Volatility Risk Premia and Exchange Rate Predictability^{*†}

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Abstract

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.

Keywords: Exchange Rates; Volatility Risk Premium; Predictability.

JEL Classification: F31; F37.

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1 Introduction

What explains currency fluctuations? Finance practitioners and academics have struggled in vain with this question for decades. An early exercise highlighting the difficulty of explaining and predicting short-run currency movements is Meese and Rogoff (1983), who originally documented that it is fiendishly difficult to find theoretically motivated variables able to beat a random walk forecasting model for currencies.¹

A recent stream of the exchange rate literature tackles a related question, namely, attempting to explain the returns to currency investment strategies. Following 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.² 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.*³ 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 currency returns. 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 interest rate differentials, these strategies appear to work poorly over the last decade for liquid currencies, and they are very difficult to exploit (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 risk premium (VRP) for exchange rate returns. Our key result is that there is economically

¹These findings have more recently been re-confirmed by Rogoff and Stavrakeva (2008) and Engel, Mark and West (2008).

²See, 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.

 $^{^{3}}$ 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.

valuable and statistically significant predictive information in the currency VRP for future spot exchange rate returns over the 1996 to 2011 period, in a cross-section of up to 20 currencies.⁴ The returns from these currency VRP-sorted portfolios are uncorrelated with the returns from carry trade and momentum strategies, and cannot be explained using the canonical risk factors used in studies of currency returns. We present an explanation for our results which is consistent with the growing theoretical and empirical literature on limits to arbitrage and the interaction between hedgers and speculators in asset markets,⁵ and find that auxiliary tests offer support for this explanation.

The currency VRP is the difference between future realized volatility and a model-free measure of expected volatility derived from currency options. A growing literature studies the variance or the volatility risk premium in different asset classes, including equity, bond, and foreign exchange markets.⁶ In general, this literature has shown that the VRP 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 the currency VRP 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), the cost of insurance is low, and vice versa.

We use the VRP to rank currencies and to build currency portfolios. Specifically, in our empirical analysis, we sort currencies into quintile portfolios according to their computed VRPs at the beginning of each month. Our trading strategy is to buy currencies in the lowest volatility insurance cost quintile, i.e., the highest VRP quintile, and short currencies in the highest volatility insurance cost quintile, i.e., the lowest VRP quintile. We track returns on this trading strategy over the subsequent period, so these returns are purely out-of-sample, conditioning only on information available at the time of portfolio construction. We find that

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

⁵See, for example, Acharya, Lochstoer, and Ramadorai (2013) and Adrian, Etula, and Muir (2013). Gromb and Vayanos (2010) provide an excellent survey of the literature.

⁶See, 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).

the long-short VRP-sorted portfolio generates sizeable currency excess returns, almost entirely obtained through prediction of spot exchange rates rather than interest rate differentials. That is, currencies with relatively cheaper 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 using the VRP is far stronger than that arising from carry and momentum strategies.

There are at least two possible interpretations of this result. One possibility is that the VRP captures fluctuations in aversion to volatility risk, so 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.

The second possible explanation 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 (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 speculative 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 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, e.g., they will reduce, say, their outstanding short put option positions in currencies.⁷ Given that speculators are limited in their ability to satisfy demand for

⁷Short 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

volatility insurance, this increased net demand will increase current option prices and make hedging more expensive, i.e., this will show up in a lower VRP for the currencies. 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 higher VRP and relatively higher returns on the spot currency position. So in the cross section of currencies, this mechanism implies that, in a world with limited and time-varying capital arbitrage, 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-sorted strategy 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 returns to the VRP-sorted strategy reverse over a period of a few months. Second, at times when funding liquidity is lower (i.e., times of high capital constraints on speculators), and demand for volatility protection is higher (capturing the 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 from the VRP-sorted strategy 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 find that the returns from the VRP-sorted strategy are related to hedging demand in the futures market, as proxied by the hedgers' positions in the CFTC's Commitments of Traders reports. Finally, we create measures of capital flows into hedge funds, and find that when such flows are high, signifying increased funding and thus lower hedge fund capital constraints, the spread returns across our volatility insurance-sorted portfolios are lower and vice versa, providing useful evidence in support of the explanation.

trading strategies implemented by hedge funds.

