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No. 9549

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*FINANCIAL ECONOMICS and  
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Discussion Paper No. 9549  
July 2013

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July 2013

## ABSTRACT

### Volatility Risk Premia and Exchange Rate Predictability\*

We investigate the predictive information content in foreign exchange volatility risk premia for exchange rate returns. The volatility risk premium is the difference between realized volatility and a model-free measure of expected volatility that is derived from currency options, and reflects the cost of insurance against volatility fluctuations in the underlying currency. We find that a portfolio that sells currencies with high insurance costs and buys currencies with low insurance costs generates sizeable out-of-sample returns and Sharpe ratios. These returns are almost entirely obtained via predictability of spot exchange rates rather than interest rate differentials, and these predictable spot returns are far stronger than those from carry trade and momentum strategies. Canonical risk factors cannot price the returns from this strategy, which can be understood, however, in terms of a simple mechanism with time-varying limits to arbitrage.

JEL Classification: F31, F37, G12 and G13

Keywords: exchange rate, hedgers, order flow, predictability, speculators and volatility risk premium

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\*We are grateful to John Campbell, Kenneth Froot, Philippos Kassimatis, Lars Lochstoer, Andrea Vedolin and Adrien Verdelhan for helpful conversations and suggestions. We also thank JP Morgan and Aslan Uddin for some of the data used in this study. Sarno acknowledges financial support from the Economic and Social Research Council (No. RES-062-23-2340). All errors remain ours.

Submitted 02 July 2013

# 1 Introduction

What explains currency fluctuations? Finance practitioners and academics have struggled in vain with this question for decades. In their seminal study, Meese and Rogoff (1983) highlight the difficulty of explaining and predicting short-run currency movements, by documenting that it is fiendishly difficult to find theoretically motivated variables able to beat a random walk forecasting model for currencies. The literature has found it difficult to move far ahead of this result in the past three decades (see, for example, Rogoff and Stavrageva, 2008, and Engel, Mark and West, 2008).

A research area which has recently seen significant activity tackles a closely-related question, which is to explain the returns to currency investment strategies. Adopting the cross-sectional asset pricing approach of constructing portfolios sorted by currency characteristics such as interest rate differentials or lagged returns, researchers have shown that there are large returns to carry and momentum strategies in currencies.<sup>1</sup> These recent findings do not help to resolve the Meese and Rogoff puzzle, and exacerbate it somewhat, in the sense that they reveal economically significant predictability in currency *excess* returns, but they have little to say about predictability in *spot exchange rates*.<sup>2</sup> On the one hand, carry trade strategies generate returns that are almost entirely driven by interest rate differentials, and not by any predictive ability for spot rate changes. On the other hand, while it is true that momentum strategies generate returns that are primarily driven by the predictability of spot rate changes rather than by interest rate differentials, these strategies appear to work poorly over the last decade for liquid currencies, and they are difficult to exploit in practice (Menkhoff, Sarno, Schmeling and Schrimpf, 2012b). Moreover, momentum strategies do not provide much insight into the underlying economic drivers of exchange rate movements, or the source of exchange rate predictability.

In this paper we investigate the predictive information content in the currency volatility

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<sup>1</sup>See, for example, Lustig and Verdelhan (2007), Ang and Chen (2010), Burnside, Eichenbaum, Kleshchelski and Rebelo (2011), Lustig, Roussanov and Verdelhan (2001), Barroso and Santa Clara (2012) and Menkhoff, Sarno, Schmeling and Schrimpf (2012a,b), who all build currency portfolios to study return predictability and/or currency risk exposure.

<sup>2</sup>We use interchangeably the terms spot 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.

risk premium for exchange rate returns. Our key result is that there is economically valuable and statistically significant predictive information in the volatility risk premium for future spot exchange rate returns over the 1996 to 2011 period, in a cross-section of up to 20 currencies.<sup>3</sup> We consider two main explanations for our results, and find support for an explanation based on limits to arbitrage and the interaction between hedgers and speculators in the currency market. This explanation is consistent with the 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).

The currency volatility risk premium is the difference between expected future realized volatility, and a model-free measure of expected volatility derived from currency options. A growing literature studies the variance of the volatility risk premium in different asset classes, including equity, bond, and foreign exchange (FX) markets.<sup>4</sup> 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 rank currencies and to build currency portfolios, sorting currencies into quintile portfolios by this variable at the beginning of each month. Our trading 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, which we dub *VRP*, over the subsequent period, meaning that these returns

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<sup>3</sup>To be clear from the outset, our strategy does not trade volatility products. We simply use the expected volatility risk premium as conditioning information to sort currencies, build currency portfolios, and uncover predictability in spot exchange rate returns.

<sup>4</sup>See, for example, Carr and Wu (2009), Eraker (2008), Bollerslev, Tauchen, and Zhou (2009), Todorov (2010), Drechsler and Yaron (2010), Han and Zhou (2010), Mueller, Vedolin and Yen (2011), Londono and Zhou (2012) and Buraschi, Trojani and Vedolin (2013).

are purely out-of-sample, conditioning only on information available at the time of portfolio construction.

We find that *VRP* generates sizeable currency excess returns, which are virtually completely obtained through prediction 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 carry and momentum strategies, as well as other currency trading strategies that we consider.

There are several possible interpretations of this result, of which we consider two as most likely. One possibility is that *VRP* captures fluctuations in aversion to volatility risk, in which 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 portfolio, 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 a framework that has gained importance in the recent literature on limits to arbitrage and the incentives of hedgers and speculators in asset markets (see, for example, Acharya, Lochstoer, and Ramadorai, 2013). This explanation relies on two ingredients, the first of which is time-variation in the amount of arbitrage capital available to natural providers of currency volatility insurance (“speculators”), such as financial institutions or hedge funds. The second ingredient is that risk-averse natural “hedgers” of currencies such as multinational firms, or financial institutions

that inherit currency positions from their clients, are more willing to hold currencies for which volatility insurance is relatively inexpensive. Such institutions will also be more likely to avoid holding, or be more likely to sell, positions in currencies with relatively expensive volatility protection. The combination of these two ingredients is sufficient to generate the patterns that we see in the data.

To better understand this explanation, consider the following scenario: assume that speculators face a shock to their available arbitrage capital. This limits their ability to provide cheap volatility insurance – for example, they may reduce their outstanding short put option positions in the currencies in which they trade.<sup>5</sup> These limits on speculators’ ability to satisfy demand for volatility insurance increases net demand in the options market, thus increasing current option prices and making hedging more expensive. As in Garleanu, Pedersen, and Poteshman (2009), this net demand imbalance shows 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. As this currency hits the spot market, it 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

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<sup>5</sup>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, are also useful in explaining our returns, and add significant additional explanatory power when interacted with the TED spread. We also 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.

We also obtain more direct evidence in favour of the limits to arbitrage explanation when we investigate the behavior of currency order flow in our insurance-cost sorted portfolios. This evidence links our work to another important stream of the exchange rate literature, on explaining and forecasting currency returns using currency order flow.<sup>6</sup> Our paper suggests an addition to the explanations that have been advanced to explain this predictive power, namely that incentives to hedge volatility risk may be a contributing factor to the observed predictive relationship. We document that *VRP* is connected to measures of customer order flow in a way that is consistent with the proposed explanation. Specifically when we investigate the behavior of net order flow in our volatility risk-premium sorted portfolios, we find that end-customers who are corporate clients tend to buy currencies which are cheaper to insure, and sell currencies which are more expensive to insure in the spot currency market. Asset managers, on the other hand, appear to satisfy demand for spot currencies at such times, trading in a way that is exactly opposite to that of corporate clients. Hedge funds appear to exacerbate the level of price pressure, trading in the same direction as corporate clients in the spot market. This analysis using observed currency order flows in the spot market serves to corroborate our other evidence suggesting that *VRP* returns are driven by the interaction of natural hedgers and speculators in currency markets.

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<sup>6</sup>Evans and Lyons (2002) show that currency order flow has substantial explanatory power for contemporaneous exchange rate returns, and authors such as Froot and Ramadorai (2005), Evans and Lyons (2005), and more recently, Menkhoff, Sarno, Schmeling and Schrimpf (2013), show that order flow has substantial predictive power for exchange rate movements.

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

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

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:

$$SW_{t,\tau} = E_t^{\mathbb{Q}} [RV_{t,\tau}] \quad (2)$$

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  $\sigma_s^2$  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.”<sup>7</sup> The replicating portfolio strategy captures variance exactly, provided that the portfolio of options contains all strikes with the 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:

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

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  $\tau$ -period domestic riskless rate.

The risk-neutral expectation of the return variance in Equation (3) delivers the strike price of a variance swap  $E_t^{\mathbb{Q}} [RV_{t,\tau}^2]$ , 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. Our empirical analysis focuses on volatility swaps, and we synthetically construct the strike price of this contract as

$$E_t^{\mathbb{Q}} [RV_{t,\tau}] = \sqrt{E_t^{\mathbb{Q}} [RV_{t,\tau}^2]} \quad (4)$$

and refer to it as model-free implied volatility.

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<sup>7</sup>The log contract is an option whose payoff is proportional to the log of the underlying at expiration (Neuberger, 1994).

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.,  $E_t^{\mathbb{Q}}[RV_{t,\tau}] \leq \sqrt{E_t^{\mathbb{Q}}[RV_{t,\tau}^2]}$ . 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.<sup>8</sup> 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  $\tau$ . In the FX market, over-the-counter options are 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, beyond which we extrapolate implied volatility by assuming it is constant as in Jiang and Tian (2005) and Carr and Wu (2009). We then compute the option values using the Garman and Kohlhagen (1983) valuation formula,<sup>9</sup> and use trapezoidal integration to solve

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

<sup>9</sup>This valuation formula can be thought of as the Black and Scholes (1973) formula adjusted for having

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.

**Volatility Risk Premium.** In this paper we study the predictive information content in volatility swaps 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 risk premium can be thought of as the difference between the physical and the risk-neutral expectations of the future realized volatility.<sup>10</sup> Formally, the  $\tau$ -period volatility risk premium at time  $t$  is defined as

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

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.<sup>11</sup> 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 at each point in time  $t$ , with high  $VRP_{t,\tau}$  as those which are relatively “cheap” to insure, as their expected realized volatility under the physical measure, 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

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both domestic and foreign currency paying a continuous interest rate.

<sup>10</sup>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.

<sup>11</sup>In our empirical work we also experiment with an AR(1) process for  $RV$  to form expectations of  $RV$ , and find that the results are virtually identical to those reported in the paper.

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 on spot and forward exchange rates, quotes on implied volatilities, and the positions of market participants that we employ in our analysis. We also describe the construction of currency portfolios using our measure of option expensiveness.

**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 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.<sup>12</sup> 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.

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<sup>12</sup>According to the Triennial Survey of the Bank for International Settlements (2010), the top 10 currencies account for 90 percent of the average daily turnover in FX markets.

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.<sup>13</sup> To convert deltas into strike prices, and implied volatilities into option 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. It is also the most liquid traded maturity.<sup>14</sup>

**Hedger Position Data.** In our empirical analysis, we also use the net position of commercial and non-commercial traders in exchange rate futures on the Chicago Mercantile Exchange. These data are collected and reported monthly by the US Commodity Futures Trading Commission (CFTC), and are often used to construct a measure of carry trade activity (Curcuro, Vega, and Hoek, 2010). Implementation of a carry trade strategy is indicated by a net long futures position in a target investment currency, say the Australian dollar, paired with a net short futures position in a target funding currency, typically the Japanese yen.

Following Acharya, Lochstoer, and Ramadorai (2013), we construct the (normalized) net

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<sup>13</sup>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  $-0.25$ .

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

short futures position (i.e., short futures less long futures) of commercial and non-commercial traders on the Australian dollar (*AUD*) and the Japanese yen (*JPY*) relative to the USD dollar, respectively. The CFTC aggregates net positions in the FX futures market according to commercial and non-commercial traders. This classification, however, has significant shortcomings as traders with a cash position in the underlying can be categorized as commercial traders – this group may therefore include corporate firms with an international line of business, as well as banks with offsetting positions in the underlying foreign currency (perhaps on account of holding a position in the swap market). Since the defining line between commercial and non-commercial traders is unclear, our measure is constructed as an aggregate measure across both types of traders, which effectively creates a measure of aggregate net short demand from these groups, following any netting across the two. In our empirical work, we winsorize this measure at the 1% and 99% percentile points.

A detailed description of the construction of this measure is reported in the Appendix.

**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 difference between the fund’s assets under management (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.

**Order Flow Data.** We employ a data set on customer order flow in the FX market in nine currency pairs over the sample period from January 2001 to May 2011. The nine currencies cover our “Developed” sample with the exception of the Danish Krone, for which



order flow data are not available. These data, used previously in Menkhoff, Sarno, Schmeling, and Schrimpf (2013) and Della Corte, Rime, Sarno, and Tsiakas (2013), are obtained from a top-tier FX dealing bank.

Customer order flow in each of the nine currencies is measured as net buying pressure against the US dollar (USD), that is, the US dollar volume of buyer-initiated minus seller-initiated trades of a currency against the USD. The data cover all trades of customers of the bank during our sample period. A positive (negative) number indicates net buying (selling) pressure in the foreign currency relative to the USD.

In our empirical analysis, when aggregating or to allow for meaningful cross-currency comparisons, we need to ensure that order flows are comparable across currencies, as the absolute size of order flows differs across currencies. We therefore standardize flows by dividing flows by their standard deviation to remove the difference in absolute order flow sizes across currencies:

$$\tilde{x}_{j,t}^R = \frac{x_{j,t}}{\sigma_{x_{j,t-3m}}}, \quad (6)$$

where  $\tilde{x}_{j,t}^R$  denotes order flow standardized over a rolling window and  $x_{j,t}$  denotes the raw order flow. We compute the standard deviation of flows over a rolling 63 trading-day (3 month) window.

Our order flow data can be distinguished into customer groups, namely, Asset Managers (AM), Hedge Funds (HF), and Corporate Clients (CO). Asset Managers comprises entities such as mutual funds and pension funds. Hedge Funds are unregulated entities in the set of asset managers, and include highly leveraged traders not included in the asset manager segment. Corporate Clients include non-financial corporations that import or export products and services around the world, or those with an international supply chain. Corporate Clients also include the treasury units of large non-financial corporations, with the exception of those pursuing a highly leveraged investment strategy, in which case they are classified as hedge funds. In our analysis, we also aggregate flows across all these segments, and refer to the resulting currency-specific time-series as “Total Flows.”

**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 an exchange rate component (i.e., the exchange rate change) minus an interest rate component (i.e., the interest rate differential):  $RX_{t+1} \simeq ((S_{t+1} - S_t) / S_t) - (i_t - i_t^*)$ , hence the moniker “excess return.”

**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 as  $-(F_t - S_t) / S_t = (i_t^* - i_t)$  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*.<sup>15</sup>

**Value Portfolios.** At the end of each period  $t$ , we form five portfolios based on the level of the real exchange rate. 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 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

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<sup>15</sup>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.

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

**Currency Portfolios Sorted on the Volatility Risk Premium.** Table 1 presents summary statistics for the annualized average realized volatility  $RV_{t,\tau}$ , synthetic volatility swap rate  $SW_{t,\tau} = E_t^{\mathbb{Q}}[RV_{t,\tau}]$ , 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  $\tau$  subscript, as it is always 1 year).

The table shows that, on average across currencies,  $RV_t$  equals 10.68 percent, with a standard deviation of 2.88 percent;  $SW_t$  equals 11.31 percent, with a standard deviation of 2.75 percent; and therefore the average volatility risk premium  $VRP_t$  across currencies is the difference between these two, and equal to  $-0.62$  percent, with a standard deviation of 1.58 percent. For the full sample of developed and emerging countries, both  $RV_t$  and  $SW_t$  are slightly larger than for the sample of only developed currencies, as 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 presents the basic result of our paper. In the table, 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; 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, with the strategy for *VAL* especially performing well in the final few years of

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. Perhaps surprisingly, 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 rather than in emerging markets. We note here that the Sharpe ratios for all of these strategies, including the *VRP*, are statistically significantly different from zero.<sup>16</sup>

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 are derived from interest rate differentials. Moreover, the Sharpe ratio for the exchange rate component of *CAR* is insignificantly different from zero, whereas the Sharpe ratio for *VRP* is statistically significant in all cases considered.

Several of the other moments in Panel B of Table 2 are also worth highlighting. First,

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<sup>16</sup>We estimate the standard error of the Sharpe ratio using the formula for non-*iid* returns via delta-method and using a generalized method of moment (GMM) estimator (Lo, 2002). Specifically, the asymptotic distribution of the Sharpe ratio is defined as  $\sqrt{T}(\widehat{SR} - SR) \overset{a}{\sim} N(0, V)$ , where  $V = \frac{\partial g}{\partial \theta} \Sigma_{\theta} \frac{\partial g}{\partial \theta'}$ ,  $\theta = (\mu, \sigma)'$ ,  $\frac{\partial g}{\partial \theta} = (1/\sigma, -\mu/\sigma^2)'$ , and  $\Sigma_{\theta}$  is the variance-covariance matrix of  $\theta$ . We estimate  $\theta$  via GMM and  $\Sigma_{\theta}$  using Newey and West (1987) with the optimal lag length according to Andrews (1991).

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) is reasonable – lying in between the very low turnover of *CAR* and the high turnover of *MOM*. The weights in the *VRP* strategy are fairly stable over time, meaning 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*.

Finally, Panel C of Table 2 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.

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 make 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 or other particular episodes or sample period as the Sharpe ratio has been relatively stable over the sample, and appears to be no more volatile than the Sharpe ratio of *CAR* and *MOM*.

