Switching Risk Off: FX Correlations and Risk Premia*

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Abstract

Risk-off refers to a change in risk preferences and the associated portfolio rebalancing. We identify these episodes using switches of foreign-exchange correlation regimes. We show that the returns of currency trading strategies strongly depend on these correlation regimes and especially on the regime transitions. We find that the effect of VIX and currency volatility on the foreign-exchange risk premia can be very different in *risk-off* versus *non risk-off* episodes. Finally, we obtain supporting evidence for the mechanism we uncover from the evolution of speculator positions.

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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 markets general nerves – suddenly shot to major highs against a range of other currencies, in a classic risk-off (or run for your lives) shift.* Wall Street Journal, 24 Aug 2010.

The poor empirical performance of macroeconomic fundamentals for currency dynamics is notorious in exchange rate academic research (Meese and Rogoff (1983)). The lack of a robust relationship of foreign-exchange with local macroeconomic fundamentals is even more evident when all currencies suddenly tend to move in lock-steps and currency correlations become highly polarised, in response to an increase in global risk aversion and crowded trading activities of institutional investors. These events, dubbed *risk-off* episodes by the financial press, are hard to predict and can have devastating consequences on investors' portfolios, as diversification benefits are eroded by exploding correlations.

In this paper, we study the variation of foreign-exchange returns when a *risk-off* episode occurs and the currency regime switches from a normal environment, with local macroeconomic fundamentals that tend to prevail, to an environment of exchange rates largely driven by global risk aversion. When risk trades prevail, institutional investors tend to concentrate their trades in the same group of currencies with the purpose of reducing the currency risk of their portfolio, and therefore tend to cause abrupt and potentially extreme foreign-exchange dynamics.

Risk-off refers to a *change* in risk preferences and associated portfolio rebalancing. The existing related literature instead traditionally investigates persistent *level* variables that are more likely to be correlated with the *levels* of risk preferences, not changes. We try to tease level and changes apart.

Our empirical strategy is straightforward and is based on the basic intuition that, during *risk-off* episodes, crowded institutional investors trades generate specific patterns of currency co-movement that are picked up by simple linear correlations. We thus estimate a regime-switching model for currency correlations, hypothesizing that one of the switches of correlation regimes should endogenously identify the *risk-off* episodes. We then analyze the relation between changes of correlation regimes and currency risk-premia, using the returns on bilateral exchange rates, carry, and momentum trading strategies. Finally, the analysis of correlation is complemented by the more traditional approach of conditioning currency returns and trading strategies on measures of volatility, such as the volatility index (VIX) and foreign-exchange volatility.

Our empirical results are intriguing. We identify two foreign-exchange correlation regimes. The first regime, dubbed high correlation, features large correlations among most currencies, with the notable exception of the Japanese yen. This is likely to correspond to realization of the *risk-off* episodes. The second correlation regime exhibits lower correlations across the board, except for the Japanese yen that in this case tends to be relatively more correlated with the other currencies than in the other regime. We find that the correlation regimes and transition between regimes are significant explanatory variables for the returns of currency and currency trading strategies. In particular, the switch of correlation from the low regime to the high regime, identified as the indicator for risk-off episodes, is associated with very large losses to risky currencies and the carry trade strategy.

The combination of correlation regimes and measures of volatility is very appealing. The extant empirical evidence shows that higher volatility forecasts lower currency carry trade returns (e.g., Menkhoff, Sarno, Schmeling, and Schrimpf (2012)), as it represents higher level of uncertainty. Our evidence uncovers richer dynamics. When correlations transit from the low to the high regime, with VIX increasing by one standard deviation, then carry trade indeed suffers a large daily loss. However, when correlations transition from the high to the low regime, a one-standard deviation increase in VIX forecasts superior carry trade profits, which is in contrast with unconditional evidence and common wisdom. We uncover similar patterns when we use realized foreign-exchange volatility and even sharper findings when we use currency implied volatility obtained from option prices.

We also show that the combination of correlation regimes with volatility offers a large improvement of explanatory power for the time-series variation of currency returns. For example, when we study the profits of carry trade strategies, VIX alone can explain 8% of the zero-cost carry trade returns. The addition of correlation regimes boosts the adjusted R-squared by one quarter to 10%. Taking a closer look at the increase in R-squared, we find it concentrates on investment currencies such as the Australian dollar and New Zealand dollar.

We look for supporting evidence for the dynamics we uncover using the evolution of speculators net futures position conditional on correlation regime transitions. We find a significant increase of long positions in safe currencies and short positions in investment currencies during *risk-off* episodes. The opposite occurs in the low-correlation regimes. This evidence is consistent with the shift of arbitrage capital induced by a change in risk preferences.

Finally, we explore the implication of FX correlation regimes for longer-horizon returns. We find that the transition in correlation regimes carry crucial predictive information for future returns to the currency trading strategies.

In the appendix, we examine the robustness of our results to emerging-country exchange rates and major equity market indices. We find broadly consistent evidence to support the strong dependence of returns on correlation regimes, especially for the risk-off episodes featuring the low-to-high correlation regime transition.

Related literature. Our paper contributes to two broad areas of research in foreign-exchange. The first is the voluminous literature on risk-based explanations for carry trade returns (e.g., Lustig and Verdelhan (2007); Lustig, Roussanov, and Verdelhan (2011)). The second is the set of papers that are related to our method for measuring the *risk-off* episodes.

In the first category, three papers are most closely related to our research. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) attribute carry trade returns to compensation for global FX volatility risk. Our findings enrich this story and suggest that higher volatility is a bad risk for the carry trades especially when correlation switches to the high regime.

The relationship between currency returns and correlation regime switching is consistent with a correlation risk story in which the carry trade loses when correlation is higher, as suggested by Mueller, Stathopoulos, and Vedolin (2012). However, our correlation states are peculiar, because what we identify as the *high correlation regime* corresponds to a specific pattern of polarized movements: risky currencies and safe currencies cluster respectively while they tend to depart from each other. In contrast, the correlation measure in Mueller et al. (2012) is a cross-sectional average on a smaller panel of currencies and therefore with higher correlation every currency tends to move in the same direction.

Finally, our paper complements foreign exchange literature that attempts to understand the time series variation of currency returns and bilateral exchange rates in particular such as Verdelhan (2013). We show that correlation regime switches have substantial incremental explanatory power for the time series variation of currency returns and this improvement is mainly concentrated to risk-off targets.

Our methodology of studying asset price dynamics is inspired by the sentiment-based co-movements of stock prices documented in the seminal work of Barberis, Shleifer, and Wurgler (2005). Our focus is, however, centered on foreign exchange markets and specifically on the relation between currency returns and the co-movement synthesized in FX correlation regimes.

Our method is thus related to the broader limits to arbitrage literature that looks at correlation between nearly identical assets as a sign of healthy arbitrage activity. For example, Xing Hu, Pan, and Wang (2012) obtain a measure of shortage of arbitrage capital using deviations of U.S. Treasury from the yield curve. In a different setting, Lou and Polk (2013) use a novel approach to measuring arbitrage activity in stock markets by co-momentum (i.e., average pairwise correlations within each equity momentum portfolios). The *risk-off* episodes that we identify in our paper are the results of shifts of arbitrage capital induced by a change in preferences. Like Lou and Polk (2013), our identification strategy uses correlation dynamics. However, we do not rely on a specific trading strategy, but on the more basic link between foreign exchange market correlations and returns to currency speculation.

Our paper is also closely related to recent work by Baele, Bekaert, Inghelbrecht, and Wei (2013), who characterize empirically flight-to-safety episodes using data on bond and stock returns. Similarly, we relate the transition to the high correlation foreign-currency regime to *risk-off* events characterized by a change in risk preferences and the associated portfolio rebalancing. However, we study the foreign-exchange market and, as a result, we focus on global episodes, unlike the country-specific events that constitute the majority of the flight-to-safety in Baele, Bekaert, Inghelbrecht, and Wei (2013).[1]

The rest of our paper is organized as follows. Section 2 describes our data, measurement and sampling method. In Section 3, we introduce the regime-switching model that we use to estimate correlation regimes and characterize their key properties. We present our empirical results on the relation between foreign-exchange rate returns and correlation regimes in Section 4. Section 5 offers additional insights from the analysis of net speculator positions. Section 6 concludes. In the appendix, we provide robustness

[1]Along similar lines, De Bock and Carvalho Filho (2013) identify risk-off episodes as periods experiencing a large increase in the VIX index, an indicator arguably exogenous to the foreign exchange market. Our paper shifts to the opposite spectrum and focus on the correlation regimes that is derived directly from the foreign exchange market. Moreover, from our longer sample analysis, we find the interactive effect between our correlation regimes and volatility is crucial to accurately understand currency returns.

checks for emerging-country exchange rates (Appendix A), major equity market indices (Appendix B), and the futures positions on US equity indices and the US Treasury bonds (Appendix C).

2 Data Description

We use the exchange rates of G10 countries, namely, Australia (AUD), Canada (CAD), Switzerland (CHF), Euro, the United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), and the United States (USD) among which the U.S. dollar is taken as the reference currency.[2] We follow the literature and obtain daily exchange rates from BBI and Reuters via Datastream. We transform the exchange rates to the U.S. dollar price of one foreign currency unit. We also obtain daily time series of the VIX index from Chicago Board Options Exchange (CBOE) and major FX option implied volatilities of major currencies including AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK from Reuters (via Datastream). Our sample spans from January 3, 1995 to October 11, 2013 [3].

Additionally, we use data on the futures positions of speculators and hedgers 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 existing literature, and the open interest of futures contracts on AUD, CAD, CHF, EUR, GBP, JPY, NZD. Because the dollar tends to act as a safe haven currency in risk-off environments, we construct synthetic long and short positions and open interest on USD futures by aggregating the corresponding quantity over AUD, CAD, EUR, GBP, and NZD. Finally, we construct the variable *net speculator position*,

[2]Prior to the introduction of euro on January 1, 1999, we use the Deutsche Mark as a representative currency for euro

[3]The modern electronic broking systems for dollar-yen, dollar-euro(mark), and dollar-pound wasn't completely established until September, 1993. Further, as Chaboud and Weinberg (2002) report, the share of inter-dealer trading volume executed through electronic platforms started very low (below 5% in 1992) and gradually grew (10% in 1995, 40% in 1998, and 60% in 2001.) Therefore, 1995 seems an ideal tradeoff between sample size and the modernization of FX market structure. (see King, Osler, and Rime (2012) for details about the evolution of foreign exchange market structure.)

obtained as the long minus short position of non-commercial traders divided by the total open interest of all traders, to proxy for trading activity, as in Brunnermeier, Nagel, and Pedersen (2008) or Moskowitz, Ooi, and Pedersen (2012). This dataset is available at the weekly frequency and our sample spans from January 3, 1995 to October 11, 2013.

The major advantage of using G10 exchange rates is that they are readily available at daily frequency for a long time span. This will be in our subsequent empirical analysis, 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.[4]

Although the correlation regimes are derived from G10 currency exchange rates, we show in Appendix A and B that the implications of our correlation regimes extend well to emerging-country exchange rates and major equity market indices, respectively. We obtain 19 emerging-country spot exchange rates from BBI and Reuters via Datastream, and 14 major equity market indices from Bloomberg for the same sample period as our main study. Details are explained in the appendix.

Furthermore, in Appendix C, we use non-commercial traders position on major US equity futures and US Treasury bonds also from CFTC and show implication of our correlation regimes for net speculators futures position also go beyond foreign exchange market to the equity and bond markets. This weekly futures data also covers the same period as in our main analyses.

[4]The popularity and liquidity of G10 currencies is also evidenced in practice. For instance, the Deutsche Bank G10 Currency Futures Harvest index employs exactly the same set of currencies as we do in our study.

3 Methodology

In this section, we first identify two foreign exchange correlation regimes via a simple regime-switching dynamic correlation (RSDC) model proposed by Pelletier (2006).[5] We then characterize key empirical properties of these two regimes.

3.1 The RSDC model

We estimate the regime-switching dynamic correlation (RSDC) model proposed by Pelletier (2006) using the EM algorithm. 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 FX returns can be written as

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

$$H_t = \text{diag}\{\sigma_t\} \, \Gamma_t \, \text{diag}\{\sigma_t\} \tag{2}$$

$$\Gamma_t = \sum_{n=1}^{N} \Gamma_n \mathbf{1}_{\Delta_t = n} \tag{3}$$

$$\epsilon_t \sim \text{Distr.}(0, I) \tag{4}$$

where $\Delta_t \in \{1, 2, \cdots, N\}$ indicates the correlation regime at time t with probability of transition from regime i to j defined as $\pi_{ij} \equiv \text{Prob}(\Delta_t = j \,|\, \Delta_{t-1} = i)$.

We separate the estimation of volatility by estimating K univariate GARCH(1,1) model for the demeaned returns and then we divide the demeaned returns by their corresponding volatility forecasts. Denoting the standardized returns as u_t, the RSDC

[5] Ang and Timmermann (2012) provides an in-depth review of the theory and applications of regime switching models in financial markets.

model then becomes

$$u_t = \Gamma_t^{1/2} \epsilon_t \tag{5}$$

$$\Gamma_t = \sum_{n=1}^{N} \Gamma_n \mathbf{1}_{\Delta_t = n} \tag{6}$$

$$\epsilon_t \sim \text{Distr.}(0, I) \tag{7}$$

MLE via the EM algorithm computes the regime-dependent correlations and transition probabilities as

$$\hat{\Gamma}_n^{(m+1)} = \frac{\sum_{t=1}^{T} u_t u_t' \, \text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})}{\sum_{t=1}^{T} \text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})} \quad , \text{ for } \forall\, n = 1, 2, \cdots, N \tag{8}$$

$$\hat{\pi}_{ij}^{(m+1)} = \frac{\sum_{t=2}^{T} \text{Prob}(\Delta_t = j,\, \Delta_{t-1} = i \,|\, \underline{u_T}; \hat{\theta}^{(m)})}{\sum_{t=2}^{T} \text{Prob}(\Delta_t = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})} \quad , \text{ for } \forall\, i, j = 1, 2, \cdots, N \tag{9}$$

$$= \frac{\sum_{t=2}^{T} \hat{\pi}_{ij}^{(m)} \text{Prob}(\Delta_t = j \,|\, \underline{u_T}; \hat{\theta}^{(m)}) \, \text{Prob}(\Delta_{t-1} = i \,|\, \underline{u_{t-1}}; \hat{\theta}^{(m)}) / \text{Prob}(\Delta_t = j \,|\, \underline{u_{t-1}}; \hat{\theta}^{(m)})}{\sum_{t=2}^{T} \text{Prob}(\Delta_{t-1} = n \,|\, \underline{u_T}; \hat{\theta}^{(m)})} \tag{10}$$

where the superscript (m) indicates the m-th iteration, and $\underline{u_t}$ denotes the information set $\{u_1, u_2, \cdots, u_t\}$.

Given the starting value of parameter vector θ and the Hamilton's filter for probabilities, we can iterate according to the above equations until the parameter estimates converge.

3.2 Features of FX correlation regimes

We identify two regimes of the FX correlations by estimating the abovementioned Markov regime-switching model ($N = 2$). In our estimation, the starting value of the first regime's correlation (Table 1, Panel a.) is the identity matrix whereas the second regime's correlation (Table 1, Panel b.) is the unconditional correlation matrix. It turns out that correlations in the first regime are generally higher than those in the second regime. For convenience, we term the first regime *the high correlation regime*, and the second regime *the low correlation regime*. Interestingly, the Japanese yen covaries uniformly and significantly less with other currencies in the high correlation regime. The Swiss franc also exhibits lower correlation for most currencies such as EUR, GBP, NOK, NZD, and SEK.

