Volatility Risk Premia and Exchange Rate Predictability*†

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Abstract

We discover a new currency strategy with highly desirable return and diversification properties, which uses the predictive capability of currency volatility risk premia for currency returns. The volatility risk premium – the difference between expected realized and model-free implied volatility – reflects the costs of insuring against currency volatility fluctuations, and the strategy sells high-insurance-cost currencies and buys low-insurance-cost currencies. The returns to the strategy are mainly generated by movements in spot exchange rates rather than interest rate differentials, and the strategy carries a greater weight in the minimum-variance currency strategy portfolio than both carry and momentum. Canonical risk factors cannot price the returns from this strategy, which appear more consistent with time-varying limits to arbitrage.

Keywords: Exchange Rates; Volatility Risk Premium; Predictability, Minimum-Variance Currency Portfolio.

JEL Classification: F31; F37.

1 Introduction

For decades, both finance practitioners and academics have struggled to understand and explain currency fluctuations.[1] More recently, the literature has focused on a closely-related question, which is to document high returns to currency investment strategies such as carry and momentum.[2] Analogous to the deficiency of definitive answers in the exchange rate determination literature, there has been limited success in explaining these currency strategy returns in terms of compensation for systematic risks. Moreover, the primary driver of the historical performance of carry has been interest differentials rather than spot currency returns.[3]

In this paper, we discover a new currency strategy with high average returns, excellent diversification benefits relative to the set of previously discovered currency strategies, and unusual properties that provide clues as to the underlying drivers of exchange rate movements. The key to this new strategy is the significant predictive power of the currency volatility risk premium (VRP) for exchange rate returns.[4] A useful summary statistic of the importance of this new currency strategy (which we dub VRP), is that over the 1996 to 2011 period, in a cross-section of up to 20 currencies, it has the highest weight (33%) in the global minimum variance portfolio of five well-known currency strategies, including carry and momentum.

The high weight of VRP in the currency strategy portfolio is primarily a reflection of its extremely desirable correlation properties relative to the other widely-studied currency strategies, as VRP does not have the highest returns among the strategies considered. This unusual low correlation partly arises from the excellent performance of VRP during crises,

[1] The difficulty of explaining and forecasting nominal exchange rates was first recorded in the seminal study of Meese and Rogoff (1983). Over the past three decades, it has continued to be difficult to find theoretically motivated variables able to beat a random walk forecasting model for currencies (e.g. see Engel, Mark and West, 2008).

[2] See, for example, Lustig and Verdelhan (2007), Ang and Chen (2010), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov, and Verdelhan (2011), Barroso and Santa Clara (2013) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a,b), who all build currency portfolios to study return predictability and/or currency risk exposure.

[3] We use interchangeably the terms spot currency returns and exchange rate returns to define the change in nominal exchange rates over time; similarly we use interchangeably the terms excess returns or portfolio returns to refer to the returns from implementing a long-short currency trading strategy that buys and sells currencies on the basis of some characteristic.

[4] To be clear from the outset, our strategy does not trade volatility products. We simply use the currency volatility risk premium as conditioning information to sort currencies, build currency portfolios, and uncover predictability in currency excess returns and spot exchange rate returns.

and primarily from the fact that the currency excess returns of VRP are almost completely obtained through prediction of spot currency returns rather than from interest rate differentials. We investigate alternative explanations for the profitability and properties of VRP, and find evidence most consistent with a simple mechanism with time-varying limits to arbitrage in the currency market.

The currency volatility risk premium is the difference between expected future realized volatility, and a model-free measure of implied volatility derived from currency options. A growing literature studies the variance or the volatility risk premium in different asset classes, including equity, bond, and foreign exchange (FX) markets.[5] In general, this literature has shown that the volatility risk premium is on average negative: expected volatility is higher than historical realized volatility, and since volatility is persistent, expected volatility is also generally higher than future realized volatility. In other words, the volatility risk premium represents compensation for providing volatility insurance. Therefore, akin to the interpretation in Garleanu, Pedersen, and Poteshman (2009), the currency volatility risk premium that we construct can be interpreted as the cost of insurance against volatility fluctuations in the underlying currency. When it is high – realized volatility is higher than the option-implied volatility – insurance is relatively cheap, and vice versa.

We use the currency volatility risk premium to sort currencies into quintile portfolios at the end of each month. The strategy is to buy currencies with relatively cheap volatility insurance, i.e., the highest volatility risk premium quintile, and short currencies with relatively expensive volatility insurance, i.e., the lowest volatility risk premium quintile. We track returns on this trading strategy (VRP) over the subsequent period, meaning that these returns are purely out-of-sample, conditioning only on information available at the time of portfolio construction.

The performance of VRP stems virtually entirely from the predictability of spot exchange rates rather than from interest rate differentials. That is, currencies with relatively cheap volatility insurance tend to appreciate over the subsequent month, while those with relatively more expensive volatility insurance tend to depreciate over the next month. The observed predictability of spot exchange rates associated with VRP is far stronger than that arising from

[5] See, for example, Carr and Wu (2009), Eraker (2008), Bollerslev, Tauchen, and Zhou (2009), Todorov (2010), Drechsler and Yaron (2010), Han and Zhou (2011), Mueller, Vedolin and Yen (2011), Londono and Zhou (2012) and Buraschi, Trojani and Vedolin (2013).

carry (which generates returns that are almost entirely driven by interest rate differentials, and not by any predictive ability for spot rate changes) and currency momentum, as well as other currency trading strategies that we consider. As mentioned earlier, this is part of the reason for the excellent diversification benefits that the VRP strategy offers in a currency portfolio.

There are several possible interpretations of our results, of which we consider two to be most likely. One possibility is that VRP captures fluctuations in aversion to volatility risk, so that currencies with high volatility insurance have low expected returns and vice versa. Note that our result is *cross-sectional,* since we are long and short currencies simultaneously. As a result, if this explanation were true, it would rely either on different currencies loading differently on a global volatility shock, or indeed on market segmentation causing expected returns on different currencies to be determined independently. We test this explanation both using cross-sectional asset pricing tests of volatility risk premium-sorted portfolios on a global FX volatility risk factor, as well as by estimating the loadings of currency returns on various proxies for global volatility risk and building portfolios sorted on these estimated loadings. Neither of these tests produces evidence consistent with the proposed explanation, with the long-short strategy generated from estimated loadings on the global volatility risk factor producing far inferior returns to VRP, which are also virtually uncorrelated with VRP returns. In sum, the data appear to reject an explanation based on fluctuations in aversion to global volatility risk.

The second explanation that we consider for our results relies on the presence of limits to arbitrage, and its effects on the interaction between hedgers and speculators in the currency market. There is a growing theoretical and empirical literature suggesting that such interactions are important in asset return determination (see, for example, Acharya, Lochstoer, and Ramadorai, 2013; Adrian, Etula, and Muir, 2013; and Gromb and Vayanos, 2010 for an excellent survey of the literature). In the currency markets, this explanation comprises two components. First, it requires time-variation in the amount of arbitrage capital available to natural providers of currency volatility insurance ("speculators"), such as financial institutions or hedge funds. Second, risk-averse natural "hedgers" of currencies such as multinational firms, or financial institutions that inherit currency positions from their clients, should be more willing to hedge and be more comfortable with holding (or entering into contracts denominated in) currencies with relatively inexpensive volatility insurance. Such institutions will also be more likely to avoid positions in currencies with relatively expensive volatility protection. The combination of these two ingredients would be sufficient to generate the patterns that we see in the data.

A simple example may be helpful: assume that speculators face a shock to their available arbitrage capital. This limits their ability to provide cheap volatility insurance, especially in currencies in which they have large positions – for example, they may reduce their outstanding short put option positions in the currencies in which they trade.[6] These limits on speculators' ability to satisfy demand for volatility insurance increases net demand in the options market for the specific currencies in which they are most active, increasing current option prices and making hedging more expensive. As in Garleanu, Pedersen, and Poteshman (2009), this net demand imbalance would show up in a lower volatility risk premium for the currencies thus affected. Given the high cost of volatility insurance, natural hedgers scale back on the amount of spot currency they are willing to hold, or are reluctant to get into new expensive hedges. This net demand will predictably depress spot prices, leading to relatively low returns on the spot currency position. When capital constraints loosen, we should see the opposite behavior, i.e., a reversal in both the volatility risk premium and the spot currency position.

In the cross-section of currencies, this mechanism implies that, in a world with limited and time-varying arbitrage capital, an institution wishing to hedge against risk (or deleveraging) in one currency position rather than another will generate excess demand for volatility insurance for the currency to which it is more exposed, in turn increasing the spread in volatility risk premia across currencies.

This explanation for our baseline result has additional testable implications. Most obviously, the explanation implies that the returns from the VRP strategy, post-formation, should be temporary, i.e., there should be reversion in currency returns once arbitrage capital returns to the market. Confirming this prediction, we find that currency volatility risk-premium sorted portfolio returns reverse over a holding period of a few months. Moreover, at times when funding liquidity is lower (i.e., times of high capital constraints on speculators), and

[6] Short put options is a favoured strategy of many hedge funds; see Agarwal and Naik (2004), for example. Also see Fung and Hsieh (1997) for how lookback options can be used to capture the returns to momentum trading strategies implemented by hedge funds.

demand for volatility protection is higher (i.e., times of increased risk aversion of natural hedgers), we should find that the spread in the cost of volatility insurance across currencies, and the spread in spot exchange rate returns across portfolios should both increase. In our empirical analysis, we find that when the TED spread – a commonly used proxy for funding liquidity (see, for example, Garleanu and Pedersen, 2011) – increases, the returns on VRP are substantially higher. Fluctuations in risk aversion, as proxied by changes in the VIX, add significant additional explanatory power when interacted with the TED spread. Next, we measure capital flows to currency and global macro hedge funds, and find that when hedge fund flows are high, signifying increased funding and thus lower hedge fund capital constraints, the returns to VRP are lower and vice versa, providing useful evidence in support of the limits to arbitrage explanation.

Finally, we inspect the positioning of commercial and financial traders in the FX market. We find that commercial traders tend to sell currencies which are more expensive to insure and buy currencies which are cheaper to insure; by contrast, financial traders appear to trade in a way that is exactly opposite to that of commercial traders. This pattern of trading behavior serves to corroborate our other evidence suggesting that VRP returns are driven by the interaction of natural hedgers and speculators in currency markets.[7]

The paper is structured as follows. Section 2 defines the volatility risk premium and its measurement in currency markets. Section 3 describes our data and some descriptive statistics. Section 4 presents our main empirical results on the volatility risk premium-sorted strategy, Section 5 reports formal asset pricing tests, while Section 6 investigates two alternative mechanisms that could explain our findings. Section 7 concludes. A separate Internet Appendix provides robustness tests and additional supporting analyses.

2 Foreign Exchange Volatility Risk Premia

Volatility Swap. A volatility swap is a forward contract on the volatility "realized" on the underlying asset over the life of the contract. The buyer of a volatility swap written at time

[7] This evidence links our work to another important stream of the exchange rate literature on forecasting currency returns using currency order flow. For example, Froot and Ramadorai (2005), Evans and Lyons (2005) and Rime, Sarno and Sojli (2010) show that order flow has substantial predictive power for exchange rate movements.

t, and maturing at time $t+\tau$, receives the payoff (per unit of notional amount):

$$VP_{t,\tau} = (RV_{t,\tau} - SW_{t,\tau}) \tag{1}$$

where $RV_{t,\tau}$ is the realized volatility of the underlying, $SW_{t,\tau}$ is the volatility swap rate, and both $RV_{t,\tau}$ and $SW_{t,\tau}$ are defined over the life of the contract from time t to time $t+\tau$, and quoted in annual terms. However, while the realized volatility is determined at the maturity date $t+\tau$, the swap rate is agreed at the start date t.

The value of a volatility swap contract is obtained as the expected present value of the future payoff in a risk-neutral world. This implies, because $VP_{t,\tau}$ is expected to be 0 under the risk-neutral measure, that the volatility swap rate equals the risk-neutral expectation of the realized volatility over the life of the contract:

$$SW_{t,\tau} = E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right] \tag{2}$$

where $E_t^{\mathbb{Q}}[\cdot]$ is the expectation under the risk-neutral measure $\mathbb{Q}$, $RV_{t,\tau} = \sqrt{\tau^{-1}\int_t^{t+\tau}\sigma_s^2 ds}$, and σ_s^2 denotes the (stochastic) volatility of the underlying asset.

Volatility Swap Rate. We synthesize the volatility swap rate using the model-free approach derived by Britten-Jones and Neuberger (2000), and further refined by Demeterfi, Derman, Kamal and Zou (1999), Jiang and Tian (2005), and Carr and Wu (2009).

Building on the pioneering work of Breeden and Litzenberger (1978), Britten-Jones and Neuberger (2000) derive the model-free implied volatility entirely from no-arbitrage conditions and without using any specific option pricing model. Specifically, they show that the risk-neutral expected integrated return variance between the current date and a future date is fully specified by the set of prices of call options expiring on the future date, provided that the price of the underlying evolves continuously with constant or stochastic volatility but without jumps.

Demeterfi, Derman, Kamal, and Zou (1999) show that the Britten-Jones and Neuberger (2000) solution is equivalent to a portfolio that combines a dynamically rebalanced long position in the underlying, and a static short position in a portfolio of options and a forward that together replicate the payoff of a "log contract."[8] The replicating portfolio strategy captures variance exactly, provided that the portfolio of options contains all strikes with the

[8]The log contract is an option whose payoff is proportional to the log of the underlying at expiration (Neuberger, 1994).

appropriate weights to match the log payoff. Jiang and Tian (2005) further demonstrate that the model-free implied variance is valid even when the underlying price exhibits jumps, thus relaxing the diffusion assumptions of Britten-Jones and Neuberger (2000).

The risk-neutral expectation of the return variance between two dates t and $t+\tau$ can be formally computed by integrating option prices expiring on these dates over an infinite range of strike prices:

$$E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right] = \kappa \left(\int_0^{F_{t,\tau}} \frac{1}{K^2} P_{t,\tau}(K) dK + \int_{F_{t,\tau}}^{\infty} \frac{1}{K^2} C_{t,\tau}(K) dK \right) \tag{3}$$

where $P_{t,\tau}(K)$ and $C_{t,\tau}(K)$ are the put and call prices at t with strike price K and maturity date $t+\tau$, $F_{t,\tau}$ is the forward price matching the maturity date of the options, S_t is the price of the underlying, $\kappa = (2/\tau)\exp(i_{t,\tau}\tau)$, and $i_{t,\tau}$ is the τ-period domestic riskless rate.

The risk-neutral expectation of the return variance in Equation (3) delivers the strike price of a variance swap $E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right]$, and is referred to as the model-free implied variance.

Even though variance emerges naturally from a portfolio of options, it is volatility that participants prefer to quote, as the payoff of a variance swap is convex in volatility and large swings in volatility, as we observed during the recent financial crisis, are more likely to cause large profits and losses to counterparties. Therefore, our empirical analysis focuses on volatility swaps, and we synthetically construct the strike price of this contract as

$$E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right] = \sqrt{E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right]} \tag{4}$$

and refer to it as model-free implied volatility.

While straightforward, this approach is subject to a convexity bias. The main complication in valuing volatility swaps arises from the fact that the strike of a volatility swap is not equal to the square root of the strike of a variance swap due to Jensen's inequality, i.e., $E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right] \leq \sqrt{E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right]}$. The convexity bias that arises from the above inequality leads to imperfect replication when a volatility swap is replicated using a buy-and-hold strategy of variance swaps (e.g., Broadie and Jain, 2008). Simply put, the payoff of variance swaps is quadratic with respect to volatility, whereas the payoff of volatility swaps is linear.

We deal with this bias in approximation in two ways. First, we measure the convexity bias using a second-order Taylor expansion as in Brockhaus and Long (2000) and find that it is empirically small.[9] More importantly, when we re-do our empirical exercise with model-free implied variances, we find virtually identical results. Hence the convexity bias has no discernible effect on our results and the approximation in Equation (4) works well in our framework, which explains why it is widely used by practitioners (e.g., Knauf, 2003).

Computing model-free implied volatility requires the existence of a continuum in the cross-section of option prices at time t with maturity date τ. In the FX market, over-the-counter options are generally quoted in terms of Garman and Kohlhagen (1983) implied volatilities at fixed deltas. Liquidity is generally spread across five levels of deltas. From these quotes, we extract five strike prices corresponding to five plain vanilla options, and follow Jiang and Tian (2005), who present a simple method to implement the model-free approach when option prices are only available on a finite number of strikes.

Specifically, we use a cubic spline around these five implied volatility points. This interpolation method is standard in the literature (e.g., Bates, 1991; Campa, Chang, and Reider, 1998; Jiang and Tian, 2005; Della Corte, Sarno, and Tsiakas, 2011) and has the advantage that the implied volatility smile is smooth between the maximum and minimum available strikes. We then compute the option values using the Garman and Kohlhagen (1983) valuation formula,[10] and use trapezoidal integration to solve the integral in Equation (3). This method introduces two types of approximation errors: (i) the truncation errors arising from observing a finite number, rather than an infinite set of strike prices, and (ii) a discretization error resulting from numerical integration. Jiang and Tian (2005), however, show that both errors are small, if not negligible, in most empirical settings. In Internet Appendix Table A.3, we present results for different interpolation methods (Castagna and Mercurio, 2007) as well as a model-free approach that is robust to price jumps (Martin, 2012).

Volatility Risk Premium. In this paper we study the predictive information content in volatility risk premia for future exchange rate returns. To this end, we work with the ex-ante payoff or 'expected volatility premium' to a volatility swap contract. The volatility

[9] Brockhaus and Long (2000) show that $E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right] = \sqrt{E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right]} - \frac{V^2}{8m^{3/2}}$ where m and V^2 denote the mean and variance of the future realized variance, respectively, under the risk-neutral measure $\mathbb{Q}$. $E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right]$ is certainly less than or equal to $\sqrt{E_t^{\mathbb{Q}}\left[RV_{t,\tau}^2\right]}$ due to the Jensen's inequality, and $V^2/8m^{3/2}$ measures the convexity error.

[10] This valuation formula can be thought of as the Black and Scholes (1973) formula adjusted for having both domestic and foreign currency paying a continuous interest rate.

risk premium can be thought of as the difference between the physical and the risk-neutral expectations of the future realized volatility.[11] Formally, the τ-period volatility risk premium at time t is defined as

$$VRP_{t,\tau} = E_t^{\mathbb{P}}[RV_{t,\tau}] - E_t^{\mathbb{Q}}[RV_{t,\tau}] \tag{5}$$

where $E_t^{\mathbb{P}}[\cdot]$ is the conditional expectation operator at time t under the physical measure $\mathbb{P}$. Following Bollerslev, Tauchen, and Zhou (2009), we proxy $E_t^{\mathbb{P}}[RV_{t,\tau}]$ by simply using the lagged realized volatility, i.e., $E_t^{\mathbb{P}}[RV_{t,\tau}] = RV_{t-\tau,\tau} = \sqrt{\frac{252}{\tau}\sum_{i=0}^{\tau} r_{t-i}^2}$, where r_t is the daily log return on the underlying security. This approach is widely used for forecasting exercises – it makes $VRP_{t,\tau}$ directly observable at time t, requires no modeling assumptions, and is consistent with the stylized fact that realized volatility is a highly persistent process. Thus, at time t, we measure the volatility risk premium over the $[t, t+\tau]$ time interval as the ex-post realized volatility over the $[t-\tau, t]$ interval and the ex-ante risk-neutral expectation of the future realized volatility over the $[t, t+\tau]$ interval, i.e., $VRP_{t,\tau} = RV_{t-\tau,\tau} - E_t^{\mathbb{Q}}[RV_{t,\tau}]$.

For our purposes, we view currencies with high $VRP_{t,\tau}$ as those which are relatively "cheap" to insure at each point in time t, as their expected realized volatility under the physical measure (i.e., the variable against which agents hedge) is lower than the cost of purchasing option-based insurance – which is primarily driven by expected volatility under the risk-neutral measure. Conversely, those currencies with relatively low $VRP_{t,\tau}$ are more "expensive" to insure at time t. Our adoption of this terminology closely follows the logic in Garleanu, Pedersen, and Poteshman (2009), who provide theory and empirical evidence to support the conjecture that end-user demand for options has effects on their prices when dealers cannot perfectly hedge.

3 Data and Currency Portfolios

We now describe the data and the construction of currency portfolios that we employ in our analysis.