Table 3 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 especially for the full sample of Developed and Emerging countries, it is still large and positive, and higher than all the competitor strategies. Even if  $VRP$  were to be used primarily as a hedge, it has very desirable properties, delivering positive returns outside of crisis periods, and very high returns within crisis periods.

Figure 2 plots the cumulative returns over of the strategies over the sample period (again, only for the Developed Countries), with a particular focus on decomposing the cumulative excess return 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 cumulative yield component has a positive but relatively minor contribution to momentum returns.  $VRP$  returns are different in that they are made up of a 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.

Table 4 provides further details and statistics to understand the properties of 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 that refine our understanding of  $VRP$ . 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 currency returns component. Second, in normal times, the  $VRP$  return stems from the long portfolio,  $P_L$ , although as the top panel of Figure 3 later reveals,  $P_S$  delivers a high

kick during the recent and other crisis periods. Third, the return from  $P_L$  can be virtually completely attributed to spot rate changes. Finally, the bottom panel of Table 4 shows the transition matrix between portfolios. This shows that, while there is a fairly persistent tendency for currency insurance costs to remain stable, there is nonetheless 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 long and short positions in particular currencies.

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 much stronger predictive power than for exchange rate returns, which is largely independent from that derived from alternative currency trading strategies. This means that a currency manager would benefit greatly from adding  $VRP$  to a currency portfolio to enhance risk-adjusted returns, and also that a spot trader interested in forecasting exchange rate fluctuations (as opposed to excess returns) would value  $VRP$  greatly.<sup>17</sup>

## 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  $VRP$  on a number of 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

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<sup>17</sup>We also compute volatility risk premia using the simple variance swap formula of Martin (2012). Results are virtually identical for developed countries and improve for developed and emerging countries. We report these results in the Internet Appendix.



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  $RX_{t+1}^i$ . The usual no-arbitrage relation applies, so risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$\mathbb{E}[M_{t+1}RX_{t+1}^i] = 0, \quad (7)$$

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  $\mu$  denotes factor means.

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

$$\mathbb{E}[RX^i] = \lambda'\beta_i \quad (8)$$

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

The relationship between the factor risk prices in equation (8) and the SDF parameters in equation (7) is simply given by  $\lambda = \Sigma_f b$ , where  $\Sigma_f$  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 (7) via generalized method of moments (GMM).<sup>18</sup> We also present results from the more traditional Fama-MacBeth (FMB) approach 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 model applied to the average realized volatility of all currencies in our sample, as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a).<sup>19</sup>

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  $HJ$  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  $\lambda$  on a factor.

Table 6 reports GMM estimates of  $b$ , portfolio-specific  $\beta$ 's, and implied  $\lambda$ 's, as well as cross-sectional  $R^2$  statistics and the Hansen-Jagannathan (HJ) distance measure (Hansen and Jagannathan, 1997). In the table, standard errors are constructed as in Newey and West (1987)

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<sup>18</sup>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).

<sup>19</sup>In the Internet Appendix, we also consider the innovations to global average percentage 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 proxy for the FX spot market and the FX option market illiquidity, respectively.

with optimal lag length selection according to Andrews (1991). Besides the GMM tests, we employ traditional 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.<sup>20</sup> Since *DOL* has virtually no cross-sectional relation to portfolio returns, it serves the same purpose as a constant that allows for a 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  $\lambda$ , 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 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*. 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 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 carry and momentum returns, 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.

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<sup>20</sup>Also see Lustig and Verdelhan (2007) and Burnside (2011) on the issue of whether or not to include a constant in these regressions.

## 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 have already tested the impacts of the global FX volatility risk factor of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and found it to be ineffective at pricing 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  $\beta_i$  coefficients, we sort currencies into five portfolios on the basis of these  $\beta_i$  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. The Internet Appendix 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 very low. Figure 3 provides a clear picture of these results in time-series, showing the dramatic difference between the returns from *VRP* displayed in the top part of the figure, and those from the construction based on correlations of currency returns with global volatility, in the bottom panel. 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 currency-market arbitrage is limited, and particular currencies are relatively expensive or cheap to insure, this results in inventory pressure on expensive-to-insure currencies as they are sold by natural hedgers, and relatively less pressure on cheap-to-insure currencies, for which natural hedgers are happy to hold higher inventories. 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.<sup>21</sup>

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

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<sup>21</sup>See the Internet Appendix for a detailed description of the conditioning factors used for this exercise.

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, again consistent with the limits to arbitrage explanation. Yet again, this result is only significant for the sample of developed countries. Similarly, the third column shows that a general financial distress indicator (FSI, constructed by the Federal Reserve Bank 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, that *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 commercial and non-commercial traders on the Australian dollar (*AUD*) and the Japanese yen (*JPY*) relative to the USD dollar, respectively. For Developed as well as Developed and Emerging samples, at times when there is greater futures-related hedging of the *AUD* by commercial and non-commercial 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 rise. As a result, net demand for 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, ..., 20 months for the *VRP*-sorted portfolios, for both samples of countries examined.<sup>22</sup> 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

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<sup>22</sup>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.

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 spot 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. We do so using actual order flow data, essentially taking the currencies ranked by their volatility insurance costs, and documenting their order flow, rather than their returns.

Table 9 presents the results of this exercise, disaggregated by end-customer type. We find that the order flow of corporate clients follows exactly the pattern implied by the limits to arbitrage explanation – such end-users of currencies sell expensive-insurance ( $P_S$ ) currencies and buy cheaper-insurance ( $P_L$ ) currencies. Asset managers demonstrate exactly the opposite behavior, acting as market-makers that provide liquidity to satisfy the buying (selling) demand for low (high)-insurance currencies. Hedge funds appear to either be susceptible to currency volatility insurance pressures, or to engage in destabilizing rational speculation, as their behavior appears similar to that of the corporate clients. Finally, total net order flow, which is the sum of the order flows of the three collectively exhaustive categories of market participants for which order flow data is available, is positive (negative) for cheaper (expensive) insurance currencies. This is consistent with the net demand of these market participants relative to FX dealers being non-zero, thus generating price pressure in the spot market on average, consistent with high returns to the *VRP* strategy.

Figure 5 plots the daily cumulated order flow in the extreme *VRP* portfolios for each group of market participants. These graphs show that the averages of order flow that we document in Table 9 display interesting time-variation, consistent with greater impacts during the crisis, though not exclusively limited to any single time-period.

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 adding currency markets to the list of venues 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 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 potentially important 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 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 see our work as adding currency markets to the growing list of markets in which understanding the interactions between hedgers and speculators is critically important.

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**Table 1. Volatility Risk Premia**

This table presents summary statistics for the average 1-year realized volatility  $RV_t$  (*Panel A*), synthetic volatility swap rate  $SW_t$  (*Panel B*), and volatility risk premium  $VRP_t = RV_t - SW_t$  (*Panel C*) in foreign exchange.  $RV_t$  is computed at time  $t$  using daily exchange rate returns over the previous year.  $SW_t$  is constructed at time  $t$  using the 1-year implied volatilities across 5 different deltas from the foreign exchange option market. The volatility risk premium  $VRP_t$  is constructed as the difference between  $RV_t$  and  $SW_t$ .  $Q_j$  refers to the  $j^{th}$  percentile.  $AC$  indicates the 1-year autocorrelation coefficient.  $RV_t$ ,  $SW_t$ , and  $VRP_t$  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.

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

**Table 2. 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 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. The superscript \* denotes positive and statistical significant *SRs* at 5% level computed via delta-method using the generalized method of moments (Lo, 2002). *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.

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



**Table 3. 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 risk reversal, and *VRP* is the volatility risk premium strategy that buys (sells) currencies with the highest (lowest) 1-year volatility risk premium. The superscript \* denotes positive and statistical significant *SRs* at 5% level computed via delta-method using the generalized method of moments (Lo, 2002). 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 B*), and from January 2007 to August 2011 (*Panel C*). January 1996 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: NBER Recession Periods										
	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>
	<i>Developed</i>					<i>Developed &amp; Emerging</i>				
<i>Mean</i>	-9.59	11.32	4.62	-7.96	11.54	-7.97	7.07	0.10	-4.80	6.50
<i>Sdev</i>	17.11	15.40	12.03	19.07	10.11	14.69	10.49	9.92	15.20	9.38
<i>Skew</i>	-0.44	0.28	-0.63	-0.90	0.12	-0.80	0.17	-0.15	-0.08	-0.45
<i>Kurt</i>	3.71	2.87	3.43	4.13	2.26	2.84	2.77	2.95	2.54	2.88
<i>SR</i>	-0.56	0.74*	0.38*	-0.42	1.14*	-0.54	0.67*	0.01	-0.32	0.69*
<i>MDD</i>	-0.40	-0.16	-0.12	-0.41	-0.09	-0.32	-0.07	-0.18	-0.29	-0.09
<i>AC<sub>1</sub></i>	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										
<i>Mean</i>	2.09	0.40	2.65	3.08	3.14	0.64	0.46	0.05	1.11	3.23
<i>Sdev</i>	9.06	8.11	8.95	9.57	7.99	8.92	7.68	8.73	9.61	7.96
<i>Skew</i>	-0.87	0.04	-0.16	0.11	0.26	-0.92	-0.19	-0.16	-0.17	0.26
<i>Kurt</i>	4.50	2.48	3.30	4.16	4.02	4.90	2.90	3.22	5.55	3.70
<i>SR</i>	0.23*	0.05	0.30*	0.32*	0.39*	0.07	0.06	0.01	0.12	0.41*
<i>MDD</i>	-0.31	-0.21	-0.22	-0.15	-0.16	-0.31	-0.20	-0.22	-0.20	-0.16
<i>AC<sub>1</sub></i>	-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										
<i>Mean</i>	1.91	0.81	3.00	2.94	2.18	1.09	0.71	0.58	1.28	3.04
<i>Sdev</i>	8.33	7.90	9.78	9.43	7.99	9.16	7.68	9.25	10.12	8.53
<i>Skew</i>	-0.91	-0.02	-0.31	0.32	0.07	-1.06	0.01	-0.25	-0.24	0.19
<i>Kurt</i>	4.92	2.46	3.26	4.14	3.46	5.20	2.59	3.10	5.41	3.47
<i>SR</i>	0.23*	0.10	0.31*	0.31*	0.27*	0.12	0.09	0.06	0.13	0.36*
<i>MDD</i>	-0.31	-0.16	-0.24	-0.15	-0.19	-0.31	-0.14	-0.23	-0.18	-0.18
<i>AC<sub>1</sub></i>	-0.05	-0.11	-0.03	-0.02	-0.01	-0.08	-0.14	-0.02	-0.03	0.02
Panel B: Crisis Period										
<i>Mean</i>	-3.34	4.88	2.81	-2.13	9.61	-4.73	3.17	-1.15	-2.25	5.30
<i>Sdev</i>	14.80	12.69	8.67	15.31	9.05	11.70	9.23	8.05	11.72	7.29
<i>Skew</i>	-0.66	0.50	-0.22	-1.13	0.54	-0.89	-0.10	0.12	-0.12	-0.07
<i>Kurt</i>	4.02	3.57	4.27	5.63	3.42	3.90	3.56	3.41	3.67	3.39
<i>SR</i>	-0.23	0.38*	0.32*	-0.14	1.06*	-0.40	0.34*	-0.14	-0.19	0.73*
<i>MDD</i>	-0.43	-0.16	-0.12	-0.40	-0.08	-0.31	-0.13	-0.15	-0.29	-0.10
<i>AC<sub>1</sub></i>	0.22	0.09	0.01	0.18	0.09	0.17	-0.10	0.12	0.25	0.10

**Table 4. 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 premia.  $H/L$  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  $t + 1$ .  $\bar{\pi}$  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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	4.70	2.24	1.04	1.78	0.67	4.03	3.59	1.93	1.34	1.40	1.26	2.34
<i>Sdev</i>	9.08	9.27	9.76	10.07	9.72	8.33	9.32	8.68	8.89	10.44	8.81	8.18
<i>Skew</i>	-0.05	0.19	0.09	-0.17	-0.26	0.28	-0.09	0.05	-0.21	-0.29	-0.39	0.12
<i>Kurt</i>	3.13	5.14	5.80	3.85	3.82	3.47	3.09	4.79	3.85	4.16	3.73	3.26
<i>SR</i>	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
<i>Freq</i>	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												
<i>Mean</i>	4.93	2.06	1.26	1.60	0.52	4.40	3.51	1.62	1.37	0.82	-0.21	3.72
<i>Sdev</i>	9.05	9.24	9.63	9.96	9.64	8.35	9.26	8.62	8.74	10.31	8.75	8.17
<i>Skew</i>	-0.12	0.15	0.06	-0.18	-0.26	0.28	-0.18	0.00	-0.26	-0.31	-0.47	0.12
<i>Kurt</i>	3.17	5.24	5.88	4.06	3.83	3.61	3.07	4.80	4.02	4.36	3.94	3.50
<i>SR</i>	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
<i>Freq</i>	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	
$\bar{\pi}$	<b>0.19</b>	<b>0.20</b>	<b>0.20</b>	<b>0.20</b>	<b>0.20</b>		<b>0.19</b>	<b>0.23</b>	<b>0.20</b>	<b>0.19</b>	<b>0.18</b>	

**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 2 in *Panel A*, the Fama and French (1992) and the equity momentum factors in *Panel B*, and the Fung and Hsieh (2001) 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 (2001) are from Hsieh's website.

Panel A: Currency Factors								
$\alpha$	<i>DOL</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	$R^2$		
<i>Developed</i>								
0.05 <sup>b</sup>	0.14	-0.22 <sup>b</sup>	0.11	0.10	-0.04	0.05		
(0.02)	(0.09)	(0.09)	(0.08)	(0.13)	(0.12)			
<i>Developed &amp; Emerging</i>								
0.04 <sup>a</sup>	-0.04	-0.31 <sup>c</sup>	0.09	0.32 <sup>b</sup>	0.08	0.15		
(0.02)	(0.07)	(0.09)	(0.08)	(0.11)	(0.09)			
Panel B: Equity Factors								
$\alpha$	$R_m^e$	<i>SMB</i>	<i>HML</i>	<i>MOME</i>	$R^2$			
<i>Developed</i>								
0.05 <sup>b</sup>	-0.07	-0.05	-0.09 <sup>a</sup>	-0.05	0.01			
(0.02)	(0.06)	(0.05)	(0.05)	(0.03)				
<i>Developed &amp; Emerging</i>								
0.05 <sup>b</sup>	-0.07 <sup>a</sup>	-0.10 <sup>a</sup>	-0.10 <sup>b</sup>	-0.05 <sup>a</sup>	0.03			
(0.02)	(0.04)	(0.05)	(0.05)	(0.03)				
Panel C: Hedge Fund Factors								
$\alpha$	<i>Bond</i>	<i>Curr</i>	<i>Comm</i>	<i>Equity</i>	<i>Size</i>	<i>Bond</i>	<i>Credit</i>	$R^2$
<i>Trend Trend Trend Market Spread Market Spread</i>								
<i>Developed</i>								
0.05 <sup>b</sup>	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)	
<i>Developed &amp; Emerging</i>								
0.04 <sup>b</sup>	0.35	-0.03	0.08	-0.02	-0.10 <sup>b</sup>	-0.16 <sup>b</sup>	-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<sub>FX</sub>*) 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 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  $\lambda$ . The  $\chi^2$  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																
	$b_{DOL}$	$b_{CAR}$	$\lambda_{DOL}$	$\lambda_{CAR}$	$R^2$	<i>Developed</i>	$\chi^2$	<i>HJ</i>	$b_{DOL}$	$b_{CAR}$	$\lambda_{DOL}$	$\lambda_{CAR}$	$R^2$	<i>Emerging</i>	$\chi^2$	<i>HJ</i>
<i>GMM</i> <sub>1</sub>	0.42 (0.36)	-0.47 (0.55)	0.02 (0.02)	-0.05 (0.07)	-0.07	3.29	4.35 [0.23]	0.16 [0.20]	0.24 (0.35)	0.01 (0.51)	0.02 (0.02)	0.01 (0.06)	-0.14	2.09	1.93 [0.59]	0.11 [0.59]
<i>GMM</i> <sub>2</sub>	0.35 (0.36)	-0.37 (0.54)	0.02 (0.02)	-0.03 (0.07)	-0.13	3.32	4.30 [0.23]	0.24 (0.35)	0.09 (0.50)	0.02 (0.02)	0.02 (0.06)	0.02 (0.06)	-0.13	2.10	1.90 [0.59]	
<i>FMB</i>	0.42 (0.37)	-0.47 (0.58)	0.02 (0.02)	-0.05 (0.07)	-0.07	3.29	4.35 [0.23]	0.24 (0.34)	0.01 (0.52)	0.02 (0.02)	0.01 (0.06)	0.01 (0.06)	-0.14	2.09	1.93 [0.59]	
<i>(sh)</i>	0.34 (0.61)	0.61 (0.08)	0.02 (0.02)	0.08 (0.08)			0.18 [0.18]	0.30 (0.30)	0.53 (0.53)	0.02 (0.02)	0.02 (0.06)	0.06 (0.06)		0.56 [0.56]		
Factor Betas																
	$\alpha$	$\beta_{DOL}$	$\beta_{CAR}$	$R^2$	$\chi^2(\alpha)$									$R^2$	$\chi^2(\alpha)$	
<i>P<sub>L</sub></i>	0.03 (0.02)	0.89 (0.06)	-0.04 (0.07)	0.62	8.75 [0.12]									0.69	3.10 [0.68]	
<i>P<sub>2</sub></i>	0.01 (0.01)	0.94 (0.08)	0.04 (0.05)	0.71										0.79		
<i>P<sub>3</sub></i>	-0.01 (0.01)	1.00 (0.05)	0.05 (0.05)	0.72										0.80		
<i>P<sub>4</sub></i>	0.01 (0.01)	1.15 (0.05)	-0.15 (0.05)	0.81										0.84		
<i>P<sub>S</sub></i>	-0.02 (0.01)	1.03 (0.04)	0.08 (0.05)	0.79										0.75		