Both correlation regimes displays strong persistence and a switch of regime is rare. The expected regime durations are 33 days for the high correlation regime and 110 days for the low correlation regime. (See Panel c. and d. in Table 1.) Despite the persistence of both correlation regimes, the upper panel of Figure 1 shows that the high correlation regimes becomes long-lasting only during the 2007-2009 financial crisis and the 2010-2012 europe debt crisis. The infrequent regime transition is illustrated in the lower panel of Figure 1. Overall, regime switching occurs rather infrequently. However, FX correlation tends to jump from a low regime to a high regime under stressed market conditions, for instance, during the 2007-2009 financial crisis.

To better establish the link between correlation regime switching and risk-off episodes, we present, in Table 2, 39 risk-off episodes identified in our sample period from January 3, 1995 to October 11, 2013 (4899 days in total) when the joint probability of transition from a low regime on day $t-1$ to a high regime on day t is in excess of 0.20, and we find these risk-off episodes corresponds to major financial market and/or economic crisis such as the Asian financial crisis, the Russian default, the burst of the Dotcom bubble, the subprime crisis, and the Europe debt crisis, etc. Although the threshold of transition probability of 0.20 seems low, we argue that it is a reasonable choice. For example, during the onset of the Russian crisis in 1998, the probability of a switch from the low correlation regime to the high correlation regime increase substantially from near zero to 0.22 and stays at this level for the next three days while the probability that the economy enters into the high correlation regime accumulates from 0.22 to 1. This is clearly a risk-off episodes with a switch of correlation regime even though the day-to-day transition probability does not exceed 0.5.

Interestingly, many risk-off episodes identified in Table 2 are not directly related to macroeconomic fundamentals or at least does not involve immediate shift in fundamentals, which squares with our intuition that risk-off episodes occurs when global risk aversion shifts whereas macroeconomic fundamentals play minor role.

On the other hand, the FX correlation regime infers information quite different from volatility indicators, e.g. the VIX and FX volatilities, because the probabilities of regime and regime transition barely covary with volatility movements (see Panel a. of Table 5). This observation is also illustrated in Figure 2: the FX correlation regime displays remarkably different dynamics than the volatility. Take the Lehman Brothers bankruptcy as an example. The VIX started to fall gradually by the end of 2008 while the FX correlation has just jumped into the high regime and remained in the high correlation regime for an extended period.

3.3 Variance ratio of principal components.

Given estimates for the USD-based exchange rate volatility and regime-dependent FX correlations, we seek for alternative interpretation of the FX correlation regime, in order to establish the link between FX correlation regime and risk-on/off episodes.

Because of the equivalence between a variance-covariance and eigenvalues, we first check the first principle component across regimes. The findings, summarized in Table 3, are consistent with our intuition that the high correlation regime signals crowded trading in the foreign exchange market and therefore the high-regime first principle component accounts for more of the total variation than the low-regime first principle component.

Among the 4899 days in our sample, there are only 1208 days in which the high-regime variance ratio is lower than the low-regime variance ratio, and the probability of the high-regime variance ratio is surpassed by the low-regime variance ratio when the economy is in the high correlation regime is only 0.03.

Moreover, the high-regime first principle component accounts for 5% more of the total variation than the low-regime first principle component on average over the full sample. This wedge increases to 11% conditional on the subsample for the high correlation regime and decreases to 3% conditional on the subsample for the low correlation regime.

Analyses of more principle components reaffirmed our finding. In the case of the variance ratio of the first three principle components, there is only 44 days in which the low-regime variance ratio exceeds the high-regime variance ratio. As Figure 3 illustrates, the first few principle components account for more variation in the high correlation regime than in the low correlation regime.

3.4 Cross-rate volatilities.

Another way to view the FX correlation regime is to translate the USD-based exchange rate covariance matrix to the volatility of cross rates. In some sense, it is advantageous to look at currency comovement through the lens of the cross-rate volatility because it is numeraire-free. To see this, we start from showing the link between correlation and cross-rate volatility as follows:

$$\sigma(i,j)^2 = \sigma(i,\$)^2 + \sigma(j,\$)^2 - 2\sigma(i,\$)\sigma(j,\$)\rho\big((i,\$),(j,\$)\big) \ , \qquad (11)$$

where σ computes the volatility, and ρ computes the correlation, and (i,j) denotes cross rate pair, i.e. the conversion of one unit currency i into currency j. Equation (11) implies that the cross rate volatility can be visualized as the (absolute) distance between currency i and currency j, whereas the correlation between USD-based rates can be visualized as the cosine of the intersection angle of a triangle connecting both currency i and currency j to the reference 'point' , which is the US dollar [6]. Apparently $\sigma(i,j)$ is invariant to the choice of reference point.

In the geometric language, we find, on average over the full sample, the high correlation

[6] See Walter and Lopez (1999) for a detailed discussion as to the application of currency trio.

regime corresponds to the case in which currencies move toward each other relative to the low correlation regime except that the Japanese yen drifts apart from all other currencies but least so from the Swiss franc and meanwhile the Swiss franc shifts away from most other currencies such as EUR, GBP, NOK, NZD and SEK. In fact, the Japanese yen and the Swiss franc are the two currencies that move least closer to other currencies in the high regime, as Table 4 shows in Panel a. This observation is enhanced by Panel c. which shows that currencies cluster more intensively for the high correlation regime relative to the low correlation regime, conditional on the subsample that the economy is in the high correlation regime. By contrast, Panel d. shows that conditional on the subsample that the economy is in the low correlation regime, the relative clustering is weaker.

We next show how the US dollar moves differently in the high correlation regime versus the low correlate regime. Because USD-based exchange rate volatilities are estimated using GARCH, our RSDC model does not provide a direct estimates for regime-dependent USD-based exchange rate volatilities. However, we conduct a reduced-form analysis and use our model -implied regime probabilities to predict GARCH-based volatility estimates. To be precise, we regress GARCH estimates for each G10 exchange rates volatility $\sigma_{i,t}$ onto the probabilities of the high correlation regime and the low correlation regime:

$$\sigma_{i,t} = \sigma_H \, Prob(\Delta_t = H \,|\, \mathcal{F}_T) + \sigma_L \, Prob(\Delta_t = L \,|\, \mathcal{F}_T) + error_{i,t}, \tag{12}$$

and we use σ_H and σ_L as our indirect estimates of USD-based exchange rate volatilities in the high and low regimes, respectively.

Consistent with the notion of the US dollar as a safe haven target, we find the US dollar behaves like the Japanese yen and the Swiss franc and drift away from other currencies in the high correlation regime relative to the low correlation regime. In particular, the US dollar tends to stay dramatically farther from the typical commodity currencies such as CAD, NZD, AUD, SEK and NOK, but only slightly away from JPY, CHF, EUR and

GBP, shown in Table 4, Panel b.

The abovementioned observations effectively imply that the correlation regimes reveal a distinct mechanism of foreign exchange rate dynamics over the global FX volatility proposed by Menkhoff et al. (2012). The global FX volatility essentially captures the average volatility dynamics across all exchange rates and therefore when correlation switches into the high regime from the low regime, it is not necessary that exchange rate volatilities are hit by positive news in general. In fact, on the basis of our regime-dependent cross-rate volatilities, low-to-high correlation regime switching sees to be accompanied with muted volatility. Even though USD-denominated exchange rate volatilities generally go up during a low-to-high correlation transition, our correlation regimes still deliver richer information beyond overall exchange rate volatility shifts as they demonstrate the diverging behavior between risky currencies and safe currencies (Table 4, Panel b).

4 FX Returns and Correlation Regimes

In this section, we proceed to show currency returns, including G10 bilateral exchange rates, and the carry and momentum strategies, depend on correlation regimes.

4.1 Empirical strategy

Given the correlation regimes implied from the regime switching model, we are now set to examine how currency returns vary across the two regimes. To this end, we regress the return to each asset r_t on the four smoothed joint probabilities of day $t-1$ regime and day t regime, all of which are derived from our estimated regime switching model. The simple linear regression framework is a natural choice for us because the independent variables are probabilities. The main regression equation is specified as follows:

$$r_t = \sum_{i=1}^{2}\sum_{j=1}^{2} \left(\alpha_{ij} + \gamma_{ij}\, dV_t\right) \text{Prob}[\,\Delta_t = j,\, \Delta_{t-1} = i \,|\, \mathcal{F}_T\,] + \epsilon_t \;, \tag{13}$$

where $\{\alpha_{ij},\, \gamma_{ij}\}_{\forall i,j=1,2}$ are parameters to be estimated. The left-hand side variable r_t refers to logarithm spot exchange rate return for individual currencies or currency portfolios. For any volatility measure V_t, the shock dV_t is the standardized first difference [7] and is measured by subtracting the full sample average and then dividing the residual by the full sample standard deviation, i.e.

$$dV_t = \frac{\Delta V_t - \overline{\Delta V_t}}{\frac{1}{T-1}\sum_{t=2}^{T}(\Delta V_t - \overline{\Delta V_t})^2} \;, \tag{14}$$

where $\Delta V_t = V_t - V_{t-1}$, and $\overline{\Delta V_t} = \frac{1}{T-1}\Delta V_t$.

We use a variety of volatility measures including the VIX index, the global FX volatility measure as in Menkhoff et al. (2012), and average implied volatility of major currency options. $\mathcal{F}_T$ indicates that the joint probability is the smoothed probability given full sample data. Note that since the joint probabilities sum up to one at each point in time, we do not include a constant in the equation.

The standardization of volatility shocks eases the interpretation of our coefficient estimates. In detail, α_{ij} estimates the average exchange return when correlation transits from regime i on day $t-1$ to regime j on day t and there is no news about volatility while γ_{ij} estimates the average exchange rate return when correlation transits from regime i on day $t-1$ to regime j on day t and volatility is heightened by one standard deviation.

For our empirical analysis, we start from two simple cases and present the results in Table 6: 1) we impose $\gamma_{ij} = 0$, for $\forall i$ and j to see whether the average exchange rate return has anything to do with correlation regimes as the stylized fact that exchange rates behave like random walks with no drift (see Panel a.); and 2) we impose $\alpha_{ij} = 0$

[7] Given the extreme persistency of volatility at the daily frequency, the first difference is a reasonable way to measure volatility innovations or shocks, as in Ang, Hodrick, Xing, and Zhang (2006).

and $\gamma_{ij} \equiv \gamma$, for $\forall i$ and j, in order to see the implication of volatility alone for currency returns (See Panel b. and c.).

We proceed to estimate the full equation (13) to investigate the interactive effects of correlation regimes and volatility on currency returns. Our results show strong dependence of returns on foreign exchange correlations. In fact, we find correlation regimes can substantially improve our understanding of asset returns beyond standard indicators such as VIX. We detail our findings below.

4.2 Dependence of Currency Returns on FX Correlation Regimes

In Table 6, Panel a, we show that currency investments yield different average returns, depending on the transition of FX correlation regimes. Let's first focus on the risk-off episodes when FX correlation transits from the low regime to the high regime shown in the column "L-H".

We can see that popular investment currencies such as the Australian dollar and the New Zealand dollar, as well as other commodity currencies such as the Canadian dollar and the Norwegian Krone, incur dramatic losses whereas financing currencies such as the Japanese yen and the Swiss franc make profits or only lose slightly.

Consistent with results for bilateral exchange rate returns, the carry trade, which is long in a basket of high-interest-rate G10 currencies and is short in a basket of low-interest rate G10 currencies, collapses by losing 49 basis points on the daily basis or 123% per annum.[8]

Unlike the carry trade, the momentum strategy, which is long in a portfolio of appreciating currencies and is short in a portfolio of depreciating currencies, earns weakly positive profits because all three momentum portfolios yield all but equally

[8]The daily average return is annualized by multiplying 252, which is assumed to be the number of trading days in one year.

negative returns.

Another interesting pattern arises as the currency performance seems not strictly monotonic in carry or interest rate. Specifically, the Norwegian krone and the Swedish krona which are typically categorized into the medium interest rate portfolios, tend to lose more than the most popular carry trade investment currencies, the "aussie" and "kiwi", implying that the risk-off episodes identified by our FX correlation regimes may uncover richer risk-return relationship beyond the dimension of carry or interest rate.

Turing to the case in which correlation switches from the high regime to the low regime, we find that all currencies reaps substantial profits with the absolute magnitude comparable to the loss in the low-to-high transition except for the Japanese yen with insignificantly negative returns. Risky currencies tends to appreciate more and therefore the carry trade earns an average daily return of 34 bps or 86% per annum.

In contrast with regime-switching, the cases when the regime persists seem to imply relatively calm foreign exchange market conditions, although when correlation remains the high regime, the Japanese yen experience an average daily return of 5 bps per day or 12% per annum and the British pound devalues by about 4 bps per day or 9% per annum. When correlation persists in the low regime, foreign exchange market seems totally calm as no exchange rates are expected move abruptly and this market condition is likely to be dominated by local macroeconomic fundamentals.

Correlation regimes versus correlation risk. We establish that when correlation enters into the high regime from the low regime, the carry trade suffers huge losses. This suggests that the carry trade is exposed to correlation risk. Mueller, Stathopoulos, and Vedolin (2012) empirically verifies that correlation risk is priced and correlation risk premium is a key component of the average excess return to the carry trade. A crucial question arises: does the FX correlation regime, especially the switch of regime, is just an alternative manifestation of the correlation risk proposed in Mueller et al. (2012)?

It turns out our FX correlation regime is quite different. Mueller et al. (2012) measure the correlation as the pairwise average of correlations between EUR, GBP, CHF and JPY. Take our correlation model as the benchmark. Using corresponding numbers in our Table 1, we can see that the average correlation of the six pairs involving EUR, GBP, CHF, and JPY is 0.36 in our *high* correlation regime and is 0.57 in our *low* correlation regime. This means that Mueller et al. (2012)'s larger correlation would probably corresponds to a state with less polarized foreign exchange rate movements as in our *low* correlation regime.

Indeed, when their average correlation is higher, it is more likely that CHF and JPY move with EUR and GBP in the same direction in order to make the average higher rather than in the opposite direction as in risk-off or flight-to-safety episodes. But their correlation estimates only involve four currencies excluding major risky currencies such as the Australian dollar, and the New Zealand dollar, which makes it difficult to make clear comparison.

Besides, we are also concerned about identifying specific episodes (risk off events) which do not seem to occur that often. We show the intimate linkage between our correlation regime-switching and well-known risk-off events, and we show the most pronounced effect on returns occurs during regime transitions while Mueller et al. (2012) focus more on the cross-sectional test of an unconditional asset pricing model featuring *average* correlation risk to explain the average excess return to the carry trade.

To sum up, although our results also tell a correlation risk story, but the economic content of our correlation regime switching differs from that of Mueller et al. (2012).

Exchange rate return and volatility shocks. Panel b, c, and d of Table 6 essentially reproduce the standard notion of volatility risk using such volatility proxies as the VIX index, the global FX volatility, and the FX implied volatility. The key message is that the carry trade crashes when volatility is unexpectedly high while the momentum seems to hedge volatility risk. [9] In the next three sections, we show richer volatility risk-return relationship uncovered by FX correlation regimes, or in risk-off versus non risk-off episodes.

4.3 Conditioning on the VIX

This section focuses on estimating equation (13) using the VIX index as a proxy for volatility. As is shown in Table 7, correlation regimes provide richer implications for volatility risk and currency returns than VIX alone. People may have presumed that when VIX is unexpectedly high, carry trade should lose. But our evidence suggests that it depends: if correlation shifts from the low regime to the high regime when VIX increases by one standard deviation, then the carry trade indeed loses 38 bps per day, whereas if correlation shifts from high to low when VIX moves up by one standard deviation, then the carry trade turns out to gain by nearly 100 bps. An investor learning from exchange rate correlation regimes beyond volatility news apparently has the edge.