Exchange Rate Data. We collect daily spot and one-month forward exchange rates vis-à-vis the US dollar (USD) from Barclays and Reuters via Datastream. The empirical analysis

[11] A number of papers define the volatility risk premium as difference between the risk-neutral and the physical expectation. Here we follow Carr and Wu (2009) and take the opposite definition as it naturally arises from the long-position in a volatility swap contract.

uses monthly data obtained by sampling end-of-month rates from January 1996 to August 2011. Our sample consists of the following 20 countries: Australia, Brazil, Canada, Czech Republic, Denmark, Euro Area, Hungary, Japan, Mexico, New Zealand, Norway, Poland, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Turkey, and United Kingdom. We refer to this cross-section as "Developed and Emerging Countries." A number of currencies in this sample may not be traded in large amounts, even though quotes on forward contracts (deliverable or non-deliverable) are available.[12] Hence, we also consider a subset of the most liquid currencies, which we refer to as "Developed Countries." This sample includes: Australia, Canada, Denmark, Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

Currency Option Data. We employ daily data from January 1996 to August 2011 on over-the-counter (OTC) currency options, obtained from JP Morgan.

The OTC currency option market is characterized by specific trading conventions. While exchange traded options are quoted at fixed strike prices and have fixed calendar expiration dates, currency options are quoted at fixed deltas and have constant maturities. More importantly, while the former are quoted in terms of option premia, the latter are quoted in terms of Garman and Kohlhagen (1983) implied volatilities on baskets of plain vanilla options.

For a given maturity, quotes are typically available for five different combinations of plain-vanilla options: at-the-money delta-neutral straddles, 10-delta and 25-delta risk-reversals, and 10-delta and 25-delta butterfly spreads. The delta-neutral straddle combines a call and a put option with the same delta but opposite sign – this is the at-the-money (ATM) implied volatility quoted in the FX market. In a risk reversal, the trader buys an out-of-the money (OTM) call and sells an OTM put with symmetric deltas. The butterfly spread is built up by buying a strangle and selling a straddle, and is equivalent to the difference between the average implied volatility of an OTM call and an OTM put, and the implied volatility of a straddle. From these data, one can recover the implied volatility smile ranging from a 10-delta put to a 10-delta call.[13] To convert deltas into strike prices, and implied volatilities into option

[12] According to the Triennial Survey of the Bank for International Settlements (2013), the top 10 currencies account for about 90 percent of the average daily turnover in FX markets.

[13] In market jargon, a 25-delta call is a call whose delta is 0.25 whereas a 25-delta put is a put with a delta equal to -0.25.

prices, we employ domestic and foreign interest rates, obtained from JP Morgan, which are equivalent to those obtained using Datastream and Bloomberg.

This recovery exercise yields data on plain-vanilla European call and put options on 20 currency pairs vis-à-vis the US dollar, with maturity of one year. Practitioner accounts suggest that natural hedgers such as corporates prefer hedging using intermediate-horizon derivative contracts to the more transactions-costs intensive strategy of rolling over short term positions in currency options, and hence the one-year volatility swap is a logical contract maturity to detect interactions between hedgers and speculators.[14]

Hedge Fund Flows. To construct a measure of new arbitrage capital available to hedge funds, we use data from a large cross-section of hedge funds and funds-of-funds from January 1996 to December 2011, which is consolidated from data in the HFR, CISDM, TASS, Morningstar, and Barclay-Hedge databases, and comprises of roughly US$ 1.5 trillion worth of assets under management (AUM) towards the end of the sample period. Patton and Ramadorai (2013) provide a detailed description of the process followed to consolidate these data.

We select the subset of 634 funds from these data, those self-reporting as currency funds or global macro funds, and construct the net flow of new assets to each fund as the change in the fund's AUM across successive months, adjusted for the returns accrued by the fund over the month – this is tantamount to an assumption that flows arrive at the end of the month, following return accrual. We then normalize the figures by dividing them by the lagged AUM, and then value-weight them across funds to create a single aggregate time-series index of capital flows to currency and global macro funds.

Positions on Currency Futures. We also employ weekly data from the Commitments of Traders, a report issued by the Commodity Futures Trading Commission (CFTC). The report aggregates the holdings of participants in the US futures markets (primarily based in Chicago and New York). It is typically released every Friday and reflects the commitments of traders for the prior Tuesday. The CFTC provides a breakdown of aggregate positions held by commercial traders and financial (or non-commercial) traders. The former are merchants,

[14] This is different from currency options per se, which tend to be most liquid at shorter maturities of one and three months.

foreign brokers, clearing members or banks using the futures market primarily to hedge their business activities. The latter are hedge funds, financial institutions and individual investors using the futures market for speculative purposes. We collect weekly data from January 1996 to August 2011 on the Australian dollar, Brazilian real, Canadian dollar, Euro, Japanese yen, Mexican peso, New Zealand dollar, South African rand, Swiss franc, and British pound relative to the USD dollar.

In our empirical analysis, we use positions on currency futures for two exercises. Firstly, we construct an aggregate hedging measure of FX risk as in Acharya, Lochstoer, and Ramadorai (2013), and report a detailed description of this measure in the Appendix. Secondly, we examine whether the buying and selling actions of different players in the futures market follow the pattern implied by the VRP strategy.

Currency Excess Returns. We define spot and forward exchange rates at time t as S_t and F_t, respectively. Exchange rates are defined as units of US dollars per unit of foreign currency such that an increase in S_t indicates an appreciation of the foreign currency. The excess return on buying a foreign currency in the forward market at time t and then selling it in the spot market at time $t+1$ is computed as $RX_{t+1} = (S_{t+1} - F_t)/S_t$, which is equivalent to the spot exchange rate return minus the forward premium $RX_{t+1} = ((S_{t+1} - S_t)/S_t) - ((F_t - S_t)/S_t)$. According to the CIP condition, the forward premium approximately equals the interest rate differential $(F_t - S_t)/S_t \simeq i_t - i_t^*$, where i_t and i_t^* represent the domestic and foreign riskless rates respectively, over the maturity of the forward contract. Since CIP holds closely in the data at daily and lower frequency (e.g., Akram, Rime and Sarno, 2008), the currency excess return is approximately equal to an exchange rate component (i.e., the exchange rate change) minus an interest rate component (i.e., the interest rate differential): $RX_{t+1} \simeq ((S_{t+1} - S_t)/S_t) - (i_t - i_t^*)$.

Carry Trade Portfolios. At the end of each period t, we allocate currencies to five portfolios on the basis of their interest rate differential relative to the US, $(i_t^* - i_t)$ or forward premia since $-(F_t - S_t)/S_t = (i_t^* - i_t)$ via CIP. This exercise implies that Portfolio 1 comprises 20% of all currencies with the highest interest rate differential (lowest forward premia) and Portfolio 5 comprises 20% of all currencies with the lowest interest rate differential (highest forward premia), and we refer to the long-short portfolio formed by going long Portfolio 1 and short Portfolio 5 as CAR. We compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio, and individually track both the interest rate differential and the spot exchange rate component that make up these excess returns.

Lustig, Roussanov, and Verdelhan (2011) study these currency portfolio returns using their first two principal components. The first principal component implies an equally weighted strategy across all long portfolios, i.e., borrowing in the US money market and investing in foreign money markets. We refer to this zero-cost strategy as DOL. The second principal component is equivalent to a long position in Portfolio 1 (*investment currencies*) and a short position in Portfolio 5 (*funding currencies*), and corresponds to borrowing in the money markets of low yielding currencies and investing in the money markets of high yielding currencies. We refer to this long/short strategy as CAR in our tables – and we use both DOL and CAR in risk-adjustment below.

Momentum Portfolios. At the end of each period t, we form five portfolios based on exchange rate returns over the previous 3-months. We assign the 20% of all currencies with the highest lagged exchange rate returns to Portfolio 1, and the 20% of all currencies with the lowest lagged exchange rate returns to Portfolio 5. We then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. A strategy that is long in Portfolio 1 (*winner currencies*) and short in Portfolio 5 (*loser currencies*) is then denoted as MOM.[15]

Value Portfolios. At the end of each period t, we form five portfolios based on the level of the real exchange rate.[16] We assign the 20% of all currencies with the lowest real exchange rate to Portfolio 1, and the 20% of all currencies with the highest real exchange rate to Portfolio 5. We then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. A strategy that is long

[15] Consistent with the results in Menkhoff, Sarno, Schmeling and Schrimpf (2012b), sorting on lagged exchange rate returns or lagged currency excess returns to form momentum portfolios makes no qualitative difference to our results below. The same is true if we sort on returns with other formation periods in the range from 1 to 12 months.

[16] We compute the real exchange rate at the end of each month as $RER_t = S_t/PPP_t$, where S_t is the nominal exchange rate and PPP_t is the purchasing power parity rate. We collect the PPP data published annually every March by the OECD, and retrieve monthly data by forward filling, i.e., we use the last available PPP rate until the next February. For Singapore and Taiwan, we use data from the PENN World Table.

in Portfolio 1 (*undervalued currencies*) and short in Portfolio 5 (*overvalued currencies*) is then denoted as VAL.

Risk Reversal Portfolios. At the end of each period t, we form five portfolios based on out-of-the-money options. We compute for each currency in each time period the risk reversal, which is the implied volatility of the 10-delta call less the implied volatility of the 10-delta put, and assign the 20% of all currencies with the lowest risk reversal to Portfolio 1, and the 20% of all currencies with the highest risk reversal to Portfolio 5. We then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. A strategy that is long in Portfolio 1 (*high-skewness currencies*) and short in Portfolio 5 (*low-skewness currencies*) is then denoted as RR.

Volatility Risk Premia Portfolios. At the end of each period t, we group currencies into five portfolios using the 1-year volatility risk premium constructed as described earlier. We allocate 20% of all currencies with the highest expected volatility premia, i.e., those which are cheapest to insure, to Portfolio 1, and 20% of all currencies with the lowest expected volatility premia, i.e., those which are expensive to insure, to Portfolio 5. We then compute the average excess return within each portfolio, and finally calculate the portfolio return from a strategy that is long in Portfolio 1 (*cheap volatility insurance*) and short in Portfolio 5 (*expensive volatility insurance*), and denote it VRP.

4 The VRP Strategy: Empirical Evidence

4.1 Summary Statistics and the Returns to VRP

Table 1 presents summary statistics for the annualized average realized volatility $RV_{t,\tau}$, synthetic volatility swap rate $SW_{t,\tau} = E_t^{\mathbb{Q}}\left[RV_{t,\tau}\right]$, and volatility risk premium $VRP_{t,\tau} = RV_{t,\tau} - SW_{t,\tau}$ for the 1-year maturity ($\tau = 1$) (in what follows, we drop the τ subscript, as it is always 1 year).

The table shows that, on average across developed currencies, RV_t equals 10.68 percent, with a standard deviation of 2.88 percent, and SW_t equals 11.31 percent, with a standard deviation of 2.75 percent. The average volatility risk premium VRP_t across these currencies, which is the difference of these two variables, is equal to -0.62 percent, with a standard deviation of 1.58 percent. For the full sample of developed and emerging countries, RV_t and SW_t are slightly larger than for the sample of only developed currencies, and so is the volatility risk premium, VRP_t, which equals -0.92 on average. We might expect to see this – the average price that natural hedgers have to pay to satisfy their demand for volatility insurance is larger when including emerging market currencies.

Table 2 describes the returns generated by our short expensive-to-insure, long cheap-to-insure currency strategy, reporting summary statistics for the five portfolios that are obtained when sorting on the volatility risk premium. In this table, P_L is the long portfolio that buys the top 20% of all currencies with the cheapest volatility insurance, P_2 buys the next 20% of all currencies ranked by expected volatility premia, and so on till the fifth portfolio, P_S which is the portfolio that buys the top 20% of all currencies which are the most expensive to insure. VRP essentially buys P_L and sells P_S, with equal weights, so that $VRP = P_L - P_S$.

The table reveals several facts about VRP. First, there is a strong general tendency of portfolio returns to decrease as we move from P_L towards P_S; the decrease is not monotonic for developed countries, but it is monotonic for the full sample for the FX returns component. Second, the VRP return stems mainly from the long portfolio, P_L. Third, the return from P_L can be almost completely attributed to spot rate changes. Finally, the bottom panel of Table 2 shows the transition matrix between portfolios. This shows that there is currency rotation across quintile portfolios such that the steady-state transition probabilities are identical. Thus the performance of the strategy cannot simply be attributed to long-lived positions in particular currencies.

The returns to VRP are very robust. We describe a few robustness checks before proceeding further. First, we compute volatility risk premia using simple at-the-money implied volatility rather than the more complicated model-free implied volatility. We also implement the simple variance swap formula of Martin (2012). In both cases, results are virtually identical for developed countries and improve for developed and emerging countries. We report these results in Internet Appendix Table A.3. Second, in our empirical work we also experiment with an AR(1) process for RV to form expectations of RV rather than using lagged RV over the previous 12 months. Again, we find that the results are virtually identical to those reported in Table 2. Third, we report the net of transactions costs returns to VRP and other currency strategies in Internet Appendix Table A.2, and show that these are similar to those reported in Table 2, especially for the more liquid Developed sample of countries. Fourth, in Internet Appendix Table A.7, we check whether a simple strategy based on sorting currencies by the difference between longer-term and short-term realized volatility effectively captures the returns from VRP. Using definitions of "long-term" ranging from six to 24 months and "short-term" from one to six months, we find that while there are a number of high-return portfolios in the set, there is substantial variation in these returns across portfolios, leading to concerns of potential data-mining. Finally, we show in Internet Appendix Table A.4 that the identities of the currencies most often found in the "corner" VRP portfolios are not easily recognizable from other currency strategies such as carry. We formalize this last exercise by explicitly comparing the returns of VRP to the conventional set of currency strategies considered in the literature thus far, which we present in the next section.

4.2 Comparing VRP with Other Currency Strategies

In Table 3, we present the returns to a number of long-short currency strategies computed using only time $t-1$ information, to compare the predictability generated by strategies previously proposed in the literature with the new VRP strategy that we propose. We compare CAR, MOM, VAL, and RR with our VRP based strategy. We report results for both subsamples (Developed, and Developed and Emerging) in our data.

Panel A of the table shows the results for the portfolio *excess* returns (including interest-rate differentials) generated by these trading strategies. Consistent with a vast empirical literature (e.g., Lustig, Roussanov, and Verdelhan, 2011, Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011, and Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a), CAR delivers a very high average excess return – indeed, the highest of all strategies considered. The Sharpe ratio of the carry trade is 0.61 for the sample of developed countries, and 0.74 for the full sample. MOM also generates positive excess returns, albeit less striking than carry, which is consistent with the recent evidence in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) that the performance of currency momentum has weakened substantially during the last decade; the Sharpe ratio is 0.27 for both samples of countries. Both VAL and RR do very well, with Sharpe ratios of 0.62 and 0.48 respectively.

In contrast, the VRP strategy that we introduce generates a Sharpe ratio of 0.48 and 0.29 for the two samples of countries considered, signifying that it outperforms the momentum strategy. The VRP strategy works better for the developed countries in our sample than for the whole sample of developed and emerging countries. One plausible explanation for this is that there is a greater prevalence of hedging using more sophisticated instruments such as currency options in developed markets than in emerging markets.

Panel A of the table suggests that the returns to the VRP strategy are somewhat modest in comparison with those of the other strategies that we provide as comparison. However, Panel B of the table introduces the main benefit of the VRP strategy, namely that the lion's share of its returns accrue as a result of spot rate predictability. This predictability is virtually twice as large as the best competitor strategy over the sample period, generating an annualized mean spot exchange rate return of 4.4% for the developed countries, and 3.72% for the full cross-section of all 20 countries in our sample. In contrast, the exchange rate return from CAR is close to zero for both samples, and while other strategies, notably VAL, have relatively better performance in predicting movements in the spot rate than CAR, the preponderance of their returns stem from interest rate differentials.

Several of the other moments presented in Panel B of Table 3 are also worth highlighting. First, the returns from VRP display desirable skewness properties, as its unconditional skewness is positive (albeit small for the full sample), and the maximum drawdown is comparable to that of MOM and far better (i.e., higher) than that of CAR. Another way to see this, of course, is to compare the (very different) returns to RR and VRP, as RR is constructed to replicate a long high skewness-short low skewness portfolio. Finally, the table shows that the portfolio turnover of the VRP strategy (measured in terms of changes in the composition of the short and long legs of the VRP strategy, $Freq_S$ and $Freq_L$ in Table 3) is reasonable – lying in between the very low turnover of CAR and the high turnover of MOM. This means that the VRP strategy is likely to perform well also for lower rebalancing periods and that transaction costs – which are known to be relatively small in currency markets – are unlikely to impact significantly on the performance of VRP.

4.3 Combining VRP with Other Currency Strategies

Panel C of Table 3 documents the correlation of the VRP strategy with the other strategies, and finds that the strategy tends to be negatively correlated with CAR (with correlations of -0.18 and -0.21 for the two samples) and only mildly positively correlated with MOM (with correlations of 0.09 and 0.10 for the two samples). The correlation with VAL for Developed countries is higher, but at 0.23 there is substantial orthogonal information in the strategy – indeed several of the other strategies are much more highly correlated with one another. Apart from showing that the strategy is distinct from those already studied in the literature, this also implies that combining VRP with CAR, MOM, VAL, and RR may well yield sizable diversification benefits to an investor. It is also useful to note that the correlations for the excess returns from the strategies, presented in the table, are very close in magnitude to the correlations acquired from the exchange rate component of these returns – in other words, it is the currency component of the returns to this strategy that is the proximate source of the diversification benefits.

Figure 1 provides a graphical illustration of the differences in the performance of the strategies highlighted in Table 2, and restricts the plot to the sample of Developed Countries to conserve space. The figure plots the one-year rolling Sharpe ratio for these strategies, and makes visually clear the marked difference in the evolution of risk-adjusted returns of VRP relative to the others. While there is a substantial improvement in the Sharpe ratio of VRP during the recent crisis, the strategy is not driven entirely by this episode – the Sharpe ratio has been relatively stable over the sample period, and appears to be no more volatile than the Sharpe ratio of CAR and MOM.

Table 4 shows the subsample performance of the currency component of these strategies as a complement to Figure 1. It is clear that the performance of VRP is greater in crisis and NBER recession periods. However it is important to highlight that, outside of these recession periods, the return to VRP is still large and positive, and higher than that of all the competitor strategies. Even if VRP were to be used primarily as a hedge for a canonical currency strategy, it has very desirable properties, delivering positive returns outside of crisis periods, and very high returns within crisis periods.

Figure 2 plots the cumulative wealth of the strategies over the sample period (again, only for the Developed Countries), decomposing it into its two constituents: the exchange rate component (FX) and the interest rate gain component (yield). Both CAR and MOM have a positive yield component, although in the case of the carry trade the yield component is the sole positive driver of the carry return because the cumulative FX return component is negative. For MOM, most of the excess return is driven by spot predictability, so the yield component has a positive but relatively minor contribution to momentum returns. VRP returns are different in that they are made up of a mildly negative yield component (for both sample of countries considered), and therefore the component due to spot return predictability is in fact larger than the full portfolio return. The performance of VRP is similar to VAL, except that VAL also has positive yield, but far lower currency returns.

Taken together, the results from this section suggest that, while the carry trade strategy is – taken in isolation – the best performing strategy in terms of excess returns and delivers the highest Sharpe ratio, the VRP strategy has creditable excess returns overall, an important tendency to deliver returns during crisis periods that are far higher than the crashes commonly experienced with the carry trade, and far stronger predictive power for exchange rate returns, which is a unique feature relative to alternative currency trading strategies. The importance of these last two features of the VRP strategy is twofold. First, a currency investor would likely gain a great deal of diversification benefit from adding VRP to a currency portfolio to enhance risk-adjusted returns. Second, a spot currency trader interested in forecasting exchange rate fluctuations (as opposed to currency excess returns) would greatly value the signals provided by VRP.

To shed light on the added value of the VRP strategy for a currency investor, we compute the optimal currency portfolio for an investor who uses all of the five strategies considered here: CAR, VAL, RR, MOM, and VRP. Specifically, consider a portfolio of N assets with covariance matrix Σ. The global minimum variance portfolio is the portfolio with the lowest return volatility and represents the solution to the following optimization problem: min $w'\Sigma w$ subject to the constraint that the weights sum to unity, $w'\iota = 1$,where w is the $N \times 1$ vector of portfolio weights on the risky assets, ι is a $N \times 1$ vector of ones, and Σ is the $N \times N$ covariance matrix of the asset returns. The weights of the global minimum variance portfolios are given by $w = \frac{\Sigma^{-1}\iota}{\iota'\Sigma^{-1}\iota}$. We compute the optimal weights for both the Developed and Developed & Emerging samples, and report the results graphically in Figure 3.