(continued)

Table 6. Asset Pricing Tests (continued)

Panel B: Global Volatility Factor																
Factor Prices																
	$b_{DOL}$	$b_{VOLFX}$	$\lambda_{DOL}$	$\lambda_{VOLFX}$	$R^2$	RMSE	$\chi^2$	HJ	$b_{DOL}$	$b_{VOLFX}$	$\lambda_{DOL}$	$\lambda_{VOLFX}$	$R^2$	RMSE	$\chi^2$	HJ
	Developed						Developed & Emerging									
$GMM_1$	0.52 (0.32)	1.25 (0.81)	0.02 (0.02)	0.16 (0.11)	0.26	2.74	3.02 [0.39]	0.13 [0.44]	0.48 (0.72)	0.55 (1.49)	0.02 (0.02)	0.08 (0.22)	-0.07	2.04	2.31 [0.51]	0.11 [0.55]
$GMM_2$	0.44 (0.32)	1.01 (0.78)	0.02 (0.02)	0.15 (0.11)	0.27	2.75	2.91 [0.41]		0.30 (0.7)	0.13 (1.43)	0.02 (0.02)	0.02 (0.22)	-0.14	2.06	2.22 [0.53]	
$FMB$	0.52 (0.36)	1.24 (0.81)	0.02 (0.02)	0.16 (0.11)	0.26	2.74	3.02 [0.39]		0.48 (0.66)	0.55 (1.34)	0.02 (0.02)	0.08 (0.22)	-0.07	2.04	2.31 [0.51]	
(sh)	0.33 (0.33)	0.92 (0.92)	0.02 (0.02)	0.13 (0.13)			3.37 [0.37]		0.71 (0.71)	1.49 (1.49)	0.02 (0.02)	0.25 (0.25)			0.54 [0.54]	
Factor Betas																
	$\alpha$	$\beta_{DOL}$	$\beta_{VOLFX}$	$R^2$	$\chi^2(\alpha)$		$\alpha$	$\beta_{DOL}$	$\beta_{VOLFX}$	$R^2$	$\chi^2(\alpha)$					
$P_L$	0.03 (0.01)	0.90 (0.06)	0.08 (0.06)	0.62	10.01 [0.07]		0.02 (0.01)	0.97 (0.05)	0.02 (0.03)	0.69	2.94 [0.71]					
$P_2$	0.00 (0.01)	0.94 (0.08)	-0.07 (0.05)	0.71			0.00 (0.01)	0.95 (0.05)	-0.02 (0.03)	0.79						
$P_3$	-0.01 (0.01)	1.02 (0.06)	0.03 (0.07)	0.71			-0.01 (0.01)	0.99 (0.04)	0.03 (0.02)	0.79						
$P_4$	-0.01 (0.01)	1.10 (0.06)	0.01 (0.04)	0.78			-0.01 (0.01)	1.19 (0.05)	0.02 (0.04)	0.83						
$P_S$	-0.02 (0.01)	1.04 (0.04)	-0.06 (0.04)	0.78			-0.01 (0.01)	0.91 (0.05)	-0.03 (0.03)	0.71						

**Table 7.  $\beta$ -Sorted Portfolios: Average Volatility Risk Premia**

This table presents descriptive statistics of  $\beta$ -sorted currency portfolios. Each  $\beta$  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)  $\beta$ .  $H/L$  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  $\beta$ 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	5.54	1.70	3.46	2.06	6.76	-1.23	4.16	2.22	3.33	3.34	5.43	-1.27
<i>Sdev</i>	9.50	10.48	9.09	10.17	11.90	10.91	8.61	10.00	9.49	9.97	11.38	10.67
<i>Skew</i>	0.27	0.05	-0.52	-0.04	-0.36	0.80	0.04	0.38	-0.29	-0.25	-0.67	1.14
<i>Kurt</i>	3.04	4.55	5.03	4.53	4.93	6.78	2.35	4.83	4.79	3.99	5.45	8.15
<i>SR</i>	0.58	0.16	0.38	0.20	0.57	-0.11	0.48	0.22	0.35	0.33	0.48	-0.12
<i>SO</i>	1.11	0.25	0.52	0.30	0.81	-0.19	0.88	0.37	0.50	0.49	0.66	-0.22
<i>MDD</i>	-0.19	-0.27	-0.31	-0.30	-0.27	-0.35	-0.19	-0.27	-0.32	-0.27	-0.27	-0.35
<i>AC<sub>1</sub></i>	0.03	0.01	0.19	0.12	0.10	0.03	0.04	0.05	0.18	0.11	0.12	0.01
<i>Freq</i>	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												
<i>Mean</i>	6.39	1.91	3.07	1.18	4.69	1.70	5.10	2.35	2.78	1.56	3.21	1.90
<i>Sdev</i>	9.41	10.41	9.06	10.08	11.88	10.97	8.52	9.94	9.44	9.82	11.33	10.72
<i>Skew</i>	0.30	0.04	-0.56	-0.07	-0.38	0.87	0.06	0.37	-0.33	-0.31	-0.76	1.30
<i>Kurt</i>	3.11	4.54	5.15	4.43	4.98	7.02	2.34	4.88	4.84	3.99	5.65	8.75
<i>SR</i>	0.68	0.18	0.34	0.12	0.39	0.15	0.60	0.24	0.29	0.16	0.28	0.18
<i>SO</i>	1.33	0.28	0.46	0.17	0.56	0.28	1.13	0.39	0.42	0.23	0.38	0.35
<i>MDD</i>	-0.16	-0.25	-0.32	-0.32	-0.29	-0.32	-0.16	-0.25	-0.33	-0.29	-0.29	-0.22
<i>AC<sub>1</sub></i>	0.02	0.01	0.19	0.12	0.10	0.05	0.04	0.04	0.18	0.09	0.11	0.02
<i>Freq</i>	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												
<i>pre-if</i>	-0.85	-0.21	0.39	0.88	2.08		-0.94	-0.13	0.55	1.78	2.22	
<i>post-if</i>	-0.85	-0.19	0.41	0.90	2.09		-0.97	-0.10	0.56	1.79	2.24	
<i>pre-<math>\beta</math></i>	-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]	
<i>post-<math>\beta</math></i>	-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-a-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*,  $\Delta VIX$ , and  $\Delta FSI$  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.

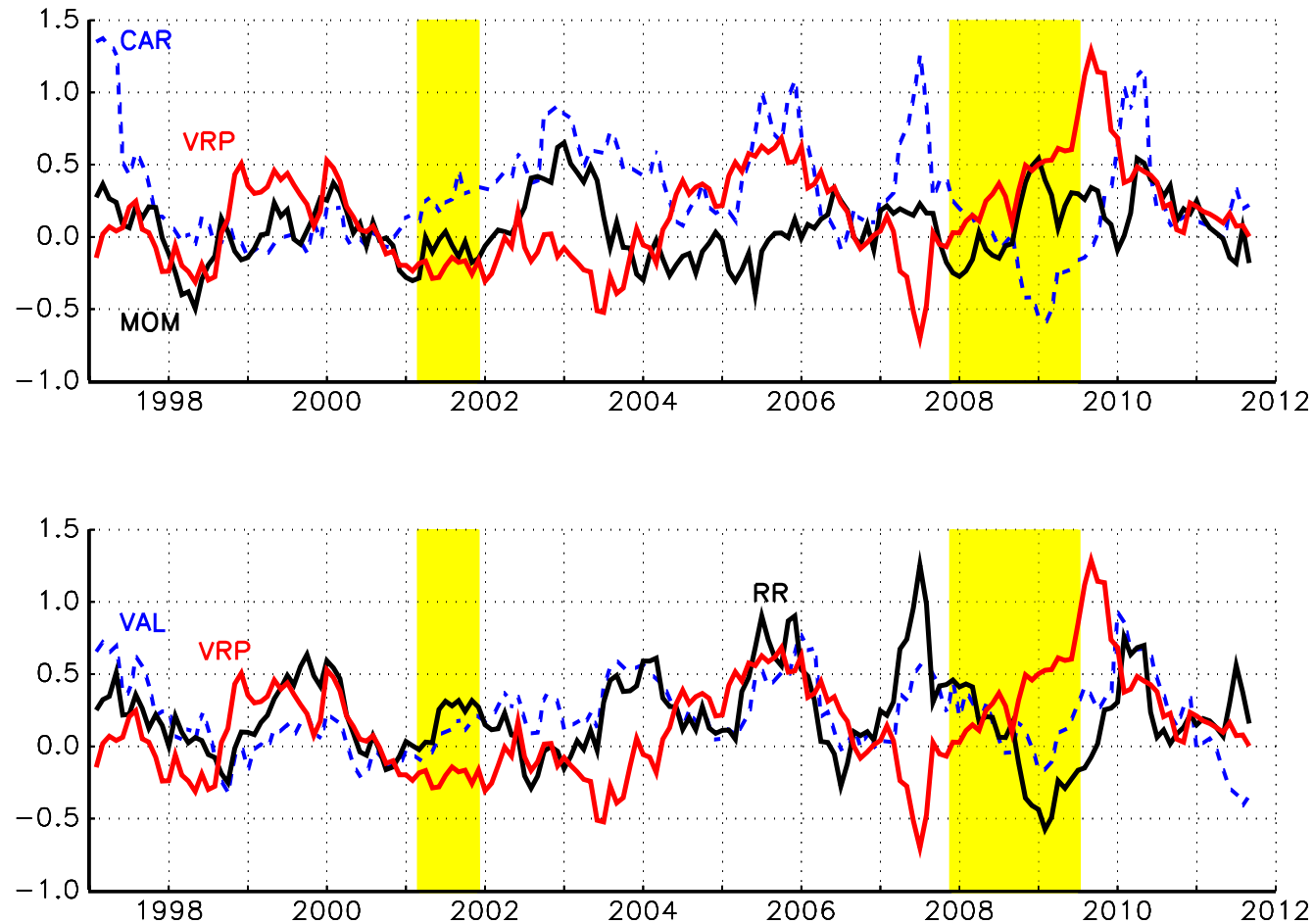
$\alpha$	<i>Developed</i>					<i>Developed &amp; Emerging</i>					<i>Fund Flows</i>	$R^2$	
	<i>TED</i>	$\Delta VIX$	$\Delta FSI$	$\frac{TED \times \Delta VIX}{\Delta VIX}$	$\frac{HED}{AUDUSD}$	$\frac{HED}{JPYUSD}$	<i>TED</i>	$\Delta VIX$	$\Delta FSI$	$\frac{TED \times \Delta VIX}{\Delta VIX}$			$\frac{HED}{AUDUSD}$
-0.04 (0.03)	0.16 <sup>b</sup> (0.07)					0.01 (0.03)	0.06 (0.06)						0.00
0.04 <sup>b</sup> (0.02)		0.05 <sup>a</sup> (0.03)				0.04 <sup>a</sup> (0.02)	0.04 (0.03)						0.01
0.04 <sup>b</sup> (0.02)			0.38 <sup>b</sup> (0.18)			0.04 <sup>a</sup> (0.02)		0.32 <sup>a</sup> (0.16)					0.01
0.03 (0.02)				0.09 <sup>c</sup> (0.02)		0.03 (0.02)			0.06 <sup>c</sup> (0.02)				0.02
0.05 <sup>b</sup> (0.02)					0.03 <sup>c</sup> (0.01)	0.04 <sup>a</sup> (0.02)				0.02 <sup>b</sup> (0.01)			0.01
0.05 <sup>b</sup> (0.02)						0.04 <sup>a</sup> (0.02)					0.01 (0.06)		-0.01
0.05 <sup>b</sup> (0.02)						0.05 <sup>b</sup> (0.02)							0.01
-0.01 (0.04)	0.12 (0.07)					0.03 (0.04)	0.03 (0.07)						0.01
0.05 <sup>b</sup> (0.02)		0.04 (0.03)				0.04 <sup>b</sup> (0.02)				0.02 <sup>b</sup> (0.01)			0.02
0.05 <sup>b</sup> (0.02)						0.04 <sup>b</sup> (0.02)							0.02
0.05 <sup>b</sup> (0.02)			0.31 <sup>a</sup> (0.18)			0.04 <sup>b</sup> (0.02)		0.26 (0.17)					0.02
0.04 <sup>a</sup> (0.02)				0.08 <sup>c</sup> (0.02)		0.04 (0.02)			0.05 <sup>c</sup> (0.02)				0.03

**Table 9. The Behaviour of Order Flow in VRP-sorted Portfolios**

This table presents descriptive statistics of currency order flow position associated with the volatility risk premia (*VRP*) strategy. *VRP* is a strategy that buys (sells) the top 25% of all currencies with the highest (lowest) 1-year volatility risk premium. We standardize order flow over a rolling window of 63 days prior to the order flow signal. The table also reports the first order autocorrelation coefficient ( $AC_1$ ). The strategies are rebalanced daily from January 2001 to May 2011. Exchange rates are from *Datastream*, implied volatility quotes are proprietary data from JP Morgan, whereas order flow data in USD billions are proprietary data from a major bank.

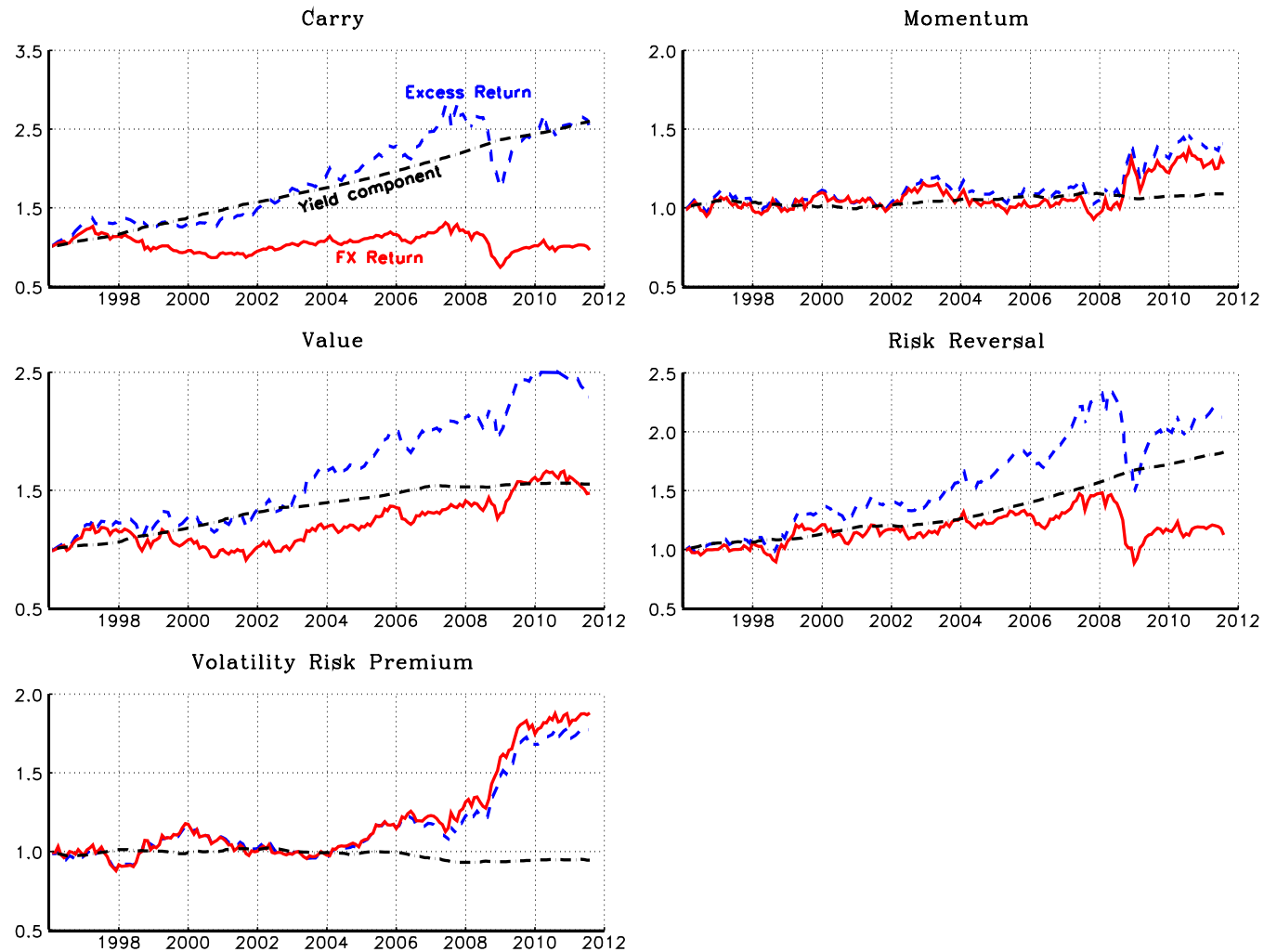
Panel A: Excess Returns				
	$P_L$	$P_2$	$P_3$	$P_S$
<i>Corporate Clients</i>				
<i>Mean</i>	0.052	0.010	-0.037	-0.080
<i>Sdev</i>	0.817	0.672	0.751	0.730
$AC_1$	0.072	0.058	0.044	0.126
<i>Asset Managers</i>				
<i>Mean</i>	0.003	0.006	0.002	0.042
<i>Sdev</i>	0.713	0.628	0.703	0.750
$AC_1$	0.092	0.074	0.014	0.012
<i>Hedge Funds</i>				
<i>Mean</i>	0.033	0.009	-0.033	-0.050
<i>Sdev</i>	0.786	0.640	0.757	0.780
$AC_1$	0.051	0.043	-0.033	0.019
<i>Total</i>				
<i>Mean</i>	0.054	0.018	-0.008	-0.019
<i>Sdev</i>	0.715	0.617	0.712	0.758
$AC_1$	0.062	0.052	0.009	0.007