The asset pricing literature has reconciled carry trade return by its exposure to volatility risk, e.g. Lustig et al. (2011) and Menkhoff et al. (2012). In this framework, carry trade is risky because of its negative volatility beta or in other words, when volatility is extraordinarily high, carry trade incurs losses; an average investor dislike volatility and therefore requires a compensation for taking on the volatility risk that carry trade is exposed to.

However, our evidence suggests the statement that carry trades have negative volatility beta is not without conditions. Again, the sign and magnitude of volatility beta depend on correlation regimes: when correlation shifts from the high regime to the low regime, volatility beta is strongly positive (carry trades hedge volatility risk!); further, when correlation stays in the low correlation regime, volatility beta is only slightly

[9] These results are most pronounced for the VIX and the FX implied volatility mainly because the shocks to the global FX volatility at the daily frequency is likely to be estimated inaccurately, as is highlighted in Section 4.5.

negative.

Hence, FX correlation regime refines the risk-return relationship: the volatility risk which the carry trade is exposed to is most severe in the risk-off episodes when correlation spikes from the low regime to the high regime, is modestly reduced when correlation persists in the high regime, is abruptly reversed to a superior hedge when correlation drops from the high regime to the low regime, and is of substantially smaller magnitude when correlation remains in the low regime.

The usefulness of correlation regimes is further highlighted by the adjusted R-squared. Panel b. of Table 6 shows that variation of VIX accounts for 8% of carry trade variations, which is consistent with the literature: although volatility risk proves successful in explaining the average carry trade return, the R^2 due to volatility variation is only modest. We find that the addition of correlation regime to the information set is able to boost the adjusted R^2 to 10%.

Moreover, our finding is also related to Verdelhan (2013) which documents large common variation of bilateral exchange rates. We find that the improvement of adjusted R-squared is more remarkable for high-yielding or investment currencies. Adjusted $R2$ for the high (H) interest rate portfolio increases from 4.6% with VIX alone to 8.6% with VIX interacted with correlation regime shifts.

The momentum strategy seems less sensitive to volatility shocks when correlation changes regime given the weakly positive and statistically insignificant coefficients. However, the positive volatility beta of the momentum strategy is concentrated in the persistent high correlation regime in which the past winner portfolio appreciates close to 10 bps a day relative to the loser portfolio.

Correlation along with VIX also accounts for the time series variation of momentum returns better than VIX alone, albeit less impressive than the R-squared improvement for the carry trade. The majority of improvement is achieved by currencies devalued in the past month: 2% for VIX only whereas nearly 5% for correlation and VIX combined.

4.4 Conditioning on the Global FX volatility.

We also conduct the same analysis using the standardized shock to the global FX volatility measure, proposed by Menkhoff et al. (2012), which is essentially the within-month time series average of cross-sectional mean absolute exchange rate returns of all currencies, developed countries as well as emerging countries.

As our analysis is in need of volatility shocks at the daily frequency, we modify the measurement by using 22-day moving average of cross sectional mean absolute exchange rate returns as the global FX volatility. Differing from Menkhoff et al. (2012) who proxy volatility shocks by the monthly residual of an AR(1) model for the FX volatility level, we use standardized the FX volatility shock as outlined by equation (14).

The results using standardized FX volatility shocks, shown in Table 8, are broadly consistent with what we find using standardized VIX shocks in Table 7. The volatility conditioning effect is to some extent stronger for the global FX volatility than the VIX as when the global FX volatility increases by one standard deviation in the risk-off episodes, the carry trade plunges by 123 bps a day, compared to the 38 bps drop when the VIX increases by one standard deviation in the risk-off episodes.

The evidence from individual bilateral exchange rates underscores more vividly that correlation implies richer characterization of currency returns beyond volatility or VIX alone. Popular investment currencies, such as the Australian dollar, New Zealand dollar, and Canadian dollar, all depreciate massively when correlation switches from the low regime to the high regime while widely-conceived safe heaven currency, the Japanese yen, typically appreciates in these episodes.

However, the increase in R-squared is less impressive when we compare correlation-volatility interactive effects with FX volatility alone, which underscores that it is difficult to uncover daily FX volatility shocks using only daily exchange rates.

4.5 Conditioning on the FX implied volatility.

To address the concern that the global (realized) FX volatility may lead to poor identification of volatility shocks on a daily basis, we further explore an alternative FX volatility measure, the *FX implied volatility*, which is the cross-sectional average implied volatility across major currencies on each day. And we measure the standardized FX implied volatility shock in the same way as is outlined by equation (14).

We find the implication of FX correlation-implied volatility interaction for currency returns is generally consistent with findings using the VIX and the global FX volatility. As Table 9 shows, it is exactly when the FX correlation switches from the low regime to the high regime that the carry trade collapses by 34 bps per day.

Aside from the effect on average return, interaction the FX implied volatility with FX correlation boosts the adjusted R-squared to even higher levels. Panel a of Table 5 suggests that the superior role of the FX implied volatility in describing time series variation is expected because the correlation of the FX implied volatility shock with the VIX shock and the global FX volatility shock is 0.35 and 0.19 respectively, whereas the correlation between the latter two volatility shocks is only 0.06.

4.6 More on the Correlation-Volatility Nexus

Volatility and correlation regime contains quite different information: 1) when correlation enters into the high regime from the low regime, it is not necessary that exchange rate volatilities rise in general (see Table 4); 2) the time series of volatility shocks are extremely noisy and covaries rather weakly with correlation regime transitions (see Table 5).

However, in this section, we aim to explore the relationship between volatility shocks and correlation regimes in greater detail in order to understand how the correlation regime helps refine the volatility risk story to explain the return to the carry trade. For this purpose, we simply regress standardized volatility shocks on the four joint probabilities of correlation regime transitions:

$$dV_t = \sum_{i,j \in \{H,L\}} \theta_{i,j} \, \mathrm{Prob}[\Delta_t = j, \, \Delta_{t-1} = i \, | \mathcal{F}_T] + \varepsilon_t \, , \tag{15}$$

where dV denotes the shock to the VIX, the global FX volatility, or the FX implied volatility.

The results for the regression equation (15) is presented in Panel b of Table 5. Despite the low correlation between volatility shocks and regime transition probabilities, volatility shocks exhibits some interesting dependence on correlation regimes. In particular, the risk-off episodes featuring the low-to-high correlation switch is strongly associated with large positive volatility news, regardless of the volatility proxy. That is, when correlation jump to the high regime from the low regime, volatility tends to surge by 1.31 to 1.55 standard deviations. This finding, combined with our findings in the previous three sections that the carry trade suffers the most severe loss during the low-to-high correlation transition, implies that volatility risk is more likely to be concentrated in the risk-off episodes.

By contrast, there is on average no significant volatility news during other correlation transitions: volatility shocks tend to be weakly negative when regime persists and weakly positive when regime shifts from high to low except that the global FX volatility increases by more than one standard deviation on average during a high-to-low correlation transition.

We proceed to show results of the regression of the absolute value of volatility shocks, a proxy for the size of volatility news, on correlation regime transition probabilities in Table 5, Panel c. It turns out that the risk-off episodes (low-to-high transition in correlation regime) not only tend to be associated with increasing volatility but also is more likely to see the most striking volatility news.

4.7 Cumulative return following a transition.

We have shown the strong dependence of returns to currency strategies on FX correlation regimes. In this section, we proceed to show how future returns are expected to evolve following a transition of FX correlation regime by examining how cumulative returns to the carry and momentum strategies depend on a transition of correlation regime. We assume that trading strategies start from day -1 and correlation state transits from day -1 to day 0, and we track cumulative returns from day -1 to day $h = 1, 2, \cdots, 60$.

We find that correlation regimes conveys important information to forecast future payoffs of currency speculations. Panel (e) of Figure 4 show that the carry trade experiences massive and significant losses following a shift from the low correlation regime to the high correlation regime. Specifically, after a drawdown of 49 bps on the day correlation switches from the low regime to the high regime, the carry trade continues its poor performance, ending up with a total loss of about 200 bps up to the 20th day and more than 500 bps by the 60th day. This continued carry downturn is contributed both by investment currency depreciation and financing currency appreciation of similar magnitude, as is shown in Panel (e) of Figure 5.

By contrast, the momentum strategy incurs only modestly negative returns over the first twenty days following the transition of correlation from the low regime to the high regime and then starts to obtain modest profits because the profit and loss of the winner portfolio and the loser portfolio reverse the sign on around day 30 (Panel (f) of Figure 5).

Additionally, a switch of correlation regime from the high to the low is followed by sizable gains from both the carry trade and the momentum strategies as can be seen in Panel (c) and (d) of Figure 4. A month or so after the correlation regime transition, the carry trade accumulates a return of 2% while the positive return of the momentum strategy seems to be short-lived and its cumulative return reaches the first peak of 1.5% on around the 10th day.

Future returns to the carry trade and the momentum strategies exhibit different patterns in the case of persisting correlation regimes. Panel (a) and (b) in Figure 4 show respectively that the carry trade sees statistically significant but modestly negative future returns whereas the momentum sees relatively small positive returns which are statistically insignificant when the high correlation regime prevails. The patterns start to reverse on about the twentieth day for both strategies.

When the low correlation regime continues, Panel (g) and (h) in Figure 4 show that both the carry trade and the momentum strategies tend to earn stable and positive future returns, especially for the momentum strategy which derives significant profits from appreciation.

Overall, FX correlation regimes, especially the switch of regime, carry important predictive information about currency returns.

5 Net Speculator Positions

In this section, we examine the implications of the FX correlation regime for speculators' net futures positions. The key variable, *net speculator position* for each futures contract, is contracted as long minus short position of non-commercial traders divided by the open interest of all traders.

To see how net speculator position evolves following a FX correlation transition, we regress the deviation of net speculator position at week $\tau = 1, 2 \cdots 10$ from its pre-event 11-week average onto the joint probability of regime transits from week $-\frac{1}{5}$ to week 0.

The findings are illustrated in Figure 6 for the case in which the high (low) correlation regime switches to the low (high) correlation regime. Consistent with our intuition that the high correlation regime signals the risk-off episodes, speculators tend to unwind futures net positions in risky currencies in this case: net position in the Australian dollar futures declines by 50% below its pre-event average.

By contrast, speculators start to load more safe currencies. Although the increase in Japanese yen net futures position is not strikingly large, but it seems very persistent. Moreover, net speculator position on the Swiss franc futures reaches more than 30% above its pre-event average following the low-to-high transition, and the effective net position on the US dollar continues to be 30%∼40% higher than its pre-event average.

Figure 7, on the other hand, shows how speculators adjust their futures positions the high correlation regime or the low correlation regime persists. The key message is that speculators maintain less (more) position on risky currencies and more (less) position on safe currencies when the high (low) correlation regime prevails.

6 Concluding Remarks

It is well received that volatility measures, for instance the VIX index, are ideal indicators for stressed financial market conditions such as the risk-on/off environments. In this paper, we identify risk-off episodes from regime-switching of foreign exchange rate correlations. We find the low-to-high transition of correlation regime is related to major risk-off events and we show that returns to currency investments depend strongly on the correlation regimes.

We proceed to show that the conventional dependence of returns on volatility is conditional on the correlation regime of the foreign exchange market. The returns to currency speculations strongly depend on the interaction between correlation regime switch and shift in volatility. We find higher volatility may not imply carry trade drawbacks; instead it is likely to be associated with positive returns when correlation drops from high regime to low regime. On the other hand, FX correlation does not have to be a bad risk for carry trade speculation as it matters whether volatility shifts upward or downward.

Next, we document that the time series variation of exchange rates and currency returns can be better accounted for using correlation regimes along with volatility. For example, VIX alone only accounts for 8% of carry trade variation; however, combining information about correlation regimes manages to increase the adjusted R-squared to 10%. Similar improvements are seen in individual bilateral exchange rate returns and currency momentum returns as well.

We conduct further analysis of long-run returns following correlation regime transitions and find that correlation regimes incorporate remarkable predictive information about future currency returns.

Finally, we examine net speculators position on currency futures during different correlation regime transitions and the evidence also supports the link between our correlation regime and risk-off episodes.

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Table 1: Correlation Regimes and Transition Probabilities (Daily; USD as the reference currency).
This table presents the regime-dependent correlations of the daily exchange rate returns of nine G10 currencies and the probability of regime transitions. In order to estimate a regime-switching model, we standardize the daily spot change of each currency by subtracting its full sample average and divide by its standard deviation forecasted by a GARCH(1,1) model. Panel (a) shows the correlation matrix in regime 1 (dubbed high correlation) and Panel (b) shows the correlation matrix in regime 2 (dubbed low correlation). The transition probability matrix and the expected duration of each regime are shown in Panel (c) and Panel (d) respectively. The sample is from 1995:1:3 to 2013:10:11.

a. Correlation when Corr=H

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
AUD	1.00								
CAD	0.70	1.00							
CHF	0.36	0.28	1.00						
EUR	0.64	0.55	0.69	1.00					
GBP	0.57	0.53	0.40	0.64	1.00				
JPY	-0.20	-0.20	0.37	0.11	-0.07	1.00			
NOK	0.74	0.64	0.53	0.82	0.60	-0.04	1.00		
NZD	0.86	0.63	0.34	0.60	0.55	-0.20	0.67	1.00	
SEK	0.69	0.61	0.56	0.87	0.60	-0.02	0.86	0.63	1.00

b. Correlation when Corr=L

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
AUD	1.00								
CAD	0.40	1.00							
CHF	0.33	0.18	1.00						
EUR	0.37	0.21	0.94	1.00					
GBP	0.36	0.20	0.64	0.65	1.00				
JPY	0.24	0.12	0.43	0.41	0.32	1.00			
NOK	0.36	0.23	0.78	0.83	0.57	0.35	1.00		
NZD	0.71	0.34	0.35	0.38	0.36	0.26	0.38	1.00	
SEK	0.38	0.26	0.73	0.78	0.54	0.32	0.77	0.36	1.00

c. Transition Probabilities / d. Duration

		t+1 H	t+1 L		# of days
t	H	0.9689	0.0311	H	33
t	L	0.0091	0.9909	L	110

Table 2: Risk-off Episodes.

This table presents risk-off episodes and events identified as days with the probability of correlation regime switching from Low to High larger than 0.2.