The results show that the optimal weight assigned to the VRP strategy is the highest across all five currency strategies, equalling 33 percent or a full third of the portfolio, and the same in both samples of currencies. The Sharpe ratio of the minimum volatility portfolio for the Developed sample, for instance, is quite impressive and equal to 0.92. However, it would drop substantially to 0.79 if the investor had no access to the VRP strategy (i.e., only employs the other four currency strategies). Similarly for the Developed & Emerging sample. These findings confirm the value of VRP in a currency portfolio despite its return not being the highest among the strategies considered. It has extremely desirable correlation properties which cannot be replicated using information from any of the other well-studied currency strategies.

5 Pricing VRP Returns

In this section we carry out both cross-sectional and time-series asset pricing tests to determine whether VRP returns can be understood as compensation for systematic risk.

5.1 Time-Series Regressions

As a first step, Table 5 simply regresses the time-series of VRP returns on a number of risk factors proposed in the literature. First, Panel A confirms the results found in Tables 2 and 3, by using DOL, CAR, MOM, VAL, and RR as right-hand side variables, and shows that for both Developed and Developed and Emerging samples, there is substantial alpha relative to these factors. Panel B uses the three Fama-French factors and adds equity market momentum, denoted $MOME$. Again, VRP has alpha relative to these factors which is virtually identical to that in the prior panel. Finally, Panel C of Table 5 employs the Fung-Hsieh (2004) factor model, which has been used in numerous previous studies; see for example, Bollen and Whaley (2009), Ramadorai (2013), and Patton and Ramadorai (2013). The set of factors comprises the excess return on the S&P 500 index; a small minus big factor constructed as the difference between the Wilshire small and large capitalization stock indexes; excess returns on portfolios of lookback straddle options on currencies, commodities, and bonds, which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the yield spread of the US 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the 10-year bond; and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration. Yet again, the table shows that the alpha of VRP is virtually unaffected by the inclusion of these factors.

5.2 Cross-Sectional Tests

Our cross-sectional tests rely on a standard stochastic discount factor (SDF) approach (Cochrane, 2005), and we focus on a set of risk factors in our investigation that are motivated by the existing currency asset pricing literature. We begin by briefly reviewing the methods employed, and denote excess returns of portfolio i in period $t+1$ by RX^i_{t+1}. The usual no-arbitrage relation applies, so risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$\mathbb{E}[M_{t+1} RX^i_{t+1}] = 0, \tag{6}$$

with a linear SDF $M_t = 1 - b'(f_t - \mu)$, where f_t denotes a vector of risk factors, b is the vector of SDF parameters, and μ denotes factor means.

This specification implies a beta pricing model in which expected excess returns depend on factor risk prices λ, and risk quantities β_i, which are the regression betas of portfolio excess returns on the risk factors:

$$\mathbb{E}\left[RX^i\right] = \lambda' \beta_i \tag{7}$$

for each portfolio i (see e.g., Cochrane, 2005).

The relationship between the factor risk prices in equation (7) and the SDF parameters in equation (6) is simply given by $\lambda = \Sigma_f b$, where Σ_f is the covariance matrix of the risk factors. Thus, factor risk prices can be easily obtained via the SDF approach, which we implement by estimating the parameters of equation (6) via the generalized method of moments (GMM) of Hansen (1982).[17] We also present results from the more traditional two-stage procedure of Fama and MacBeth (1973) in our empirical implementation.

In our asset pricing tests we consider a two-factor linear model that comprises DOL and one additional risk factor, which is one of CAR and VOL_{FX}. DOL denotes the average return from borrowing in the US money market and equally investing in foreign money markets. CAR is the carry portfolio described earlier. VOL_{FX} is a global FX volatility risk factor constructed as the innovations to global FX volatility, i.e., the residuals from an autoregressive

[17] Estimation is based on a pre-specified weighting matrix and we focus on unconditional moments (i.e., we do not use instruments other than a constant vector of ones) since our interest lies in the performance of the model to explain the cross-section of expected currency excess returns (see Cochrane, 2005; Burnside, 2011).

model applied to the average realized volatility of all currencies in our sample, as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a).[18]

In assessing our results, we are aware of the statistical problems plaguing standard asset pricing tests, recently emphasized by Lewellen, Nagel, and Shanken (2010). Asset pricing tests can often be highly misleading, in the sense that they can indicate strong but illusory explanatory power through high cross-sectional R^2 statistics, and small pricing errors, when in fact a risk factor has weak or even non-existent pricing power. Given the relatively small cross-section of currencies in our data, as well as the relatively short time span of our sample, these problems can be severe in our tests. As a result, when interpreting our results, we only consider the cross-sectional R^2 and Hansen-Jagannathan (HJ) tests on the pricing errors, if we can confidently detect a statistically significant risk factor, i.e., if the GMM estimates clearly point to a statistically significant market price of risk λ on a factor.

Table 6 reports GMM estimates of b, portfolio-specific β's, and implied λ's, as well as cross-sectional R^2 statistics and the HJ distance measure (Hansen and Jagannathan, 1997). In the table, standard errors are constructed as in Newey and West (1987) with optimal lag length selection according to Andrews (1991). Besides the GMM tests, we employ traditional Fama-MacBeth (FMB) two-pass OLS regressions to estimate portfolio betas and factor risk prices. Note that we do not include a constant in the second stage of the FMB regressions, i.e. we do not allow a common over- or under-pricing in the cross-section of returns - however our results are virtually identical when we replace the DOL factor with a constant in the second stage regressions.[19] Since DOL has virtually no cross-sectional relation to portfolio returns, it serves the same purpose as a constant that allows for common mispricing.

Panels A and B of Table 6 show clearly how neither of the risk factors considered enters the SDF with a statistically significant risk price λ, and that this is the case for both the developed countries and the full sample. As expected, the FMB results in the table are qualitatively, and

[18] In Internet Appendix Table A.8 and A.9, we also consider innovations to global average precentage bid-ask spreads in the spot market (BAS_{FX}) and the option market (BAS_{IV}). BAS_{FX} is constructed by averaging over a month the daily average bid-ask spread of the spot exchange rates. BAS_{IV} is constructed by averaging over a month the daily average bid-ask spread of the 1-year at-the-money implied volatilities. Innovations are computed as the residuals to a first-order autoregressive process. Higher bid-ask spreads indicate lower liquidity, so that our aggregate measures can be seen as global proxies for the FX spot market and the FX option market illiquidity, respectively.

[19] Also see Lustig and Verdelhan (2007) and Burnside (2011) on the issue of whether or not to include a constant in these regressions.

in most cases also quantitatively identical to the one-step GMM results. The bottom part of the panels show that there is little cross-sectional variation across the 5 portfolios sorted by the cost of currency insurance, which is what we confirm more formally in the asset pricing tests.

The best performing SDF in these tests includes DOL and VOL_{FX}, and generates a respectable cross-sectional R^2 (0.27), but the market price of risk is insignificantly different from zero. The HJ test delivers large p-values for the null of zero pricing errors in all cases but we attach no information to this result given the lack of clear statistical significance of the market price of risk. We also carried out asset pricing tests using the same methods and risk factors in which we attempt to price only the exchange rate component of the returns from VRP. In that exercise, the results are equally disappointing in that all risk factors included in the various SDF specifications are statistically insignificant.

Overall, the asset pricing tests reveal that it is not possible to understand the returns from the VRP strategy as compensation for global risk, using the carry risk factor, global volatility risk, or illiquidity in the FX market of the kind used in the literature. These results are consistent with our earlier results that indicate that VRP returns are very different from the returns of conventional currency strategies, and hence their source is likely to stem from a different mechanism than compensation for canonical sources of systematic risk. Therefore, we now turn to examining potential explanations.

6 Understanding the Drivers of VRP

We consider two possible alternative explanations for our results. The first is **Aversion to Volatility Risk.** It might be the case that the currency-specific volatility risk premium captures fluctuations in aversion to volatility risk. As a result, currencies with relatively expensive volatility insurance would have low expected returns and vice versa.

Our VRP strategy is *cross-sectional,* since we are long and short currencies simultaneously. As a result, if this explanation were correct, it would rely either on different currencies loading differently on a global volatility shock, or indeed on market segmentation causing expected returns on different currencies to be determined independently. This latter possibility is very difficult to evaluate, and if our strategy did indeed provide evidence of this, it would have far-reaching consequences.

To evaluate the first of these possibilities, i.e., currencies loading differently on a global volatility shock, we describe above the ineffectiveness of using the global FX volatility risk factor of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) to price the returns from our portfolio. However, it could be the case that this proxy is not the best suited to capture the returns from our strategy, and we try other possibilities. We do so by estimating the loadings of currency returns on various proxies for global volatility risk, and building portfolios sorted on these estimated loadings. Specifically, we estimate the following regression:

$$RX_{it} = \alpha_i + \beta_i GVOL_t + \varepsilon_{it},$$

for each currency i. Here $GVOL$ is a proxy for global volatility risk premia and we employ various measures, including the average volatility risk premium across our currencies (with equal weights); the first principal component of the currencies' volatility risk premia; and the equity volatility risk premium computed as the difference between the time-t one-month realized volatility on the S&P500 and the VIX index.

We estimate these regressions using rolling windows of 36 months. After obtaining estimates of the β_i coefficients, we sort currencies into five portfolios on the basis of these β_i estimates. Finally, we construct a long-short strategy which buys currencies with low betas and sells currencies with high betas. In essence, this strategy exploits differences in exposure of individual currencies to global measures of volatility risk premia, which is a direct test of the above hypothesis.

The results using our three measures for $GVOL$ are qualitatively identical and we report in Table 7 the results for $GVOL$ set equal to the average volatility risk-premium across the currencies in our sample. Internet Appendix Tables A.5 and A.6 contains results for the other two measures. The table shows that the performance of this strategy is strictly inferior to the performance of the VRP strategy, and the correlation between the returns from the two strategies is tiny. On the basis of this evidence, we conclude that there is little support for VRP returns being driven by aversion to global volatility risk in the data.

The second possible explanation that we consider is **Limits to Arbitrage**, in the spirit of Acharya, Lochstoer, and Ramadorai (2013). According to this explanation, the returns to VRP arise from the interaction between natural hedgers of FX risk, and currency market speculators. When the risk-bearing capacity of currency-market speculators is affected by shocks to the availability of arbitrage capital, this will make currency options across the board more expensive, with particular impacts on those currencies to which speculators have high exposure. This will result in selling pressure on expensive-to-insure currencies as natural hedgers such as corporations sell pre-existing currency holdings, abandon expensive currency hedges, and become more reluctant to denominate contracts in these currencies. Conversely, this mechanism results in relatively less pressure on cheap-to-insure currencies, for which natural hedgers are happy to hold higher inventories or take on more "real" currency exposure. This yields the positive long-short returns in the VRP portfolio.

This explanation has implications which we test in Table 8. The table presents coefficients from predictive time-series regressions of the exchange rate component of VRP on a number of conditioning factors implied by this mechanism. We report results from the exchange rate component of VRP since we are primarily interested in understanding the predictive power for spot exchange rates, but the results for excess returns are, not surprisingly, qualitatively identical and quantitatively very similar.[20]

The first column in both panels shows the univariate regression of the exchange rate component of VRP on the 12-month rolling average of the lagged TED spread. When funding liquidity is lower (i.e., times of high capital constraints on speculators), we should find that the expected (exchange rate) return from VRP should increase, and Table 8 provides strong confirmation for this for developed countries. While the sign of the coefficient on TED is positive for the full sample of countries, it is not statistically significant. This could be because the TED spread is possibly less useful as a proxy for funding liquidity constraints in emerging markets.

The second column shows that when the 12-month rolling average of changes in VIX (our proxy for increases in the risk aversion of market participants, yielding both greater limits to arbitrage and an increased desire to hedge) is positive, VRP returns increase (significantly for the sample of developed countries), again consistent with the limits to arbitrage explanation. This is similar to the results in Nagel (2012), who shows that a strategy of liquidity provision in equity markets has returns which are highly correlated with VIX. Similarly, the third column shows that a general financial distress indicator (FSI, constructed by the Federal Reserve Bank

[20] See the Internet Appendix for a detailed description of the conditioning factors used for this exercise.

of St. Louis) that captures the principal component of a variety of liquidity and volatility indicators is statistically significant.

The fourth column of the table interacts TED with changes in VIX, and finds strong statistically significant predictive power of this interaction for the FX returns on our strategy in both developed and emerging countries, suggesting that when funding liquidity is constrained *and* risk aversion is high, VRP returns increase.

The next three columns check the predictive ability for VRP of market participants' positioning information. The first two of these columns use the (normalized) net short futures position of (both commercial and financial) traders on the Australian dollar (AUD) and the Japanese yen (JPY) relative to the USD dollar, respectively.[21] For Developed as well as Developed and Emerging samples, at times when there is greater futures-related hedging of the AUD by FX traders, the returns to the VRP strategy increase. However, we find no real impact for the net short position on the JPY. The final column of the table adds in measures of capital flows into hedge funds. When aggregate capital flows into hedge funds are high, signifying that they experience fewer constraints on their ability to engage in arbitrage transactions, we find that returns for our VRP strategy are lower and vice versa.

The final three rows of Table 8 consider several of the variables described above simultaneously to test their joint and separate explanatory power. We include TED, changes in VIX and the interaction separately to avoid potential collinearity in the regressions as these variables are highly correlated with one another. More generally, it is clear that the variables used in the univariate regressions are likely to contain a substantial common component. Nonetheless, we find that all these variables retain their signs and are generally statistically significant in these multivariate predictive regressions, offering support to the limits to arbitrage explanation of our results.

Next, we examine post-formation portfolio returns. If the limits to arbitrage explanation is correct, the predictability of volatility insurance costs cannot be long-lived. According to this explanation, either speculators face a shock that reduces their available arbitrage capital and limits their ability to provide cheap volatility insurance, or there is an increase in hedger risk aversion causing their demand for hedging to increase. As a result, net demand for

[21] AUD is taken as representative of a typical high-interest currency bought by carry traders, whereas JPY is a traditional 'safe haven' currency.

volatility insurance increases, making hedging more expensive, which will be reflected in a lower volatility risk premium, i.e., more expensive currency options. In the face of high volatility insurance costs, natural hedgers scale back on the amount of spot currency they are willing to hold, predictably depressing spot prices and leading to relatively low returns on the spot currency position. When capital constraints loosen, however, we should see the opposite behavior, i.e., the volatility risk premium reverts to the mean, and reversals in currency returns.

This yields an additional testable implication, namely, reversal in post-formation cumulative returns on the VRP strategy, which is exactly what we find in Figure 4. The figure plots cumulative post-formation risk-adjusted excess returns (left panel) and risk-adjusted currency returns (right panel) over periods of $1, 2, \ldots, 20$ months for the VRP-sorted portfolios, for both samples of countries examined.[22] Returns in the post-formation period are overlapping, as we form new portfolios each month, but track these portfolios for 20 months.

In the figure, the excess returns increase and peak after 3 months for the Developed Countries sample and 4 months for the full sample, and subsequently decline. Looking at spot exchange rate returns, the peak in cumulative post-formation exchange rate return occurs around 4 months for the developed sample and 5-6 months for the full sample. This evidence of a reversal appears consistent with the prediction of the limits to arbitrage explanation of the economic source of VRP predictive power. Moreover the relatively high frequency of the reversal suggests that an explanation based on risk aversion to volatility combined with market segmentation, an explanation described earlier, is somewhat less likely.

Finally, we examine whether the observed buying and selling actions of different players in the currency market follow the pattern implied by the limits to arbitrage explanation, i.e., that currencies in the high volatility-insurance portfolio are sold and those in the low volatility insurance portfolio are bought by natural hedgers, with speculators taking the opposite position. We do so using the CFTC data on the position of commercial and financial traders in FX markets, essentially taking the currencies ranked by their volatility insurance costs, and

[22]Specifically, we plot returns net of the exposure to carry trade risk, i.e., we use the residuals from a regression of VRP returns on CAR, so that the returns can be considered as alphas over and above carry trade returns. Using raw portfolio returns or their exchange rate component produces a very similar pattern for the full sample, and a virtually identical pattern for the developed sample, as expected given that we know already from previous analyses that CAR has little pricing power for VRP portfolios.

documenting the traders' positions (cumulative net positions), rather than returns.[23] We view the CFTC position data as a proxy for cumulative order flow across different segments of FX market participants and a large proportion of the total FX market, given that there is evidence that the CFTC position data and currency order flow capture very similar information (e.g., Klitgaard and Weir, 2004).

The results of this exercise are reported in Figure 5, which plots the cumulative position in the currencies in the VRP portfolio for financial and commercial traders. We find that the position of commercial traders follows exactly the pattern implied by the limits to arbitrage explanation – such traders sell expensive-insurance currencies and buy cheaper-insurance currencies. Financial traders display exactly the opposite behavior, with a strongly negative position in the VRP portfolio, acting as market-makers that provide liquidity to satisfy the buying (selling) demand for low (high)-insurance currencies.[24]

Taken together, the results in this section lend support to a limits to arbitrage explanation for the predictability of spot exchange rates associated with VRP. There is a growing theoretical and empirical literature that highlights the role of limits to arbitrage and the interaction between hedgers and speculators in asset markets, and we view our results as suggestive that currency markets may be another venue in which such mechanisms are at work.

7 Conclusions

We show that the currency volatility risk premium has substantial predictive power for the cross-section of currency returns. Sorting currencies by their volatility risk premia generates economically significant returns in a standard multi-currency portfolio setting. This predictive power is specifically related to spot exchange rate returns, and not to interest

[23] To allow for meaningful cross-currency comparisons, we need to ensure that net positions are comparable across currencies, as their absolute size differs across currencies. We therefore divide net positions by their standard deviation computed over a rolling window of 3 month.

[24] We also replicate this exercise using a data set on customer order flow in the FX market from a major bank over the sample period from January 2001 to December 2010. The data cover all currencies in our "Developed" sample with the exception of the Danish Krone, and order flow is measured as net buying pressure against the US dollar (i.e., buyer-initiated minus seller-initiated trades). The flow data are categorized into two groups: commercial and financial customers. The results, available upon request, suggest a qualitatively identical pattern to the one obtained using the CFTC data.

rate differentials, and the spot rate predictability is much stronger than that observed from carry, currency momentum, currency value, or risk-reversal strategies. Moreover, the returns from the volatility risk premium strategy are largely uncorrelated with these other currency strategies, thus providing a substantial diversification gain to investors.

We find that currencies for which volatility insurance is relatively cheap predictably appreciate, while currencies for which volatility hedging using options is relatively more expensive predictably depreciate. Standard risk factors cannot price the returns from the long-short portfolio that we construct from these components. We consider two candidate explanations for these findings, and provide suggestive evidence that they can be rationalized in terms of the time-variation of limits to arbitrage capital and the incentives of hedgers and speculators in currency markets. Overall, the results in our paper provide new insights into the predictability of exchange rate returns, an area in which evidence has been difficult to obtain. We also introduce a new currency strategy with useful diversification properties into the expanding and important research area on this topic.