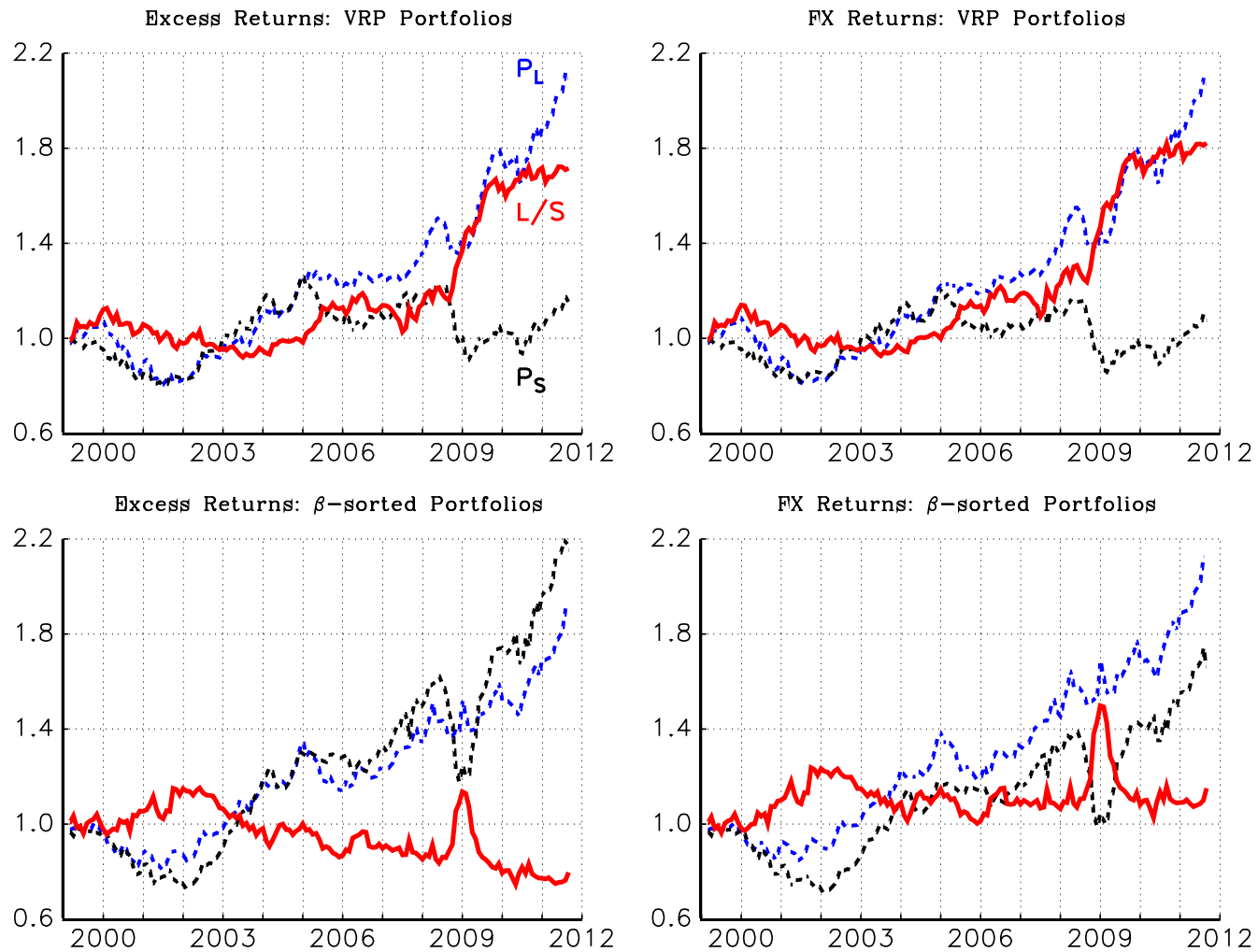
**Figure 1. Rolling Sharpe Ratios**

The figure presents the 1-year rolling Sharpe ratios of currency strategies formed using  $t - 1$  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 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, and refer to developed countries. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.



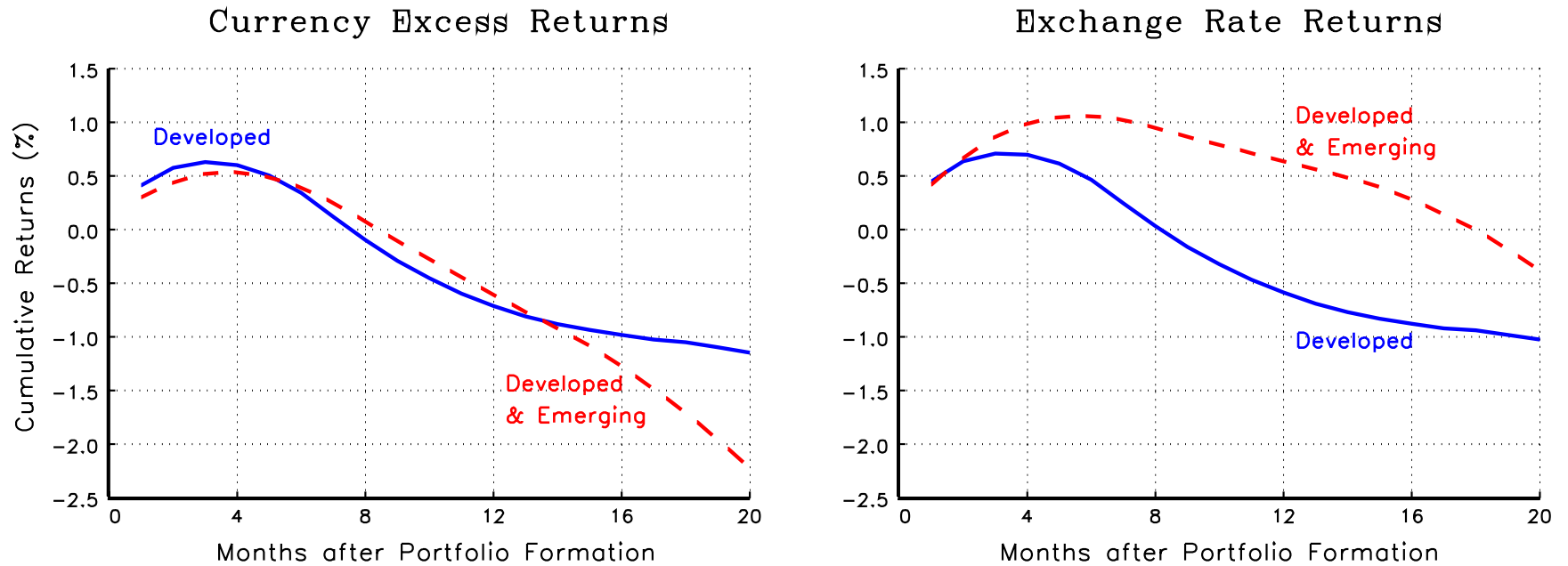
**Figure 2. Currency Strategies and Payoffs**

The figure presents the cumulative wealth to currency strategies formed using  $t - 1$ . *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 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, and refer to developed countries. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.



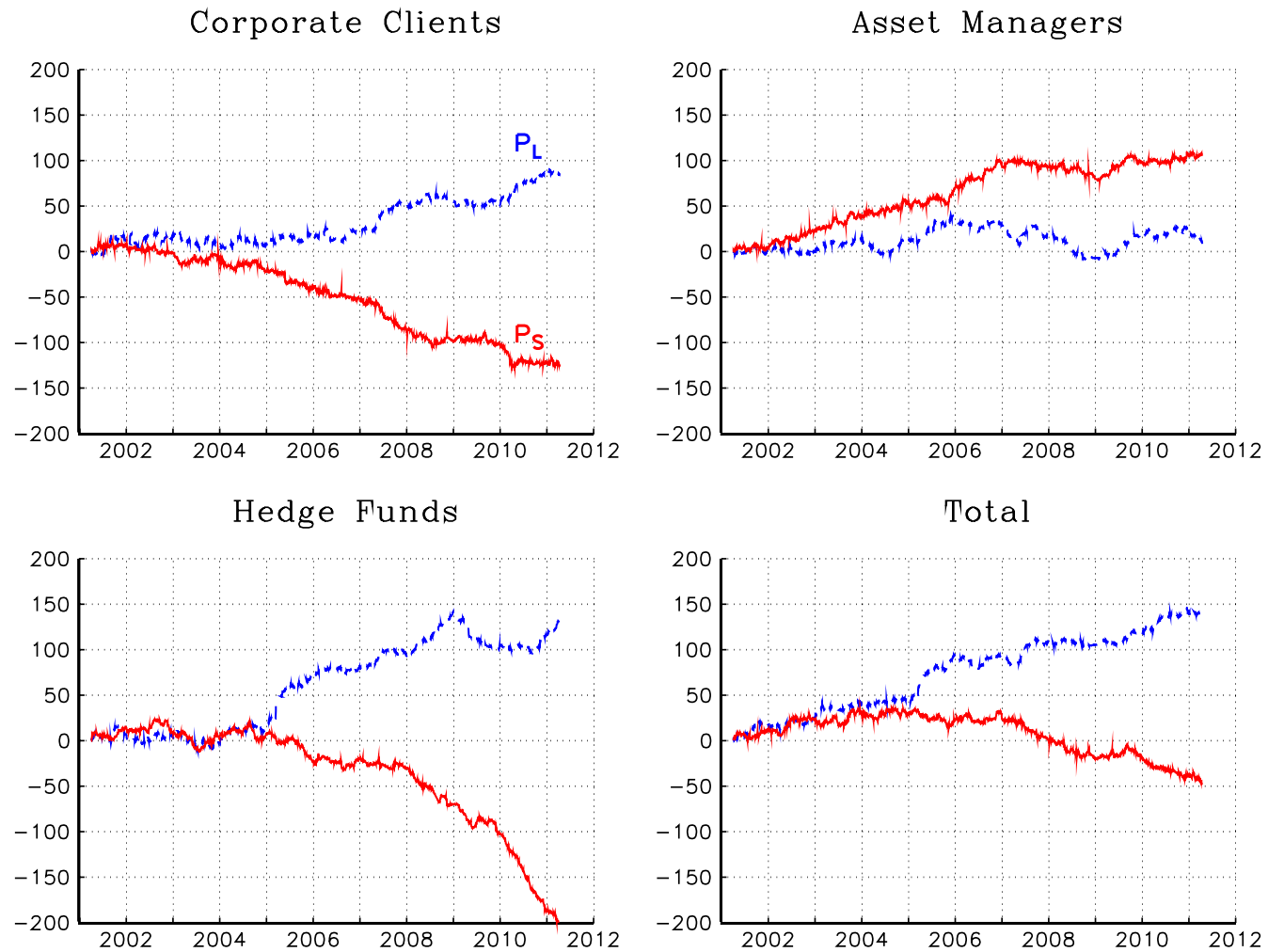
**Figure 3. Returns to VRP and  $\beta$ -sorted Portfolios**

The figure presents the cumulative wealth to long ( $P_L$ ), short ( $P_S$ ), and long/short ( $L/S$ ) portfolios. The *VRP* portfolios are computed by sorting currencies into 5 portfolios using the volatility risk premia at time  $t - 1$ :  $P_L$  ( $P_S$ ) contains the currencies with the highest (lowest) 1-year volatility risk premium. The  $\beta$ -sorted portfolios are obtained by regressing individual currency excess returns on the average volatility risk premium using a 36-month moving window:  $P_L$  ( $P_S$ ) contains the top 20% of all currencies with the lowest (highest)  $\beta$ . The strategies are rebalanced monthly from January 1996 to August 2011, and refer to developed countries. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.



**Figure 4. Reversals in VRP over Longer Horizons**

This figure presents cumulative average returns to the long/short *VRP* strategy after portfolio formation. *VRP* buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia known at time  $t - 1$ . Post-formation returns are constructed for 1, 2, ..., 20 months following the formation period. This is equivalent to building new portfolios every month and recording them for the subsequent 20 months (using overlapping horizons). We cumulate risk-adjusted (with respect to the carry trade strategy) currency 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. Order Flow Positions**

The figure presents the cumulative daily order flow associated with the volatility risk premium strategy (VRP).  $P_L$  ( $P_S$ ) denotes the order flow into the long (short) portfolio of the VRP strategy. We standardize order flow over a rolling window of 63 days prior to the order flow signal. The strategies are rebalanced daily from January 2001 to May 2011. Exchange rates are from Datastream, implied volatility quotes are proprietary data from JP Morgan, whereas customer order flow data are proprietary data a major bank.

Web Appendix for:  
Volatility Risk Premia and Exchange Rate Predictability  
(not for publication)

July 2013

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## A Data Construction for Table 8

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. We use the rolling average over the past 12-month window.
- $\Delta VIX$  is the change in the VIX index. We use the rolling average over the past 12-month window.
- $\Delta FSI$  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 net short position on currency futures contracts of commercial ( $com$ ) and non-commercial ( $non$ ) traders. We measure the net position for each category on the Australian dollar (AUD) as follows

$$HED_t^{non} = \frac{ShortPosition_t^{non} - LongPosition_t^{non}}{ShortPosition_{t-1}^{non} + LongPosition_{t-1}^{non}}$$

$$HED_t^{com} = \frac{ShortPosition_t^{com} - LongPosition_t^{com}}{ShortPosition_{t-1}^{com} + LongPosition_{t-1}^{com}}$$

where the normalization means that the net positions are measured relative to the aggregate open interest of commercial and non-commercial traders in the previous period, respectively. Note that when the normalizing component is equal to zero, we simply use previous period non-zero value. The classification used by CFTC to aggregate the net positions in commercial and non-commercial traders has significant shortcomings. For instance, a trader with a cash position in the underlying can be categorized as a commercial trader. This category, however, may include both corporate firms with an international line of business as well as banks that have offsetting positions in the underlying foreign currency. Since the defining line between commercial and non-commercial traders is unclear, our measure is constructed as an aggregate measure across both types of traders as

$$HED_t = HED_t^{non} + HED_t^{com}$$

Finally, we winsorize  $HED_t$  at 99%. We also construct the net position on the Japanese yen (JPY) relative to the US dollar in a similar manner.

- *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

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

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  $\kappa$  indicates the available number of hedge funds at time  $t$ .



**Table 1. Volatility Risk Premia**

This table presents summary statistics for the 1-year volatility risk premia (*Panel A*) and the 1-year realized volatility premia (*Panel B*).  $RV_t$  ( $RV_{t+\tau}$ ) denotes the 1-year realized volatility computed between times  $t - \tau$  and  $t$  ( $t$  and  $t + \tau$ ).  $\tau$  indicates the number of trading days in a calendar year.  $SW_t$  is constructed at time  $t$  using the 1-year implied volatilities across 5 different deltas from the foreign exchange option market.  $Q_j$  refers to the  $j^{th}$  percentile.  $AC_\tau$  indicates the  $\tau^{th}$ -order autocorrelation coefficient. Premia 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.