Our findings are related to another stream of the literature, on explaining and forecasting currency returns using currency order flow. 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. 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. In future work, we intend to check whether the VRP strategy can be connected to measures of order flow to confirm this conjecture.

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, and Section 5 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 of the underlying asset 'realized' over the life of the contract. The buyer of a volatility swap written at time t which matures at time $t + \tau$ receives per unit of notional amount the payoff

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

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

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 that the volatility swap rate equals the risk-neutral expectation of the realized volatility over the life of the contract

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

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

Volatility Swap Rate. We synthesize the volatility swap rate using the model-free approach derived by Britten-Jones and Neuberger (2000), and further refined by Demeterfi, Derman, Kamal and Zou (1999), Jiang and Tian (2005), and Carr and Wu (2009). Building on the pioneering work of Breeden and Litzerberger (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 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 this is equivalent to a portfolio that combines a dynamically rebalanced long position in the underlying and a static short position in a portfolio of options and a forward that together replicate the payoff of a "log contract".⁸ The replicating portfolio strategy captures variance exactly, provided that the portfolio of options contains all strikes with the appropriate weights to match the log payoff. Jiang and Tian (2005) further demonstrate that the model-free implied variance is valid even when the underlying price exhibits jumps, thus relaxing the diffusion assumptions of Britten-Jones and Neuberger (2000).

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

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

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

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

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

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

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

and refer to it as model-free implied volatility. However, this approach is subject to a convexity bias. Volatility swaps are more difficult to replicate than variance swaps, as their replication requires a dynamic strategy involving variance swaps (e.g., Broadie and Jain, 2008). 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 Simply put, the payoff of variance swaps is quadratic with respect to of variance swaps. volatility, whereas the payoff of volatility swaps is linear. We deal with this approximation in two ways. First, we measure the convexity bias using a second-order Taylor expansion as in Brockhaus and Long (2000) and find that it is empirically small.⁹ More importantly, we also work in our empirical exercise with model-free implied variances and 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).

The model-free implied volatility requires the existence of a continuum in the cross-section of option prices at time t with maturity date τ . In the FX market, over-the-counter options are 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.,

⁹Brockhaus 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.

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 formula¹⁰ and use trapezoidal integration to solve the integral in Equation (3). This method introduces two types of approximation errors: (i) the truncation errors arising from observing a finite number rather than an infinite set of strike prices, and (ii) a discretization error resulting from numerical integration. Jiang and Tian (2005), however, show that both errors are small, if not negligible, in most empirical settings.

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.¹¹ Formally, the τ -period volatility risk premium at time t is defined as

$$VRP_{t,\tau} = E_t^{\mathbb{P}} \left[RV_{t,\tau} \right] - E_t^{\mathbb{Q}} \left[RV_{t,\tau} \right]$$
(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.¹² 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

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

¹¹A 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 n a volatility swap contract.

¹²In our empirical work we also experiment with an AR(1) process for RV for form expectations of RV, and find that the results are virtually identical to the ones reported in the paper.

realized volatility over the $[t, t + \tau]$ interval, i.e., $VRP_{t,\tau} = RV_{t-\tau,\tau} - E_t^{\mathbb{Q}}[RV_{t,\tau}]$.

3 Data and Currency Portfolios

This section describes the main datasets used for our empirical analysis: data on spot and forward exchange rates, quotes on implied volatilities, and the hedger position data. We go on to describe the construction of currency portfolios, and our implied volatility strategies.

Exchange Rate Data. We collect daily spot and one-month forward exchange rates visà-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 call this sample '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.¹³ 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. Turning to implied volatility data, we employ daily data from January 1996 to August 2011 on over-the-counter (OTC) currency options from JP Morgan. The dataset consists of plain-vanilla European call and put options on 20 currency pairs visà-vis the US dollar, with a 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 maturity traded.¹⁴ The

¹³According 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.