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Table 1. Volatility Risk Premia

This table presents summary statistics for the 1-year volatility risk premium (VRP) defined as difference between the realized volatility (RV) and the synthetic volatility swap rate (SW). RV is computed at time t using daily exchange rate returns over the previous year. SW is constructed at time t using the implied volatilities across 5 different deltas from 1-year currency options. Q_j refers to the j^{th} percentile. AC indicates the 1-year autocorrelation coefficient. VPR, RV, and SW are expressed in percent per annum. The sample period comprises daily data from January 1996 to August 2011. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

	VRP	RV	SW	VRP	RV	SW
	Developed			*Developed & Emerging*		
$Mean$	-0.62	10.68	11.31	-0.92	10.82	11.74
$Sdev$	1.58	2.88	2.75	1.78	3.10	3.22
$Skew$	0.54	1.85	1.42	-0.31	2.12	2.07
$Kurt$	5.97	6.86	5.29	7.88	7.85	8.06
Q_5	-3.06	7.15	7.77	-3.67	7.23	8.36
Q_{95}	1.65	18.40	16.76	1.57	19.43	17.86
AC	-0.19	0.33	0.53	-0.17	0.27	0.46

Table 2. Volatility Risk Premia Portfolios

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia at time $t-1$. The long (short) portfolio P_L (P_S) contains the top 20% of all currencies with the highest (lowest) volatility risk premium. H/L denotes a long-short strategy that buys P_L and sells P_S. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), and the frequency of portfolio switches ($Freq$). *Panel A* displays the overall excess return, whereas *Panel B* reports the exchange rate component only. *Panel C* presents the transition probability from portfolio i to portfolio j between time t and time $t+1$. $\overline{\pi}$ indicates the steady state probability. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	P_L	P_2	P_3	P_4	P_S	H/L	P_L	P_2	P_3	P_4	P_S	H/L
	Developed						*Developed & Emerging*					
Panel A: Excess Returns												
$Mean$	4.70	2.24	1.04	1.78	0.67	4.03	3.59	1.93	1.34	1.40	1.26	2.34
$Sdev$	9.08	9.27	9.76	10.07	9.72	8.33	9.32	8.68	8.89	10.44	8.81	8.18
$Skew$	−0.05	0.19	0.09	−0.17	−0.26	0.28	−0.09	0.05	−0.21	−0.29	−0.39	0.12
$Kurt$	3.13	5.14	5.80	3.85	3.82	3.47	3.09	4.79	3.85	4.16	3.73	3.26
SR	0.52	0.24	0.11	0.18	0.07	0.48	0.39	0.22	0.15	0.13	0.14	0.29
AC_1	0.10	0.04	0.13	0.15	0.01	0.04	0.10	0.14	0.15	0.13	0.11	0.05
$Freq$	0.24	0.44	0.52	0.48	0.32	0.32	0.26	0.43	0.53	0.48	0.27	0.27
Panel B: FX Returns												
$Mean$	4.93	2.06	1.26	1.60	0.52	4.40	3.51	1.62	1.37	0.82	−0.21	3.72
$Sdev$	9.05	9.24	9.63	9.96	9.64	8.35	9.26	8.62	8.74	10.31	8.75	8.17
$Skew$	−0.12	0.15	0.06	−0.18	−0.26	0.28	−0.18	0.00	−0.26	−0.31	−0.47	0.12
$Kurt$	3.17	5.24	5.88	4.06	3.83	3.61	3.07	4.80	4.02	4.36	3.94	3.50
SR	0.54	0.22	0.13	0.16	0.05	0.53	0.38	0.19	0.16	0.08	−0.02	0.46
AC_1	0.10	0.03	0.11	0.13	−0.01	0.04	0.10	0.13	0.13	0.10	0.10	0.04
$Freq$	0.24	0.44	0.52	0.48	0.32	0.32	0.26	0.43	0.53	0.48	0.27	0.27
Panel C: Transition Matrix												
P_L	0.77	0.18	0.03	0.01	0.01		0.75	0.20	0.03	0.01	0.01	
P_2	0.17	0.56	0.20	0.06	0.02		0.16	0.57	0.20	0.05	0.02	
P_3	0.03	0.20	0.49	0.20	0.08		0.03	0.22	0.48	0.22	0.05	
P_4	0.01	0.05	0.21	0.52	0.21		0.01	0.08	0.23	0.52	0.16	
P_S	0.00	0.02	0.08	0.21	0.69		0.01	0.02	0.05	0.19	0.73	
$\overline{\pi}$	**0.19**	**0.20**	**0.20**	**0.20**	**0.20**		**0.19**	**0.23**	**0.20**	**0.19**	**0.18**	

Table 3. Currency Strategies

This table presents descriptive statistics of currency strategies formed using time $t-1$ information. CAR is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential relative to the US dollar. Similarly, MOM is the momentum strategy that buys (sells) currencies with the highest (lowest) past 3-month exchange rate return, VAL is the value strategy that buys (sells) currencies with lowest (highest) real exchange rate, RR is the risk reversal strategy that buys (sells) currencies with the lowest (highest) 1-year 10-delta risk reversal, and VRP is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), the Sortino ratio (SO), the maximum drawdown (MDD), and the frequency of portfolio switches for the long ($Freq_L$) and the short ($Freq_S$) position. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. *Panel C* presents the sample correlations of the currency excess returns. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	CAR	MOM	VAL	RR	VRP	CAR	MOM	VAL	RR	VRP
Panel A: Excess Returns										
	Developed					*Developed & Emerging*				
$Mean$	6.49	2.58	5.78	5.30	4.03	7.42	2.22	3.55	5.38	2.34
$Sdev$	10.66	9.55	9.38	11.40	8.33	9.97	8.30	8.90	10.60	8.18
$Skew$	−0.92	0.35	−0.26	−0.72	0.28	−0.92	−0.03	−0.15	−0.14	0.12
$Kurt$	5.65	3.86	3.50	6.58	3.47	4.53	2.95	3.17	4.43	3.26
SR	0.61	0.27	0.62	0.46	0.48	0.74	0.27	0.40	0.51	0.29
SO	0.72	0.50	0.94	0.58	0.87	0.94	0.47	0.62	0.75	0.49
MDD	−0.37	−0.16	−0.14	−0.37	−0.18	−0.21	−0.13	−0.14	−0.24	−0.18
AC_1	0.09	0.00	−0.03	0.07	0.04	0.01	−0.09	0.01	0.08	0.05
$Freq_L$	0.13	0.48	0.09	0.17	0.24	0.15	0.49	0.07	0.22	0.26
$Freq_S$	0.07	0.43	0.07	0.27	0.32	0.16	0.46	0.06	0.26	0.27
Panel B: FX Returns										
$Mean$	0.34	2.03	2.95	1.42	4.40	−0.65	1.45	0.06	0.22	3.72
$Sdev$	10.66	9.57	9.44	11.48	8.35	9.99	8.16	8.89	10.60	8.17
$Skew$	−0.93	0.42	−0.29	−0.75	0.28	−1.05	−0.02	−0.16	−0.21	0.12
$Kurt$	5.82	4.17	3.51	6.83	3.61	4.84	3.13	3.19	4.74	3.50
SR	0.03	0.21	0.31	0.12	0.53	−0.07	0.18	0.01	0.02	0.46
SO	0.04	0.40	0.47	0.15	0.93	−0.08	0.30	0.01	0.03	0.75
MDD	−0.43	−0.20	−0.24	−0.40	−0.19	−0.35	−0.15	−0.27	−0.29	−0.18
AC_1	0.11	0.00	−0.02	0.08	0.04	0.03	−0.12	0.01	0.08	0.04
$Freq_L$	0.13	0.48	0.09	0.17	0.24	0.15	0.49	0.07	0.22	0.26
$Freq_S$	0.07	0.43	0.07	0.27	0.32	0.16	0.46	0.06	0.26	0.27
Panel C: Correlations										
CAR	1.00	−0.17	0.44	0.68	−0.18	1.00	−0.03	0.54	0.57	−0.21
MOM	−0.17	1.00	−0.17	−0.17	0.09	−0.03	1.00	−0.14	−0.15	0.10
VAL	0.44	−0.17	1.00	0.49	0.23	0.54	−0.14	1.00	0.64	−0.10
RR	0.68	−0.17	0.49	1.00	−0.01	0.57	−0.15	0.64	1.00	−0.12
VRP	−0.18	0.09	0.23	−0.01	1.00	−0.21	0.10	−0.10	−0.12	1.00

Table 4. Currency Strategies: Sub-Samples

This table presents descriptive statistics of foreign exchange (FX) returns to currency strategies formed using time $t-1$ information. CAR is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential relative to the US dollar. Similarly, MOM is the momentum strategy that buys (sells) currencies with the highest (lowest) past 3-month exchange rate return, VAL is the value strategy that buys (sells) currencies with lowest (highest) real exchange rate, RR is the risk reversal strategy that buys (sells) currencies with the lowest (highest) 1-year 10-delta risk reversal, and VRP is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from March 2001 to November 2001, and from December 2007 to June 2009 (*Panel A*), from January 1996 to December 2006 (*Panel C*), and from January 2007 to August 2011 (*Panel D*). January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	CAR	MOM	VAL	RR	VRP	CAR	MOM	VAL	RR	VRP
	Developed					*Developed & Emerging*				
Panel A: NBER Recession Periods										
$Mean$	−9.59	11.32	4.62	−7.96	11.54	−7.97	7.07	0.10	−4.80	6.50
$Sdev$	17.11	15.40	12.03	19.07	10.11	14.69	10.49	9.92	15.20	9.38
$Skew$	−0.44	0.28	−0.63	−0.90	0.12	−0.80	0.17	−0.15	−0.08	−0.45
$Kurt$	3.71	2.87	3.43	4.13	2.26	2.84	2.77	2.95	2.54	2.88
SR	−0.56	0.74	0.38	−0.42	1.14	−0.54	0.67	0.01	−0.32	0.69
MDD	−0.40	−0.16	−0.12	−0.41	−0.09	−0.32	−0.07	−0.18	−0.29	−0.09
AC_1	0.35	0.12	−0.09	0.23	0.27	0.17	−0.04	0.09	0.31	0.22
Panel B: non-NBER Recession Periods										
$Mean$	2.09	0.40	2.65	3.08	3.14	0.64	0.46	0.05	1.11	3.23
$Sdev$	9.06	8.11	8.95	9.57	7.99	8.92	7.68	8.73	9.61	7.96
$Skew$	−0.87	0.04	−0.16	0.11	0.26	−0.92	−0.19	−0.16	−0.17	0.26
$Kurt$	4.50	2.48	3.30	4.16	4.02	4.90	2.90	3.22	5.55	3.70
SR	0.23	0.05	0.30	0.32	0.39	0.07	0.06	0.01	0.12	0.41
MDD	−0.31	−0.21	−0.22	−0.15	−0.16	−0.31	−0.20	−0.22	−0.20	−0.16
AC_1	−0.07	−0.09	−0.02	−0.04	−0.03	−0.06	−0.15	0.00	−0.02	−0.02
Panel C: Pre-Crisis Period										
$Mean$	1.91	0.81	3.00	2.94	2.18	1.09	0.71	0.58	1.28	3.04
$Sdev$	8.33	7.90	9.78	9.43	7.99	9.16	7.68	9.25	10.12	8.53
$Skew$	−0.91	−0.02	−0.31	0.32	0.07	−1.06	0.01	−0.25	−0.24	0.19
$Kurt$	4.92	2.46	3.26	4.14	3.46	5.20	2.59	3.10	5.41	3.47
SR	0.23	0.10	0.31	0.31	0.27	0.12	0.09	0.06	0.13	0.36
MDD	−0.31	−0.16	−0.24	−0.15	−0.19	−0.31	−0.14	−0.23	−0.18	−0.18
AC_1	−0.05	−0.11	−0.03	−0.02	−0.01	−0.08	−0.14	−0.02	−0.03	0.02
Panel D: Crisis Period										
$Mean$	−3.34	4.88	2.81	−2.13	9.61	−4.73	3.17	−1.15	−2.25	5.30
$Sdev$	14.80	12.69	8.67	15.31	9.05	11.70	9.23	8.05	11.72	7.29
$Skew$	−0.66	0.50	−0.22	−1.13	0.54	−0.89	−0.10	0.12	−0.12	−0.07
$Kurt$	4.02	3.57	4.27	5.63	3.42	3.90	3.56	3.41	3.67	3.39
SR	−0.23	0.38	0.32	−0.14	1.06	−0.40	0.34	−0.14	−0.19	0.73
MDD	−0.43	−0.16	−0.12	−0.40	−0.08	−0.31	−0.13	−0.15	−0.29	−0.10
AC_1	0.22	0.09	0.01	0.18	0.09	0.17	−0.10	0.12	0.25	0.10

Table 5. Exchange Rate Returns and Risk Factors

This table presents time-series regression estimates. The dependent variable is the volatility risk premium strategy (VRP) that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. As explanatory variables, we use the currency strategies described in Table 3 in *Panel A*, the Fama and French (1992) and the equity momentum factors in *Panel B*, and the Fung and Hsieh (2004) factors in *Panel C*. Newey and West (1987) with Andrews (1991) optimal lag selection are reported in parenthesis. The superscripts a, b, and c indicate statistical significance at 10%, 5%, and 1%, respectively. Returns are annualized. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan. Fama and French (1992) factors are from French's website whereas the Fung and Hsieh (2004) factors are from Hsieh's website.

Panel A: Currency Factors								
α	DOL	CAR	MOM	VAL	RR			R^2
Developed								
0.05^b	0.14	-0.22^b	0.11	0.10	-0.04			0.05
(0.02)	(0.09)	(0.09)	(0.08)	(0.13)	(0.12)			
Developed & Emerging								
0.04^a	-0.04	-0.31^c	0.09	0.32^b	0.08			0.15
(0.02)	(0.07)	(0.09)	(0.08)	(0.11)	(0.09)			
Panel B: Equity Factors								
α	R_m^e	SMB	HML	$MOME$				R^2
Developed								
0.05^b	-0.07	-0.05	-0.09^a	-0.05				0.01
(0.02)	(0.06)	(0.05)	(0.05)	(0.03)				
Developed & Emerging								
0.05^b	-0.07^a	-0.10^a	-0.10^b	-0.05^a				0.03
(0.02)	(0.04)	(0.05)	(0.05)	(0.03)				
Panel C: Hedge Fund Factors								
α	*Bond Trend*	*Curr Trend*	*Comm Trend*	*Equity Market*	*Size Spread*	*Bond Market*	*Credit Spread*	R^2
Developed								
0.05^b	0.14	-0.17	0.09	-0.04	-0.05	-0.09	0.07	0.01
(0.02)	(0.12)	(0.11)	(0.17)	(0.05)	(0.05)	(0.11)	(0.21)	
Developed & Emerging								
0.04^b	0.35	-0.03	0.08	-0.02	-0.10^b	-0.16^b	-0.07	0.06
(0.02)	(0.1)	(0.13)	(0.16)	(0.04)	(0.05)	(0.07)	(0.10)	

Table 6. Asset Pricing Tests

This table reports asset pricing results. In *Panel A* the linear factor model includes the dollar (DOL) and the carry trade (CAR) factors. In *Panel B* the linear factor model includes the dollar (DOL) and the innovations to the global FX volatility (VOL_{FX}) factors. CAR is a long-short strategy that buys (sells) the top 20% of all currencies currencies with the highest (lowest) interest rate differential relative to the US dollar. DOL is equivalent to a strategy that borrows in the US money market and equally invests in foreign currencies, and serves as a constant in the cross-section. The test assets are excess returns to five portfolios sorted on the 1-year volatility risk premium (VRP) available at time $t-1$. *Factor Prices* reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ. The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. *Factor Betas* reports least-squares estimates of time series regressions. The $\chi^2(\alpha)$ test statistic tests the null that all intercepts are jointly zero. Newey and West (1987) with Andrews (1991) optimal lag selection are reported in parenthesis. *sh* denotes Shanken (1992) standard errors. The *p-values* are reported in brackets. Returns are annualized. The portfolios are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Carry Trade Factor

Factor Prices

	b_{DOL}	b_{CAR}	λ_{DOL}	λ_{CAR}	R^2	$RMSE$	χ^2	HJ	b_{DOL}	b_{CAR}	λ_{DOL}	λ_{CAR}	R^2	$RMSE$	χ^2	HJ
	Developed								*Developed & Emerging*							
GMM_1	0.42	−0.47	0.02	−0.05	−0.07	3.29	4.35	0.16	0.24	0.01	0.02	0.01	−0.14	2.09	1.93	0.11
	(0.36)	(0.55)	(0.02)	(0.07)			[0.23]	[0.20]	(0.35)	(0.51)	(0.02)	(0.06)			[0.59]	[0.59]
GMM_2	0.35	−0.37	0.02	−0.03	−0.13	3.32	4.30		0.24	0.09	0.02	0.02	−0.13	2.10	1.90	
	(0.36)	(0.54)	(0.02)	(0.07)			[0.23]		(0.35)	(0.50)	(0.02)	(0.06)			[0.59]	
FMB	0.42	−0.47	0.02	−0.05	−0.07	3.29	4.35		0.24	0.01	0.02	0.01	−0.14	2.09	1.93	
	(0.37)	(0.58)	(0.02)	(0.07)			[0.23]		(0.34)	(0.52)	(0.02)	(0.06)			[0.59]	
(sh)	(0.34)	(0.61)	(0.02)	(0.08)			[0.18]		(0.30)	(0.53)	(0.02)	(0.06)			[0.56]	

Factor Betas

	α	β_{DOL}	β_{CAR}	R^2	$\chi^2(\alpha)$	α	β_{DOL}	β_{CAR}	R^2	$\chi^2(\alpha)$
P_L	0.03	0.89	−0.04	0.62	8.75	0.02	0.96	−0.02	0.69	3.10
	(0.02)	(0.06)	(0.07)		[0.12]	(0.01)	(0.04)	(0.05)		[0.68]
P_2	0.01	0.94	0.04	0.71		0.01	0.96	−0.02	0.79	
	(0.01)	(0.08)	(0.05)			(0.01)	(0.04)	(0.04)		
P_3	−0.01	1.00	0.05	0.72		0.01	1.00	−0.08	0.80	
	(0.01)	(0.05)	(0.05)			(0.01)	(0.04)	(0.04)		
P_4	0.01	1.15	−0.15	0.81		0.01	1.20	−0.09	0.84	
	(0.01)	(0.05)	(0.05)			(0.01)	(0.05)	(0.06)		
P_S	−0.02	1.03	0.08	0.79		−0.02	0.87	0.17	0.75	
	(0.01)	(0.04)	(0.05)			(0.01)	(0.05)	(0.05)		

(continued)

Table 6. Asset Pricing Tests *(continued)*

Panel B: Global Volatility Factor

Factor Prices

	b_{DOL}	$b_{VOL_{FX}}$	λ_{DOL}	$\lambda_{VOL_{FX}}$	R^2	$RMSE$	χ^2	HJ	b_{DOL}	$b_{VOL_{FX}}$	λ_{DOL}	$\lambda_{VOL_{FX}}$	R^2	$RMSE$	χ^2	HJ
	Developed								*Developed & Emerging*							
GMM_1	0.52	1.25	0.02	0.16	0.26	2.74	3.02	0.13	0.48	0.55	0.02	0.08	−0.07	2.04	2.31	0.11
	(0.32)	(0.81)	(0.02)	(0.11)			[0.39]	[0.44]	(0.72)	(1.49)	(0.02)	(0.22)			[0.51]	[0.55]
GMM_2	0.44	1.01	0.02	0.15	0.27	2.75	2.91		0.30	0.13	0.02	0.02	−0.14	2.06	2.22	
	(0.32)	(0.78)	(0.02)	(0.11)			[0.41]		(0.7)	(1.43)	(0.02)	(0.22)			[0.53]	
FMB	0.52	1.24	0.02	0.16	0.26	2.74	3.02		0.48	0.55	0.02	0.08	−0.07	2.04	2.31	
	(0.36)	(0.81)	(0.02)	(0.11)			[0.39]		(0.66)	(1.34)	(0.02)	(0.22)			[0.51]	
(sh)	(0.33)	(0.92)	(0.02)	(0.13)			[0.37]		(0.71)	(1.49)	(0.02)	(0.25)			[0.54]	

Factor Betas

	α	β_{DOL}	$\beta_{VOL_{FX}}$	R^2	$\chi^2(\alpha)$	α	β_{DOL}	$\beta_{VOL_{FX}}$	R^2	$\chi^2(\alpha)$
P_L	0.03	0.90	0.08	0.62	10.01	0.02	0.97	0.02	0.69	2.94
	(0.01)	(0.06)	(0.06)		[0.07]	(0.01)	(0.05)	(0.03)		[0.71]
P_2	0.00	0.94	−0.07	0.71		0.00	0.95	−0.02	0.79	
	(0.01)	(0.08)	(0.05)			(0.01)	(0.05)	(0.03)		
P_3	−0.01	1.02	0.03	0.71		−0.01	0.99	0.03	0.79	
	(0.01)	(0.06)	(0.07)			(0.01)	(0.04)	(0.02)		
P_4	−0.01	1.10	0.01	0.78		−0.01	1.19	0.02	0.83	
	(0.01)	(0.06)	(0.04)			(0.01)	(0.05)	(0.04)		
P_S	−0.02	1.04	−0.06	0.78		−0.01	0.91	−0.03	0.71	
	(0.01)	(0.04)	(0.04)			(0.01)	(0.05)	(0.03)		