	Panel A: Volatility Risk Premium ( $RV_t - SW_t$ )								Panel B: Realized Volatility Premia ( $RV_{t+\tau} - SW_t$ )							
	<i>Mean</i>	<i>Med</i>	<i>Sdev</i>	<i>Skew</i>	<i>Kurt</i>	$Q_5$	$Q_{95}$	$AC_\tau$	<i>Mean</i>	<i>Med</i>	<i>Sdev</i>	<i>Skew</i>	<i>Kurt</i>	$Q_5$	$Q_{95}$	$AC_\tau$
<i>AUD</i>	0.39	0.21	2.43	1.79	9.51	-3.08	4.19	-0.14	0.84	-0.27	4.61	1.37	5.49	-5.13	12.56	0.02
<i>CAD</i>	-0.59	-0.61	1.29	-0.16	4.85	-2.34	1.45	0.22	-0.26	-0.65	2.78	0.46	4.01	-5.02	4.96	0.15
<i>CHF</i>	-0.51	-0.47	1.53	0.10	3.12	-2.97	1.78	-0.20	-0.17	-0.64	2.23	0.72	3.28	-3.16	4.48	-0.13
<i>DKK</i>	-1.25	-1.02	1.66	-0.61	4.90	-3.89	0.74	-0.13	-1.04	-1.28	2.38	0.60	4.13	-4.30	4.11	-0.09
<i>EUR</i>	-1.16	-0.75	1.75	-0.73	4.55	-4.30	0.78	-0.12	-1.00	-1.23	2.49	0.54	4.14	-4.49	4.78	-0.09
<i>GBP</i>	-1.15	-1.36	1.76	0.23	6.52	-3.54	1.17	-0.07	-1.01	-1.02	2.91	1.18	5.90	-5.21	4.55	0.07
<i>JPY</i>	-0.45	-0.52	1.72	0.30	3.30	-3.14	1.75	0.03	-0.57	-0.61	3.18	0.28	2.46	-5.11	5.29	0.26
<i>NOK</i>	-0.73	-0.58	2.03	0.74	5.19	-3.83	2.24	-0.14	-0.32	-0.70	3.16	1.17	4.97	-4.61	7.02	0.05
<i>NZD</i>	-0.11	-0.40	2.07	0.74	5.37	-3.21	4.38	-0.09	0.47	-0.31	3.81	0.59	3.18	-4.80	7.15	0.08
<i>SEK</i>	-0.70	-0.76	2.22	1.13	7.33	-3.69	3.52	-0.34	-0.26	-0.73	3.09	2.33	9.78	-3.58	7.39	-0.04
<i>BRL</i>	-3.78	-4.04	5.60	-0.29	5.03	-13.28	7.14	-0.15	-4.48	-4.96	9.12	0.14	3.49	-19.68	13.32	-0.05
<i>CZK</i>	-0.68	-0.60	2.61	1.22	6.63	-4.61	5.77	-0.35	-0.21	-0.96	4.28	0.86	5.17	-5.12	9.54	-0.16
<i>HUF</i>	-2.21	-2.29	2.85	-0.31	6.43	-6.96	2.27	-0.34	-1.22	-1.77	5.37	0.66	4.53	-9.30	11.55	-0.31
<i>KRW</i>	-1.68	-1.59	4.39	-0.35	11.47	-7.54	5.25	-0.23	-1.47	-2.24	8.79	1.04	5.88	-13.89	21.41	-0.22
<i>MXN</i>	-5.47	-3.96	4.93	-1.50	6.45	-15.40	-0.77	0.34	-5.43	-4.74	7.27	0.09	5.10	-18.81	11.16	0.09
<i>PLN</i>	-1.73	-1.66	3.39	0.05	5.52	-7.39	3.96	-0.06	-0.98	-1.52	5.88	1.53	6.14	-8.14	15.20	-0.10
<i>SGD</i>	-1.40	-1.13	1.47	-2.03	9.06	-4.27	0.23	0.17	-1.02	-0.81	1.99	-1.34	5.99	-5.16	2.02	-0.15
<i>TRY</i>	-4.59	-4.84	2.90	0.84	4.28	-8.51	1.95	0.04	-4.77	-5.14	5.16	0.36	2.23	-12.38	4.33	-0.37
<i>TWD</i>	-2.34	-2.10	1.86	-1.00	4.23	-5.65	0.03	0.23	-2.30	-1.95	2.20	-0.83	3.33	-6.76	0.69	0.03
<i>ZAR</i>	-2.57	-2.42	3.49	0.12	3.63	-8.24	4.77	0.07	-2.01	-2.71	6.08	0.04	2.69	-12.26	8.35	-0.20
<i>Mean</i>	-1.64	-1.55	2.60	0.01	5.87	-5.79	2.63	-0.06	-1.36	-1.71	4.34	0.59	4.59	-7.85	7.99	-0.06

**Table 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 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.

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

**Table 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.

Panel A: Excess Returns						
	$VRP$	$VRP_{atm}$	$VRP_{si}$	$VRP$	$VRP_{atm}$	$VRP_{si}$
	<i>Developed</i>			<i>Developed &amp; Emerging</i>		
<i>Mean</i>	4.03	4.35	4.01	2.34	3.05	3.53
<i>Sdev</i>	8.33	8.21	8.24	8.18	8.18	7.95
<i>Skew</i>	0.28	-0.04	0.12	0.12	-0.02	0.25
<i>Kurt</i>	3.47	3.46	3.34	3.26	3.23	3.32
<i>SR</i>	0.48	0.53	0.49	0.29	0.37	0.44
<i>SO</i>	0.87	0.85	0.82	0.49	0.62	0.82
<i>MDD</i>	-0.18	-0.21	-0.18	-0.18	-0.20	-0.18
<i>AC<sub>1</sub></i>	0.04	0.02	0.11	0.05	0.05	0.07
<i>Freq<sub>L</sub></i>	0.24	0.26	0.24	0.26	0.25	0.23
<i>Freq<sub>S</sub></i>	0.32	0.35	0.33	0.27	0.31	0.28
Panel B: FX Returns						
<i>Mean</i>	4.40	4.11	4.00	3.72	3.03	4.05
<i>Sdev</i>	8.35	8.20	8.23	8.17	8.17	7.95
<i>Skew</i>	0.28	-0.06	0.09	0.12	-0.01	0.24
<i>Kurt</i>	3.61	3.61	3.45	3.50	3.43	3.63
<i>SR</i>	0.53	0.50	0.49	0.46	0.37	0.51
<i>SO</i>	0.93	0.78	0.80	0.75	0.59	0.89
<i>MDD</i>	-0.19	-0.21	-0.19	-0.18	-0.21	-0.19
<i>AC<sub>1</sub></i>	0.04	0.02	0.11	0.04	0.04	0.06
<i>Freq<sub>L</sub></i>	0.24	0.26	0.24	0.26	0.25	0.23
<i>Freq<sub>S</sub></i>	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 4. Currency Strategies: NBER Recession Periods**

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 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. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. 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. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Excess Returns										
	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>
	<i>Developed</i>					<i>Developed &amp; Emerging</i>				
<i>Mean</i>	-3.81	10.78	6.85	-3.92	11.98	2.23	7.20	4.93	1.91	4.64
<i>Sdev</i>	16.85	15.20	11.91	18.76	9.92	14.46	10.58	9.95	15.16	9.35
<i>Skew</i>	-0.46	0.18	-0.64	-0.89	0.14	-0.74	0.10	-0.24	0.02	-0.49
<i>Kurt</i>	3.69	2.79	3.42	4.13	2.32	2.73	2.67	3.06	2.63	2.78
<i>SR</i>	-0.23	0.71	0.58	-0.21	1.21	0.15	0.68	0.50	0.13	0.50
<i>SO</i>	-0.32	1.45	0.80	-0.24	3.14	0.19	1.29	0.75	0.20	0.71
<i>MDD</i>	-0.34	-0.16	-0.11	-0.37	-0.08	-0.21	-0.06	-0.14	-0.24	-0.10
$AC_1$	0.35	0.10	-0.09	0.22	0.24	0.16	-0.04	0.09	0.30	0.21
$Freq_L$	0.13	0.52	0.11	0.21	0.38	0.12	0.43	0.06	0.17	0.33
$Freq_S$	0.02	0.32	0.02	0.25	0.29	0.14	0.43	0.01	0.33	0.19
Panel B: FX Returns										
<i>Mean</i>	-9.59	11.32	4.62	-7.96	11.54	-7.97	7.07	0.10	-4.80	6.50
<i>Sdev</i>	17.11	15.40	12.03	19.07	10.11	14.69	10.49	9.92	15.20	9.38
<i>Skew</i>	-0.44	0.28	-0.63	-0.90	0.12	-0.80	0.17	-0.15	-0.08	-0.45
<i>Kurt</i>	3.71	2.87	3.43	4.13	2.26	2.84	2.77	2.95	2.54	2.88
<i>SR</i>	-0.56	0.74	0.38	-0.42	1.14	-0.54	0.67	0.01	-0.32	0.69
<i>SO</i>	-0.75	1.57	0.54	-0.48	3.01	-0.66	1.26	0.02	-0.49	0.94
<i>MDD</i>	-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
$Freq_L$	0.13	0.52	0.11	0.21	0.38	0.12	0.43	0.06	0.17	0.33
$Freq_S$	0.02	0.32	0.02	0.25	0.29	0.14	0.43	0.01	0.33	0.19
Panel C: Correlations										
<i>CAR</i>	1.00	-0.63	0.53	0.90	-0.22	1.00	-0.28	0.69	0.80	-0.26
<i>MOM</i>	-0.63	1.00	-0.52	-0.46	0.10	-0.28	1.00	-0.51	-0.31	-0.18
<i>VAL</i>	0.53	-0.52	1.00	0.39	0.23	0.69	-0.51	1.00	0.77	-0.28
<i>RR</i>	0.90	-0.46	0.39	1.00	-0.23	0.80	-0.31	0.77	1.00	-0.46
<i>VRP</i>	-0.22	0.10	0.23	-0.23	1.00	-0.26	-0.18	-0.28	-0.46	1.00

**Table 5. Currency Strategies: non-NBER Recession Periods**

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 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. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to February 2001, from December 2001 to November 2007, and from July 2009 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Excess Returns										
	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>
	<i>Developed</i>					<i>Developed &amp; Emerging</i>				
<i>Mean</i>	8.31	1.14	5.59	6.92	2.64	8.34	1.35	3.31	5.99	1.93
<i>Sdev</i>	9.13	8.17	8.91	9.55	7.99	8.99	7.84	8.73	9.63	7.99
<i>Skew</i>	-0.84	0.09	-0.11	0.10	0.25	-0.83	-0.17	-0.13	-0.16	0.27
<i>Kurt</i>	4.43	2.43	3.29	3.92	3.77	4.71	2.76	3.18	4.96	3.42
<i>SR</i>	0.91	0.14	0.63	0.72	0.33	0.93	0.17	0.38	0.62	0.24
<i>SO</i>	1.15	0.26	0.99	1.18	0.55	1.25	0.29	0.60	0.93	0.43
<i>MDD</i>	-0.13	-0.17	-0.14	-0.14	-0.14	-0.13	-0.14	-0.14	-0.15	-0.19
$AC_1$	-0.09	-0.06	-0.03	-0.04	-0.03	-0.07	-0.11	-0.01	-0.02	0.00
$Freq_L$	0.14	0.48	0.09	0.17	0.21	0.16	0.50	0.07	0.23	0.24
$Freq_S$	0.08	0.45	0.08	0.27	0.32	0.16	0.46	0.07	0.25	0.28
Panel B: FX Returns										
<i>Mean</i>	2.09	0.40	2.65	3.08	3.14	0.64	0.46	0.05	1.11	3.23
<i>Sdev</i>	9.06	8.11	8.95	9.57	7.99	8.92	7.68	8.73	9.61	7.96
<i>Skew</i>	-0.87	0.04	-0.16	0.11	0.26	-0.92	-0.19	-0.16	-0.17	0.26
<i>Kurt</i>	4.50	2.48	3.30	4.16	4.02	4.90	2.90	3.22	5.55	3.70
<i>SR</i>	0.23	0.05	0.30	0.32	0.39	0.07	0.06	0.01	0.12	0.41
<i>SO</i>	0.29	0.09	0.45	0.50	0.65	0.09	0.10	0.01	0.16	0.70
<i>MDD</i>	-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
$Freq_L$	0.14	0.48	0.09	0.17	0.21	0.16	0.50	0.07	0.23	0.24
$Freq_S$	0.08	0.45	0.08	0.27	0.32	0.16	0.46	0.07	0.25	0.28
Panel C: Correlations										
<i>CAR</i>	1.00	0.12	0.42	0.54	-0.16	1.00	0.06	0.50	0.47	-0.20
<i>MOM</i>	0.12	1.00	-0.02	0.02	0.08	0.06	1.00	-0.04	-0.09	0.18
<i>VAL</i>	0.42	-0.02	1.00	0.55	0.23	0.50	-0.04	1.00	0.62	-0.06
<i>RR</i>	0.54	0.02	0.55	1.00	0.10	0.47	-0.09	0.62	1.00	-0.01
<i>VRP</i>	-0.16	0.08	0.23	0.10	1.00	-0.20	0.18	-0.06	-0.01	1.00

**Table 6. Currency Strategies: Pre-Crisis Period**

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 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. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 1996 to December 2006. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Excess Returns										
	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>
	<i>Developed</i>					<i>Developed &amp; Emerging</i>				
<i>Mean</i>	8.64	1.48	6.92	6.53	1.82	8.61	1.39	4.06	5.55	2.52
<i>Sdev</i>	8.42	7.99	9.68	9.40	7.98	9.22	7.86	9.23	10.10	8.51
<i>Skew</i>	-0.86	0.07	-0.31	0.28	0.11	-0.98	0.06	-0.23	-0.22	0.18
<i>Kurt</i>	4.84	2.42	3.31	3.93	3.37	5.01	2.44	3.07	4.88	3.23
<i>SR</i>	1.03	0.19	0.71	0.69	0.23	0.93	0.18	0.44	0.55	0.30
<i>SO</i>	1.34	0.35	1.07	1.23	0.38	1.19	0.34	0.66	0.79	0.51
<i>MDD</i>	-0.13	-0.14	-0.14	-0.14	-0.18	-0.13	-0.12	-0.14	-0.16	-0.16
$AC_1$	-0.06	-0.09	-0.05	-0.03	-0.01	-0.10	-0.10	-0.03	-0.03	0.01
$Freq_L$	0.16	0.49	0.06	0.22	0.23	0.19	0.51	0.05	0.25	0.25
$Freq_S$	0.09	0.44	0.07	0.33	0.32	0.18	0.45	0.07	0.31	0.28
Panel B: Rate Returns										
<i>Mean</i>	1.91	0.81	3.00	2.94	2.18	1.09	0.71	0.58	1.28	3.04
<i>Sdev</i>	8.33	7.90	9.78	9.43	7.99	9.16	7.68	9.25	10.12	8.53
<i>Skew</i>	-0.91	-0.02	-0.31	0.32	0.07	-1.06	0.01	-0.25	-0.24	0.19
<i>Kurt</i>	4.92	2.46	3.26	4.14	3.46	5.20	2.59	3.10	5.41	3.47
<i>SR</i>	0.23	0.10	0.31	0.31	0.27	0.12	0.09	0.06	0.13	0.36
<i>SO</i>	0.30	0.19	0.46	0.52	0.44	0.15	0.17	0.09	0.17	0.59
<i>MDD</i>	-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
$Freq_L$	0.16	0.49	0.06	0.22	0.23	0.19	0.51	0.05	0.25	0.25
$Freq_S$	0.09	0.44	0.07	0.33	0.32	0.18	0.45	0.07	0.31	0.28
Panel C: Correlations										
<i>CAR</i>	1.00	0.12	0.58	0.40	0.06	1.00	0.07	0.54	0.42	-0.09
<i>MOM</i>	0.12	1.00	-0.04	-0.03	0.07	0.07	1.00	-0.01	-0.10	0.08
<i>VAL</i>	0.58	-0.04	1.00	0.71	0.28	0.54	-0.01	1.00	0.65	0.07
<i>RR</i>	0.40	-0.03	0.71	1.00	0.30	0.42	-0.10	0.65	1.00	0.11
<i>VRP</i>	0.06	0.07	0.28	0.30	1.00	-0.09	0.08	0.07	0.11	1.00

**Table 7. Currency Strategies: Crisis Period**

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 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. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return whereas *Panel B* reports the exchange rate return component only. Returns are expressed in percentage per annum. The strategies are rebalanced monthly from January 2007 to August 2011. Exchange rates are from *Datastream* whereas implied volatility quotes are proprietary data from JP Morgan.

Panel A: Excess Returns										
	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>	<i>CAR</i>	<i>MOM</i>	<i>VAL</i>	<i>RR</i>	<i>VRP</i>
	<i>Developed</i>					<i>Developed &amp; Emerging</i>				
<i>Mean</i>	1.47	5.15	3.11	2.42	9.22	4.65	4.18	2.35	4.98	1.90
<i>Sdev</i>	14.62	12.53	8.67	15.15	9.01	11.59	9.30	8.14	11.78	7.43
<i>Skew</i>	-0.63	0.37	-0.16	-1.10	0.46	-0.75	-0.22	0.11	-0.02	-0.11
<i>Kurt</i>	3.95	3.40	4.15	5.55	3.26	3.59	3.47	3.45	3.64	3.14
<i>SR</i>	0.10	0.41	0.36	0.16	1.02	0.40	0.45	0.29	0.42	0.26
<i>SO</i>	0.13	0.77	0.56	0.17	2.20	0.51	0.67	0.50	0.65	0.42
<i>MDD</i>	-0.37	-0.16	-0.12	-0.37	-0.10	-0.21	-0.13	-0.14	-0.24	-0.12
$AC_1$	0.21	0.07	0.02	0.17	0.10	0.16	-0.08	0.13	0.25	0.14
$Freq_L$	0.07	0.46	0.16	0.06	0.27	0.07	0.46	0.10	0.14	0.28
$Freq_S$	0.04	0.41	0.05	0.12	0.31	0.11	0.46	0.03	0.15	0.23
Panel B: FX Returns										
<i>Mean</i>	-3.34	4.88	2.81	-2.13	9.61	-4.73	3.17	-1.15	-2.25	5.30
<i>Sdev</i>	14.80	12.69	8.67	15.31	9.05	11.70	9.23	8.05	11.72	7.29
<i>Skew</i>	-0.66	0.50	-0.22	-1.13	0.54	-0.89	-0.10	0.12	-0.12	-0.07
<i>Kurt</i>	4.02	3.57	4.27	5.63	3.42	3.90	3.56	3.41	3.67	3.39
<i>SR</i>	-0.23	0.38	0.32	-0.14	1.06	-0.40	0.34	-0.14	-0.19	0.73
<i>SO</i>	-0.28	0.75	0.50	-0.15	2.38	-0.50	0.51	-0.24	-0.28	1.18
<i>MDD</i>	-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
$Freq_L$	0.07	0.46	0.16	0.06	0.27	0.07	0.46	0.10	0.14	0.28
$Freq_S$	0.04	0.41	0.05	0.12	0.31	0.11	0.46	0.03	0.15	0.23
Panel C: Correlations										
<i>CAR</i>	1.00	-0.41	0.27	0.91	-0.47	1.00	-0.19	0.56	0.81	-0.48
<i>MOM</i>	-0.41	1.00	-0.39	-0.31	0.12	-0.19	1.00	-0.41	-0.24	0.17
<i>VAL</i>	0.27	-0.39	1.00	0.17	0.13	0.56	-0.41	1.00	0.66	-0.62
<i>RR</i>	0.91	-0.31	0.17	1.00	-0.41	0.81	-0.24	0.66	1.00	-0.65
<i>VRP</i>	-0.47	0.12	0.13	-0.41	1.00	-0.48	0.17	-0.62	-0.65	1.00

