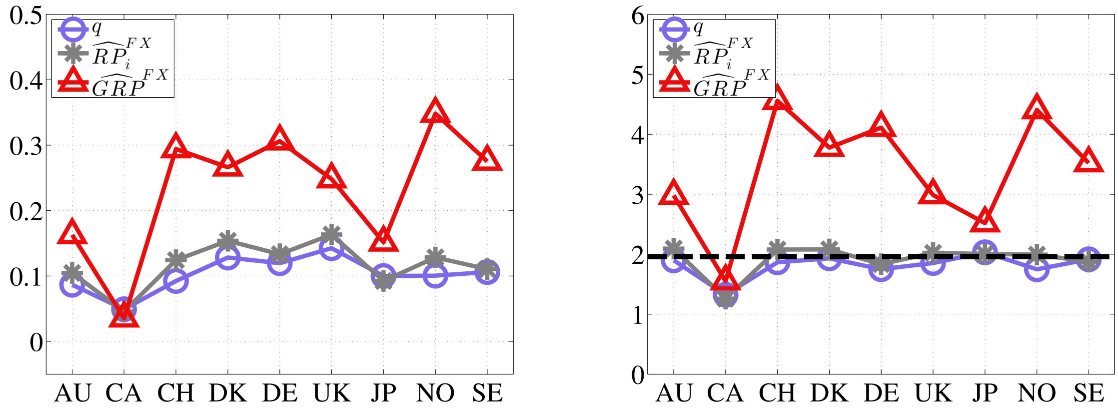


(a) R^2 **(b)** t-stat of β

Figure 4.4. Univariate Predictive Regressions of International Bond Returns. We estimate the following return-forecasting model

$$rx^B_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12}\,,$$

where rx^B_{t+12} is log excess return of international bond markets, and x_t denotes the predictor, including the term spread $y_t^{(10yr)} - y_t^{tbill}$, the "local" risk premium factor $\widehat{RP}_t^B$ for the corresponding bond market, and the global bond risk premium factor $\widehat{GRP}_t^B$, respectively. The figure plots the R-squared of the regression for each specification and each country in Panel (a) and the corresponding t-statistic for the estimate of the coefficient β based on the reverse regression approach (See Wei and Wright (2013)) in Panel (b). All regressions are based on monthly observations running from January, 1970 to March, 2014.