Table 7. β-Sorted Portfolios: Average Volatility Risk Premia

This table presents descriptive statistics of β-sorted currency portfolios. Each β is obtained by regressing individual currency excess returns on the average volatility risk premia using a 36-month moving window. The long (short) portfolio P_L (P_S) contains the top 20% of all currencies with the lowest (highest) β. H/L denotes a long-short strategy that buys P_L and sells P_S. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), and the frequency of portfolio switches ($Freq$). *Panel A* displays the overall excess return, whereas *Panel B* reports the exchange rate component only. *Panel C* presents the pre- and post-formation βs, and the pre- and post-formation interest rate differential (if) relative to the US dollar. Standard deviations are reported in brackets whereas standard errors are reported in parentheses. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2001. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

	P_L	P_2	P_3	P_4	P_S	H/L	P_L	P_2	P_3	P_4	P_S	H/L
	Developed						*Developed & Emerging*					
Panel A: Excess Returns												
$Mean$	5.54	1.70	3.46	2.06	6.76	−1.23	4.16	2.22	3.33	3.34	5.43	−1.27
$Sdev$	9.50	10.48	9.09	10.17	11.90	10.91	8.61	10.00	9.49	9.97	11.38	10.67
$Skew$	0.27	0.05	−0.52	−0.04	−0.36	0.80	0.04	0.38	−0.29	−0.25	−0.67	1.14
$Kurt$	3.04	4.55	5.03	4.53	4.93	6.78	2.35	4.83	4.79	3.99	5.45	8.15
SR	0.58	0.16	0.38	0.20	0.57	−0.11	0.48	0.22	0.35	0.33	0.48	−0.12
SO	1.11	0.25	0.52	0.30	0.81	−0.19	0.88	0.37	0.50	0.49	0.66	−0.22
MDD	−0.19	−0.27	−0.31	−0.30	−0.27	−0.35	−0.19	−0.27	−0.32	−0.27	−0.27	−0.35
AC_1	0.03	0.01	0.19	0.12	0.10	0.03	0.04	0.05	0.18	0.11	0.12	0.01
$Freq$	0.18	0.25	0.32	0.29	0.09	0.09	0.16	0.18	0.28	0.26	0.10	0.10
Panel B: FX Returns												
$Mean$	6.39	1.91	3.07	1.18	4.69	1.70	5.10	2.35	2.78	1.56	3.21	1.90
$Sdev$	9.41	10.41	9.06	10.08	11.88	10.97	8.52	9.94	9.44	9.82	11.33	10.72
$Skew$	0.30	0.04	−0.56	−0.07	−0.38	0.87	0.06	0.37	−0.33	−0.31	−0.76	1.30
$Kurt$	3.11	4.54	5.15	4.43	4.98	7.02	2.34	4.88	4.84	3.99	5.65	8.75
SR	0.68	0.18	0.34	0.12	0.39	0.15	0.60	0.24	0.29	0.16	0.28	0.18
SO	1.33	0.28	0.46	0.17	0.56	0.28	1.13	0.39	0.42	0.23	0.38	0.35
MDD	−0.16	−0.25	−0.32	−0.32	−0.29	−0.32	−0.16	−0.25	−0.33	−0.29	−0.29	−0.22
AC_1	0.02	0.01	0.19	0.12	0.10	0.05	0.04	0.04	0.18	0.09	0.11	0.02
$Freq$	0.18	0.25	0.32	0.29	0.09	0.09	0.16	0.18	0.28	0.26	0.10	0.10
Panel C: Portfolio Formation												
pre-if	−0.85	−0.21	0.39	0.88	2.08		−0.94	−0.13	0.55	1.78	2.22	
post-if	−0.85	−0.19	0.41	0.90	2.09		−0.97	−0.10	0.56	1.79	2.24	
pre-β	−0.35	−0.14	0.13	0.35	0.60		−0.42	−0.17	0.12	0.40	0.81	
	[0.46]	[0.50]	[0.46]	[0.32]	[0.32]		[0.71]	[0.73]	[0.61]	[0.51]	[0.56]	
post-β	−0.26	−0.29	0.15	0.06	0.11		−0.26	−0.22	0.09	0.14	0.08	
	(0.11)	(0.10)	(0.08)	(0.08)	(0.06)		(0.09)	(0.11)	(0.08)	(0.06)	(0.07)	

Table 8. Risk Factors: Liquidity and Hedging

This table presents predictive regressions estimates. The dependent variable is the exchange rate return component of the VRP strategy at time t. This strategy is a long/short portfolio that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year expected volatility premia at time $t-1$. The predictors are measured at time $t-1$, and include the TED spread, the change in the VIX index, the change in the St. Louis Fed Financial Stress Index FSI, the net short futures position (HED) of commercial and non-commercial traders on the Australian dollar (AUD) and the Japanese yen (JPY) vis-à-vis the US dollar (USD), respectively, and the *Fund Flows* constructed as the AUM-weighted net flows into hedge funds (currency and global macro funds) scaled by the lagged AUM. TED, ΔVIX, and ΔFSI are averaged on a 12-month rolling window. HED is winsorized at 99%. Newey and West (1987) with Andrews (1991) optimal lag selection are reported in parenthesis. The superscripts a, b, and c indicate statistical significance at 10%, 5%, and 1%, respectively. Exchange rate returns are annualized. Exchange rates are from *Datastream*, implied volatility quotes are from JP Morgan, futures positions are from the US Commodity Futures Trading Commission (CFTC), hedge fund flows are from Patton and Ramadorai (2013), FSI is from St. Louis Fed's website, whereas all other data are from Bloomberg.

α	TED	ΔVIX	ΔFSI	$TED\times$ ΔVIX	HED $AUDUSD$	HED $JPYUSD$	$Fund$ $Flows$	R^2	α	TED	ΔVIX	ΔFSI	$TED\times$ ΔVIX	HED $AUDUSD$	HED $JPYUSD$	$Fund$ $Flows$	R^2
				Developed									*Developed & Emerging*				
-0.04	0.16^b							0.03	0.01	0.06							0.00
(0.03)	(0.07)								(0.03)	(0.06)							
0.04^b		0.05^a						0.01	0.04^a		0.04						0.01
(0.02)		(0.03)							(0.02)		(0.03)						
0.04^b			0.38^b					0.02	0.04^a			0.32^a					0.01
(0.02)			(0.18)						(0.02)			(0.16)					
0.03				0.09^c				0.05	0.03				0.06^c				0.02
(0.02)				(0.02)					(0.02)				(0.02)				
0.05^b					0.03^c			0.01	0.04^a					0.02^b			0.01
(0.02)					(0.01)				(0.02)					(0.01)			
0.05^b						-0.02		0.00	0.04^a						0.01		-0.01
(0.02)						(0.06)			(0.02)						(0.06)		
0.05^b							-1.50^b	0.02	0.05^b							-1.14^a	0.01
(0.02)							(0.72)		(0.02)							(0.74)	
-0.01	0.12				0.02^b		-0.93	0.04	0.03	0.03				0.02^a		-0.93	0.01
(0.04)	(0.07)				(0.01)		(0.73)		(0.04)	(0.07)				(0.01)		(0.75)	
0.05^b		0.04			0.02^b		-1.15^a	0.03	0.04^b		0.03			0.02^b		-0.86	0.02
(0.02)		(0.03)			(0.01)		(0.68)		(0.02)		(0.03)			(0.01)		(0.67)	
0.05^b			0.31^a		0.02^b		-1.15^a	0.04	0.04^b			0.26		0.02^b		-0.83	0.02
(0.02)			(0.18)		(0.01)		(0.68)		(0.02)			(0.17)		(0.01)		(0.69)	
0.04^a				0.08^c	0.02^b		-0.93	0.06	0.04				0.05^c	0.02^b		-0.72	0.03
(0.02)				(0.02)	(0.01)		(0.65)		(0.02)				(0.02)	(0.01)		(0.66)	

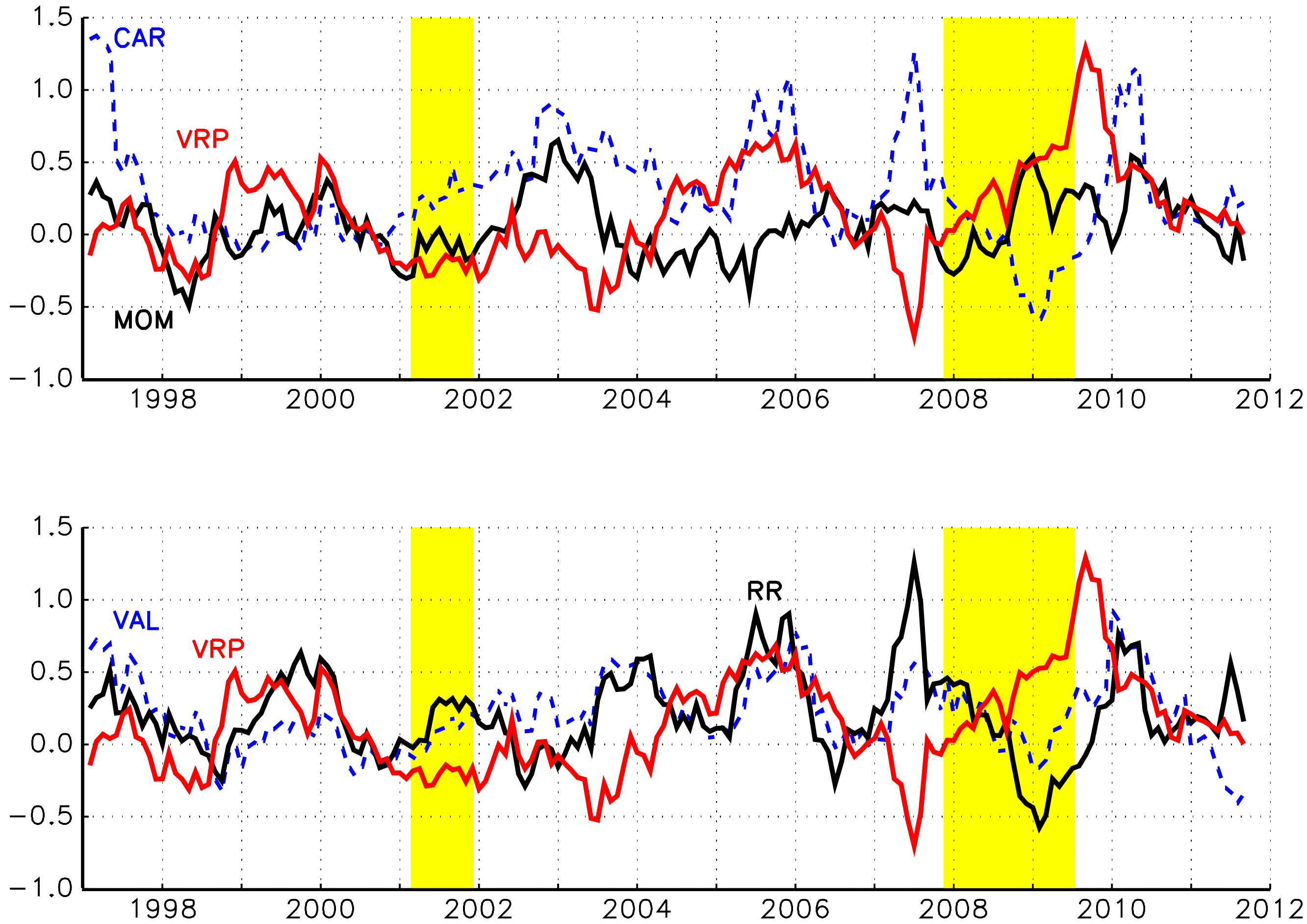

Figure 1. Rolling Sharpe Ratios

The figure presents for developed countries the 1-year rolling Sharpe ratios of currency strategies formed using $t-1$ information. CAR is the carry strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential relative to the US dollar. Similarly, MOM is the momentum strategy that buys (sells) currencies with the highest (lowest) past 3-month exchange rate return, VAL is the value strategy that buys (sells) currencies with lowest (highest) real exchange rate, RR is the risk reversal strategy that buys (sells) currencies with the lowest (highest) 1-year 10-delta risk reversal, and VRP is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan. In Internet Appendix Figure A.1 presents the 1-year rolling Sharpe ratios for developed & emerging countries.

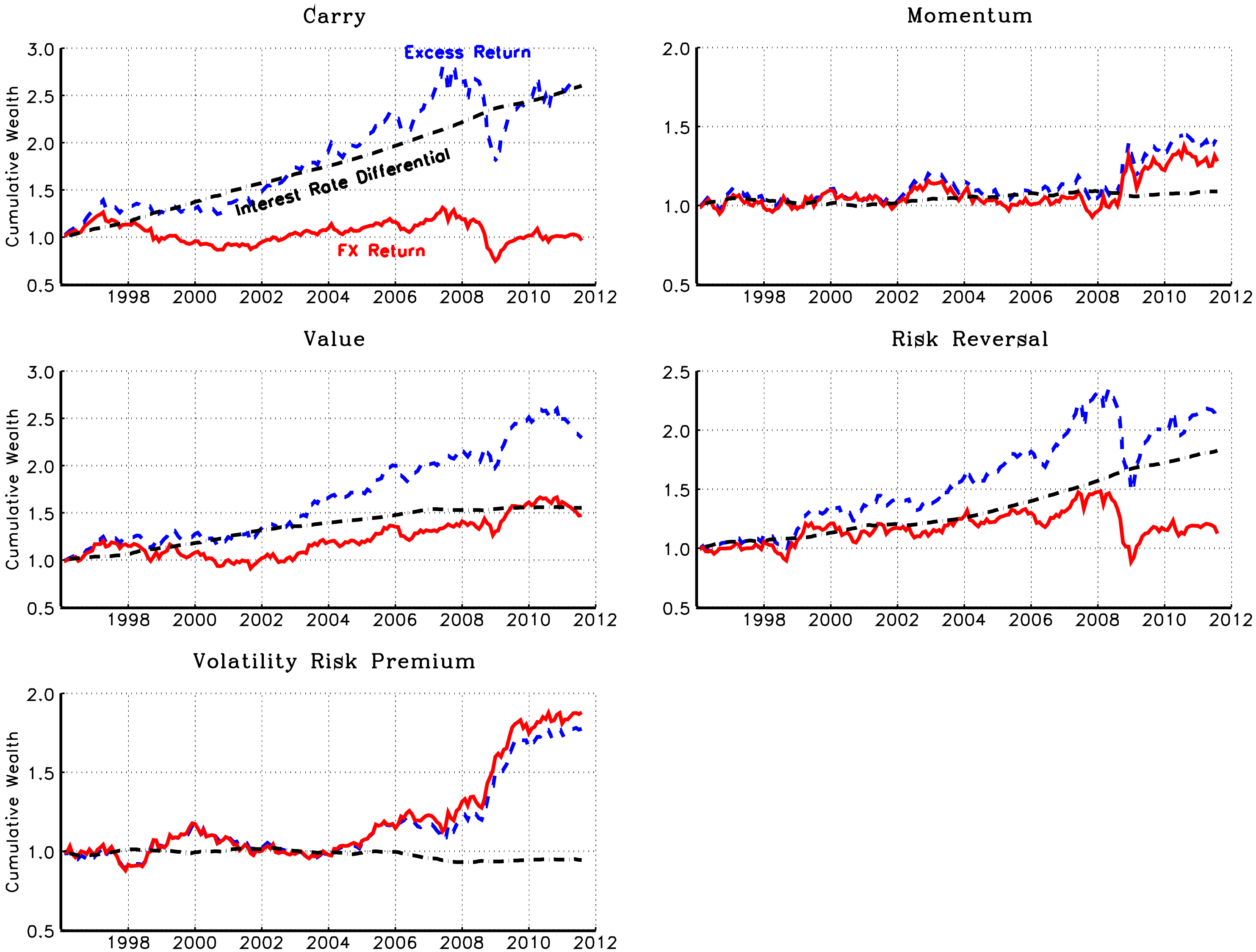

Figure 2. Currency Strategies and Payoffs

The figure presents for developed countries the cumulative wealth to currency strategies formed using $t-1$ information. The strategies are rebalanced monthly from January 1996 to August 2011, and described in Figure 1. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan. In Internet Appendix Figure A.2 presents the cumulative wealth to currency strategies for developed & emerging countries.

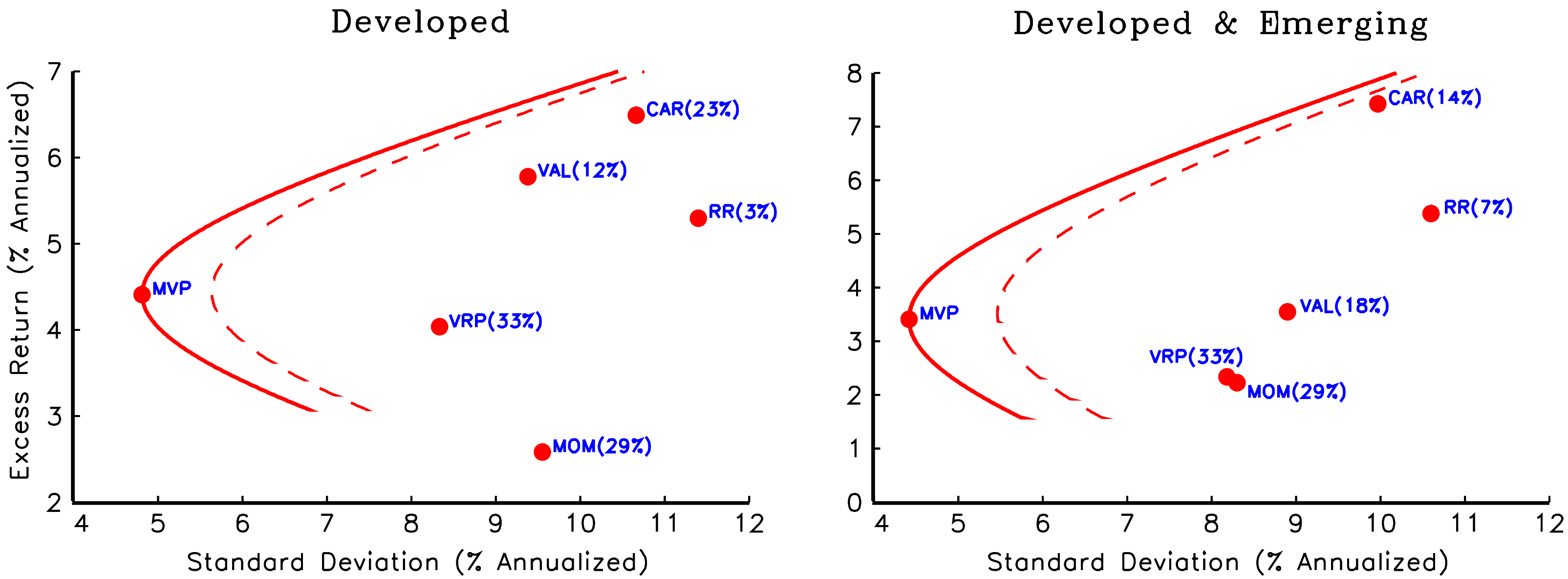

Figure 3. Global Minimum Volatility Portfolios

The figure presents the global minimum volatility portfolio (MVP) and the efficient frontier (*solid line*) built using the currency strategies described in Figure 1. The portfolio weights ($N \times 1$) are reported in parentheses and computed as $w = (\Sigma^{-1}\iota)/(\iota'\Sigma^{-1}\iota)$ where Σ is the $N \times N$ covariance matrix of the strategies' returns, ι is a $N \times 1$ vector of ones, and N denotes the number of strategies. The dashed line denotes the efficient frontier that excludes the volatility risk premium (VRP) strategy. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