**Table 8. Carry Trade Portfolios**

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia  $VRP$  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 premia.  $DOL$  is the average of the currency portfolios.  $H/L$  is 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 ( $SR$ ), the Sortino ratio ( $SO$ ), the maximum drawdown ( $MDD$ ), and the frequency of portfolio switches ( $Freq$ ). Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return, whereas *Panel B* reports only the exchange rate component. 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	6.31	3.00	1.82	0.06	-0.18	6.49	6.07	3.34	2.34	-0.61	-1.36	7.42
<i>Sdev</i>	10.97	9.19	9.23	9.21	9.21	10.66	10.43	9.68	9.54	8.38	8.63	9.97
<i>Skew</i>	-0.17	-0.53	-0.02	0.15	0.63	-0.92	-0.48	-0.82	-0.29	0.03	0.59	-0.92
<i>Kurt</i>	5.06	6.47	4.26	3.70	3.88	5.65	5.02	6.43	4.89	3.66	4.49	4.53
<i>SR</i>	0.58	0.33	0.20	0.01	-0.02	0.61	0.58	0.35	0.24	-0.07	-0.16	0.74
$AC_1$	0.16	0.08	0.11	0.12	0.03	0.09	0.23	0.08	0.17	0.08	0.02	0.01
<i>Freq</i>	0.13	0.21	0.29	0.23	0.07	0.07	0.15	0.20	0.26	0.28	0.16	0.16
Panel B: FX Returns												
<i>Mean</i>	3.10	1.94	1.96	0.87	2.76	0.34	1.12	1.56	2.21	0.33	1.77	-0.65
<i>Sdev</i>	10.90	9.14	9.16	9.13	9.11	10.66	10.33	9.64	9.46	8.34	8.54	9.99
<i>Skew</i>	-0.20	-0.55	-0.02	0.18	0.66	-0.93	-0.63	-0.92	-0.34	0.05	0.65	-1.05
<i>Kurt</i>	5.18	6.48	4.26	3.66	3.97	5.82	5.34	6.80	4.98	3.67	4.73	4.84
<i>SR</i>	0.28	0.21	0.21	0.10	0.30	0.03	0.11	0.16	0.23	0.04	0.21	-0.07
$AC_1$	0.16	0.07	0.10	0.11	0.01	0.11	0.23	0.08	0.16	0.07	0.00	0.03
<i>Freq</i>	0.13	0.21	0.29	0.23	0.07	0.07	0.15	0.20	0.26	0.28	0.16	0.16
Panel C: Transition Matrix												
$P_L$	0.87	0.09	0.03	0.01	0.01		0.85	0.10	0.03	0.01	0.01	
$P_2$	0.07	0.80	0.10	0.03	0.00		0.08	0.80	0.09	0.03	0.00	
$P_3$	0.02	0.10	0.71	0.15	0.02		0.02	0.10	0.75	0.11	0.02	
$P_4$	0.01	0.03	0.14	0.78	0.04		0.01	0.04	0.09	0.73	0.12	
$P_S$	0.00	0.00	0.02	0.04	0.94		0.00	0.00	0.03	0.11	0.85	
$\bar{\pi}$	<b>0.18</b>	<b>0.21</b>	<b>0.21</b>	<b>0.21</b>	<b>0.20</b>		<b>0.17</b>	<b>0.24</b>	<b>0.20</b>	<b>0.19</b>	<b>0.20</b>	



**Table 9. Momentum Portfolios**

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia  $VRP$  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 premia.  $DOL$  is the average of the currency portfolios.  $H/L$  is 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 ( $SR$ ), the Sortino ratio ( $SO$ ), the maximum drawdown ( $MDD$ ), and the frequency of portfolio switches ( $Freq$ ). Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return, whereas *Panel B* reports only the exchange rate component. 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	2.93	2.31	0.79	3.33	0.34	2.58	2.10	3.06	0.56	3.32	-0.13	2.22
<i>Sdev</i>	9.60	9.42	8.97	10.22	10.00	9.55	9.31	9.13	9.19	9.45	9.61	8.30
<i>Skew</i>	0.39	0.01	-0.14	0.19	-0.11	0.35	-0.10	0.04	-0.57	-0.15	-0.03	-0.03
<i>Kurt</i>	4.06	4.81	4.00	4.81	6.11	3.86	3.36	3.78	4.88	5.84	4.09	2.95
<i>SR</i>	0.30	0.25	0.09	0.33	0.03	0.27	0.23	0.34	0.06	0.35	-0.01	0.27
<i>AC<sub>1</sub></i>	0.09	-0.02	0.12	0.14	0.12	0.00	0.18	0.05	0.15	0.12	0.08	-0.09
<i>Freq</i>	0.48	0.66	0.68	0.63	0.43	0.43	0.49	0.66	0.68	0.68	0.46	0.46
Panel B: FX Returns												
<i>Mean</i>	2.62	1.76	0.84	3.76	0.59	2.03	1.07	2.25	0.25	3.23	-0.38	1.45
<i>Sdev</i>	9.46	9.33	8.91	10.15	9.92	9.57	9.17	9.01	9.14	9.35	9.48	8.16
<i>Skew</i>	0.41	-0.03	-0.15	0.16	-0.15	0.42	-0.19	-0.03	-0.63	-0.17	-0.10	-0.02
<i>Kurt</i>	4.20	4.96	3.93	5.02	6.31	4.17	3.64	3.84	5.08	6.21	4.15	3.13
<i>SR</i>	0.28	0.19	0.09	0.37	0.06	0.21	0.12	0.25	0.03	0.35	-0.04	0.18
<i>AC<sub>1</sub></i>	0.07	-0.03	0.12	0.13	0.11	0.00	0.16	0.05	0.14	0.11	0.06	-0.12
<i>Freq</i>	0.48	0.66	0.68	0.63	0.43	0.43	0.49	0.66	0.68	0.68	0.46	0.46
Panel C: Transition Matrix												
$P_L$	0.52	0.24	0.13	0.07	0.05		0.51	0.28	0.12	0.05	0.04	
$P_2$	0.22	0.34	0.24	0.12	0.08		0.22	0.35	0.25	0.13	0.06	
$P_3$	0.10	0.23	0.33	0.22	0.12		0.09	0.25	0.32	0.23	0.11	
$P_4$	0.07	0.15	0.22	0.37	0.19		0.07	0.17	0.21	0.32	0.23	
$P_S$	0.05	0.07	0.10	0.22	0.58		0.03	0.08	0.10	0.25	0.55	
$\bar{\pi}$	<b>0.19</b>	<b>0.20</b>	<b>0.20</b>	<b>0.20</b>	<b>0.20</b>		<b>0.18</b>	<b>0.23</b>	<b>0.20</b>	<b>0.20</b>	<b>0.20</b>	

**Table 10. Value Portfolios**

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia  $VRP$  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 premia.  $DOL$  is the average of the currency portfolios.  $HML$  is 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 ( $SR$ ), the Sortino ratio ( $SO$ ), the maximum drawdown ( $MDD$ ), and the frequency of portfolio switches ( $Freq$ ). Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return, whereas *Panel B* reports only the exchange rate component. 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	5.29	0.35	3.39	1.79	-0.48	5.78	3.25	1.71	3.34	1.48	-0.68	3.93
<i>Sdev</i>	10.11	8.16	9.31	9.36	10.58	9.38	9.10	9.19	8.70	9.22	9.81	8.99
<i>Skew</i>	-0.33	0.19	0.06	0.09	0.20	-0.26	-0.05	-0.74	-0.55	0.36	0.04	-0.13
<i>Kurt</i>	6.60	3.20	4.71	3.27	5.01	3.50	3.76	5.11	6.38	3.48	3.18	3.16
<i>SR</i>	0.52	0.04	0.36	0.19	-0.05	0.62	0.36	0.19	0.38	0.16	-0.07	0.44
$AC_1$	0.10	0.11	0.08	0.13	0.03	-0.03	0.12	0.22	0.15	0.12	0.08	0.01
<i>Freq</i>	0.09	0.12	0.10	0.14	0.07	0.07	0.08	0.10	0.11	0.14	0.06	0.06
Panel B: FX Returns												
<i>Mean</i>	4.21	-0.15	2.92	2.03	1.26	2.95	1.45	0.13	2.50	1.52	1.14	0.31
<i>Sdev</i>	10.08	8.10	9.21	9.27	10.47	9.44	8.99	9.16	8.63	9.12	9.70	8.97
<i>Skew</i>	-0.40	0.18	0.04	0.08	0.16	-0.29	-0.14	-0.87	-0.60	0.35	0.01	-0.15
<i>Kurt</i>	6.73	3.29	4.71	3.33	5.15	3.51	3.74	5.54	6.58	3.50	3.26	3.16
<i>SR</i>	0.42	-0.02	0.32	0.22	0.12	0.31	0.16	0.01	0.29	0.17	0.12	0.03
$AC_1$	0.10	0.09	0.06	0.12	0.01	-0.02	0.10	0.23	0.14	0.11	0.05	0.01
<i>Freq</i>	0.09	0.12	0.10	0.14	0.07	0.07	0.08	0.10	0.11	0.14	0.06	0.06
Panel C: Transition Matrix												
$P_L$	0.91	0.09	0.00	0.00	0.00		0.94	0.06	0.00	0.00	0.00	
$P_2$	0.09	0.88	0.03	0.00	0.00		0.05	0.91	0.04	0.00	0.00	
$P_3$	0.00	0.03	0.91	0.06	0.00		0.00	0.03	0.90	0.07	0.00	
$P_4$	0.00	0.00	0.06	0.87	0.06		0.00	0.00	0.07	0.88	0.06	
$P_S$	0.00	0.00	0.00	0.06	0.94		0.00	0.00	0.00	0.05	0.95	
$\bar{\pi}$	<b>0.20</b>	<b>0.19</b>	<b>0.19</b>	<b>0.20</b>	<b>0.21</b>		<b>0.15</b>	<b>0.17</b>	<b>0.21</b>	<b>0.22</b>	<b>0.25</b>	

**Table 11. Risk Reversal Portfolios**

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia  $VRP$  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 premia.  $DOL$  is the average of the currency portfolios.  $HML$  is 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 ( $SR$ ), the Sortino ratio ( $SO$ ), the maximum drawdown ( $MDD$ ), and the frequency of portfolio switches ( $Freq$ ). Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return, whereas *Panel B* reports only the exchange rate component. 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	5.41	1.68	1.06	1.60	0.11	5.30	4.49	2.16	3.00	0.27	-0.89	5.38
<i>Sdev</i>	12.02	8.23	9.41	9.64	8.62	11.40	11.16	9.70	9.01	9.62	7.85	10.60
<i>Skew</i>	-0.28	-0.72	-0.09	0.01	0.43	-0.72	-0.29	-1.11	0.00	-0.18	0.53	-0.14
<i>Kurt</i>	5.26	5.01	3.84	3.97	2.84	6.58	4.78	7.19	3.43	3.58	3.38	4.43
<i>SR</i>	0.45	0.20	0.11	0.17	0.01	0.46	0.40	0.22	0.33	0.03	-0.11	0.51
$AC_1$	0.14	0.16	0.13	0.08	0.08	0.07	0.17	0.09	0.12	0.17	0.07	0.08
<i>Freq</i>	0.17	0.34	0.50	0.47	0.27	0.27	0.22	0.29	0.42	0.41	0.26	0.26
Panel B: FX Returns												
<i>Mean</i>	3.33	1.29	1.26	1.95	1.90	1.42	1.17	0.63	2.93	0.69	0.94	0.22
<i>Sdev</i>	12.02	8.15	9.37	9.53	8.48	11.48	11.12	9.67	8.91	9.54	7.70	10.60
<i>Skew</i>	-0.30	-0.70	-0.10	0.00	0.42	-0.75	-0.37	-1.27	-0.03	-0.21	0.54	-0.21
<i>Kurt</i>	5.40	4.98	3.81	3.98	2.83	6.83	5.10	7.80	3.47	3.56	3.34	4.74
<i>SR</i>	0.28	0.16	0.13	0.20	0.22	0.12	0.10	0.07	0.33	0.07	0.12	0.02
$AC_1$	0.13	0.16	0.12	0.07	0.05	0.08	0.16	0.09	0.11	0.17	0.04	0.08
<i>Freq</i>	0.17	0.34	0.50	0.47	0.27	0.27	0.22	0.29	0.42	0.41	0.26	0.26
Panel C: Transition Matrix												
$P_L$	0.83	0.11	0.02	0.02	0.02		0.79	0.15	0.02	0.02	0.02	
$P_2$	0.09	0.67	0.17	0.05	0.03		0.11	0.72	0.12	0.03	0.01	
$P_3$	0.02	0.17	0.51	0.23	0.07		0.02	0.14	0.59	0.20	0.06	
$P_4$	0.01	0.07	0.23	0.54	0.15		0.01	0.04	0.20	0.59	0.15	
$P_S$	0.01	0.02	0.06	0.17	0.74		0.01	0.02	0.07	0.15	0.76	
$\bar{\pi}$	<b>0.16</b>	<b>0.21</b>	<b>0.21</b>	<b>0.21</b>	<b>0.21</b>		<b>0.15</b>	<b>0.23</b>	<b>0.21</b>	<b>0.20</b>	<b>0.20</b>	

**Table 12. Volatility Risk Premia Portfolios: Currency Breakdown**

The table presents the composition of the volatility risk premia portfolios: the number of times (and the frequency in brackets) a currency enters each of the five currency 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 an 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.

	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>AUD</i>	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]
<i>CAD</i>	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]
<i>CHF</i>	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]
<i>DKK</i>	–	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]
<i>EUR</i>	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]
<i>GBP</i>	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]
<i>JPY</i>	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]
<i>NOK</i>	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]
<i>NZD</i>	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]
<i>SEK</i>	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]
<i>BRL</i>							5 [0.07]	10 [0.15]	5 [0.07]	5 [0.07]	42 [0.63]	67 [1.00]
<i>CZK</i>							11 [0.16]	13 [0.19]	23 [0.34]	17 [0.25]	3 [0.04]	67 [1.00]
<i>HUF</i>							10 [0.18]	4 [0.07]	3 [0.05]	18 [0.33]	20 [0.36]	55 [1.00]
<i>KRW</i>							28 [0.42]	5 [0.07]	10 [0.15]	12 [0.18]	12 [0.18]	67 [1.00]
<i>MXN</i>							–	3 [0.04]	7 [0.10]	13 [0.19]	44 [0.66]	67 [1.00]
<i>PLN</i>							31 [0.46]	17 [0.25]	8 [0.12]	5 [0.07]	6 [0.09]	67 [1.00]
<i>SGD</i>							2 [0.03]	16 [0.24]	22 [0.33]	19 [0.28]	8 [0.12]	67 [1.00]
<i>TRY</i>							3 [0.04]	–	6 [0.09]	5 [0.07]	53 [0.79]	67 [1.00]
<i>TWD</i>							3 [0.02]	12 [0.09]	15 [0.12]	27 [0.21]	70 [0.55]	127 [1.00]
<i>ZAR</i>							8 [0.09]	7 [0.08]	7 [0.08]	18 [0.21]	46 [0.53]	86 [1.00]

**Table 13. Carry Trade Portfolios: Currency Breakdown**

The table presents the composition of the carry trade portfolios: the number of times (and the frequency in brackets) a currency enters each of the five currency 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 an 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.

	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>AUD</i>	105 [0.56]	75 [0.40]	5 [0.03]	1 [0.01]	1 [0.01]	187 [1.00]	32 [0.17]	145 [0.78]	8 [0.04]	1 [0.01]	1 [0.01]	187 [1.00]
<i>CAD</i>	3 [0.02]	56 [0.30]	59 [0.32]	68 [0.36]	1 [0.01]	187 [1.00]	3 [0.02]	39 [0.21]	65 [0.35]	78 [0.42]	2 [0.01]	187 [1.00]
<i>CHF</i>	1 [0.01]	–	2 [0.01]	5 [0.03]	179 [0.96]	187 [1.00]	1 [0.01]	–	2 [0.01]	32 [0.17]	152 [0.81]	187 [1.00]
<i>DKK</i>	1 [0.01]	30 [0.16]	99 [0.53]	56 [0.30]	1 [0.01]	187 [1.00]	1 [0.01]	15 [0.08]	103 [0.55]	64 [0.34]	4 [0.02]	187 [1.00]
<i>EUR</i>	1 [0.01]	–	58 [0.36]	100 [0.61]	4 [0.02]	163 [1.00]	1 [0.01]	1 [0.01]	49 [0.30]	108 [0.66]	4 [0.02]	163 [1.00]
<i>GBP</i>	22 [0.12]	106 [0.57]	44 [0.24]	14 [0.07]	1 [0.01]	187 [1.00]	22 [0.12]	111 [0.59]	17 [0.09]	35 [0.19]	2 [0.01]	187 [1.00]
<i>JPY</i>	–	–	1 [0.01]	6 [0.03]	177 [0.96]	184 [1.00]	–	–	1 [0.01]	2 [0.01]	181 [0.98]	184 [1.00]
<i>NOK</i>	51 [0.27]	55 [0.30]	31 [0.17]	48 [0.26]	–	185 [1.00]	49 [0.26]	17 [0.09]	70 [0.38]	47 [0.25]	2 [0.01]	185 [1.00]
<i>NZD</i>	160 [0.86]	14 [0.07]	11 [0.06]	2 [0.01]	–	187 [1.00]	106 [0.57]	65 [0.35]	14 [0.07]	2 [0.01]	–	187 [1.00]
<i>SEK</i>	2 [0.01]	38 [0.20]	64 [0.34]	73 [0.39]	8 [0.04]	185 [1.00]	2 [0.01]	35 [0.19]	63 [0.34]	56 [0.30]	29 [0.16]	185 [1.00]
<i>BRL</i>							65 [0.97]	1 [0.01]	–	–	1 [0.01]	67 [1.00]
<i>CZK</i>							–	1 [0.01]	42 [0.63]	20 [0.30]	4 [0.06]	67 [1.00]
<i>HUF</i>							24 [0.44]	31 [0.56]	–	–	–	55 [1.00]
<i>KRW</i>							–	2 [0.03]	42 [0.63]	9 [0.13]	14 [0.21]	67 [1.00]
<i>MXN</i>							10 [0.15]	56 [0.84]	1 [0.01]	–	–	67 [1.00]
<i>PLN</i>							–	35 [0.52]	31 [0.46]	1 [0.01]	–	67 [1.00]
<i>SGD</i>							–	–	11 [0.16]	24 [0.36]	32 [0.48]	67 [1.00]
<i>TRY</i>							67 [1.00]	–	–	–	–	67 [1.00]
<i>TWD</i>							3 [0.02]	10 [0.08]	8 [0.06]	28 [0.22]	78 [0.61]	127 [1.00]
<i>ZAR</i>							82 [0.95]	4 [0.05]	–	–	–	86 [1.00]

**Table 14. Momentum Portfolios: Currency Breakdown**

The table presents the composition of the momentum portfolios: the number of times (and the frequency in brackets) a currency enters each of the five currency 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 an 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.