	Date	$P(H)$	$P(L \to H)$	Risk-off episodes
Uncertainty over TIPS	18-Dec-1996	0.28	0.22	Bias of CPI leads to uncertainty over the design of TIPS to be introduced in 1997.
Asian Financial Crisis	26-May-1997	0.34	0.34	Thailand baht under speculative attacks
	28-May-1997	0.96	0.43	
	8-Oct-1997	0.30	0.20	Indonesia seeks for IMF and Work Bank help after its central bank intervention fails to avoid Rupiah's devaluation.
	9-Oct-1997	0.99	0.69	
	19-May-1998	0.33	0.31	Indonesia political disturbance; IMF aid postphoned.
	20-May-1998	0.62	0.29	
Russian Turmoil	24-Aug-1998	0.22	0.22	Politicial instability as Yeltsin dismisses government.
	25-Aug-1998	0.42	0.20	Ruble falls sharply; trade in the currency suspended.
	26-Aug-1998	0.66	0.23	
	27-Aug-1998	1.00	0.34	Russian crisis spills over to world markets, pushing US Treasuries yield to record lows; LTCM collapses.
Dot-com Bubble Burst	11-Sep-2000	1.00	0.88	NASDAQ starts to fall sharply.
	20-Sep-2001	0.32	0.32	US President Bush Declares War on Terror (9/11)
	21-Sep-2001	1.00	0.68	Nasdaq hits 1,423.19. FTSE Techmark hits record low of 1,064.98.
	24-Dec-2001	1.00	0.96	DJIA hits 8,235.81 one day before.
	16-Jan-2002	0.25	0.22	Worldcom Scandal (Worldcom goes bankrupt in July)
	30-Apr-2003	0.67	0.48	Equity markets reach bottom.
Credit Crunch and Downturn	22-Feb-2007	0.47	0.23	Freddie Mac officially terminates the purchase of subprime mortgages and related securities. 27 Feb
	31-Jul-2007	0.86	0.42	Bear Sterns liquidates two hedge funds that invested in various types of MBS's.
	7-Aug-2008	0.76	0.61	AHMIQ files for bankruptcy (6 Aug.); highest jobless claims in 6 years; AIG reports $11.6bn investment losses.
	8-Aug-2008	0.96	0.20	Fannie Mae reports a $2.3bn loss, much larger than expected.
	10-Oct-2008	1.00	0.23	Financial crisis reaches peak after Lehman Bro. bankruptcy and AIG bailout.
	23-Mar-2009	0.62	0.34	US Treasury and the Fed launch TALF to help boost lending and the economy.
	15-Jun-2009	0.49	0.20	President Barack Obama proposes a major overhaul of the U.S. financial system.
	18-Jun-2009	0.89	0.25	World economy is near the bottom of the worst recession in post-war history (OECD:Jun.24)
Europe Debt Crisis	28-Oct-2009	0.82	0.39	EU debt concerns start to grow following Dubai sovereign debt crisis.
	31-Dec-2009	0.51	0.25	Greece is downgraded as its debt amounts to 113% of GDP.
	12-Mar-2010	0.72	0.24	Greek auterity plan leads to social riots; euro continues to fall against the dollar and the pound.
	6-May-2010	1.00	0.32	EU/IMF agrees a 110bn-euro bailout package for Greece; Ireland's debt starts to come under scrutiny.
	3-Mar-2011	1.00	0.65	ECB shocks analyst with warns of interest rate increase that could bankrupt Ireland and Portugal.
	5-Aug-2011	0.67	0.64	EU Commission President Barroso warns that the crisis is spreading beyond the eurozone periphery (Aug.5)
	8-Aug-2011	1.00	0.33	US is downgraded to AA+ by S&P (Aug.7)
	17-May-2012	0.29	0.22	Fears of Greece euro exit and double-dip recession grow.
	9-Jan-2013	0.40	0.21	Eurozone unemployment rate hits new high; Germany threatens to block Cyprus bailout.
	11-Jan-2013	0.80	0.28	Cyprus awaits the 17bn-euro bailout.
	25-Feb-2013	0.42	0.31	US stock market drops as Italy election reignites fears of europe debt crisis; the eurozone recession is set to continue.
	26-Feb-2013	0.96	0.55	
"Taper Tantrums"	17-May-2013	0.52	0.25	Fed SF President J. Williams: the Fed may start tapering the stimulus program if job market keeps improving.
	21-May-2013	0.96	0.26	Ben Bernanke suggests gradually reducing or tapering the Federal Reserve Boards monetary expansion

Note: Events are sourced from BBC, Bloomberg, Fed St. Louis, Financial Times, PBS, The Guardian, Wall Street Journal.

Table 3: Regime-dependent Principle Components.
This table reports statistics regarding the variance ratio of principles components over the total variance, given our estimated correlation regimes. The variance ratio of PC(1) in the high correlation regime, VR_H (VR_L), is calculated as the sum of the largest $i = 1, 2, 3$ eigenvalues over the sum of all eigenvalues of the covariance matrix in the high (low) regime using our estimated regime-dependent correlation matrix and GARCH estimates for variances. The first row reports the total number of observations (# of trading days). The second row shows the number of days when variance ratio in the high correlation regime is smaller than in the low correlation regime. The third row shows the probability that variance ratio in the high correlation regime is smaller than in the low correlation regime, the fourth row the probability conditional on the high correlation regime, and the fifth row the probability conditional on low correlation regime. The sixth row shows the average wedge of variance ratios between the high correlation regime and the low correlation regime. Row 10 and 11, reports average wedge of variance ratios across the two correlation regimes conditional on the economy is actually in high correlation regime and low correlation regime, respectively. The column for 'PC(1)' reports variance ratios based on the first principle component, the column for 'PC(1,2)' the first two principle components, and the column for 'PC(1,2,3)' the first three principle components.

	$PC(1)$	$PC(1,2)$	$PC(1,2,3)$
# of Obs. (days)	4899	4899	4899
# of $VR_H < VR_L$	1208	141	44
$P[VR_H < VR_L]$	0.25	0.03	0.01
$P[VR_H < VR_L \mid H]$	0.03	0.00	0.00
$P[VR_H < VR_L \mid L]$	0.31	0.03	0.01
$E[VR_H - VR_L]$	0.05	0.05	0.03
$E[VR_H - VR_L \mid H]$	0.11	0.06	0.04
$E[VR_H - VR_L \mid L]$	0.03	0.05	0.03

Table 4: Regime-dependent Volatility of Cross-rates.

This table presents regime-dependent volatilities of cross rates, given our estimated regime-switching model for the correlation matrix and GARCH forecasts for the USD-based bilateral rate volatilities. The numbers are reported in the unit of basis points per day.

a. Cross Rates Volatility Difference: $(\sigma_H - \sigma_L)$ bps

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD
AUD								
CAD	-17							
CHF	-2	-4						
EUR	-18	-16	28					
GBP	-12	-14	14	1				
JPY	21	12	4	16	17			
NOK	-28	-21	21	1	-1	20		
NZD	-17	-16	1	-14	-11	23	-21	
SEK	-23	-18	13	-10	-4	18	-11	-19

b. USD-denominated Exchange Rate Volatiilty: bps

	σ_H	σ_L	$\sigma_H - \sigma_L$
AUD	102	64	38
CAD	75	40	35
CHF	77	65	12
EUR	70	59	11
GBP	66	49	17
JPY	72	67	5
NOK	94	64	30
NZD	107	68	39
SEK	94	63	31

c. Cross Rates Volatility in Regime H: $(\sigma_H - \sigma_L)$ bps

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD
AUD								
CAD	-26							
CHF	-2	-6						
EUR	-21	-22	31					
GBP	-15	-20	17	1				
JPY	25	16	4	17	20			
NOK	-39	-32	25	2	-2	24		
NZD	-24	-24	1	-17	-14	28	-29	
SEK	-30	-27	16	-12	-5	21	-14	-26

d. Cross Rates Volatility in Regime L: $(\sigma_H - \sigma_L)$ bps

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD
AUD								
CAD	-14							
CHF	-2	-4						
EUR	-17	-14	27					
GBP	-11	-12	13	1				
JPY	20	11	4	15	16			
NOK	-25	-18	20	1	-1	19		
NZD	-15	-13	1	-13	-10	22	-19	
SEK	-20	-15	13	-9	-4	17	-10	-17

Note: All estimates are statistically significant at the level of 1%

Table 5: Correlation Regime Transitions and Volatility Shocks.
This table shows the dependence between the estimated regime probabilities and shocks to the VIX index, the global FX volatility, and the FX implied volatility, measured by standardized first differences. Each volatility innovation is standardized by subtracting the full sample average and dividing the residual by the full sample standard deviation. The sample spans from 1995:1:3 to 2013:10:11. Panel a. shows the correlation between regime transition probabilities and volatility shocks. Panel b. shows the dependence of volatility shocks on correlation regimes. Panel c. shows the dependence of the size of volatility shock s, or the absolute value of volatility shocks, on correlation regimes.

a. Correlation between Regime Probabilities and Volatility Shocks

	P(H)	P(L→H)	dVIX	dFXVOL	dFXIV
P(H)	1.00				
P(L→H)	0.14	1.00			
dVIX	0.00	0.05	1.00		
dFXVOL	0.02	0.05	0.06	1.00	
dFXIV	0.01	0.06	0.35	0.19	1.00

b. Regime-dependence of Volatility Shocks

		P(H→H)	P(H→L)	P(L→H)	P(L→L)
(1)	dVIX	-0.03	0.15	1.31	-0.01
	s.e.	(0.03)	(0.34)	(0.36)	(0.02)
(2)	dFXVOL	0.00	1.04	1.32	-0.02
	s.e.	(0.03)	(0.34)	(0.36)	(0.02)
(3)	dFXIV	-0.01	0.39	1.55	-0.02
	s.e.	(0.03)	(0.34)	(0.36)	(0.02)

c. Regime-dependence of the Size of Volatility Shocks

		P(H→H)	P(H→L)	P(L→H)	P(L→L)
(1)	|dVIX|	0.99	0.20	1.29	0.50
	s.e.	(0.03)	(0.26)	(0.27)	(0.12)
(2)	|dFXVOL|	0.93	1.21	1.23	0.61
	s.e.	(0.02)	(0.24)	(0.25)	(0.01)
(3)	|dFXIV|	1.08	0.53	1.13	0.50
	s.e.	(0.02)	(0.25)	(0.26)	(0.01)

Note: We use P(i→j) to denote the joint probability Prob($\Delta_t = j$, $\Delta_{t-1} = i \,|\mathcal{F}_T$).

Table 6: Average Return during State Transition (Daily; USD as the reference currency).

This table presents the average returns on G10 bilateral exchange rates against the dollar, the carry trade, and the FX momentum strategy during transitions between correlation states. We regress daily return $r_{t-1,t}$ on state-transition indicators: in Panel (a), the regressor is the smoothed joint probabilities of regimes on day $t-1$ and day t implied by our regime-switching dynamic correlation model; in Panel (b) (c) (d), the regressors are the standardized shocks to the VIX index, the global FX volatility measure and the FX implied volatility, respectively. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

			a. Corr. Regimes					b. VIX shocks		c. FXVOL shocks		c. FXIV shocks	
Strategy		stats	H-H	H-L	L-H	L-L	adj.R2	dVIX_s	R2	dFXVOL_s	R2	dFXIV_s	R2
bilateral	AUD	_b_	**0.73**	**54.39**	**-73.00**	**0.46**	0.15%	**-18.30**	5.39%	**-2.46**	0.08%	**-25.01**	10.09%
		_se_	(2.55)	(26.45)	(28.04)	(1.31)		(1.09)		(1.12)		(1.07)	
	CAD	_b_	**0.52**	**30.98**	**-69.33**	**1.03**	0.29%	**-11.12**	4.48%	**0.22**	-0.02%	**-13.29**	6.40%
		_se_	(1.70)	(17.62)	(18.68)	(0.87)		(0.73)		(0.75)		(0.73)	
	CHF	_b_	**1.48**	**61.78**	**-22.75**	**0.20**	0.10%	**4.75**	0.45%	**5.58**	0.63%	**4.57**	0.41%
		_se_	(2.25)	(23.37)	(24.78)	(1.16)		(0.99)		(0.99)		(0.99)	
	EUR	_b_	**-0.62**	**57.26**	**-48.17**	**0.26**	0.17%	**-2.66**	0.16%	**3.17**	0.24%	**-4.43**	0.48%
		_se_	(2.03)	(21.07)	(22.33)	(1.05)		(0.90)		(0.89)		(0.89)	
	GBP	_b_	**-3.70**	**68.30**	**-11.66**	**0.62**	0.28%	**-3.83**	0.46%	**2.32**	0.15%	**-8.57**	2.37%
		_se_	(1.79)	(18.63)	(19.74)	(0.92)		(0.79)		(0.79)		(0.78)	
	JPY	_b_	**5.36**	**-6.39**	**23.80**	**-1.66**	0.10%	**10.71**	2.30%	**5.09**	0.50%	**19.35**	7.56%
		_se_	(2.28)	(23.66)	(25.08)	(1.17)		(0.99)		(1.00)		(0.97)	
	NOK	_b_	**-1.41**	**106.64**	**-101.56**	**0.67**	0.63%	**-8.57**	1.34%	**0.82**	-0.01%	**-12.66**	2.94%
		_se_	(2.38)	(24.67)	(26.15)	(1.22)		(1.05)		(1.05)		(1.04)	
	NZD	_b_	**-0.62**	**51.46**	**-52.73**	**0.89**	0.07%	**-16.62**	4.20%	**-0.68**	-0.01%	**-20.56**	6.44%
		_se_	(2.62)	(27.20)	(28.83)	(1.35)		(1.13)		(1.16)		(1.12)	
	SEK	_b_	**0.24**	**86.98**	**-103.16**	**0.49**	0.49%	**-9.49**	1.63%	**2.20**	0.07%	**-12.36**	2.78%
		_se_	(2.39)	(24.82)	(26.31)	(1.23)		(1.05)		(1.06)		(1.04)	
carry	HML	_b_	**-2.48**	**34.14**	**-48.55**	**0.81**	0.15%	**-16.56**	8.00%	**-5.45**	0.85%	**-24.28**	17.22%
		_se_	(1.89)	(19.67)	(20.85)	(0.98)		(0.80)		(0.83)		(0.76)	
	L	_b_	**1.87**	**37.66**	**-15.44**	**-0.31**	0.06%	**2.57**	0.21%	**4.67**	0.75%	**4.75**	0.78%
		_se_	(1.72)	(17.90)	(18.97)	(0.89)		(0.76)		(0.76)		(0.76)	
	M	_b_	**-0.60**	**61.00**	**-73.44**	**0.81**	0.48%	**-6.93**	1.64%	**1.52**	0.06%	**-9.54**	3.12%
		_se_	(1.74)	(18.05)	(19.14)	(0.90)		(0.76)		(0.77)		(0.76)	
	H	_b_	**-0.61**	**71.80**	**-63.99**	**0.50**	0.31%	**-14.00**	4.62%	**-0.77**	-0.01%	**-19.53**	9.03%
		_se_	(2.10)	(21.82)	(23.13)	(1.08)		(0.91)		(0.93)		(0.89)	
mom1	HML	_b_	**-1.02**	**24.57**	**6.76**	**0.68**	-0.02%	**6.33**	1.34%	**-0.96**	0.01%	**8.12**	2.21%
		_se_	(1.76)	(18.30)	(19.39)	(0.91)		(0.77)		(0.78)		(0.77)	
	L	_b_	**0.48**	**38.96**	**-45.06**	**-0.13**	0.09%	**-9.30**	2.43%	**2.06**	0.10%	**-11.85**	3.97%
		_se_	(1.92)	(19.97)	(21.17)	(0.99)		(0.84)		(0.85)		(0.83)	
	M	_b_	**0.72**	**67.96**	**-69.50**	**0.58**	0.46%	**-6.10**	1.18%	**2.28**	0.15%	**-8.73**	2.43%
		_se_	(1.80)	(18.71)	(19.83)	(0.93)		(0.79)		(0.80)		(0.79)	
	H	_b_	**-0.54**	**63.53**	**-38.31**	**0.55**	0.24%	**-2.96**	0.26%	**1.09**	0.02%	**-3.73**	0.42%
		_se_	(1.82)	(18.91)	(20.04)	(0.94)		(0.80)		(0.80)		(0.80)	

Table 7: Average Return during Interactive Transitions of Correlation Regimes and VIX Changes (Daily; USD as the reference currency).