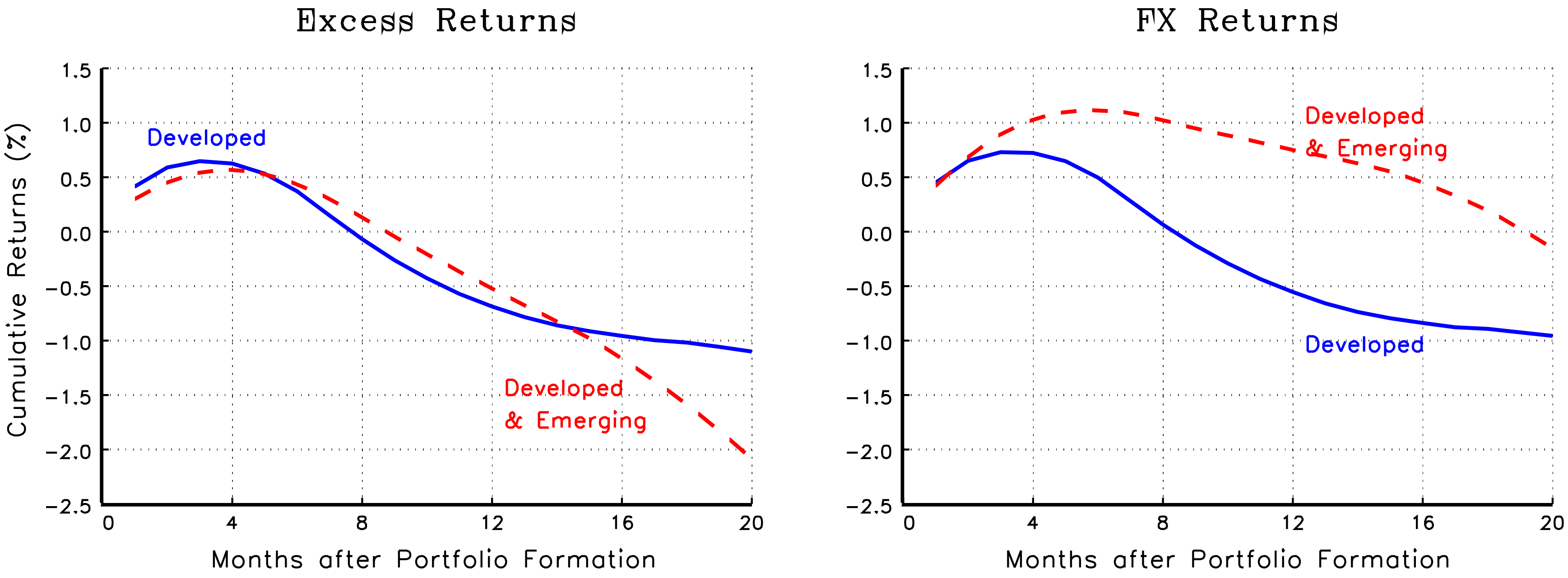

Figure 4. Reversal in the Volatility Risk Premium Strategy

This figure presents cumulative average returns to the volatility risk premium (VRP) strategy after portfolio formation. VRP buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia. Post-formation returns are constructed for $1, 2, \ldots, 20$ months following the formation period. This is equivalent to building new portfolios every month and recording them for the subsequent $1, 2, \ldots, 20$ months (using overlapping horizons). We cumulate risk-adjusted (with respect to the carry trade strategy) excess returns and exchange rate returns. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

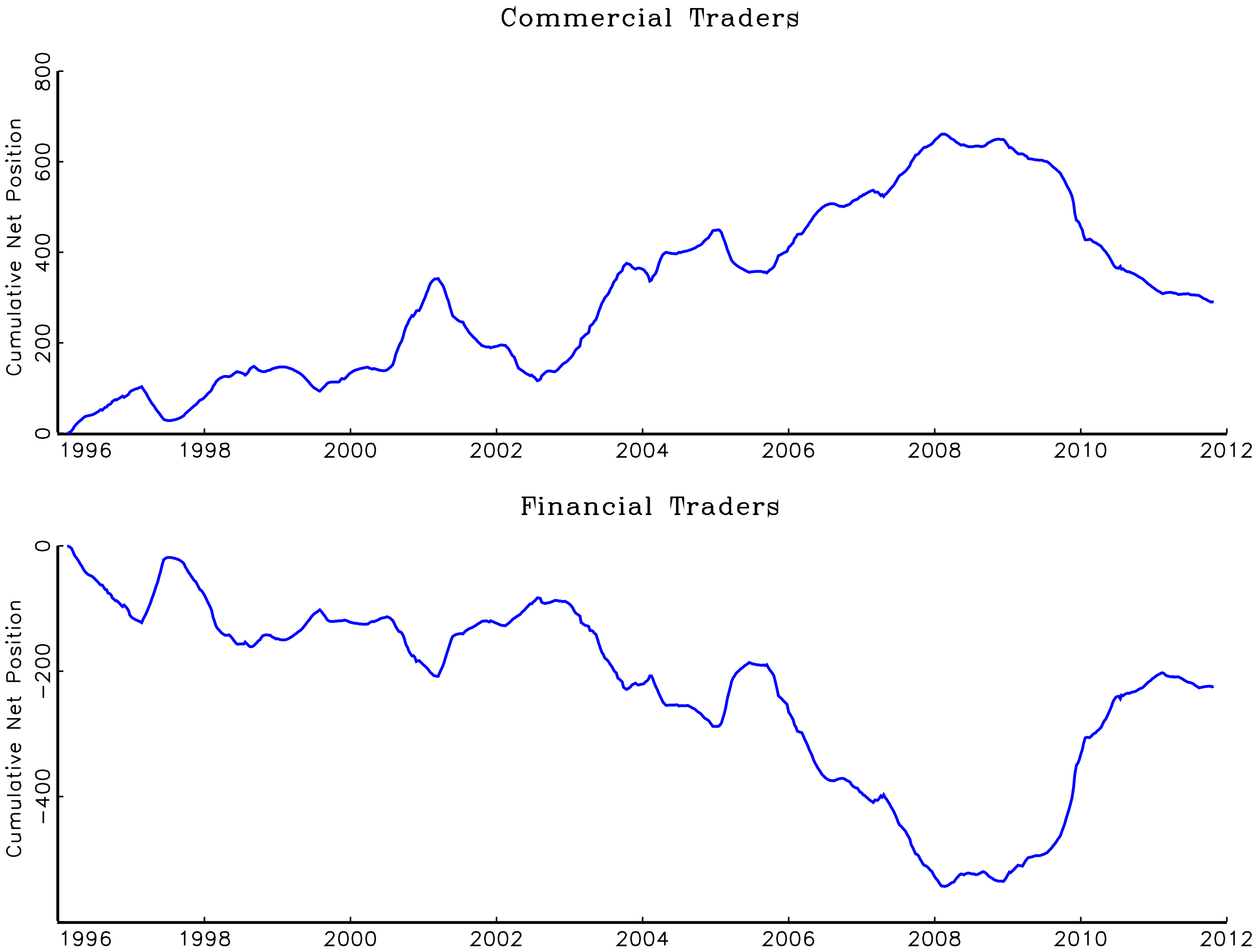

Figure 5. Futures Net Positions and Volatility Risk Premium Strategy

The figure presents the net position on currency futures in the volatility risk premium (VRP) strategy. We rank currencies by volatility risk premia into four baskets at time t, and then compute the average net position on futures at time t. Finally, we take the difference between the first (currencies with the cheapest volatility insurance) and the last (currencies with the most expensive volatility insurance) portfolio. The net (long minus short) position on futures is standardized over a 3-month rolling window. Commercial traders use the futures market primarily to hedge their business activities whereas financial (or non-commercial) traders use the futures market for speculative purposes. The data runs from January 1996 to August 2011 at weekly frequency (collected every Tuesday). Exchange rates are from Datastream, implied volatility quotes are proprietary data from JP Morgan, whereas futures positions are from the Commodity Futures Trading Commission (CFTC).

Internet Appendix for:

Volatility Risk Premia and Exchange Rate Predictability*

(not for publication)

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This Internet Appendix provides a detailed description of additional tests and robustness checks.

A Data Construction

Below we provide a detailed description of the predictive variables used in Table 8.

- TED denotes the spread between the 3-month LIBOR and 3-month T-bill rate. We use the rolling average over the past 12-month window.
- ΔVIX is the change in the VIX index. We use the rolling average over the past 12-month window.
- ΔFSI is the change in the St. Louis Fed Financial Stress index. We use the rolling average over the past 12-month window.
- HED is the aggregate hedging measure on foreign exchange risk based on currency futures positions of commercial (com) and financial (fin) traders from the Commodity Futures Trading Commission (CFTC). We first measure the hedging position on each of the market segment as

$$HED_t^i = \frac{S_t^i - L_t^i}{S_{t-1}^i + L_{t-1}^i}$$

where S_t^i (L_t^i) denotes the short (long) futures position at time t, and i denotes either commercial or financial traders. The normalization means that the net positions are measured relative to the aggregate open interest in the previous period, respectively.[1] Finally, we construct the aggregate hedging measure on foreign exchange risk as

$$HED_t = HED_t^{com} + HED_t^{fin},$$

and winsorize it at 99%. We the aggregate hedging measure on foreign exchange risk for the Australian dollar (AUD) and the Japanese yen (JPY) relative to the US dollar as these currency pairs are typically used for the carry trade strategy.

[1] When the normalizing component is equal to zero, we simply use previous period non-zero value.

- *Fund Flows* denotes capital flows into hedge funds. We measure it as the AUM-weighted net flow of currency and global macro funds scaled by the lagged AUM. Specifically, we employ the AUM and the returns for 634 currency and global macro funds from Patton and Ramadorai (2013). For each fund i, we measure time-t net flow as follows

  $$Flow_t^i = AUM_t^i - AUM_{t-1}^i \left(1 + r_t^i\right).$$

  We then construct the AUM-weighted net flow scaled by the lagged AUM as

  $$Flow_t = \sum_{i=1}^{\kappa} w_{t-1}^i \frac{Flow_t^i}{AUM_{t-1}^i}$$

  where

  $$w_{t-1}^i = \frac{AUM_{t-1}^i}{\sum_i^{\kappa} AUM_{t-1}^i}$$

  and κ indicates the available number of hedge funds at time t.

Table A.1. Country-Specific Volatility Risk Premia

This table presents summary statistics for the 1-year volatility risk premia (VRP) defined as difference between the realized volatility (RV) and the synthetic volatility swap rate (SW). RV is computed at time t using daily exchange rate returns over the previous year. SW is constructed at time t using the implied volatilities across 5 different deltas from 1-year currency options. Q_j refers to the j^{th} percentile. AC indicates the 1-year autocorrelation coefficient. VPR, RV, and SW are expressed in percentage per annum. The sample period comprises daily data from January 1996 to August 2011. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

	$Mean$	Med	$Sdev$	$Skew$	$Kurt$	Q_5	Q_{95}	AC
AUD	0.39	0.21	2.43	1.79	9.51	−3.08	4.19	−0.14
CAD	−0.59	−0.61	1.29	−0.16	4.85	−2.34	1.45	0.22
CHF	−0.51	−0.47	1.53	0.10	3.12	−2.97	1.78	−0.20
DKK	−1.25	−1.02	1.66	−0.61	4.90	−3.89	0.74	−0.13
EUR	−1.16	−0.75	1.75	−0.73	4.55	−4.30	0.78	−0.12
GBP	−1.15	−1.36	1.76	0.23	6.52	−3.54	1.17	−0.07
JPY	−0.45	−0.52	1.72	0.30	3.30	−3.14	1.75	0.03
NOK	−0.73	−0.58	2.03	0.74	5.19	−3.83	2.24	−0.14
NZD	−0.11	−0.40	2.07	0.74	5.37	−3.21	4.38	−0.09
SEK	−0.70	−0.76	2.22	1.13	7.33	−3.69	3.52	−0.34
BRL	−3.78	−4.04	5.60	−0.29	5.03	−13.28	7.14	−0.15
CZK	−0.68	−0.60	2.61	1.22	6.63	−4.61	5.77	−0.35
HUF	−2.21	−2.29	2.85	−0.31	6.43	−6.96	2.27	−0.34
KRW	−1.68	−1.59	4.39	−0.35	11.47	−7.54	5.25	−0.23
MXN	−5.47	−3.96	4.93	−1.50	6.45	−15.40	−0.77	0.34
PLN	−1.73	−1.66	3.39	0.05	5.52	−7.39	3.96	−0.06
SGD	−1.40	−1.13	1.47	−2.03	9.06	−4.27	0.23	0.17
TRY	−4.59	−4.84	2.90	0.84	4.28	−8.51	1.95	0.04
TWD	−2.34	−2.10	1.86	−1.00	4.23	−5.65	0.03	0.23
ZAR	−2.57	−2.42	3.49	0.12	3.63	−8.24	4.77	0.07
$Mean$	−1.64	−1.55	2.60	0.01	5.87	−5.79	2.63	−0.06

Table A.2. Currency Strategies: Net of Bid-Ask

This table presents descriptive statistics of currency strategies formed using time $t-1$ information. CAR is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential relative to the US dollar. Similarly, MOM is the momentum strategy that buys (sells) currencies with the highest (lowest) past 3-month exchange rate return, VAL is the value strategy that buys (sells) currencies with lowest (highest) real exchange rate, RR is the risk reversal strategy that buys (sells) currencies with the lowest (highest) 1-year 10-delta risk reversal, and VRP is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), the Sortino ratio (SO), the maximum drawdown (MDD), and the frequency of portfolio switches for the long ($Freq_L$) and the short ($Freq_S$) position. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. *Panel C* presents the sample correlations of the currency excess returns. Returns are expressed in percentage per annum and adjusted for transaction costs. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	CAR	MOM	VAL	RR	VRP	CAR	MOM	VAL	RR	VRP
	Developed					*Developed & Emerging*				
Panel A: Excess Returns										
$Mean$	5.74	1.87	5.03	4.55	3.31	6.35	1.21	2.50	4.23	1.29
$Sdev$	10.66	9.55	9.38	11.39	8.33	9.96	8.30	8.90	10.60	8.17
$Skew$	−0.93	0.35	−0.26	−0.72	0.28	−0.94	−0.04	−0.15	−0.15	0.13
$Kurt$	5.65	3.85	3.49	6.57	3.47	4.55	2.96	3.17	4.45	3.28
SR	0.54	0.20	0.54	0.40	0.40	0.64	0.15	0.28	0.40	0.16
SO	0.64	0.36	0.81	0.50	0.70	0.80	0.25	0.44	0.58	0.26
MDD	−0.38	−0.19	−0.15	−0.37	−0.21	−0.22	−0.15	−0.15	−0.25	−0.21
AC_1	0.09	0.00	−0.03	0.07	0.04	0.01	−0.09	0.01	0.08	0.04
$Freq_L$	0.13	0.48	0.09	0.17	0.24	0.15	0.49	0.07	0.22	0.26
$Freq_S$	0.07	0.43	0.07	0.27	0.32	0.16	0.46	0.06	0.26	0.27
Panel B: FX Returns										
$Mean$	0.24	1.63	2.88	1.21	4.17	−0.84	0.83	−0.02	−0.03	3.38
$Sdev$	10.67	9.58	9.44	11.48	8.35	9.99	8.18	8.89	10.59	8.16
$Skew$	−0.93	0.42	−0.29	−0.75	0.28	−1.04	−0.02	−0.16	−0.21	0.12
$Kurt$	5.82	4.17	3.51	6.82	3.61	4.83	3.13	3.19	4.73	3.50
SR	0.02	0.17	0.31	0.11	0.50	−0.08	0.10	0.00	0.00	0.41
SO	0.03	0.32	0.46	0.13	0.88	−0.10	0.17	0.00	0.00	0.68
MDD	−0.43	−0.21	−0.24	−0.40	−0.19	−0.37	−0.18	−0.28	−0.29	−0.18
AC_1	0.11	0.00	−0.02	0.08	0.04	0.03	−0.12	0.01	0.08	0.04
$Freq_L$	0.13	0.48	0.09	0.17	0.24	0.15	0.49	0.07	0.22	0.26
$Freq_S$	0.07	0.43	0.07	0.27	0.32	0.16	0.46	0.06	0.26	0.27
Panel C: Correlations										
CAR	1.00	−0.16	0.44	0.68	−0.18	1.00	−0.03	0.54	0.57	−0.21
MOM	−0.16	1.00	−0.17	−0.17	0.10	−0.03	1.00	−0.13	−0.15	0.10
VAL	0.44	−0.17	1.00	0.48	0.23	0.54	−0.13	1.00	0.64	−0.10
VRP	0.68	−0.17	0.48	1.00	−0.01	0.57	−0.15	0.64	1.00	−0.12
RR	−0.18	0.10	0.23	−0.01	1.00	−0.21	0.10	−0.10	−0.12	1.00

Table A.3. Currency Strategies: VRP Measures

This table presents descriptive statistics of currency strategies sorted on the 1-year volatility risk premia, defined as the realized volatility (RV_t) minus the synthetic volatility swap rate (SW_t). VRP denotes a strategy where SW_t is computed by interpolating implied volatilities using the cubic spline method (Jiang and Tian, 2005). VRP_{vv} denotes a strategy where SW_t is constructed by interpolating implied volatilities using the Vanna-Volga method (Castagna and Mercurio, 2007). VRP_{atm} denotes a strategy where SW_t is set equal to the at-the-money implied volatility. VRP_{si} denotes a strategy where SW_t is computed using the simple variance swap method (Martin, 2012). The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), the Sortino ratio (SO), the maximum drawdown (MDD), and the frequency of portfolio switches for the long ($Freq_L$) and the short ($Freq_S$) position. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. *Panel C* presents the sample correlations of the currency excess returns. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	VRP	VRP_{atm}	VRP_{si}	VRP	VRP_{atm}	VRP_{si}
	Developed			*Developed & Emerging*		
Panel A: Excess Returns						
$Mean$	4.03	4.35	4.01	2.34	3.05	3.53
$Sdev$	8.33	8.21	8.24	8.18	8.18	7.95
$Skew$	0.28	−0.04	0.12	0.12	−0.02	0.25
$Kurt$	3.47	3.46	3.34	3.26	3.23	3.32
SR	0.48	0.53	0.49	0.29	0.37	0.44
SO	0.87	0.85	0.82	0.49	0.62	0.82
MDD	−0.18	−0.21	−0.18	−0.18	−0.20	−0.18
AC_1	0.04	0.02	0.11	0.05	0.05	0.07
$Freq_L$	0.24	0.26	0.24	0.26	0.25	0.23
$Freq_S$	0.32	0.35	0.33	0.27	0.31	0.28
Panel B: FX Returns						
$Mean$	4.40	4.11	4.00	3.72	3.03	4.05
$Sdev$	8.35	8.20	8.23	8.17	8.17	7.95
$Skew$	0.28	−0.06	0.09	0.12	−0.01	0.24
$Kurt$	3.61	3.61	3.45	3.50	3.43	3.63
SR	0.53	0.50	0.49	0.46	0.37	0.51
SO	0.93	0.78	0.80	0.75	0.59	0.89
MDD	−0.19	−0.21	−0.19	−0.18	−0.21	−0.19
AC_1	0.04	0.02	0.11	0.04	0.04	0.06
$Freq_L$	0.24	0.26	0.24	0.26	0.25	0.23
$Freq_S$	0.32	0.35	0.33	0.27	0.31	0.28
Panel C: Correlations						
VRP	1.00	0.84	0.84	1.00	0.82	0.87
VRP_{atm}	0.84	1.00	0.90	0.82	1.00	0.91
VRP_{si}	0.84	0.90	1.00	0.87	0.91	1.00

Table A.4. Volatility Risk Premia Portfolios: Currency Breakdown

The table presents the number of times (and the frequency in brackets) a currency enters each of the five volatility risk premia portfolios. The frequency is computed as ratio between the number of times a currency appears in a given portfolio and the total number of times (Tot) the currency is available to our investor. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