	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>AUD</i>	46 [0.25]	51 [0.27]	28 [0.15]	19 [0.10]	43 [0.23]	187 [1.00]	40 [0.21]	61 [0.33]	31 [0.17]	17 [0.09]	38 [0.20]	187 [1.00]
<i>CAD</i>	55 [0.29]	23 [0.12]	34 [0.18]	35 [0.19]	40 [0.21]	187 [1.00]	49 [0.26]	30 [0.16]	39 [0.21]	34 [0.18]	35 [0.19]	187 [1.00]
<i>CHF</i>	35 [0.19]	32 [0.17]	37 [0.20]	46 [0.25]	37 [0.20]	187 [1.00]	35 [0.19]	36 [0.19]	40 [0.21]	40 [0.21]	36 [0.19]	187 [1.00]
<i>DKK</i>	12 [0.06]	44 [0.24]	59 [0.32]	56 [0.30]	16 [0.09]	187 [1.00]	14 [0.07]	48 [0.26]	56 [0.30]	52 [0.28]	17 [0.09]	187 [1.00]
<i>EUR</i>	12 [0.07]	46 [0.28]	49 [0.30]	35 [0.21]	21 [0.13]	163 [1.00]	9 [0.06]	58 [0.36]	44 [0.27]	39 [0.24]	13 [0.08]	163 [1.00]
<i>GBP</i>	26 [0.14]	44 [0.24]	42 [0.22]	37 [0.20]	38 [0.20]	187 [1.00]	24 [0.13]	47 [0.25]	44 [0.24]	43 [0.23]	29 [0.16]	187 [1.00]
<i>JPY</i>	42 [0.23]	13 [0.07]	26 [0.14]	41 [0.22]	62 [0.34]	184 [1.00]	38 [0.21]	20 [0.11]	31 [0.17]	39 [0.21]	56 [0.30]	184 [1.00]
<i>NOK</i>	31 [0.17]	44 [0.24]	45 [0.24]	30 [0.16]	35 [0.19]	185 [1.00]	26 [0.14]	53 [0.28]	37 [0.20]	39 [0.21]	30 [0.16]	185 [1.00]
<i>NZD</i>	55 [0.29]	39 [0.21]	20 [0.11]	26 [0.14]	47 [0.25]	187 [1.00]	48 [0.26]	48 [0.26]	22 [0.12]	26 [0.14]	43 [0.23]	187 [1.00]
<i>SEK</i>	32 [0.17]	38 [0.20]	34 [0.18]	48 [0.26]	33 [0.18]	185 [1.00]	25 [0.13]	41 [0.22]	46 [0.25]	40 [0.22]	33 [0.18]	185 [1.00]
<i>BRL</i>							24 [0.36]	10 [0.15]	12 [0.18]	12 [0.18]	9 [0.13]	67 [1.00]
<i>CZK</i>							20 [0.30]	17 [0.25]	11 [0.16]	11 [0.16]	8 [0.12]	67 [1.00]
<i>HUF</i>							15 [0.27]	8 [0.15]	10 [0.18]	6 [0.11]	16 [0.29]	55 [1.00]
<i>KRW</i>							9 [0.13]	10 [0.15]	17 [0.25]	15 [0.22]	16 [0.24]	67 [1.00]
<i>MXN</i>							10 [0.15]	10 [0.15]	11 [0.16]	15 [0.22]	21 [0.31]	67 [1.00]
<i>PLN</i>							18 [0.27]	15 [0.22]	10 [0.15]	14 [0.21]	10 [0.15]	67 [1.00]
<i>SGD</i>							7 [0.10]	16 [0.24]	22 [0.33]	13 [0.19]	9 [0.13]	67 [1.00]
<i>TRY</i>							16 [0.24]	6 [0.09]	16 [0.24]	10 [0.15]	19 [0.28]	67 [1.00]
<i>TWD</i>							22 [0.17]	18 [0.14]	17 [0.13]	25 [0.20]	45 [0.35]	127 [1.00]
<i>ZAR</i>							19 [0.22]	16 [0.19]	11 [0.13]	17 [0.20]	23 [0.27]	86 [1.00]

**Table 15. Value Portfolios: Currency Breakdown**

The table presents the composition of the value portfolios: the number of times (and the frequency in brackets) a currency enters each of the five currency 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 an 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.

	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>AUD</i>	77 [0.41]	57 [0.30]	37 [0.20]	16 [0.09]	–	187 [1.00]	16 [0.09]	96 [0.51]	23 [0.12]	36 [0.19]	16 [0.09]	187 [1.00]
<i>CAD</i>	81 [0.43]	105 [0.56]	1 [0.01]	–	–	187 [1.00]	50 [0.27]	68 [0.36]	11 [0.06]	58 [0.31]	–	187 [1.00]
<i>CHF</i>	–	–	–	35 [0.19]	152 [0.81]	187 [1.00]	–	–	–	4 [0.02]	183 [0.98]	187 [1.00]
<i>DKK</i>	–	–	3 [0.02]	108 [0.58]	76 [0.41]	187 [1.00]	–	–	1 [0.01]	95 [0.51]	91 [0.49]	187 [1.00]
<i>EUR</i>	11 [0.07]	130 [0.8]	22 [0.13]	–	–	163 [1.00]	–	77 [0.47]	29 [0.18]	57 [0.35]	–	163 [1.00]
<i>GBP</i>	29 [0.16]	21 [0.11]	137 [0.73]	–	–	187 [1.00]	–	9 [0.05]	140 [0.75]	38 [0.20]	–	187 [1.00]
<i>JPY</i>	17 [0.09]	6 [0.03]	31 [0.17]	53 [0.29]	77 [0.42]	184 [1.00]	–	–	25 [0.14]	61 [0.33]	98 [0.53]	184 [1.00]
<i>NOK</i>	–	–	2 [0.01]	116 [0.62]	67 [0.36]	185 [1.00]	–	–	2 [0.01]	97 [0.52]	86 [0.46]	185 [1.00]
<i>NZD</i>	131 [0.70]	55 [0.29]	1 [0.01]	–	–	187 [1.00]	67 [0.36]	50 [0.27]	57 [0.30]	13 [0.07]	–	187 [1.00]
<i>SEK</i>	–	–	140 [0.75]	45 [0.24]	–	185 [1.00]	–	–	105 [0.56]	48 [0.26]	32 [0.17]	185 [1.00]
<i>BRL</i>							1 [0.01]	26 [0.39]	40 [0.60]	–	–	67 [1.00]
<i>CZK</i>							3 [0.04]	41 [0.61]	23 [0.34]	–	–	67 [1.00]
<i>HUF</i>							12 [0.22]	42 [0.76]	1 [0.02]	–	–	55 [1.00]
<i>KRW</i>							4 [0.06]	38 [0.57]	25 [0.37]	–	–	67 [1.00]
<i>MXN</i>							49 [0.73]	16 [0.24]	2 [0.03]	–	–	67 [1.00]
<i>PLN</i>							20 [0.30]	45 [0.67]	2 [0.03]	–	–	67 [1.00]
<i>SGD</i>							–	26 [0.39]	41 [0.61]	–	–	67 [1.00]
<i>TRY</i>							54 [0.81]	13 [0.19]	–	–	–	67 [1.00]
<i>TWD</i>							127 [1.00]	–	–	–	–	127 [1.00]
<i>ZAR</i>							65 [0.76]	21 [0.24]	–	–	–	86 [1.00]

**Table 16. Risk Reversal Portfolios: Currency Breakdown**

The table presents the composition of the risk reversal portfolios: the number of times (and the frequency in brackets) a currency enters each of the five currency 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 an 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.

	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$Tot$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>AUD</i>	142 [0.76]	32 [0.17]	7 [0.04]	3 [0.02]	3 [0.02]	187 [1.00]	64 [0.34]	95 [0.51]	38 [0.20]	3 [0.02]	3 [0.02]	203 [1.09]
<i>CAD</i>	25 [0.13]	83 [0.44]	17 [0.09]	29 [0.16]	27 [0.14]	181 [0.97]	19 [0.10]	72 [0.39]	25 [0.13]	32 [0.17]	49 [0.26]	197 [1.05]
<i>CHF</i>	–	2 [0.01]	11 [0.06]	54 [0.29]	116 [0.62]	183 [0.98]	–	4 [0.02]	10 [0.05]	66 [0.35]	117 [0.63]	197 [1.05]
<i>DKK</i>	3 [0.02]	23 [0.12]	56 [0.30]	73 [0.39]	28 [0.15]	183 [0.98]	2 [0.01]	13 [0.07]	49 [0.26]	100 [0.53]	35 [0.19]	199 [1.06]
<i>EUR</i>	–	16 [0.10]	70 [0.43]	56 [0.34]	19 [0.12]	161 [1.00]	–	4 [0.02]	60 [0.37]	85 [0.52]	28 [0.17]	177 [1.09]
<i>GBP</i>	8 [0.04]	115 [0.61]	36 [0.19]	16 [0.09]	9 [0.05]	184 [0.98]	6 [0.03]	69 [0.37]	81 [0.43]	26 [0.14]	18 [0.10]	200 [1.07]
<i>JPY</i>	11 [0.06]	16 [0.09]	19 [0.10]	5 [0.03]	133 [0.72]	184 [1.00]	9 [0.05]	19 [0.10]	18 [0.10]	5 [0.03]	150 [0.81]	201 [1.09]
<i>NOK</i>	–	19 [0.10]	64 [0.34]	86 [0.46]	12 [0.06]	181 [0.97]	–	9 [0.05]	57 [0.31]	115 [0.62]	16 [0.09]	197 [1.06]
<i>NZD</i>	138 [0.74]	42 [0.22]	3 [0.02]	1 [0.01]	–	184 [0.98]	65 [0.35]	95 [0.51]	39 [0.21]	1 [0.01]	–	200 [1.07]
<i>SEK</i>	5 [0.03]	25 [0.13]	89 [0.48]	48 [0.26]	15 [0.08]	182 [0.98]	5 [0.03]	12 [0.06]	82 [0.44]	91 [0.49]	9 [0.05]	199 [1.07]
<i>BRL</i>							71 [1.06]	9 [0.13]	–	–	–	80 [1.19]
<i>CZK</i>							–	4 [0.06]	71 [1.06]	8 [0.12]	–	83 [1.24]
<i>HUF</i>							32 [0.58]	40 [0.73]	–	–	–	72 [1.31]
<i>KRW</i>							46 [0.69]	10 [0.15]	7 [0.10]	9 [0.13]	12 [0.18]	84 [1.25]
<i>MXN</i>							22 [0.33]	51 [0.76]	10 [0.15]	–	–	83 [1.24]
<i>PLN</i>							8 [0.12]	64 [0.96]	11 [0.16]	–	–	83 [1.24]
<i>SGD</i>							–	–	23 [0.34]	24 [0.36]	35 [0.52]	82 [1.22]
<i>TRY</i>							45 [0.67]	37 [0.55]	1 [0.01]	–	–	83 [1.24]
<i>TWD</i>							23 [0.18]	7 [0.06]	8 [0.06]	5 [0.04]	88 [0.69]	131 [1.03]
<i>ZAR</i>							84 [0.98]	18 [0.21]	–	–	–	102 [1.19]



**Table 17.  $\beta$ -Sorted Portfolios: Principal Component of Volatility Risk Premia**

This table presents descriptive statistics of  $\beta$ -sorted currency portfolios. Each  $\beta$  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)  $\beta$ .  $H/L$  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  $\beta$ 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	5.76	2.07	2.72	1.45	7.15	-1.40	3.69	2.62	3.13	2.48	5.70	-2.00
<i>Sdev</i>	9.51	10.45	8.84	10.66	11.69	10.80	8.61	9.97	10.13	9.37	11.19	10.65
<i>Skew</i>	0.24	0.03	-0.51	0.00	-0.38	0.79	0.08	0.35	-0.20	-0.49	-0.49	0.96
<i>Kurt</i>	3.03	4.58	5.33	4.17	5.20	6.94	2.43	4.78	4.22	5.58	4.65	6.46
<i>SR</i>	0.61	0.20	0.31	0.14	0.61	-0.13	0.43	0.26	0.31	0.26	0.51	-0.19
<i>SO</i>	1.15	0.30	0.42	0.20	0.86	-0.22	0.80	0.43	0.47	0.38	0.71	-0.36
<i>MDD</i>	-0.17	-0.26	-0.31	-0.33	-0.26	-0.36	-0.24	-0.23	-0.31	-0.29	-0.26	-0.33
<i>AC<sub>1</sub></i>	0.01	0.01	0.21	0.11	0.08	0.04	0.08	0.06	0.15	0.14	0.08	-0.01
<i>Freq</i>	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												
<i>Mean</i>	6.52	2.26	2.41	0.67	5.02	1.50	4.59	2.56	2.49	1.15	3.52	1.06
<i>Sdev</i>	9.43	10.40	8.79	10.53	11.67	10.88	8.52	9.90	10.06	9.25	11.17	10.75
<i>Skew</i>	0.28	0.02	-0.55	-0.04	-0.40	0.86	0.10	0.34	-0.22	-0.58	-0.61	1.14
<i>Kurt</i>	3.08	4.56	5.48	4.11	5.25	7.16	2.40	4.85	4.25	5.48	4.84	7.02
<i>SR</i>	0.69	0.22	0.27	0.06	0.43	0.14	0.54	0.26	0.25	0.12	0.32	0.10
<i>SO</i>	1.36	0.33	0.38	0.09	0.60	0.24	1.04	0.42	0.37	0.17	0.42	0.20
<i>MDD</i>	-0.15	-0.25	-0.32	-0.33	-0.28	-0.32	-0.20	-0.21	-0.32	-0.30	-0.32	-0.23
<i>AC<sub>1</sub></i>	0.00	0.01	0.22	0.10	0.07	0.05	0.07	0.06	0.14	0.13	0.08	0.00
<i>Freq</i>	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												
<i>pre-if</i>	-0.77	-0.18	0.31	0.78	2.13		-0.89	0.06	0.64	1.33	2.17	
<i>post-if</i>	-0.69	-0.24	0.38	0.84	2.13		-0.94	0.10	0.68	1.34	2.18	
<i>pre-<math>\beta</math></i>	-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]	
<i>post-<math>\beta</math></i>	-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 18.  $\beta$ -Sorted Portfolios: Equity Volatility Risk Premium**

This table presents descriptive statistics of  $\beta$ -sorted currency portfolios. Each  $\beta$  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)  $\beta$ .  $H/L$  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  $\beta$ 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	6.22	3.65	2.43	2.33	3.50	2.72	7.04	2.46	3.52	1.98	3.29	3.76
<i>Sdev</i>	11.04	10.24	10.19	10.47	8.73	10.07	10.85	10.37	9.67	10.37	7.59	9.96
<i>Skew</i>	-0.58	-0.17	0.02	-0.06	0.30	-1.10	-0.72	-0.28	-0.04	0.43	-0.19	-1.08
<i>Kurt</i>	4.98	4.41	4.21	4.56	3.74	7.83	6.03	4.05	4.31	4.69	2.62	10.41
<i>SR</i>	0.56	0.36	0.24	0.22	0.40	0.27	0.65	0.24	0.36	0.19	0.43	0.38
<i>SO</i>	0.78	0.56	0.38	0.33	0.73	0.33	0.88	0.36	0.56	0.32	0.71	0.47
<i>MDD</i>	-0.27	-0.28	-0.32	-0.28	-0.20	-0.32	-0.23	-0.30	-0.30	-0.28	-0.20	-0.25
<i>AC<sub>1</sub></i>	0.11	0.12	0.24	0.06	-0.05	0.03	0.14	0.15	0.21	0.04	0.00	0.05
<i>Freq</i>	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												
<i>Mean</i>	4.55	3.15	2.18	2.43	3.68	0.87	4.74	1.28	3.12	2.16	3.76	0.98
<i>Sdev</i>	10.97	10.22	10.04	10.42	8.76	10.18	10.72	10.33	9.48	10.30	7.62	10.03
<i>Skew</i>	-0.61	-0.21	0.00	-0.06	0.32	-1.17	-0.80	-0.35	-0.08	0.43	-0.19	-1.23
<i>Kurt</i>	5.07	4.57	4.14	4.55	3.84	8.21	6.37	4.17	4.20	4.77	2.68	11.27
<i>SR</i>	0.41	0.31	0.22	0.23	0.42	0.09	0.44	0.12	0.33	0.21	0.49	0.10
<i>SO</i>	0.57	0.47	0.34	0.34	0.75	0.10	0.59	0.18	0.50	0.35	0.80	0.12
<i>MDD</i>	-0.29	-0.29	-0.32	-0.27	-0.21	-0.36	-0.24	-0.34	-0.28	-0.27	-0.21	-0.30
<i>AC<sub>1</sub></i>	0.10	0.12	0.23	0.06	-0.05	0.04	0.12	0.15	0.20	0.04	0.00	0.05
<i>Freq</i>	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												
<i>pre-if</i>	1.67	0.50	0.25	-0.10	-0.18		2.31	1.17	0.40	-0.18	-0.47	
<i>post-if</i>	1.70	0.54	0.24	-0.15	-0.12		2.33	1.21	0.38	-0.26	-0.41	
<i>pre-<math>\beta</math></i>	-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]	
<i>post-<math>\beta</math></i>	-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 19.  $\beta$ -Sorted Portfolios: VRP Strategy**

This table presents descriptive statistics of  $\beta$ -sorted currency portfolios. Each  $\beta$  is obtained by regressing individual currency excess returns on the VRP strategy using a 36-month moving window. The long (short) portfolio  $P_L$  ( $P_S$ ) contains the top 20% of all currencies with the highest (lowest)  $\beta$ .  $H/L$  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  $\beta$ 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.