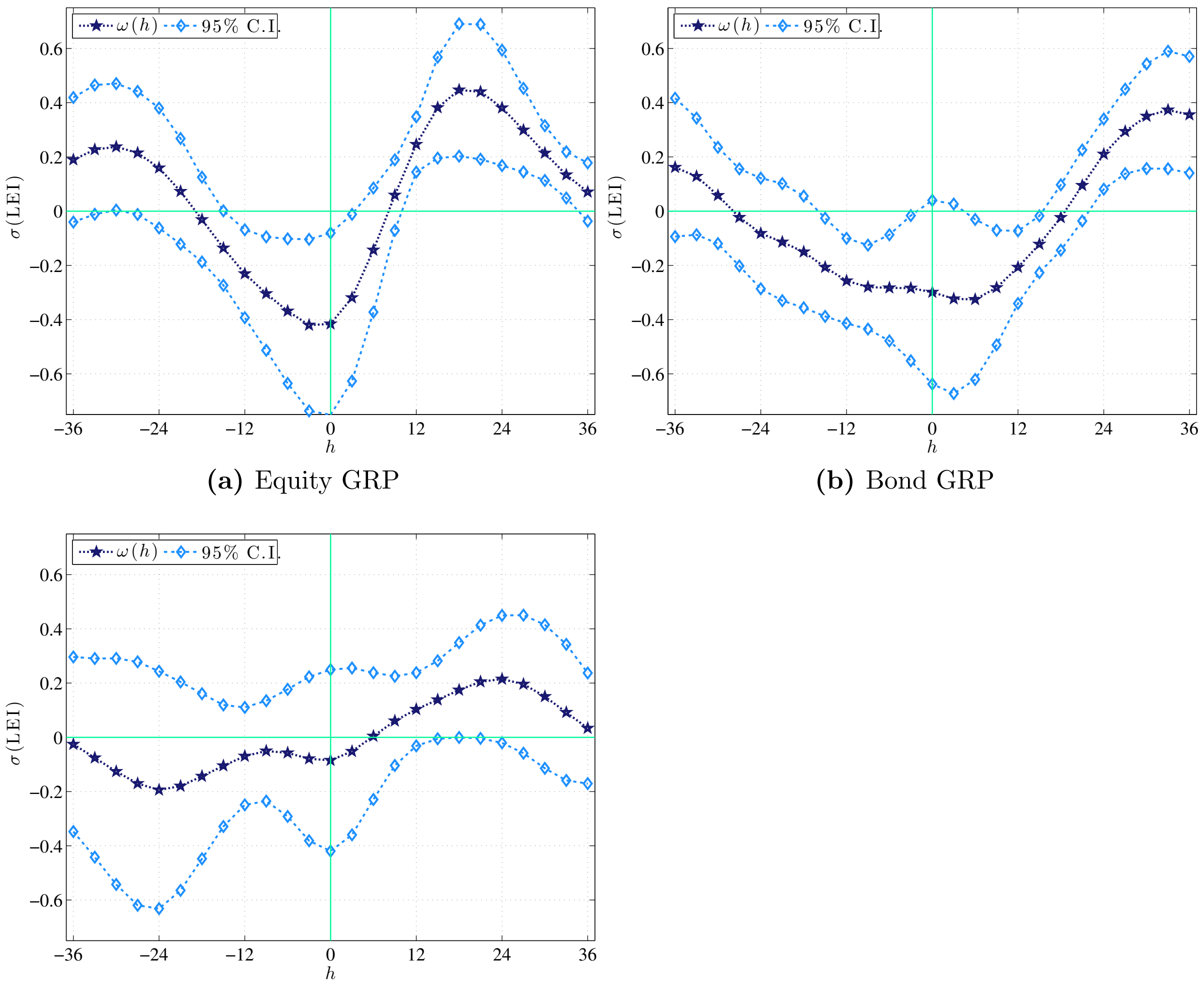


(a) R^2 **(b)** t-stat of β

Figure 4.5. Univariate Predictive Regressions of Currency Returns. We estimate the following return-forecasting model

$$rx^{FX}_{t+12} = \alpha + \beta X_t + \varepsilon_{t+12}\,,$$

where rx^{FX}_{t+12} is log excess return of currencies, and x_t denotes the predictor, including the log real exchange rate q_t, the "local" currency risk premium factor $\widehat{RP}_t^{FX}$ for the corresponding stock market, and the global currency risk premium factor $\widehat{GRP}_t^{FX}$, respectively. The figure plots the R-squared of the regression for each specification and each country in Panel (a) and the corresponding t-statistic for the estimate of the coefficient β based on the reverse regression approach (See Wei and Wright (2013)) in Panel (b). All regressions are based on monthly observations running from January, 1970 to March, 2014.



(a) Equity GRP

(b) Bond GRP

(c) FX GRP

Figure 4.6. Global Risk Premiums and the Macroeconomy. We estimate

$$\frac{LEI_{t+L}}{\sigma(LEI)} = \omega_0 + \omega_1(h)\,\frac{GRP_t}{\sigma(GRP)} + \varepsilon_{t+L}\,,$$

where LEI is the OECD leading economic indictor, and GRP denotes the global risk premium for the stock, bond, and currency markets, respectively. The dependent variable and the independent variables are standardized by the corresponding unconditional standard deviations $\sigma(LEI)$, and $\sigma(GRP)$. The figure plots the estimate of the coefficient $\omega_1(h)$ as a function of the lead $L > 0$ or the lag $L < 0$ for the global equity risk premium in Panel (a), the global bond risk premium in Panel (b), and the global currency risk premium in Panel (c). All regressions are based on monthly observations running from January, 1970 to March, 2014.

Chapter 5

Conclusion

My PhD thesis studies three topics in international finance.

Chapter 1 documents currency carry trade and momentum returns in the interwar period (1921-1936). We find that (i) active currency trading strategies generate average excess return of 7% per annum in the interwar period, similar in magnitude to modern sample estimates; (ii) global FX volatility risk premium accounts for the carry trade returns in the interwar sample as well as in modern samples, it is also a key contributor to currency momentum returns in the interwar sample; (iii) Our empirical results suggest that the returns of currency trading strategies cannot be fully explained by pure rare disaster based theories.

Chapter 2 provides a scientific account of the risk-off phenomenon: its detection, its relation with economic conditions and other risk measures, and its consequences on the financial landscape. We find that (i) risk-off transitions are relatively infrequent but have become increasingly frequent over time, and are associated with geopolitical events; (ii) risk-off switches are unrelated to changes in microeconomic fundamentals and volatility or average implied correlation shocks; (iii) risk-off shifts impact broad asset classes and active trading strategies and are also associated with significant changes in the positions of institutional investors.

Chapter 3 explores the broader implications of the present value approach to forecasting returns. We estimate global risk premiums in international stock markets, international bond markets, and the currency markets using the whole cross-section of present value measures. Our findings are (i) global risk premiums substantially improve the predictability of returns relative to standard present value based predictors; ii) they are intimately linked with past and future economic prospects; and iii) global risk premiums imply stronger and more consistent exchange rate predictability than standard exchange rate predictors, such as interest differentials and real exchange rates.

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