This table presents the average returns on G10 bilateral exchange rates against the dollar, the carry trade, and the FX momentum strategy during transitions between correlation states and their interaction with VIX innovations. We regress daily return $r_{t-1,t}$ on both the smoothed joint probabilities of regimes on day $t-1$ and day t implied by our regime-switching dynamic correlation model and the products of these probabilities with the standardized VIX shock. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

Strategy		stats	H-H	H-L	L-H	L-L	(H-H)*v	(H-L)*v	(L-H)*v	(L-L)*v	adj.R2
bilateral	AUD	_b_	**0.20**	**33.86**	**-40.40**	**0.44**	**-27.48**	**200.94**	**-30.29**	**-8.16**	7.82%
		_se_	(2.45)	(25.64)	(27.61)	(1.26)	(1.51)	(30.36)	(16.40)	(1.69)	
	CAD	_b_	**0.18**	**24.56**	**-48.29**	**0.99**	**-16.24**	**66.86**	**-22.45**	**-4.68**	6.05%
		_se_	(1.65)	(17.25)	(18.58)	(0.85)	(1.02)	(20.43)	(11.03)	(1.14)	
	CHF	_b_	**1.48**	**50.56**	**-34.74**	**0.30**	**-2.06**	**105.94**	**28.70**	**11.70**	1.67%
		_se_	(2.23)	(23.39)	(25.19)	(1.15)	(1.38)	(27.70)	(14.96)	(1.54)	
	EUR	_b_	**-0.81**	**44.90**	**-41.91**	**0.30**	**-11.43**	**120.70**	**0.47**	**7.43**	2.82%
		_se_	(2.00)	(20.96)	(22.58)	(1.03)	(1.24)	(24.83)	(13.41)	(1.38)	
	GBP	_b_	**-3.90**	**57.22**	**-5.20**	**0.66**	**-11.12**	**108.27**	**1.27**	**4.18**	2.93%
		_se_	(1.77)	(18.54)	(19.96)	(0.91)	(1.09)	(21.95)	(11.85)	(1.22)	
	JPY	_b_	**5.74**	**-16.52**	**-1.81**	**-1.53**	**13.96**	**85.00**	**38.28**	**4.63**	2.95%
		_se_	(2.25)	(23.52)	(25.33)	(1.16)	(1.39)	(27.85)	(15.04)	(1.55)	
	NOK	_b_	**-1.71**	**84.63**	**-81.14**	**0.71**	**-19.18**	**212.09**	**-20.57**	**3.57**	5.24%
		_se_	(2.32)	(24.30)	(26.17)	(1.20)	(1.43)	(28.78)	(15.54)	(1.60)	
	NZD	_b_	**-1.13**	**29.87**	**-28.64**	**0.91**	**-25.92**	**209.99**	**-11.25**	**-7.14**	6.41%
		_se_	(2.54)	(26.55)	(28.60)	(1.31)	(1.57)	(31.45)	(16.98)	(1.75)	
	SEK	_b_	**-0.16**	**71.41**	**-92.94**	**0.53**	**-19.06**	**153.04**	**8.22**	**0.87**	4.26%
		_se_	(2.34)	(24.55)	(26.44)	(1.21)	(1.45)	(29.08)	(15.70)	(1.62)	
carry	HML	_b_	**-2.96**	**24.49**	**-16.03**	**0.75**	**-22.89**	**99.15**	**-38.06**	**-8.74**	9.98%
		_se_	(1.80)	(18.84)	(20.29)	(0.93)	(1.11)	(22.31)	(12.05)	(1.24)	
	L	_b_	**1.90**	**26.35**	**-24.64**	**-0.23**	**-1.09**	**104.76**	**22.96**	**5.51**	1.07%
		_se_	(1.72)	(17.96)	(19.35)	(0.88)	(1.06)	(21.27)	(11.49)	(1.19)	
	M	_b_	**-0.88**	**49.63**	**-59.72**	**0.82**	**-14.43**	**112.26**	**-10.40**	**1.87**	4.74%
		_se_	(1.70)	(17.82)	(19.19)	(0.88)	(1.05)	(21.10)	(11.39)	(1.18)	
	H	_b_	**-1.06**	**50.84**	**-40.67**	**0.52**	**-23.99**	**203.91**	**-15.10**	**-3.24**	8.60%
		_se_	(2.01)	(21.07)	(22.70)	(1.04)	(1.24)	(24.96)	(13.48)	(1.39)	
mom1	HML	_b_	**-0.77**	**23.38**	**-2.68**	**0.71**	**9.64**	**5.56**	**5.37**	**2.09**	1.69%
		_se_	(1.75)	(18.30)	(19.70)	(0.90)	(1.08)	(21.67)	(11.70)	(1.21)	
	L	_b_	**0.12**	**26.41**	**-31.34**	**-0.12**	**-17.40**	**124.36**	**-3.48**	**-0.35**	4.95%
		_se_	(1.88)	(19.65)	(21.16)	(0.97)	(1.16)	(23.27)	(12.56)	(1.30)	
	M	_b_	**0.48**	**50.63**	**-59.68**	**0.63**	**-14.34**	**166.64**	**-0.95**	**2.75**	4.90%
		_se_	(1.76)	(18.44)	(19.86)	(0.91)	(1.09)	(21.84)	(11.80)	(1.22)	
	H	_b_	**-0.64**	**49.79**	**-34.02**	**0.60**	**-7.76**	**129.92**	**1.88**	**1.74**	1.79%
		_se_	(1.81)	(18.92)	(20.38)	(0.93)	(1.12)	(22.41)	(12.10)	(1.25)	

Table 8: Average Return during Interactive Transitions of Correlation Regimes and the Global FX Volatility Changes (Daily; USD as the reference currency).

This table presents the average returns on G10 bilateral exchange rates against the dollar, the carry trade, and the FX momentum strategy during transitions between correlation states and their interaction with FX volatility innovations. We regress daily return $r_{t-1,t}$ on both the smoothed joint probabilities of regimes on day $t-1$ and day t implied by our regime-switching dynamic correlation model and the products of these probabilities with the standardized global FX volatility shock. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

Strategy		stats	H-H	H-L	L-H	L-L	(H-H)*v	(H-L)*v	(L-H)*v	(L-L)*v	adj.R2
bilateral	AUD	_b_	**1.17**	**-7.42**	**33.04**	**0.28**	**-3.01**	**69.88**	**-184.24**	**-0.46**	1.79%
		_se_	(2.53)	(29.07)	(31.33)	(1.30)	(1.86)	(13.98)	(25.54)	(1.50)	
	CAD	_b_	**0.70**	**-1.40**	**-19.06**	**0.96**	**2.00**	**36.48**	**-90.91**	**-0.05**	1.12%
		_se_	(1.69)	(19.44)	(20.96)	(0.87)	(1.24)	(9.35)	(17.08)	(1.00)	
	CHF	_b_	**1.95**	**6.26**	**-20.19**	**0.47**	**4.47**	**61.20**	**-12.22**	**5.41**	1.08%
		_se_	(2.24)	(25.77)	(27.78)	(1.16)	(1.65)	(12.40)	(22.64)	(1.33)	
	EUR	_b_	**-0.20**	**3.48**	**-5.71**	**0.35**	**1.80**	**59.73**	**-78.97**	**4.34**	1.26%
		_se_	(2.02)	(23.21)	(25.02)	(1.04)	(1.49)	(11.17)	(20.39)	(1.20)	
	GBP	_b_	**-3.31**	**22.05**	**9.53**	**0.75**	**1.77**	**51.45**	**-40.91**	**2.29**	0.99%
		_se_	(1.79)	(20.56)	(22.17)	(0.92)	(1.32)	(9.89)	(18.07)	(1.06)	
	JPY	_b_	**5.74**	**-44.34**	**-9.46**	**-1.34**	**3.43**	**41.45**	**52.23**	**4.59**	0.78%
		_se_	(2.27)	(26.12)	(28.16)	(1.17)	(1.67)	(12.57)	(22.95)	(1.35)	
	NOK	_b_	**-0.50**	**-0.70**	**-18.48**	**0.78**	**-0.91**	**120.18**	**-148.33**	**2.09**	3.13%
		_se_	(2.35)	(26.99)	(29.09)	(1.21)	(1.73)	(12.99)	(23.71)	(1.39)	
	NZD	_b_	**-0.00**	**-27.36**	**21.20**	**0.89**	**0.10**	**88.65**	**-131.61**	**-0.82**	1.29%
		_se_	(2.61)	(29.96)	(32.29)	(1.34)	(1.92)	(14.41)	(26.32)	(1.54)	
	SEK	_b_	**0.84**	**11.06**	**-49.93**	**0.60**	**2.33**	**84.81**	**-98.43**	**2.21**	1.67%
		_se_	(2.38)	(27.34)	(29.46)	(1.23)	(1.75)	(13.15)	(24.02)	(1.41)	
carry	HML	_b_	**-2.24**	**1.52**	**24.81**	**0.60**	**-4.66**	**37.68**	**-123.27**	**-4.84**	2.06%
		_se_	(1.88)	(21.59)	(23.27)	(0.97)	(1.38)	(10.38)	(18.96)	(1.11)	
	L	_b_	**2.28**	**-9.51**	**-14.02**	**-0.09**	**3.41**	**51.97**	**-8.72**	**4.74**	1.27%
		_se_	(1.72)	(19.71)	(21.25)	(0.88)	(1.26)	(9.48)	(17.32)	(1.02)	
	M	_b_	**-0.20**	**4.69**	**-16.48**	**0.83**	**1.84**	**62.98**	**-103.76**	**1.91**	2.07%
		_se_	(1.73)	(19.84)	(21.39)	(0.89)	(1.27)	(9.55)	(17.43)	(1.02)	
	H	_b_	**0.05**	**-7.99**	**10.79**	**0.51**	**-1.25**	**89.65**	**-131.99**	**-0.11**	2.31%
		_se_	(2.08)	(23.93)	(25.80)	(1.07)	(1.53)	(11.51)	(21.03)	(1.23)	
mom1	HML	_b_	**-0.78**	**4.91**	**-4.51**	**0.77**	**-1.39**	**22.12**	**20.94**	**-1.61**	0.08%
		_se_	(1.76)	(20.26)	(21.84)	(0.91)	(1.30)	(9.75)	(17.80)	(1.04)	
	L	_b_	**0.79**	**-7.62**	**7.77**	**-0.13**	**2.58**	**52.01**	**-97.13**	**2.38**	1.13%
		_se_	(1.92)	(22.01)	(23.72)	(0.99)	(1.41)	(10.59)	(19.34)	(1.13)	
	M	_b_	**1.34**	**-2.49**	**-30.75**	**0.73**	**0.22**	**78.47**	**-71.16**	**3.39**	2.18%
		_se_	(1.79)	(20.55)	(22.15)	(0.92)	(1.32)	(9.88)	(18.05)	(1.06)	
	H	_b_	**0.00**	**-2.70**	**3.27**	**0.65**	**1.19**	**74.13**	**-76.18**	**0.77**	1.65%
		_se_	(1.81)	(20.80)	(22.42)	(0.93)	(1.33)	(10.01)	(18.27)	(1.07)	

Table 9: Average Return during Interactive Transitions of Correlation Regimes and the FX Implied Volatility Changes (Daily; USD as the reference currency).

This table presents the average returns on G10 bilateral exchange rates against the dollar, the carry trade, and the FX momentum strategy during transitions between correlation states and their interaction with FX volatility innovations. We regress daily return $r_{t-1,t}$ on both the smoothed joint probabilities of regimes on day $t-1$ and day t implied by our regime-switching dynamic correlation model and the products of these probabilities with the standardized FX implied volatility changes. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

Strategy		stats	H-H	H-L	L-H	L-L	(H-H)*v	(H-L)*v	(L-H)*v	(L-L)*v	adj.R2
bilateral	AUD	_b_	**0.78**	**30.19**	**-5.61**	**0.25**	**-38.60**	**93.67**	**-58.59**	**-8.23**	14.12%
		_se_	(2.36)	(25.53)	(28.00)	(1.22)	(1.49)	(23.96)	(17.59)	(1.62)	
	CAD	_b_	**0.60**	**12.84**	**-30.25**	**0.90**	**-18.97**	**67.51**	**-38.36**	**-6.10**	8.50%
		_se_	(1.63)	(17.57)	(19.27)	(0.84)	(1.02)	(16.48)	(12.10)	(1.11)	
	CHF	_b_	**1.67**	**39.86**	**-25.13**	**0.39**	**-2.31**	**74.66**	**3.92**	**12.39**	1.67%
		_se_	(2.23)	(24.13)	(26.46)	(1.15)	(1.41)	(22.64)	(16.62)	(1.53)	
	EUR	_b_	**-0.49**	**37.79**	**-18.14**	**0.28**	**-14.07**	**69.98**	**-33.02**	**7.86**	3.81%
		_se_	(1.99)	(21.52)	(23.60)	(1.03)	(1.25)	(20.19)	(14.82)	(1.36)	
	GBP	_b_	**-3.64**	**53.79**	**11.01**	**0.62**	**-17.48**	**54.17**	**-14.78**	**1.90**	5.66%
		_se_	(1.75)	(18.85)	(20.68)	(0.90)	(1.10)	(17.69)	(12.99)	(1.19)	
	JPY	_b_	**5.49**	**-11.29**	**-5.29**	**-1.33**	**18.05**	**10.46**	**19.11**	**21.13**	7.62%
		_se_	(2.19)	(23.67)	(25.96)	(1.13)	(1.38)	(22.21)	(16.30)	(1.50)	
	NOK	_b_	**-1.13**	**62.15**	**-60.32**	**0.71**	**-24.99**	**158.32**	**-36.20**	**1.71**	7.58%
		_se_	(2.29)	(24.76)	(27.16)	(1.18)	(1.44)	(23.23)	(17.06)	(1.57)	
	NZD	_b_	**-0.48**	**18.02**	**-13.50**	**0.83**	**-33.57**	**123.35**	**-19.21**	**-6.14**	9.64%
		_se_	(2.49)	(26.92)	(29.53)	(1.29)	(1.57)	(25.26)	(18.54)	(1.71)	
	SEK	_b_	**0.43**	**53.68**	**-66.46**	**0.48**	**-21.14**	**119.27**	**-32.81**	**-2.02**	5.34%
		_se_	(2.33)	(25.19)	(27.63)	(1.20)	(1.47)	(23.64)	(17.35)	(1.60)	
carry	HML	_b_	**-2.48**	**16.73**	**-1.29**	**0.57**	**-30.83**	**68.66**	**-33.56**	**-16.94**	19.04%
		_se_	(1.71)	(18.43)	(20.21)	(0.88)	(1.07)	(17.29)	(12.69)	(1.17)	
	L	_b_	**2.00**	**23.45**	**-15.05**	**-0.16**	**-1.20**	**48.09**	**-1.97**	**11.95**	2.32%
		_se_	(1.70)	(18.41)	(20.19)	(0.88)	(1.07)	(17.27)	(12.68)	(1.17)	
	M	_b_	**-0.45**	**35.36**	**-39.85**	**0.79**	**-17.80**	**92.28**	**-32.48**	**0.55**	6.96%
		_se_	(1.68)	(18.17)	(19.92)	(0.87)	(1.06)	(17.04)	(12.51)	(1.15)	
	H	_b_	**-0.47**	**40.19**	**-16.34**	**0.41**	**-32.03**	**116.75**	**-35.53**	**-4.99**	14.08%
		_se_	(1.95)	(21.08)	(23.12)	(1.01)	(1.23)	(19.78)	(14.52)	(1.34)	
mom1	HML	_b_	**-0.85**	**9.82**	**0.50**	**0.77**	**13.08**	**46.45**	**-8.17**	**1.98**	3.16%
		_se_	(1.73)	(18.74)	(20.55)	(0.90)	(1.09)	(17.58)	(12.91)	(1.19)	
	L	_b_	**0.52**	**24.86**	**-12.24**	**-0.18**	**-22.41**	**54.29**	**-24.77**	**1.06**	7.83%
		_se_	(1.85)	(19.96)	(21.89)	(0.95)	(1.16)	(18.73)	(13.75)	(1.26)	
	M	_b_	**0.89**	**39.47**	**-47.27**	**0.65**	**-19.29**	**102.10**	**-12.28**	**3.41**	7.31%
		_se_	(1.74)	(18.79)	(20.60)	(0.90)	(1.09)	(17.63)	(12.94)	(1.19)	
	H	_b_	**-0.33**	**34.68**	**-11.74**	**0.59**	**-9.33**	**100.73**	**-32.94**	**3.04**	2.52%
		_se_	(1.80)	(19.45)	(21.33)	(0.93)	(1.13)	(18.25)	(13.40)	(1.23)	