	P_L	P_2	P_3	P_4	P_S	Tot	P_L	P_2	P_3	P_4	P_S	Tot
	Developed						*Developed & Emerging*					
AUD	89 [0.48]	52 [0.28]	19 [0.10]	11 [0.06]	16 [0.09]	187 [1.00]	93 [0.50]	59 [0.32]	18 [0.10]	17 [0.09]	–	187 [1.00]
CAD	32 [0.17]	56 [0.30]	37 [0.20]	31 [0.17]	31 [0.17]	187 [1.00]	39 [0.21]	59 [0.32]	41 [0.22]	37 [0.20]	11 [0.06]	187 [1.00]
CHF	38 [0.20]	60 [0.32]	65 [0.35]	15 [0.08]	9 [0.05]	187 [1.00]	40 [0.21]	77 [0.41]	48 [0.26]	13 [0.07]	9 [0.05]	187 [1.00]
DKK	–	10 [0.05]	31 [0.17]	84 [0.45]	62 [0.33]	187 [1.00]	–	25 [0.13]	51 [0.27]	87 [0.47]	24 [0.13]	187 [1.00]
EUR	5 [0.03]	12 [0.07]	36 [0.22]	68 [0.42]	42 [0.26]	163 [1.00]	5 [0.03]	24 [0.15]	60 [0.37]	65 [0.40]	9 [0.06]	163 [1.00]
GBP	14 [0.07]	26 [0.14]	53 [0.28]	41 [0.22]	53 [0.28]	187 [1.00]	15 [0.08]	40 [0.21]	59 [0.32]	30 [0.16]	43 [0.23]	187 [1.00]
JPY	71 [0.38]	30 [0.16]	24 [0.13]	15 [0.08]	44 [0.24]	184 [1.00]	76 [0.41]	34 [0.18]	22 [0.12]	21 [0.11]	31 [0.17]	184 [1.00]
NOK	21 [0.11]	56 [0.30]	38 [0.2]	29 [0.16]	41 [0.22]	185 [1.00]	25 [0.13]	65 [0.35]	39 [0.21]	21 [0.11]	35 [0.19]	185 [1.00]
NZD	49 [0.26]	44 [0.24]	28 [0.15]	32 [0.17]	34 [0.18]	187 [1.00]	49 [0.26]	52 [0.28]	39 [0.21]	38 [0.20]	9 [0.05]	187 [1.00]
SEK	27 [0.15]	28 [0.15]	43 [0.23]	47 [0.25]	40 [0.22]	185 [1.00]	25 [0.13]	46 [0.25]	44 [0.24]	39 [0.21]	31 [0.17]	185 [1.00]
BRL							5 [0.07]	10 [0.15]	5 [0.07]	5 [0.07]	42 [0.63]	67 [1.00]
CZK							11 [0.16]	13 [0.19]	23 [0.34]	17 [0.25]	3 [0.04]	67 [1.00]
HUF							10 [0.18]	4 [0.07]	3 [0.05]	18 [0.33]	20 [0.36]	55 [1.00]
KRW							28 [0.42]	5 [0.07]	10 [0.15]	12 [0.18]	12 [0.18]	67 [1.00]
MXN							–	3 [0.04]	7 [0.10]	13 [0.19]	44 [0.66]	67 [1.00]
PLN							31 [0.46]	17 [0.25]	8 [0.12]	5 [0.07]	6 [0.09]	67 [1.00]
SGD							2 [0.03]	16 [0.24]	22 [0.33]	19 [0.28]	8 [0.12]	67 [1.00]
TRY							3 [0.04]	–	6 [0.09]	5 [0.07]	53 [0.79]	67 [1.00]
TWD							3 [0.02]	12 [0.09]	15 [0.12]	27 [0.21]	70 [0.55]	127 [1.00]
ZAR							8 [0.09]	7 [0.08]	7 [0.08]	18 [0.21]	46 [0.53]	86 [1.00]

Table A.5. β-Sorted Portfolios: Principal Component of Volatility Risk Premia

This table presents descriptive statistics of β-sorted currency portfolios. Each β is obtained by regressing individual currency excess returns on the first principal component of volatility risk premia using a 36-month moving window. The long (short) portfolio P_L (P_S) contains the top 20% of all currencies with the lowest (highest) β. H/L denotes a long-short strategy that buys P_L and sells P_S. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), and the frequency of portfolio switches ($Freq$). *Panel A* displays the overall excess return, whereas *Panel B* reports the exchange rate component only. *Panel C* presents the pre- and post-formation β's, and the pre- and post-formation interest rate differential (if) relative to the US dollar. Standard deviations are reported in brackets whereas standard errors are reported in parentheses. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2001. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

	P_L	P_2	P_3	P_4	P_S	H/L	P_L	P_2	P_3	P_4	P_S	H/L
	Developed						*Developed & Emerging*					
	Panel A: Excess Returns											
$Mean$	5.76	2.07	2.72	1.45	7.15	−1.40	3.69	2.62	3.13	2.48	5.70	−2.00
$Sdev$	9.51	10.45	8.84	10.66	11.69	10.80	8.61	9.97	10.13	9.37	11.19	10.65
$Skew$	0.24	0.03	−0.51	0.00	−0.38	0.79	0.08	0.35	−0.20	−0.49	−0.49	0.96
$Kurt$	3.03	4.58	5.33	4.17	5.20	6.94	2.43	4.78	4.22	5.58	4.65	6.46
SR	0.61	0.20	0.31	0.14	0.61	−0.13	0.43	0.26	0.31	0.26	0.51	−0.19
SO	1.15	0.30	0.42	0.20	0.86	−0.22	0.80	0.43	0.47	0.38	0.71	−0.36
MDD	−0.17	−0.26	−0.31	−0.33	−0.26	−0.36	−0.24	−0.23	−0.31	−0.29	−0.26	−0.33
AC_1	0.01	0.01	0.21	0.11	0.08	0.04	0.08	0.06	0.15	0.14	0.08	−0.01
$Freq$	0.15	0.25	0.31	0.29	0.11	0.11	0.14	0.17	0.22	0.23	0.11	0.11
	Panel B: FX Returns											
$Mean$	6.52	2.26	2.41	0.67	5.02	1.50	4.59	2.56	2.49	1.15	3.52	1.06
$Sdev$	9.43	10.40	8.79	10.53	11.67	10.88	8.52	9.90	10.06	9.25	11.17	10.75
$Skew$	0.28	0.02	−0.55	−0.04	−0.40	0.86	0.10	0.34	−0.22	−0.58	−0.61	1.14
$Kurt$	3.08	4.56	5.48	4.11	5.25	7.16	2.40	4.85	4.25	5.48	4.84	7.02
SR	0.69	0.22	0.27	0.06	0.43	0.14	0.54	0.26	0.25	0.12	0.32	0.10
SO	1.36	0.33	0.38	0.09	0.60	0.24	1.04	0.42	0.37	0.17	0.42	0.20
MDD	−0.15	−0.25	−0.32	−0.33	−0.28	−0.32	−0.20	−0.21	−0.32	−0.30	−0.32	−0.23
AC_1	0.00	0.01	0.22	0.10	0.07	0.05	0.07	0.06	0.14	0.13	0.08	0.00
$Freq$	0.15	0.25	0.31	0.29	0.11	0.11	0.14	0.17	0.22	0.23	0.11	0.11
	Panel C: Portfolio Formation											
pre-if	−0.77	−0.18	0.31	0.78	2.13		−0.89	0.06	0.64	1.33	2.17	
post-if	−0.69	−0.24	0.38	0.84	2.13		−0.94	0.10	0.68	1.34	2.18	
pre-β	−0.11	−0.05	0.05	0.11	0.21		−0.11	−0.05	0.05	0.11	0.21	
	[0.12]	[0.13]	[0.12]	[0.11]	[0.14]		[0.12]	[0.13]	[0.12]	[0.11]	[0.14]	
post-β	−0.10	−0.04	0.04	0.02	0.07		−0.07	−0.05	0.02	0.03	0.02	
	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	

Table A.6. β-Sorted Portfolios: Equity Volatility Risk Premium

This table presents descriptive statistics of β-sorted currency portfolios. Each β is obtained by regressing individual currency excess returns on the US equity volatility risk premium using a 36-month moving window. The volatility risk premium is defined as the 1-month realized volatility on the S&P500 minus the VIX index. The long (short) portfolio P_L (P_S) contains the top 20% of all currencies with the lowest (highest) β. H/L denotes a long-short strategy that buys P_L and sells P_S. The table also reports the first order autocorrelation coefficient (AC_1), the annualized Sharpe ratio (SR), and the frequency of portfolio switches ($Freq$). *Panel A* displays the overall excess return, whereas *Panel B* reports the exchange rate component only. *Panel C* presents the pre- and post-formation β's, and the pre- and post-formation interest rate differential (if) relative to the US dollar. Standard deviations are reported in brackets whereas standard errors are reported in parentheses. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to August 2001. Data are from Datastream.

	P_L	P_2	P_3	P_4	P_S	H/L	P_L	P_2	P_3	P_4	P_S	H/L
	Developed						*Developed & Emerging*					
Panel A: Excess Returns												
Mean	6.22	3.65	2.43	2.33	3.50	2.72	7.04	2.46	3.52	1.98	3.29	3.76
Sdev	11.04	10.24	10.19	10.47	8.73	10.07	10.85	10.37	9.67	10.37	7.59	9.96
Skew	−0.58	−0.17	0.02	−0.06	0.30	−1.10	−0.72	−0.28	−0.04	0.43	−0.19	−1.08
Kurt	4.98	4.41	4.21	4.56	3.74	7.83	6.03	4.05	4.31	4.69	2.62	10.41
SR	0.56	0.36	0.24	0.22	0.40	0.27	0.65	0.24	0.36	0.19	0.43	0.38
SO	0.78	0.56	0.38	0.33	0.73	0.33	0.88	0.36	0.56	0.32	0.71	0.47
MDD	−0.27	−0.28	−0.32	−0.28	−0.20	−0.32	−0.23	−0.30	−0.30	−0.28	−0.20	−0.25
AC_1	0.11	0.12	0.24	0.06	−0.05	0.03	0.14	0.15	0.21	0.04	0.00	0.05
Freq	0.12	0.25	0.29	0.30	0.16	0.16	0.16	0.25	0.32	0.33	0.17	0.17
Panel B: FX Returns												
Mean	4.55	3.15	2.18	2.43	3.68	0.87	4.74	1.28	3.12	2.16	3.76	0.98
Sdev	10.97	10.22	10.04	10.42	8.76	10.18	10.72	10.33	9.48	10.30	7.62	10.03
Skew	−0.61	−0.21	0.00	−0.06	0.32	−1.17	−0.80	−0.35	−0.08	0.43	−0.19	−1.23
Kurt	5.07	4.57	4.14	4.55	3.84	8.21	6.37	4.17	4.20	4.77	2.68	11.27
SR	0.41	0.31	0.22	0.23	0.42	0.09	0.44	0.12	0.33	0.21	0.49	0.10
SO	0.57	0.47	0.34	0.34	0.75	0.10	0.59	0.18	0.50	0.35	0.80	0.12
MDD	−0.29	−0.29	−0.32	−0.27	−0.21	−0.36	−0.24	−0.34	−0.28	−0.27	−0.21	−0.30
AC_1	0.10	0.12	0.23	0.06	−0.05	0.04	0.12	0.15	0.20	0.04	0.00	0.05
Freq	0.12	0.25	0.29	0.30	0.16	0.16	0.16	0.25	0.32	0.33	0.17	0.17
Panel C: Portfolio Formation												
pre-if	1.67	0.50	0.25	−0.10	−0.18		2.31	1.17	0.40	−0.18	−0.47	
post-if	1.70	0.54	0.24	−0.15	−0.12		2.33	1.21	0.38	−0.26	−0.41	
pre-β	−0.23	−0.14	−0.08	−0.02	0.07		−0.23	−0.14	−0.08	−0.02	0.07	
	[0.15]	[0.12]	[0.12]	[0.10]	[0.11]		[0.15]	[0.12]	[0.12]	[0.10]	[0.11]	
post-β	−0.04	−0.03	0.00	0.09	0.02		−0.04	−0.03	0.00	0.09	0.02	
	(0.03)	(0.02)	(0.02)	(0.03)	(0.06)		(0.03)	(0.02)	(0.02)	(0.03)	(0.06)	

Table A.7. Volatility Spread Strategies

This table presents selected descriptive statistics of realized volatility spread (RVS_{LS}) strategies formed using time $t-1$ information. The strategy buys (sells) the top 20% of all currencies with the highest (lowest) volatility spread defined as long-maturity (L) minus short-maturity (S) realized volatility. Realized volatilities are constructed using daily exchange rate returns. The table reports the annualized Sharpe ratio based on the overall excess (exchange rate) returns in *Panel A* (*Panel B*), the sample correlation with the carry trade (CAR) strategy in *Panel C*, and the sample correlation with the volatility risk premium (VRP) strategy in *Panel D*. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream*.

	L_{M6}	L_{M9}	L_{M12}	L_{M18}	L_{M24}	L_{M6}	L_{M9}	L_{M12}	L_{M18}	L_{M24}
	Developed (G10)					*Developed & Emerging (G20)*				
	Sharpe Ratios: Excess Returns									
S_{M1}	0.60	0.41	0.39	0.58	0.45	0.64	0.38	0.45	0.39	0.38
S_{M2}	0.59	0.45	0.49	0.34	0.45	0.53	0.45	0.49	0.31	0.21
S_{M3}	0.53	0.52	0.45	0.24	0.31	0.43	0.40	0.17	0.20	0.32
S_{M6}		0.19	0.12	0.02	0.02		0.04	0.07	0.01	0.08
	Sharpe Ratios: FX Returns									
S_{M1}	0.60	0.44	0.43	0.60	0.47	0.59	0.34	0.41	0.35	0.34
S_{M2}	0.60	0.47	0.49	0.36	0.47	0.53	0.41	0.43	0.27	0.17
S_{M3}	0.54	0.53	0.47	0.27	0.32	0.44	0.37	0.15	0.17	0.28
S_{M6}		0.22	0.15	0.04	0.04		0.04	0.09	0.01	0.07
	Correlation with CAR: Excess Returns									
S_{M1}	−0.11	−0.17	−0.24	−0.20	−0.28	0.02	0.03	−0.02	0.05	−0.03
S_{M2}	−0.12	−0.07	−0.09	−0.10	−0.23	−0.05	0.02	0.04	0.03	−0.01
S_{M3}	−0.20	−0.17	−0.10	−0.12	−0.24	−0.12	0.00	0.06	0.08	0.00
S_{M6}		−0.13	−0.03	−0.04	−0.13		0.14	0.15	0.13	−0.01
	Correlation with VRP: Excess Returns									
S_{M1}	0.20	0.30	0.26	0.23	0.16	0.00	0.03	0.02	0.02	−0.08
S_{M2}	0.28	0.30	0.30	0.19	0.09	0.13	0.18	0.09	0.02	−0.09
S_{M3}	0.32	0.39	0.38	0.23	0.09	0.12	0.17	0.11	−0.05	−0.13
S_{M6}		0.14	0.11	0.04	−0.10		0.01	0.03	−0.06	−0.13

Table A.8. Asset Pricing Tests: Illiquidity Factors

This table reports asset pricing results. The linear factor model includes the dollar (DOL) factor and innovations to global average percentage bid-ask spreads in the spot market, denoted as BAS_{FX} (*Panel A*), and the option market, denoted as BAS_{IV} (*Panel B*). BAS_{FX} is constructed by averaging over a month the daily average bid-ask spread of the spot exchange rate. BAS_{IV} is constructed by averaging over a month the daily average bid-ask spread of the 1-year at-the-money (ATM) implied volatility. Innovations are computed as the residual to a first-order autoregressive process. The test assets are currency excess returns to five portfolios sorted on the 1-year volatility risk premia (VRP) available at time $t-1$. *Factor Prices* reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ. The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. *Factor Betas* reports least-squares estimates of time series regressions. The $\chi^2(\alpha)$ test statistic tests the null that all intercepts are jointly zero. Newey and West (1987) with Andrews (1991) optimal lag selection are reported in parenthesis. *sh* denotes Shanken (1992) standard errors. The *p-values* are reported in brackets. Returns are annualized. The portfolios are rebalanced monthly from January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Illiquidity in the Spot Market

Factor Prices

	b_{DOL}	$b_{BAS_{FX}}$	λ_{DOL}	$\lambda_{BAS_{FX}}$	R^2	$RMSE$	χ^2	HJ	b_{DOL}	$b_{BAS_{FX}}$	λ_{DOL}	$\lambda_{BAS_{FX}}$	R^2	$RMSE$	χ^2	HJ
	Developed								*Developed & Emerging*							
GMM_1	0.43	−38.89	0.02	−0.06	0.36	2.54	1.00	0.15	0.16	−4.65	0.02	−0.06	−0.02	1.98	2.07	0.11
	(0.45)	(53.27)	(0.02)	(0.04)			[0.80]	[0.80]	(0.4)	(10.46)	(0.02)	(0.11)			[0.56]	[0.60]
GMM_2	0.49	−56.89	0.02	−0.05	0.29	2.58	0.82		0.28	−0.45	0.02	−0.03	−0.11	2.01	1.87	
	(0.43)	(44.17)	(0.02)	(0.04)			[0.84]		(0.39)	(9.98)	(0.02)	(0.11)			[0.60]	
FMB	0.43	−38.68	0.02	−0.06	0.36	2.54	1.01		0.16	−4.62	0.02	−0.06	−0.02	1.98	2.07	
	(0.33)	(22.75)	(0.02)	(0.04)			[0.80]		(0.32)	(9.07)	(0.02)	(0.11)			[0.56]	
(sh)	0.32	42.21	0.02	0.07			[0.79]		0.31	10.44	0.02	0.12			[0.57]	

Factor Betas

	α	β_{DOL}	$\beta_{BAS_{FX}}$	R^2	$\chi^2(\alpha)$	α	β_{DOL}	$\beta_{BAS_{FX}}$	R^2	$\chi^2(\alpha)$
P_L	0.03	0.88	−0.17	0.62	9.67	0.02	0.96	−0.03	0.69	2.95
	(0.01)	(0.07)	(0.32)		[0.09]	(0.01)	(0.04)	(0.09)		[0.71]
P_2	0.00	0.96	−0.05	0.70		0.00	0.95	0.01	0.79	
	(0.01)	(0.07)	(0.12)			(0.01)	(0.04)	(0.09)		
P_3	−0.01	1.01	0.00	0.71		−0.01	0.98	−0.03	0.79	
	(0.01)	(0.06)	(0.11)			(0.01)	(0.03)	(0.07)		
P_4	−0.01	1.10	−0.15	0.78		−0.01	1.18	−0.02	0.83	
	(0.01)	(0.05)	(0.29)			(0.01)	(0.04)	(0.09)		
P_S	−0.02	1.05	0.31	0.78		−0.01	0.92	0.11	0.71	
	(0.01)	(0.04)	(0.17)			(0.01)	(0.04)	(0.10)		

(continued)

Table A.8. Asset Pricing Tests: Illiquidity Factors *(continued)*

Panel B: Illiquidity Factor in the Option Market																
Factor Prices																
	b_{DOL}	$b_{BAS_{IV}}$	λ_{DOL}	$\lambda_{BAS_{IV}}$	R^2	$RMSE$	χ^2	HJ	b_{DOL}	$b_{BAS_{IV}}$	λ_{DOL}	$\lambda_{BAS_{IV}}$	R^2	$RMSE$	χ^2	HJ
	Developed								*Developed & Emerging*							
GMM_1	0.41	8.91	0.02	0.01	−0.16	3.42%	4.32	0.16	0.13	−8.13	0.02	−0.02	−0.04	2.00%	1.27	0.11
	(0.52)	(22.04)	(0.02)	(0.03)			[0.23]	[0.22]	(0.51)	(18.14)	(0.02)	(0.04)			[0.74]	[0.61]
GMM_2	0.30	8.99	0.02	0.01	−0.16	3.43%	4.18		0.20	−8.88	0.02	−0.01	−0.09	2.01%	1.24	
	(0.51)	(21.44)	(0.02)	(0.03)			[0.24]		(0.48)	(17.89)	(0.02)	(0.04)			[0.74]	
FMB	0.41	8.86	0.02	0.01	−0.16	3.42%	4.32		0.13	−8.09	0.02	−0.02	−0.04	2.00%	1.27	
	(0.52)	(21.07)	(0.02)	(0.03)			[0.23]		(0.36)	(16.49)	(0.02)	(0.04)			[0.74]	
(sh)	(0.49)	(23)	(0.02)	(0.03)			[0.21]		(0.34)	(16.97)	(0.02)	(0.04)			[0.59]	
Factor Betas																
		α	β_{DOL}	$\beta_{BAS_{IV}}$	R^2	$\chi^2(\alpha)$				α	β_{DOL}	$\beta_{BAS_{IV}}$	R^2	$\chi^2(\alpha)$		
P_L		0.03	0.88	0.05	0.62	9.69				0.02	0.96	−0.04	0.69	2.92		
		(0.01)	(0.06)	(0.54)		(0.08)				(0.01)	(0.05)	(0.32)		(0.71)		
P_2		0.00	0.95	−0.19	0.71					0.00	0.95	−0.06	0.79			
		(0.01)	(0.07)	(0.48)						(0.01)	(0.04)	(0.26)				
P_3		−0.01	1.02	0.12	0.71					−0.01	0.98	−0.17	0.79			
		(0.01)	(0.05)	(0.57)						(0.01)	(0.03)	(0.22)				
P_4		−0.01	1.10	0.24	0.79					−0.01	1.18	0.28	0.83			
		(0.01)	(0.05)	(0.43)						(0.01)	(0.04)	(0.26)				
P_S		−0.02	1.05	−0.25	0.78					−0.01	0.92	−0.05	0.71			
		(0.01)	(0.04)	(0.37)						(0.01)	(0.04)	(0.21)				

Table A.9. Risk Factors: Liquidity and Hedging

This table presents predictive regressions estimates. The dependent variable is the exchange rate return component of the VRP strategy at time t. This strategy is a long/short portfolio that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year expected volatility premia at time $t-1$. The predictors are measured at time $t-1$, and include the TED spread, the change in the VIX index, the change in the St. Louis Fed Financial Stress Index FSI, the net short futures position (HED) of commercial and non-commercial traders on the Australian dollar (AUD) and the Japanese yen (JPY) vis-à-vis the US dollar (USD), respectively, and the $Fund\ Flows$ constructed as the AUM-weighted net flows into hedge funds (currency and global macro funds) scaled by the lagged AUM. Newey and West (1987) with Andrews (1991) optimal lag selection are reported in parenthesis. The superscripts a, b, and c indicate statistical significance at 10%, 5%, and 1%, respectively. Exchange rate returns are annualized. Exchange rates are from *Datastream*, implied volatility quotes are from JP Morgan, futures positions are from the US Commodity Futures Trading Commission (CFTC), hedge fund flows are from Patton and Ramadorai (2013), FSI is from St. Louis Fed's website, whereas all other data are from Bloomberg.