Panel A: Excess Returns												
	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$	$P_L$	$P_2$	$P_3$	$P_4$	$P_S$	$H/L$
	<i>Developed</i>						<i>Developed &amp; Emerging</i>					
<i>Mean</i>	6.73	3.93	2.39	1.57	3.79	2.95	5.94	2.40	4.11	2.51	2.39	3.55
<i>Sdev</i>	9.75	9.51	9.53	10.40	11.89	11.22	9.92	9.00	9.30	11.04	10.44	10.76
<i>Skew</i>	0.13	-0.01	-0.08	-0.19	-0.28	0.32	0.16	-0.21	0.16	-0.18	-0.66	0.44
<i>Kurt</i>	3.47	5.90	4.16	4.04	5.08	5.88	3.30	4.29	3.62	3.99	6.54	8.21
<i>SR</i>	0.69	0.41	0.25	0.15	0.32	0.26	0.60	0.27	0.44	0.23	0.23	0.33
<i>SO</i>	1.22	0.61	0.39	0.22	0.46	0.42	1.11	0.39	0.76	0.34	0.31	0.49
<i>MDD</i>	-0.23	-0.21	-0.28	-0.28	-0.32	-0.36	-0.23	-0.21	-0.25	-0.32	-0.28	-0.27
<i>AC<sub>1</sub></i>	0.09	-0.02	0.11	0.10	0.12	0.12	0.08	0.04	0.09	0.12	0.13	0.06
<i>Freq</i>	0.09	0.16	0.18	0.21	0.09	0.09	0.06	0.11	0.16	0.17	0.10	0.10
Panel B: FX Returns												
<i>Mean</i>	6.38	3.46	1.91	1.32	3.33	3.05	5.71	2.27	3.65	1.38	1.11	4.60
<i>Sdev</i>	9.66	9.48	9.43	10.30	11.83	11.25	9.80	8.96	9.26	10.91	10.31	10.75
<i>Skew</i>	0.09	0.00	-0.05	-0.21	-0.36	0.47	0.13	-0.23	0.13	-0.20	-0.83	0.68
<i>Kurt</i>	3.56	5.84	4.13	4.15	5.27	6.41	3.36	4.17	3.64	4.14	7.08	9.10
<i>SR</i>	0.66	0.36	0.20	0.13	0.28	0.27	0.58	0.25	0.39	0.13	0.11	0.43
<i>SO</i>	1.12	0.54	0.32	0.19	0.39	0.44	1.05	0.37	0.66	0.19	0.14	0.65
<i>MDD</i>	-0.23	-0.22	-0.29	-0.28	-0.34	-0.32	-0.23	-0.22	-0.26	-0.34	-0.32	-0.21
<i>AC<sub>1</sub></i>	0.07	-0.02	0.11	0.08	0.12	0.12	0.06	0.04	0.10	0.11	0.12	0.05
<i>Freq</i>	0.09	0.16	0.18	0.21	0.09	0.09	0.06	0.11	0.16	0.17	0.10	0.10
Panel C: Portfolio Formation												
<i>pre-if</i>	0.35	0.47	0.48	0.24	0.46		0.22	0.13	0.46	1.13	1.27	
<i>post-if</i>	0.39	0.48	0.48	0.24	0.48		0.26	0.16	0.44	1.13	1.28	
<i>pre-<math>\beta</math></i>	0.26	-0.07	-0.24	-0.33	-0.50		0.51	0.23	0.07	-0.05	-0.29	
	[0.33]	[0.27]	[0.24]	[0.24]	[0.29]		[0.22]	[0.17]	[0.19]	[0.23]	[0.34]	
<i>post-<math>\beta</math></i>	0.31	0.11	-0.10	-0.06	-0.17		0.47	0.24	0.07	-0.04	-0.16	
	(0.1)	(0.06)	(0.05)	(0.06)	(0.07)		(0.06)	(0.05)	(0.06)	(0.06)	(0.08)	

**Table 20. Double-Sorted Currency Strategies**

This table presents descriptive statistics of long/short currency strategies formed by double-sorting currencies into 4 groups using time  $t-1$  information. Currencies are first sorted into 2 groups according to the 3-month exchange rate returns (or volatility risk premia) and then re-sorted using the interest rate differentials relative to the US dollar. *MOM* (*VRP*) is the high-minus-low currency strategy on the 3-month exchange rate returns (the 1-year expected volatility premia) whereas *FX* is the high-minus-low currency strategy on the interest rate differentials relative to the US dollar. 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. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. *Panel A* displays the overall currency excess return whereas *Panel B* reports only the exchange rate component. 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.

Panel A: Excess Returns												
	$\Rightarrow$		$\Rightarrow$		$\Rightarrow$		$\Rightarrow$		$\Rightarrow$		$\Rightarrow$	
	<i>MOM</i>	<i>FX</i>	<i>VRP</i>	<i>FX</i>	<i>VRP</i>	<i>MOM</i>	<i>MOM</i>	<i>FX</i>	<i>VRP</i>	<i>FX</i>	<i>VRP</i>	<i>MOM</i>
	<i>Developed</i>				<i>Developed &amp; Emerging</i>							
<i>Mean</i>	1.43	3.28	2.38	3.34	2.02	1.64	1.03	3.33	1.08	4.27	0.84	2.12
<i>Sdev</i>	6.42	5.51	4.73	5.68	4.80	5.65	5.73	5.08	4.76	5.67	4.80	5.03
<i>Skew</i>	0.09	-0.59	-0.33	-0.69	-0.03	0.11	-0.37	-0.84	0.03	-1.00	0.20	-0.10
<i>Kurt</i>	4.54	5.09	3.42	4.15	3.29	3.66	3.87	4.17	3.78	4.63	3.79	4.34
<i>SR</i>	0.22	0.60	0.50	0.59	0.42	0.29	0.18	0.66	0.23	0.75	0.18	0.42
<i>SO</i>	0.33	0.77	0.77	0.78	0.70	0.50	0.25	0.84	0.37	0.99	0.30	0.64
<i>MDD</i>	-0.16	-0.15	-0.13	-0.18	-0.14	-0.11	-0.16	-0.10	-0.15	-0.17	-0.15	-0.09
$AC_1$	0.04	-0.05	-0.07	0.03	0.05	0.05	0.07	-0.06	-0.02	0.14	0.03	-0.01
$Freq_L$	0.36	0.36	0.27	0.27	0.47	0.47	0.38	0.38	0.27	0.27	0.43	0.43
$Freq_S$	0.38	0.38	0.31	0.31	0.47	0.47	0.38	0.38	0.29	0.29	0.42	0.42
Panel B: FX Returns												
<i>Mean</i>	0.22	0.32	1.97	0.38	2.08	1.19	0.17	-0.57	1.52	0.32	1.54	1.57
<i>Sdev</i>	6.42	5.52	4.74	5.71	4.83	5.65	5.67	5.11	4.81	5.73	4.85	5.01
<i>Skew</i>	0.18	-0.58	-0.40	-0.72	-0.08	0.17	-0.31	-0.92	-0.01	-1.10	0.19	-0.09
<i>Kurt</i>	4.84	5.16	3.42	4.24	3.33	3.95	3.92	4.33	3.90	4.98	3.95	4.64
<i>SR</i>	0.03	0.06	0.42	0.07	0.43	0.21	0.03	-0.11	0.32	0.06	0.32	0.31
<i>SO</i>	0.05	0.07	0.61	0.09	0.71	0.35	0.04	-0.14	0.51	0.07	0.55	0.47
<i>MDD</i>	-0.25	-0.20	-0.15	-0.21	-0.14	-0.14	-0.23	-0.19	-0.15	-0.20	-0.15	-0.11
$AC_1$	0.03	-0.04	-0.07	0.04	0.05	0.05	0.05	-0.04	-0.01	0.16	0.03	-0.02
$Freq_L$	0.36	0.36	0.27	0.27	0.56	0.56	0.38	0.38	0.27	0.27	0.43	0.43
$Freq_S$	0.38	0.38	0.31	0.31	0.58	0.58	0.38	0.38	0.29	0.29	0.42	0.42

**Table 21. 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  $\lambda$ . The  $\chi^2$  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.

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Panel A: Illiquidity in the Spot Market																
Factor Prices																
	$b_{DOL}$	$b_{BAS_{FX}}$	$\lambda_{DOL}$	$\lambda_{BAS_{FX}}$	$R^2$	$RMSE$	$\chi^2$	$HJ$	$b_{DOL}$	$b_{BAS_{FX}}$	$\lambda_{DOL}$	$\lambda_{BAS_{FX}}$	$R^2$	$RMSE$	$\chi^2$	$HJ$
	<i>Developed</i>								<i>Developed &amp; Emerging</i>							
$GMM_1$	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]	
( <i>sh</i> )	0.32	42.21	0.02	0.07			[0.79]		0.31	10.44	0.02	0.12			[0.57]	
Factor Betas																
	$\alpha$	$\beta_{DOL}$	$\beta_{BAS_{FX}}$	$R^2$	$\chi^2(\alpha)$				$\alpha$	$\beta_{DOL}$	$\beta_{BAS_{FX}}$	$R^2$	$\chi^2(\alpha)$			
$P_L$	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 21. Asset Pricing Tests: Illiquidity Factors** (*continued*)

Panel B: Illiquidity Factor in the Option Market																
Factor Prices																
	$b_{DOL}$	$b_{BASIV}$	$\lambda_{DOL}$	$\lambda_{BASIV}$	$R^2$	$RMSE$	$\chi^2$	$HJ$	$b_{DOL}$	$b_{BASIV}$	$\lambda_{DOL}$	$\lambda_{BASIV}$	$R^2$	$RMSE$	$\chi^2$	$HJ$
	<i>Developed</i>							<i>Developed &amp; Emerging</i>								
$GMM_1$	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]	
( <i>sh</i> )	(0.49)	(23)	(0.02)	(0.03)			[0.21]		(0.34)	(16.97)	(0.02)	(0.04)			[0.59]	
Factor Betas																
	$\alpha$	$\beta_{DOL}$	$\beta_{BASIV}$	$R^2$	$\chi^2(\alpha)$				$\alpha$	$\beta_{DOL}$	$\beta_{BASIV}$	$R^2$	$\chi^2(\alpha)$			
$P_L$	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 22. Principal Component Analysis: Volatility Risk Premia**

This table presents principal component analysis of the 1-year volatility risk premia. We apply the EM algorithm proposed by Stock and Watson (2002) for an unbalanced set of data. Implied volatility quotes are from JP Morgan.

	<b>P1</b>	<b>P2</b>	<b>P3</b>	<b>P4</b>	<b>P5</b>	<b>P1</b>	<b>P2</b>	<b>P3</b>	<b>P4</b>	<b>P5</b>
	<i>Developed Countries</i>					<i>Developed &amp; Emerging Countries</i>				
AUD	0.31	0.70	0.11	0.01	0.50	0.12	-0.43	0.22	-0.30	0.01
CAD	0.21	-0.09	-0.15	-0.15	0.50	0.12	-0.04	-0.05	-0.05	0.08
CHF	0.27	-0.07	-0.15	0.28	-0.05	0.13	-0.10	0.00	0.02	0.30
DKK	0.35	-0.33	0.04	-0.24	-0.08	0.19	-0.01	0.00	0.15	0.21
EUR	0.35	-0.31	0.03	-0.29	-0.03	0.19	-0.02	0.02	0.14	0.21
GBP	0.34	-0.27	0.14	-0.25	0.29	0.19	-0.05	-0.03	0.09	0.07
JPY	0.21	0.03	-0.89	0.17	-0.06	0.10	-0.02	-0.09	-0.27	0.44
NOK	0.38	0.00	0.09	0.39	-0.06	0.18	-0.19	0.05	0.07	0.22
NZD	0.28	0.46	-0.05	-0.53	-0.57	0.13	-0.28	-0.01	-0.15	0.00
SEK	0.39	0.00	0.35	0.48	-0.28	0.19	-0.21	0.08	0.14	0.17
BRL						0.33	0.04	0.09	-0.53	-0.29
CZK						0.18	-0.22	0.16	0.27	-0.10
HUF						0.27	0.05	0.01	0.47	-0.24
KRW						0.31	-0.33	-0.21	-0.14	-0.18
MXN						0.42	0.26	-0.41	-0.16	-0.15
PLN						0.20	-0.28	-0.18	0.34	-0.23
SGD						0.19	0.18	-0.17	0.03	0.17
TRY						0.33	0.41	0.57	-0.01	-0.24
TWD						0.22	0.36	-0.26	0.05	0.31
ZAR						0.18	0.04	0.47	0.02	0.33
<b>Var</b>	<b>0.74</b>	<b>0.87</b>	<b>0.92</b>	<b>0.95</b>	<b>0.97</b>	<b>0.68</b>	<b>0.80</b>	<b>0.86</b>	<b>0.91</b>	<b>0.94</b>

**Table 23. 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-a-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.

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$\alpha$	<i>TED</i>	$\Delta VIX$	$\Delta FSI$	<i>TED</i> × $\Delta VIX$	<i>HED</i> <i>AUDUSD</i> <i>JPYUSD</i>		<i>Fund</i> <i>Flows</i>	$R^2$	$\alpha$	<i>TED</i>	$\Delta VIX$	$\Delta FSI$	<i>TED</i> × $\Delta VIX$	<i>Hedging</i> <i>AUDUSD</i> <i>JPYUSD</i>		<i>Fund</i> <i>Flows</i>	$R^2$
<i>Developed</i>									<i>Developed &amp; Emerging</i>								
-0.03 (0.03)	0.15 <sup>c</sup> (0.05)							0.04	0.00 (0.03)	0.08 <sup>a</sup> (0.04)							0.01
0.04 <sup>b</sup> (0.02)		0.01 (0.01)						< .01	0.04 <sup>a</sup> (0.02)		0.01 < .01						< .01
0.04 <sup>b</sup> (0.02)			0.07 (0.07)					< .01	0.04 <sup>a</sup> (0.02)			0.08 (0.06)					< .01
0.04 <sup>b</sup> (0.02)				0.01 <sup>a</sup> (< .01)				0.02	0.04 <sup>a</sup> (0.02)				< .01 <sup>c</sup> (< .01)				< .01
0.04 <sup>b</sup> (0.02)					0.02 <sup>c</sup> (< .01)			0.01	0.04 <sup>a</sup> (0.02)					0.01 <sup>c</sup> (< .01)			0.01
0.05 <sup>b</sup> (0.02)						-0.02 (0.06)		< .01	0.04 <sup>a</sup> (0.02)						0.01 (0.06)		< .01
0.05 <sup>b</sup> (0.02)							-1.50 <sup>b</sup> (0.77)	0.02	0.05 <sup>b</sup> (0.02)							-1.14 (0.74)	0.01
-0.01 (0.04)	0.12 <sup>b</sup> (0.06)				0.01 <sup>c</sup> (< .01)			0.06	0.02 (0.03)	0.05 (0.05)				0.01 <sup>c</sup> (< .01)		-0.81 (0.72)	0.02
0.05 <sup>b</sup> (0.02)		0.00 (0.01)			0.01 <sup>c</sup> (< .01)			0.03	0.04 <sup>a</sup> (0.02)		< .01 (< .01)			0.01 <sup>c</sup> (< .01)		-0.99 (0.72)	0.02
0.05 <sup>b</sup> (0.02)			0.06 (0.06)		0.01 <sup>c</sup> (< .01)			0.03	0.04 <sup>a</sup> (0.02)			0.07 (0.06)		0.01 <sup>c</sup> (< .01)		-0.97 (0.69)	0.02
0.04 <sup>b</sup> (0.02)				0.01 <sup>b</sup> (< .01)	0.01 <sup>c</sup> (< .01)			0.05	0.04 (0.02)				< .01 <sup>c</sup> (< .01)	0.01 <sup>c</sup> (< .01)		-0.99 (0.70)	0.02