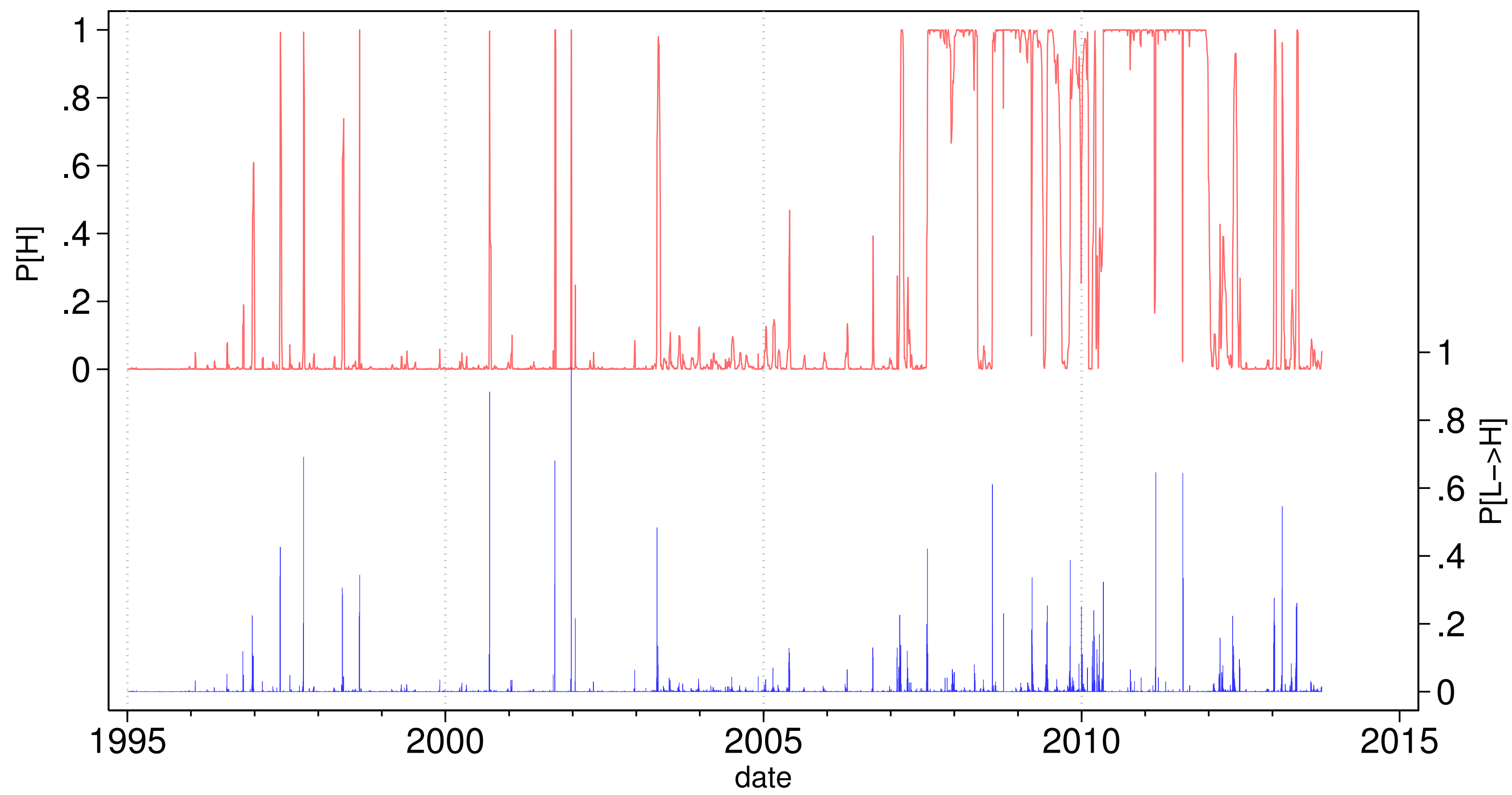


Figure 1: Probability of Correlation Regimes (Daily; USD as the reference currency).
This figure plots the time series of the full sample smoothed probability of the high correlation regime and the full sample smoothed joint probability of high correlation regime on day t and low correlation regime on day $t-1$. The sample spans from 1995:1:3 to 2013:10:11.

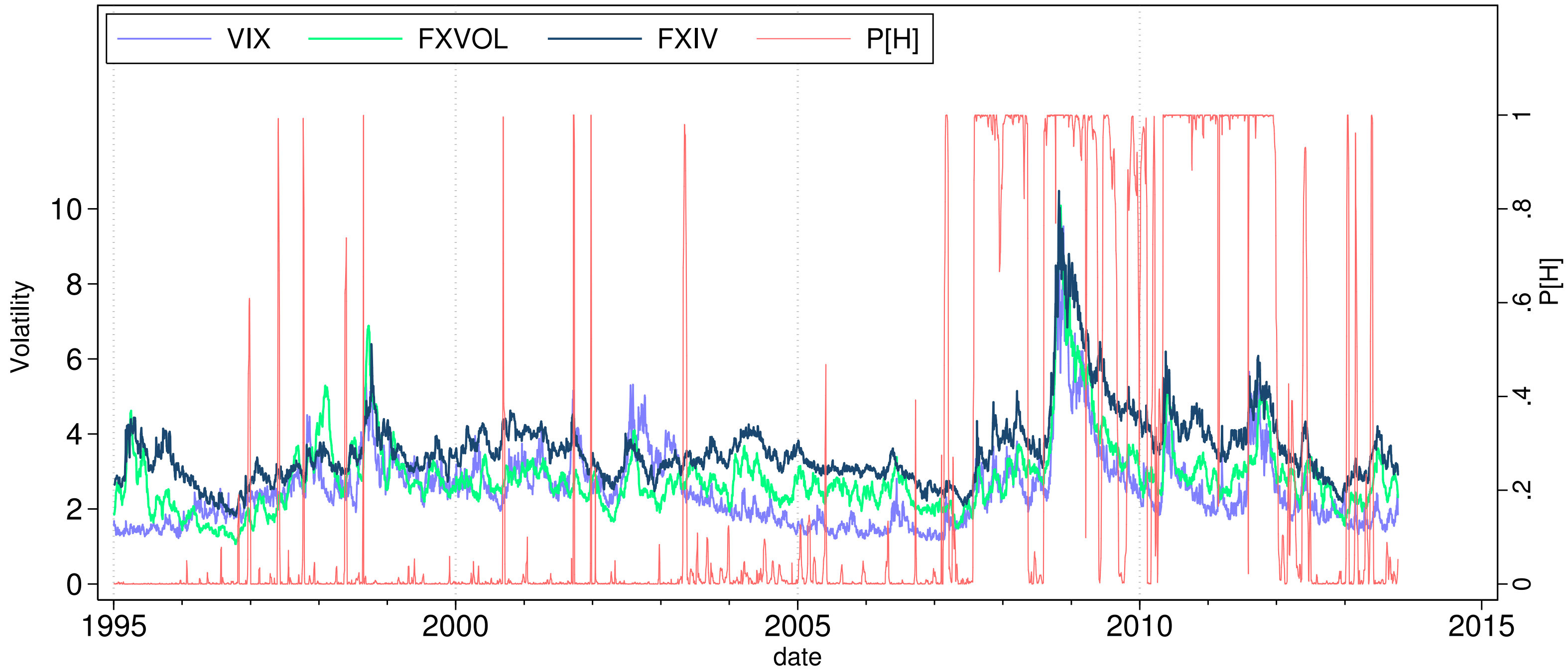
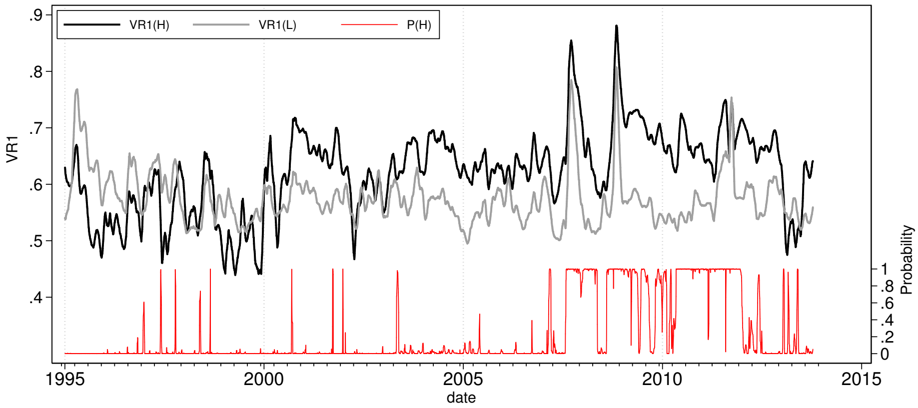
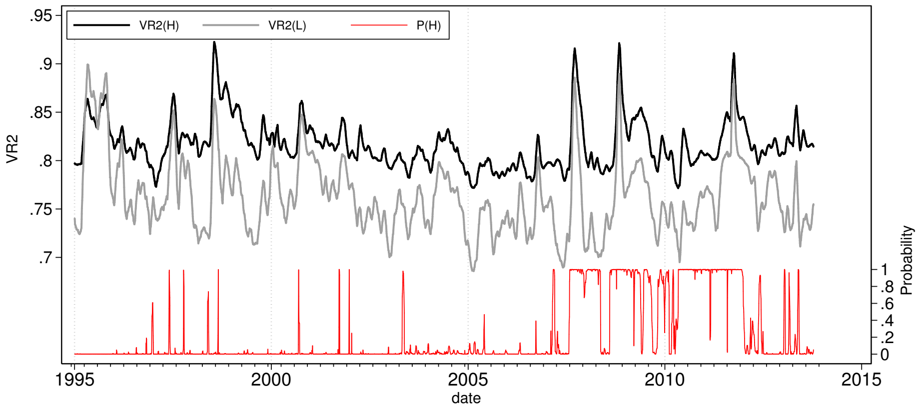


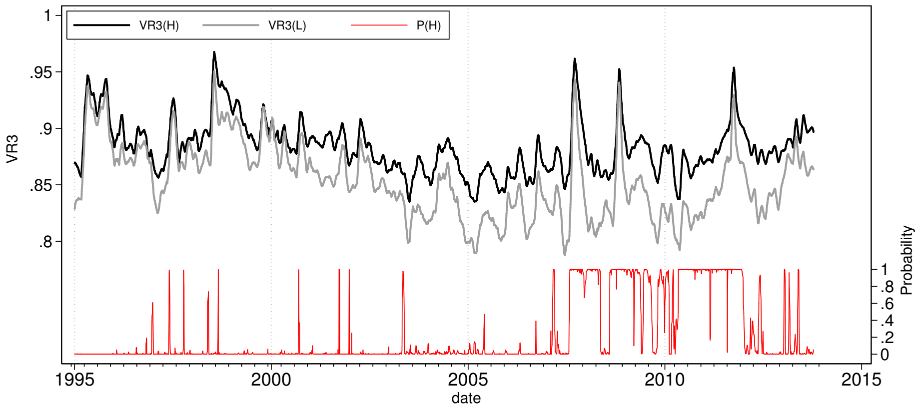
Figure 2: Volatilities in contrast to correlation regimes (Daily; USD as the reference currency).
This figure plots the time series of volatilities: the VIX index, the global FX volatility and the FX implied volatility. For better visualization, all volatilities are scaled by their corresponding full sample standard deviations. The sample spans from 1995:1:3 to 2013:10:11.



(a) PC(1)

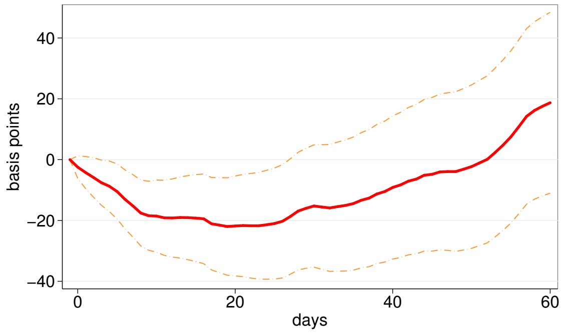


(b) PC(1,2)

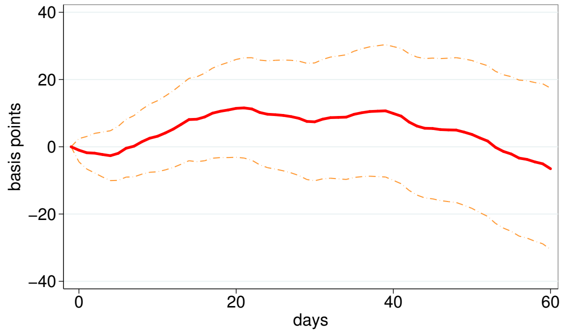


(c) PC(1,2,3)

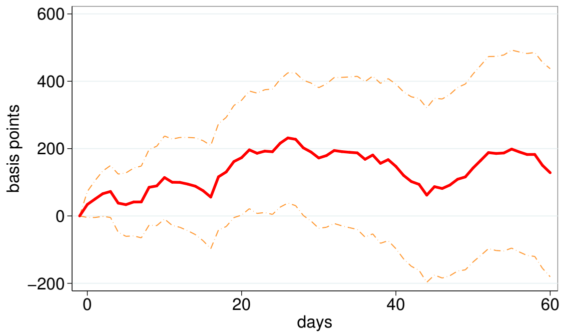
Figure 3: Regime-dependent Variance Ratio of Principle Components.
This figure plots the time series of the regime-dependent variance ratio of principle components, measured as the portion of total variance accounted for by a subset of principle components against the left axis. Panel a. presents the case for the first principle component, panel b. the first two principle components, and panel c. the first three principle components. Each panel also plots the probability of the high correlation regime against the right axis.