Developed

				$TED\times$	HED		$Fund$	
α	TED	ΔVIX	ΔFSI	ΔVIX	$AUDUSD$	$JPYUSD$	$Flows$	R^2
-0.03	0.15^c							0.04
(0.03)	(0.05)							
0.04^b		0.01						$<.01$
(0.02)		(0.01)						
0.04^b			0.07					$<.01$
(0.02)			(0.07)					
0.04^b				0.01^a				0.02
(0.02)				$(<.01)$				
0.04^b					0.02^c			0.01
(0.02)					$(<.01)$			
0.05^b						-0.02		$<.01$
(0.02)						(0.06)		
0.05^b							-1.50^b	0.02
(0.02)							(0.77)	
-0.01	0.12^b				0.01^c		-0.89	0.06
(0.04)	(0.06)				$(<.01)$		(0.72)	
0.05^b		0.00			0.01^c		-1.34^a	0.03
(0.02)		(0.01)			$(<.01)$		(0.76)	
0.05^b			0.06		0.01^c		-1.34^a	0.03
(0.02)			(0.06)		$(<.01)$		(0.73)	
0.04^b				0.01^b	0.01^c		-1.31^a	0.05
(0.02)				$(<.01)$	$(<.01)$		(0.73)	

Developed & Emerging

				$TED\times$	$Hedging$		$Fund$	
α	TED	ΔVIX	ΔFSI	ΔVIX	$AUDUSD$	$JPYUSD$	$Flows$	R^2
0.00	0.08^a							0.01
(0.03)	(0.04)							
0.04^a		0.01						$<.01$
(0.02)		$<.01$						
0.04^a			0.08					$<.01$
(0.02)			(0.06)					
0.04^a				$<.01^c$				$<.01$
(0.02)				$(<.01)$				
0.04^a					0.01^c			0.01
(0.02)					$(<.01)$			
0.04^a						0.01		$<.01$
(0.02)						(0.06)		
0.05^b							-1.14	0.01
(0.02)							(0.74)	
0.02	0.05				0.01^c		-0.81	0.02
(0.03)	(0.05)				$(<.01)$		(0.72)	
0.04^a		$<.01$			0.01^c		-0.99	0.02
(0.02)		$(<.01)$			$(<.01)$		(0.72)	
0.04^a			0.07		0.01^c		-0.97	0.02
(0.02)			(0.06)		$(<.01)$		(0.69)	
0.04				$<.01^c$	0.01^c		-0.99	0.02
(0.02)				$(<.01)$	$(<.01)$		(0.70)	

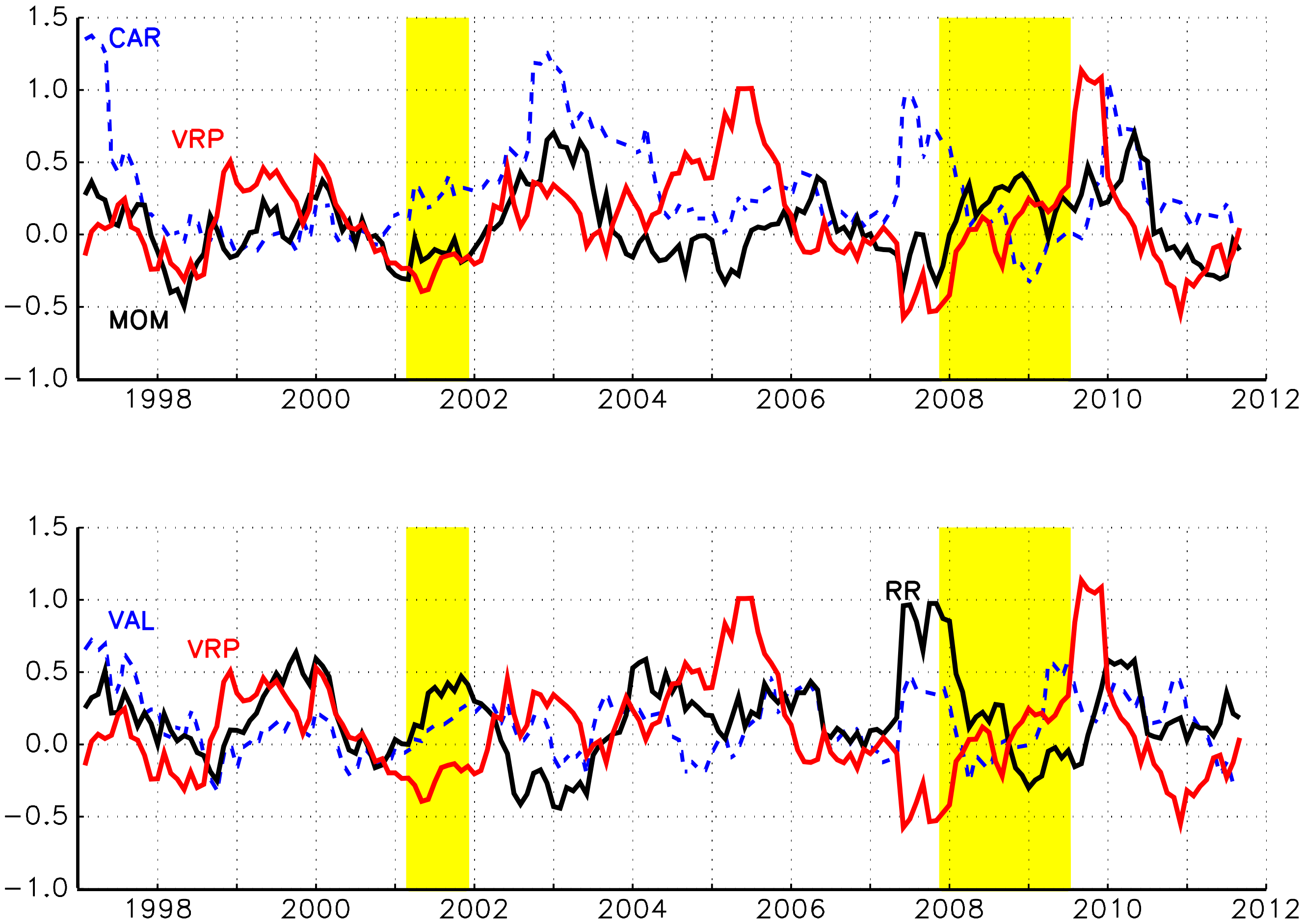

Figure A.1. Rolling Sharpe Ratios: Developed & Emerging Countries

The figure presents for developed & emerging countries the 1-year rolling Sharpe ratios of currency strategies formed using $t-1$ information. CAR is the carry strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential relative to the US dollar. Similarly, MOM is the momentum strategy that buys (sells) currencies with the highest (lowest) past 3-month exchange rate return, VAL is the value strategy that buys (sells) currencies with lowest (highest) real exchange rate, RR is the risk reversal strategy that buys (sells) currencies with the lowest (highest) 1-year 10-delta risk reversal, and VRP is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. The strategies are rebalanced monthly from January 1996 to August 2011. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

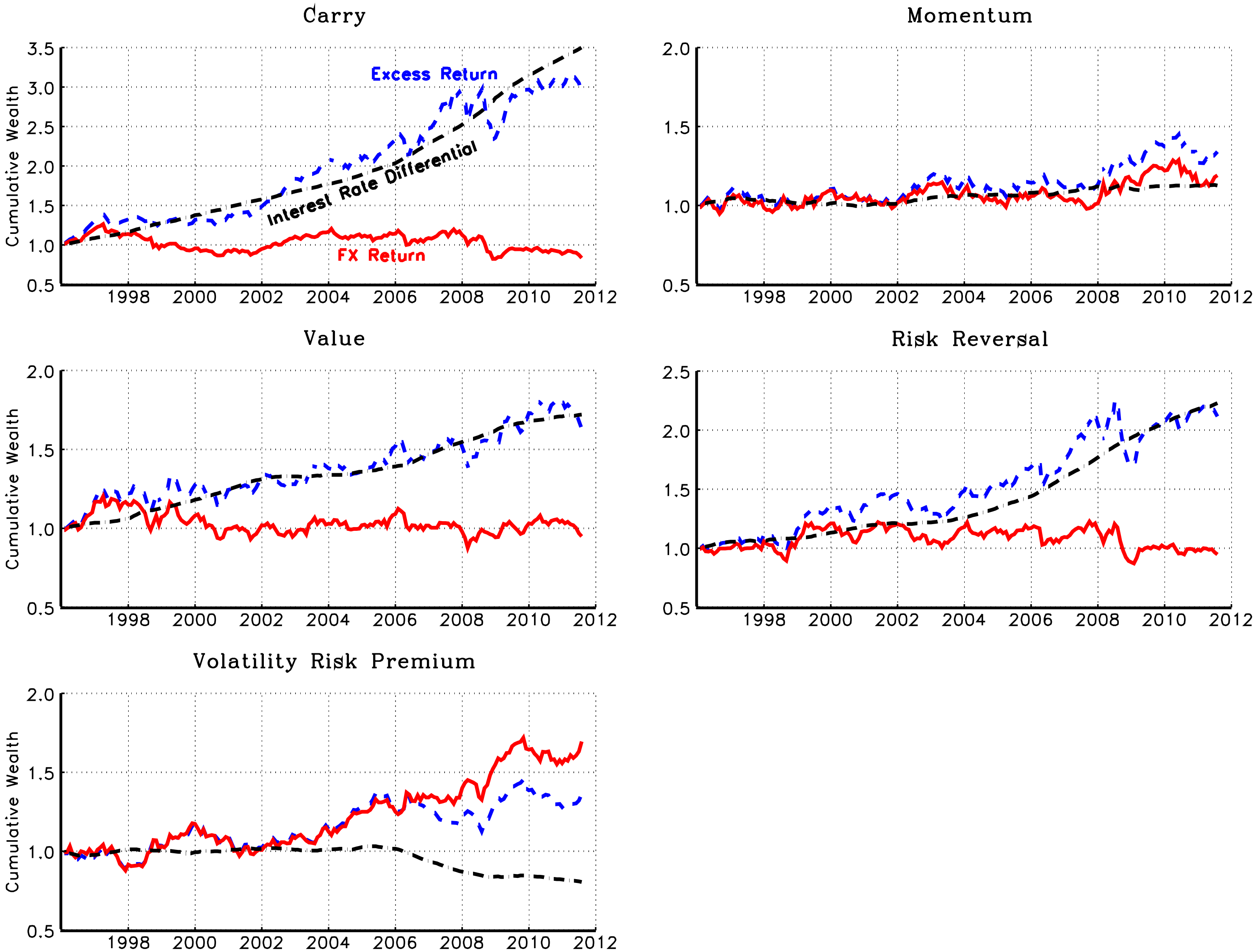

Figure A.2. Currency Strategies and Payoffs: Developed & Emerging Countries

The figure presents for developed & emerging countries the cumulative wealth to currency strategies formed using $t-1$ information. The strategies are rebalanced monthly from January 1996 to August 2011, and described in Figure A.1. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

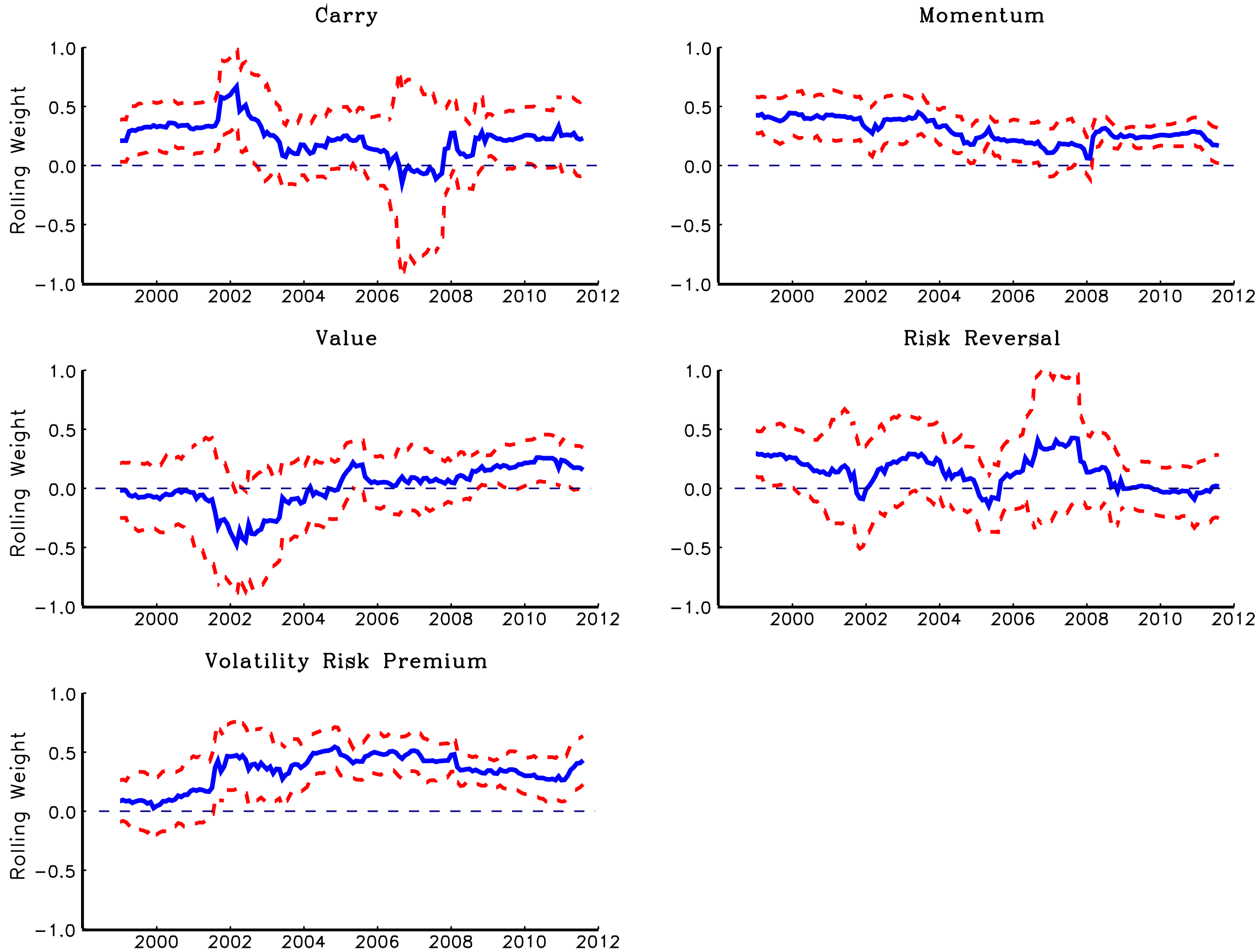

Figure A.3. Rolling Portfolio Weights: Developed Countries

The figure presents the weights of the global minimum volatility portfolio computed over a rolling windows of 3 years. The dashed lines denote the 95% confidence interval. The sample period runs from January 1996 to August 2011. The strategies are rebalanced monthly from January 1996 to August 2011, and described in Figure A.1. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

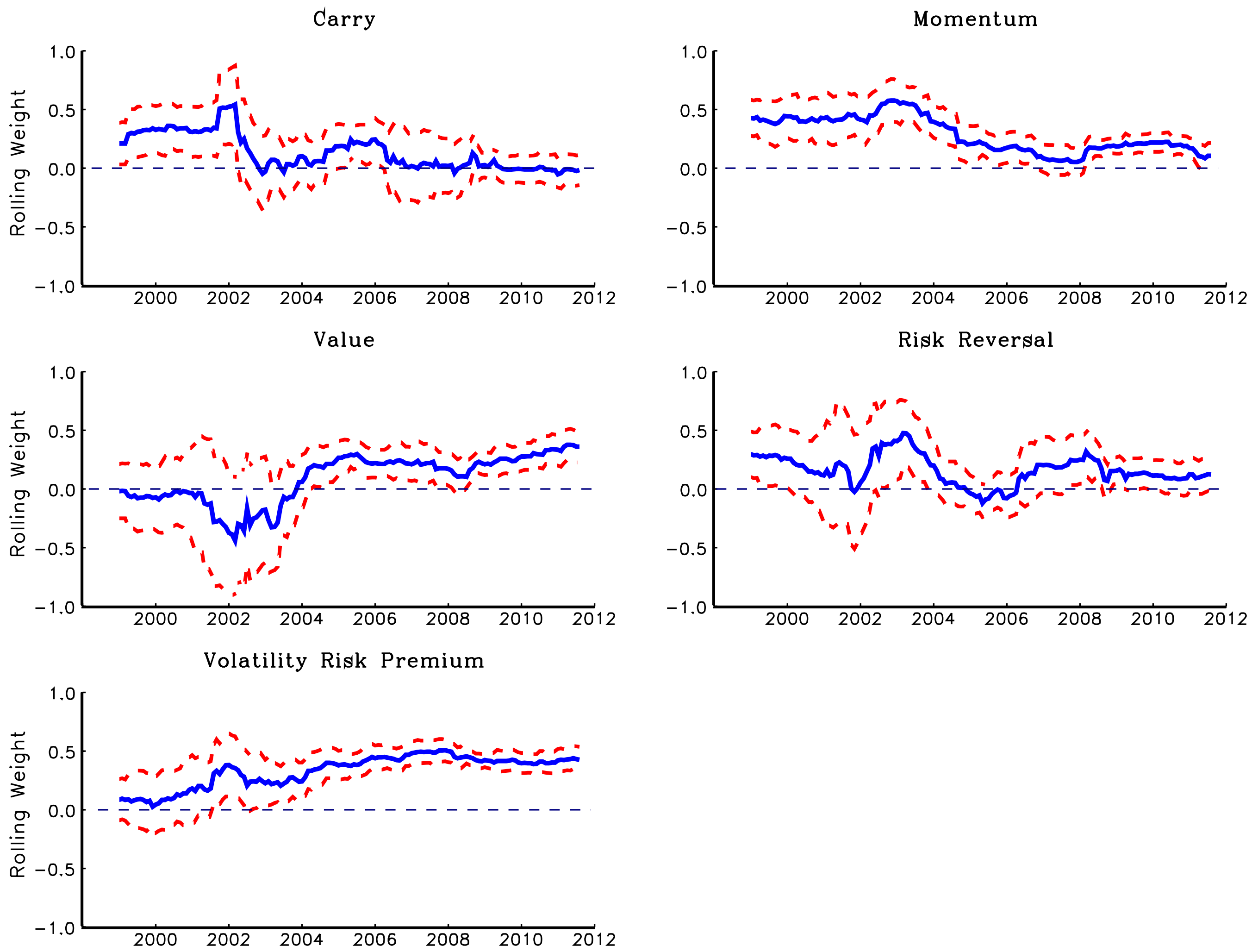

Figure A.4. Rolling Portfolio Weights: Developed & Emerging Countries

The figure presents the weights of the global minimum volatility portfolio computed over a rolling windows of 3 years. The dashed lines denote the 95% confidence interval. The sample period runs from January 1996 to August 2011. The strategies are rebalanced monthly from January 1996 to August 2011, and described in Figure A.1. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.