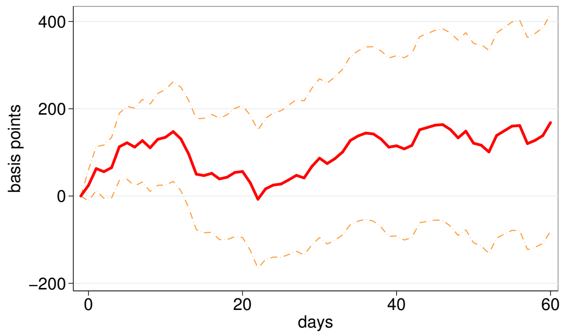
(a) Carry: H→H



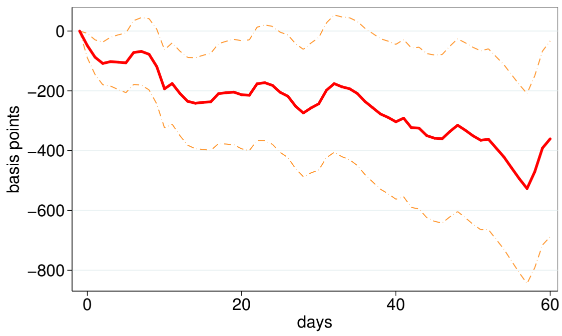
(b) Mom1: H→H



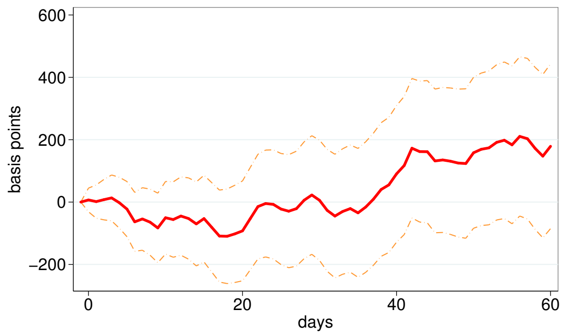
(c) Carry: H→L



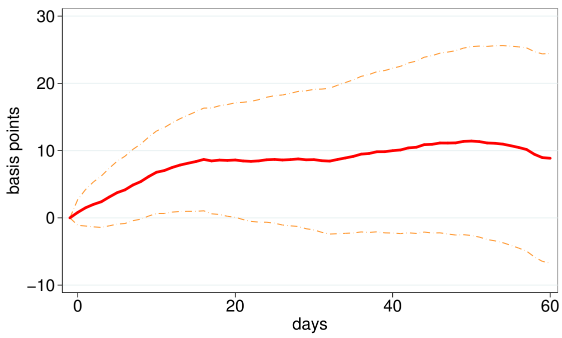
(d) Mom1: H→L



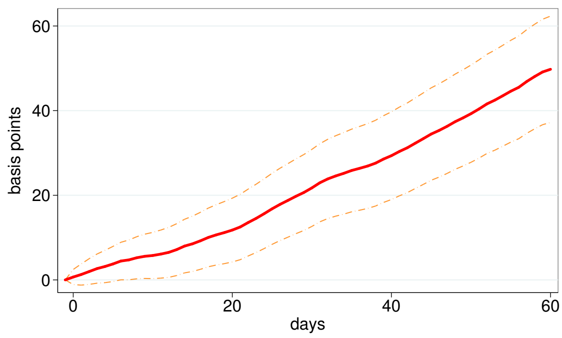
(e) Carry: L→H



(f) Mom1: L→H

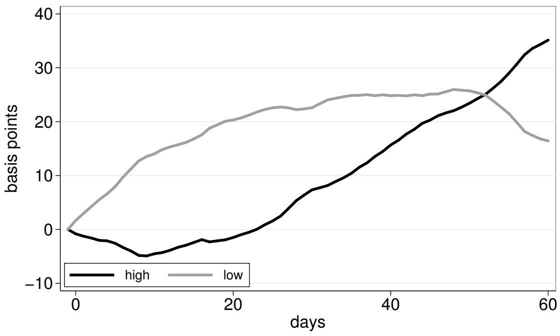


(g) Carry: L→L

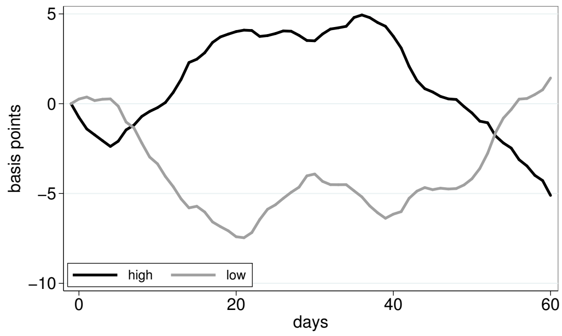


(h) Mom1: L→L

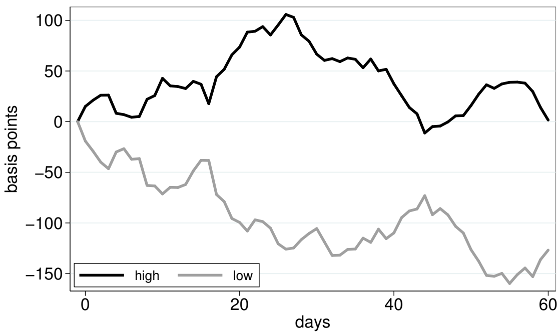
Figure 4: State Dependent Cumulative Exchange Rate Returns of zero-cost Carry and Momentum. (Daily; USD as the reference currency).



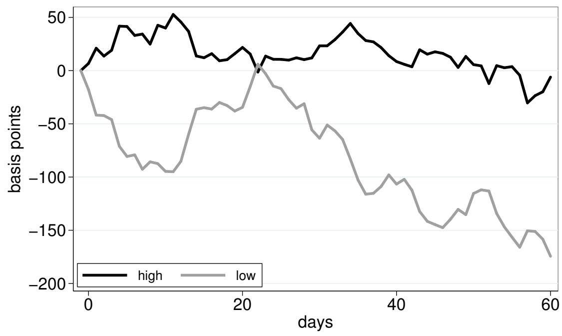
(a) Carry: H→H



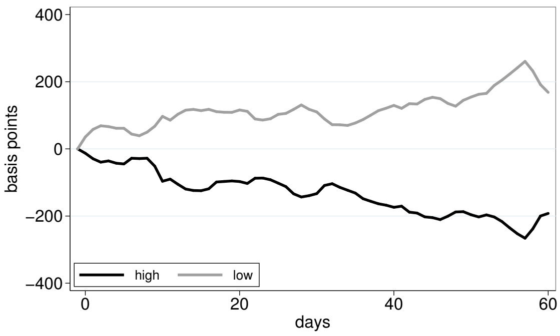
(b) Mom1: H→H



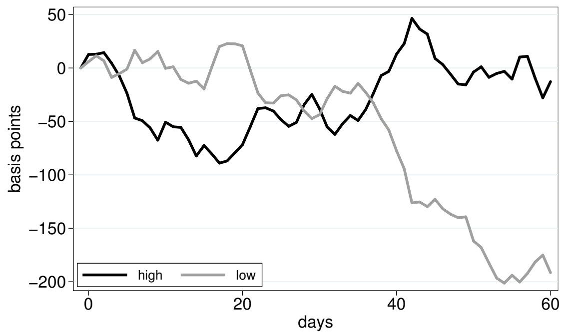
(c) Carry: H→L



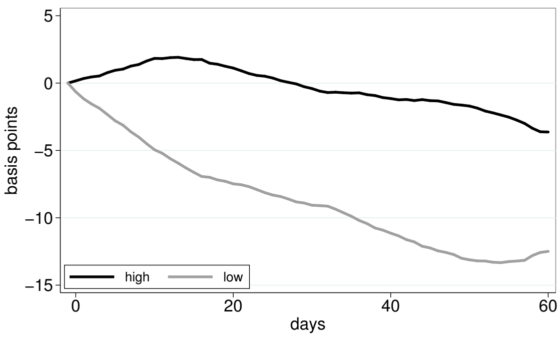
(d) Mom1: H→L



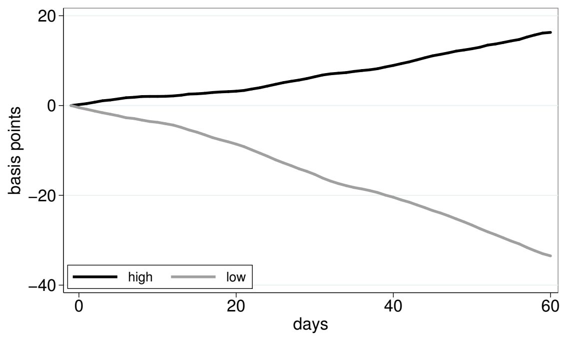
(e) Carry: L→H



(f) Mom1: L→H

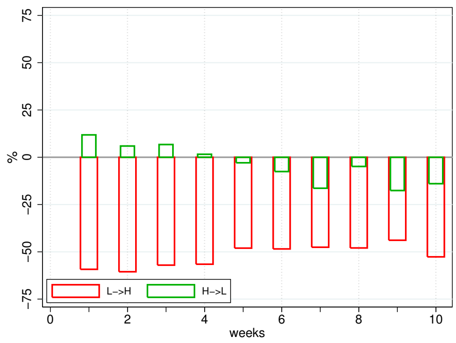


(g) Carry: L→L

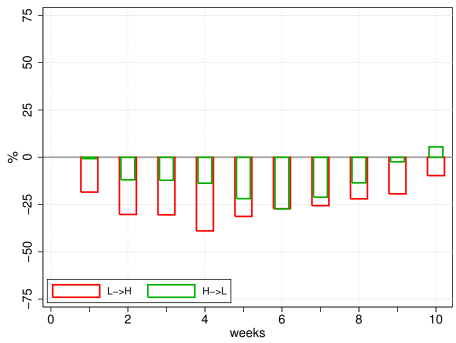


(h) Mom1: L→L

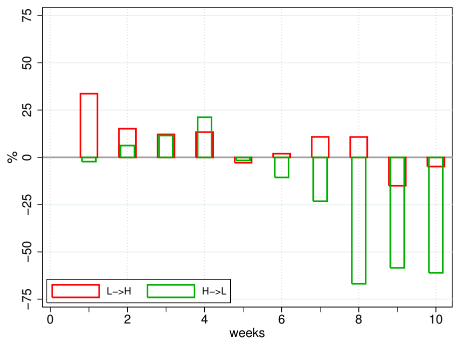
Figure 5: State Dependent Cumulative Exchange Rate Returns of Investment Currencies vs Financing Currencies in the Carry and Momentum Strategies (Daily; USD as the reference currency). Investment currency portfolio ("high") is represented by the black line while financing currency portfolio ("low") is represented by the gray line. Both portfolios are cross-sectionally demeaned by subtracting the cross-sectional average return of H, M, and L.



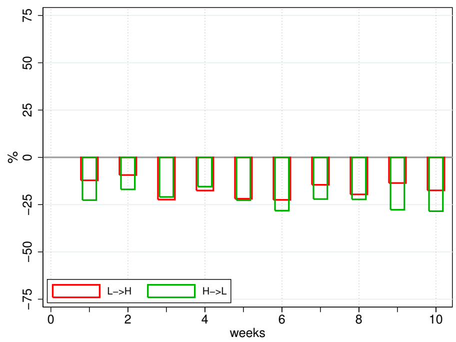
(a) AUD



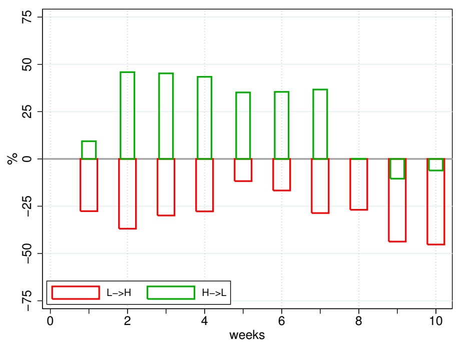
(b) CAD



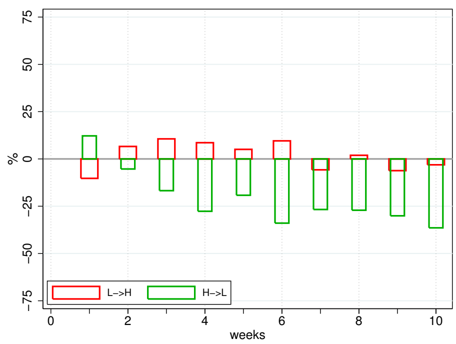
(c) CHF



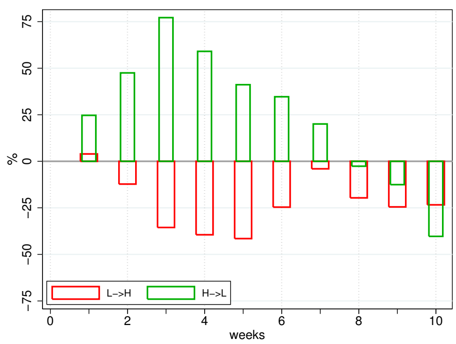
(d) EUR



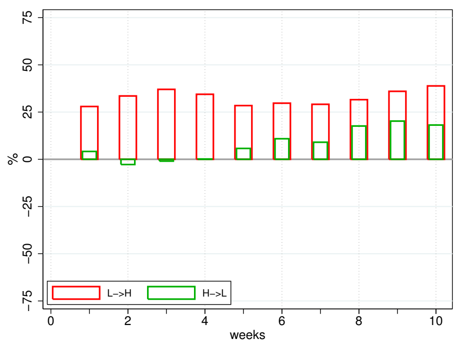
(e) GBP



(f) JPY

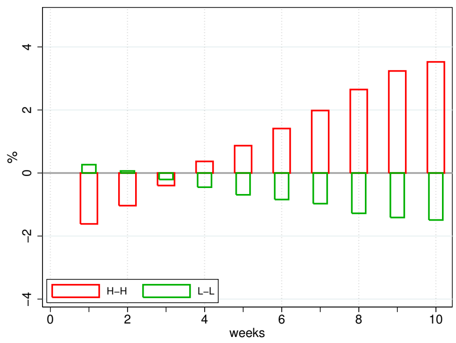


(g) NZD

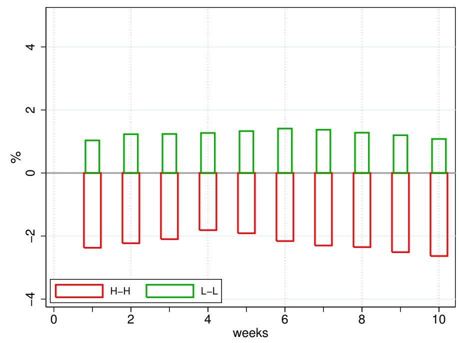


(h) USD

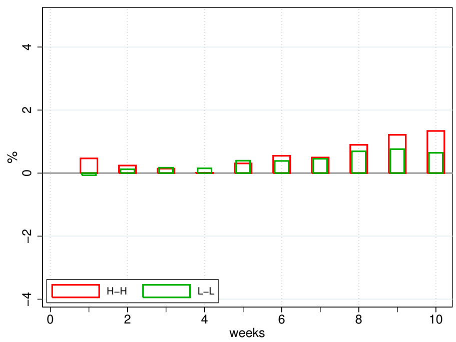
Figure 6: Net Speculator Positions when the Regime Switches.
This figure plots, for each futures contract in the corresponding panel, the average net speculator position in the 10 weeks following a regime transition, relative to pre-event 10-week average net position, when the high (low) correlation regime switches to the low (high) correlation regime.



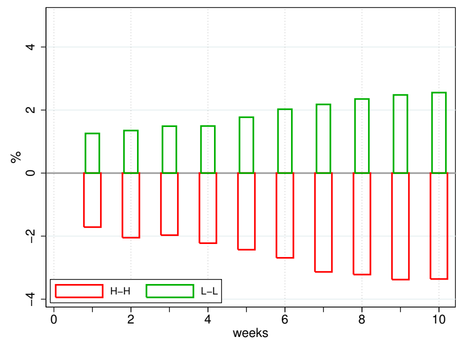
(a) AUD



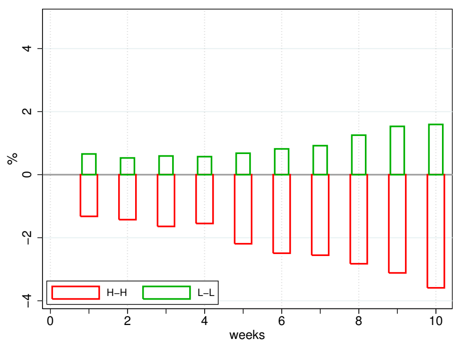
(b) CAD



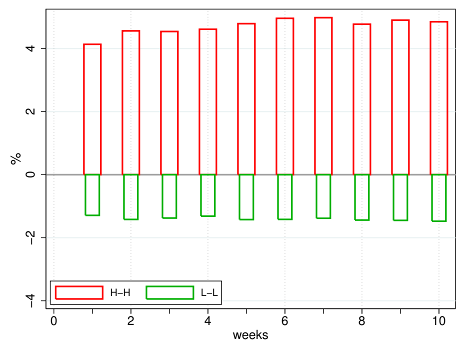
(c) CHF



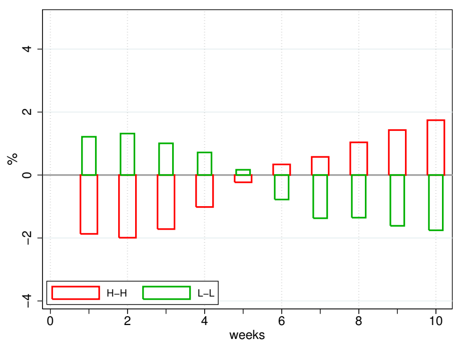
(d) EUR



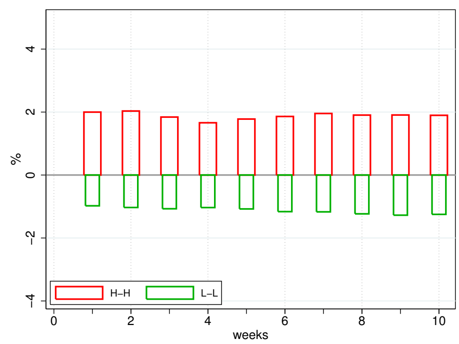
(e) GBP



(f) JPY



(g) NZD



(h) USD

Figure 7: Net Speculator Positions when the Regime Persists.
This figure plots, for each currency futures contract in the corresponding panel, the average net speculator position in the 10 weeks following a regime transition, relative to pre-event 10-week average position, when the high or low correlation regime persists.

Appendices

A Emerging-country Exchange Rates

In this section, we check if our findings about the dependence of returns on correlation regime is robust to emerging countries.

For this purpose, we run the same regression as in equation (13), imposing $\gamma_{ij} \equiv 0$, for exchange rate returns of currencies of major emerging economies, namely, Brazil (BRL), Czech (CZK), Egypt (EGP), Hong Kong (HKD), Hungary (HUF), Israel (ILS), India (INR), Korea (KRW), Kuwait (KWD), Mexico (MXN), Philippine (PHP), Poland (PLN), Russia (RUB), Saudi Arabia (SAR), Singapore (SGD), Thailand (THB), Taiwan (TWD), and South Africa (ZAR), whose spot exchange rates are available for the majority of the period from January 3, 1995 to October 11, 2013. We obtain the data from BBI and Reuters via Datastream.

The results, shown in Table A.1, delivers a consistent message with our main findings: most emerging-country currencies devalues substantially when correlation enters into the high regime except for a few asian currencies probably because these asian currencies are pegged to the US dollar and the US dollar is a safe target in risk-off episodes.

Table A.1: Average Return during State Transitions: emerging countries

This table presents the average returns on emerging country bilateral exchange rates during state transitions. We regress daily return $r_{t-1,t}$ on state-transition indicators. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

	stats	H-H	H-L	L-H	L-L	adj.R2
BRL	_b_	**-2.00**	**28.21**	**-62.88**	**-1.63**	0.04%
	_se_	(3.11)	(32.31)	(34.24)	(1.60)	
CZK	_b_	**0.08**	**69.07**	**-85.22**	**1.18**	0.29%
	_se_	(2.46)	(25.53)	(27.05)	(1.27)	
EGP	_b_	**-0.63**	**-12.24**	**-17.00**	**-1.43**	0.16%
	_se_	(1.08)	(11.23)	(11.90)	(0.56)	
HKD	_b_	**0.12**	**-0.85**	**-1.61**	**-0.02**	-0.01%
	_se_	(0.10)	(1.05)	(1.11)	(0.05)	
HUF	_b_	**-2.22**	**30.07**	**-108.14**	**-0.39**	0.24%
	_se_	(2.72)	(28.25)	(29.94)	(1.40)	
ILS	_b_	**1.75**	**-8.81**	**-52.28**	**-0.37**	0.15%
	_se_	(1.51)	(15.66)	(16.60)	(0.78)	
INR	_b_	**-3.76**	**19.24**	**-24.05**	**-0.66**	0.26%
	_se_	(1.23)	(12.73)	(13.49)	(0.63)	
ISK	_b_	**-7.53**	**25.84**	**-7.22**	**0.58**	0.08%
	_se_	(2.87)	(30.06)	(32.03)	(1.62)	
KRW	_b_	**-3.63**	**-15.57**	**5.73**	**0.31**	-0.04%
	_se_	(2.97)	(30.90)	(32.75)	(1.53)	
KWD	_b_	**-0.13**	**7.69**	**0.46**	**0.12**	-0.03%
	_se_	(0.52)	(5.44)	(5.77)	(0.27)	
MXN	_b_	**-2.72**	**-12.73**	**-63.61**	**-1.12**	0.07%
	_se_	(2.76)	(28.68)	(30.40)	(1.42)	
PHP	_b_	**0.42**	**-18.16**	**23.32**	**-1.68**	0.04%
	_se_	(1.76)	(18.23)	(19.33)	(0.90)	
PLN	_b_	**-2.15**	**5.65**	**-64.07**	**0.53**	0.04%
	_se_	(2.64)	(27.37)	(29.01)	(1.36)	
RUB	_b_	**-7.07**	**287.14**	**-291.28**	**-3.27**	1.19%
	_se_	(5.17)	(53.69)	(56.91)	(2.78)	
SAR	_b_	**-0.01**	**2.69**	**-2.08**	**-0.00**	0.30%
	_se_	(0.07)	(0.78)	(0.82)	(0.04)	
SGD	_b_	**1.35**	**-7.32**	**-13.52**	**0.22**	-0.03%
	_se_	(1.21)	(12.54)	(13.29)	(0.62)	
THB	_b_	**1.23**	**-9.72**	**-4.51**	**-0.80**	-0.05%
	_se_	(1.87)	(19.42)	(20.58)	(0.96)	
TWD	_b_	**0.45**	**0.25**	**-4.21**	**-0.39**	-0.06%
	_se_	(0.90)	(9.33)	(9.89)	(0.46)	
ZAR	_b_	**-4.61**	**23.52**	**-79.42**	**-0.91**	0.10%
	_se_	(3.21)	(33.37)	(35.37)	(1.65)	

B Global Equity Markets

We obtain 14 major equity market indices: S&P 500 (SPX), Dow Jones Industrial Average (DJI), NASDAQ100 (NDX) for the US, and Canada S&P TSE 60 (TSX), UK FTSE100 (UKX), France (CAC), Germany (DAX), Spain (IBEX), The Netherlands (AEX), Sweden (OMX), Switzerland (SMI), Japan Nikkei (NKY), Hong Kong Heng Seng (HSI), and Australia S&P ASX 200 (AS51) from Bloomberg. We then run the same regression as in equation (13), imposing $\gamma_{ij} \equiv 0$ on logarithm returns to the above equity indexes.

Results shown in Table B.2 extends the dependence of returns on FX correlation regimes to global equity markets. All indices of major equity markets throughout the world suffer extraordinary losses in risk-off episodes featuring low-to-high correlation transition. By contrast, all equity markets seem to reward stable and largely significant positive returns if and only if FX correlation remains in the low regime.

Table B.2: Average Return during State Transitions: international equity markets. This table presents the average returns on international equity indices during state transitions. We regress daily return $r_{t-1,t}$ on state-transition indicators. We report the coefficient estimates as average daily return in basis points, the corresponding OLS standard errors in the parentheses, and the corresponding adjusted R-squared. The sample is from 1995:1:3 to 2013:10:11.

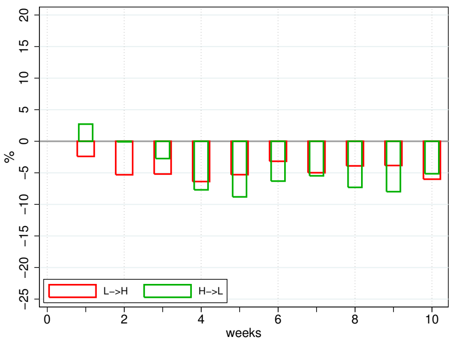
	stats	H-H	H-L	L-H	L-L	adj.R2
SPX	_b_	**0.65**	**-23.50**	**-116.50**	**4.55**	0.14%
	_se_	(4.16)	(42.36)	(44.84)	(2.14)	
DJI	_b_	**1.20**	**-27.16**	**-108.67**	**4.42**	0.15%
	_se_	(3.92)	(39.87)	(42.20)	(2.01)	
NDX	_b_	**1.96**	**-49.26**	**-166.86**	**7.17**	0.13%
	_se_	(6.41)	(65.31)	(69.13)	(3.30)	
AEX	_b_	**-3.15**	**-29.17**	**-170.15**	**3.47**	0.20%
	_se_	(4.79)	(50.64)	(52.08)	(2.47)	
AS51	_b_	**-2.89**	**-34.80**	**-129.21**	**4.76**	0.39%
	_se_	(3.27)	(34.31)	(35.33)	(1.69)	
CAC	_b_	**-4.06**	**3.60**	**-197.24**	**3.95**	0.28%
	_se_	(4.84)	(51.25)	(52.66)	(2.51)	
DAX	_b_	**-1.89**	**-2.78**	**-173.57**	**5.03**	0.17%
	_se_	(5.04)	(52.98)	(58.26)	(2.60)	
UKX	_b_	**-0.16**	**-41.80**	**-139.80**	**3.09**	0.19%
	_se_	(4.00)	(41.74)	(43.41)	(2.05)	
HSI	_b_	**-3.88**	**-33.72**	**-151.78**	**4.24**	0.10%
	_se_	(5.71)	(58.77)	(62.24)	(2.94)	
IBEX	_b_	**-2.73**	**-1.59**	**-218.85**	**4.55**	0.30%
	_se_	(4.92)	(51.92)	(57.06)	(2.56)	
NKY	_b_	**-10.28**	**-59.54**	**-147.88**	**1.06**	0.20%
	_se_	(5.20)	(51.37)	(60.41)	(2.65)	
OMX	_b_	**-0.96**	**-47.90**	**-144.32**	**5.44**	0.13%
	_se_	(5.15)	(53.77)	(59.37)	(2.66)	
SMI	_b_	**-1.37**	**20.66**	**-207.99**	**4.15**	0.42%
	_se_	(4.04)	(42.30)	(46.91)	(2.08)	
TSX	_b_	**-2.15**	**33.04**	**-138.69**	**3.49**	0.21%
	_se_	(4.01)	(42.68)	(43.30)	(2.06)	

C Futures Positions: Equities vs Bonds

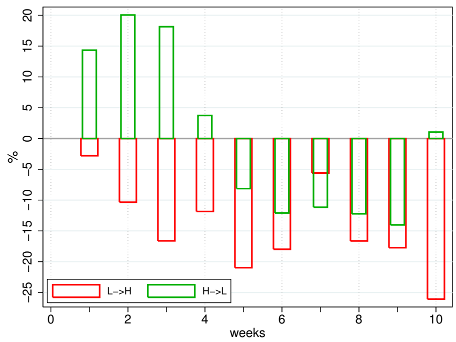
In risk-off episodes, investors unwind position on risky currencies and resort to safe currencies. In this section, we explore the implication of our risk-off episodes identified from the switch of foreign exchange rate correlation regimes for flight-to-safety episodes in which investors depart from risky assets, e.g. the stock markets, and rush into safer government bond markets, e.g. the US Treasury bond market. Specifically, we construct net speculators positions on major US equity index futures and the US Treasury bond futures in the same way as we construct net speculators position on currency futures.

The results are shown in Figure C.1 for low-to-high and high-to-low correlation transition, and in Figure C.2 for the case in which correlation regime persists.

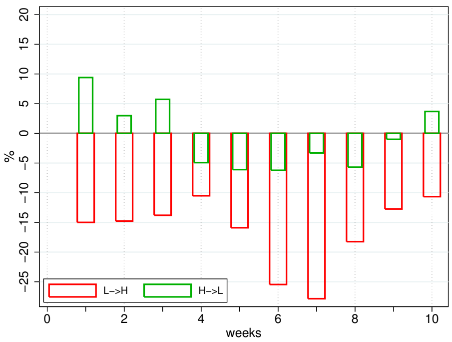
Overall, the results indicate that risk-off episodes, albeit derived from exchange rate comovements, seems to have broader implications as they coincides with the flight-to-safety phenomenon in which investors rush into the US Treasury market from the equity markets.



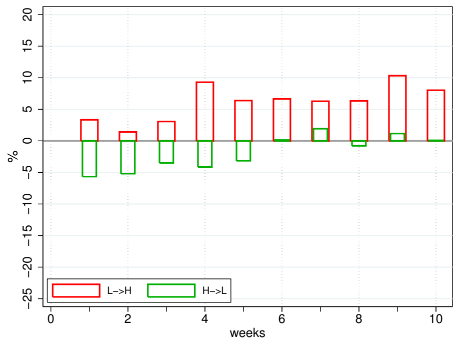
(a) S&P 500



(b) Dow Jones



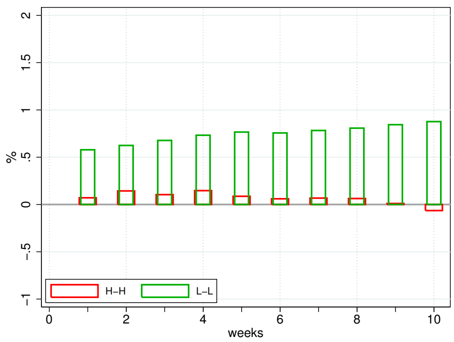
(c) NASDAQ100



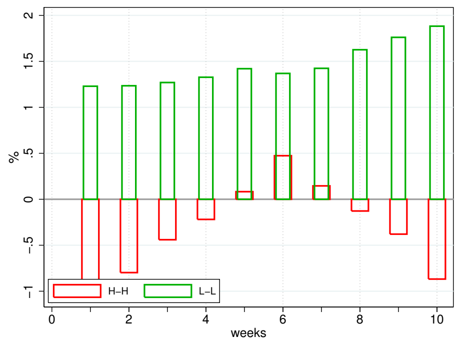
(d) US Treasury Bond

Figure C.1: Net Speculator Positions on Equities and Bonds when the Regime Switches.

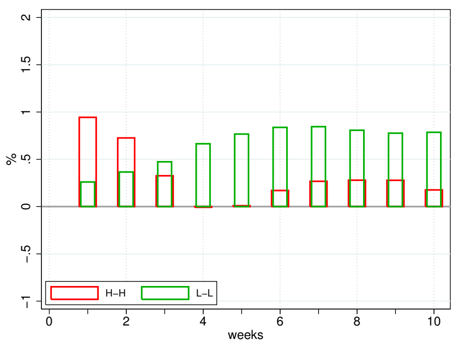
This figure plots, for each futures contract in the corresponding panel, the average net speculator position in the 10 weeks following a regime transition, relative to pre-event 51-week average net position (10 weeks for TBond), when the high (low) correlation regime switches to the low (high) correlation regime.



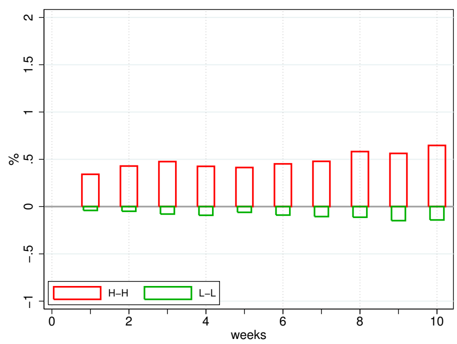
(a) S&P 500



(b) Dow Jones



(c) NASDAQ100



(d) US Treasury Bond

Figure C.2: Net Speculator Positions on Equities and Bonds when the Regime Persists. This figure plots, for each futures contract in the corresponding panel, the average net speculator position in the 10 weeks following a regime transition, relative to pre-event 51-week average position (10 weeks for TBond), when the high or low correlation regime persists.