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

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 traded in terms of Garman and Kohlhagen (1983) implied volatilities on a basket of plain vanilla options. For a given maturity, quotes are typically available for five different combinations of plain-vanilla options: at-the-money delta-neutral straddle, 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.¹⁵ To convert deltas into strike prices and the implied volatilities into option prices, we employ domestic and foreign interest rates from the same data source.

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 (Curcuru, Vega and Hoek, 2010). Engagement in 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. We consider the reversal and interpret it as a measure of hedging to the carry trade activity. As data are available only for positions for which one of the currencies is the US dollar, we first construct the net long futures position in Japanese yen (¥) and the net short futures position

¹⁵According to the 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.

in the Australian dollar (A both with respect to the US dollar as

$$NetLongPos_t(\mathfrak{Y}) = \frac{LongPos_t(\mathfrak{Y}) - ShortPos_t(\mathfrak{Y})}{LongPos_{t-1}(\mathfrak{Y}) + ShortPos_{t-1}(\mathfrak{Y})}$$
(6)

$$NetShortPos_t(A\$) = \frac{ShortPos_t(A\$) - LongPos_t(A\$)}{LongPos_{t-1}(A\$) + ShortPos_{t-1}(A\$)}$$
(7)

where the normalization indicates that the net positions are measured relative to the aggregate open interest in the previous month. Finally, our measure of hedging to the carry trade activity is simply computed as¹⁶

$$HedgingPos_t = NetLongPos_t(\mathfrak{X}) + NetShortPos_t(A\mathfrak{S}).$$
(8)

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 a commercial trader. This category may include both corporate firms with an international line of business as well as banks that have 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.

Hedge Fund Flows. We also employ a large cross-section of hedge funds and fundsof-funds from January 1996 to December 2011, which is consolidated from data in the HFR, CISDM, TASS, Morningstar and Barclay-Hedge databases. Patton and Ramadorai (2013) provide a detailed description of the process followed to consolidate these data. We construct the net flow of the new assets to hedge funds as the difference between the change in the funds' asset under management (AUM) and the funds' monthly dollar returns. We then normalize the figures by dividing them by the lagged AUM.

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

¹⁶As a robustness, we replace the Japanese yen with the Swiss franc (SFr), and reconstruct our measure of hedging to the carry trade activity between the Swiss franc and the Australian dollar.

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): $RX_{t+1} \simeq ((S_{t+1} - S_t)/S_t) - (i_t - i_t^*).$

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 contains 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). We refer to these carry trade portfolios as FX portfolios. We then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. We also track both the interest rate differential and the spot exchange rate component that make these excess returns. Ultimately we aim at understanding what fraction of the excess return is driven by accurate prediction of spot rate movements relative to interest rate differentials. Lustig, Roussanov, and Verdelhan (2011) study these currency portfolio returns using the 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 the 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 HML_{FX} . Note that this strategy is dollar-neutral as the dollar component cancels out when taking the difference between any two portfolios.

Momentum Portfolios. At the end of each period t, we form five portfolios based on the exchange rate returns over the previous 3-months. We assign 20% of all currencies with the highest lagged exchange rate returns to Portfolio 1, and 20% of all currencies with the lowest lagged exchange rate returns to Portfolio 5. We denote these five momentum portfolios as MOM portfolios. 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 HML_{MOM} .

Volatility Risk Premia Portfolios. At the end of each period t, we group currencies into five portfolios using the volatility risk premium VRP_t .¹⁷ We allocate 20% of all currencies with the highest expected volatility premia to Portfolio 1, and 20% of all currencies with the lowest expected volatility premia to Portfolio 5. We then compute the average excess return within each portfolio, and finally calculate the portfolio return from a strategy that is long in Portfolio 1 (*high volatility risk premia*) and short in Portfolio 5 (*low volatility risk premia*), denoted HML_{VRP} . The volatility risk premium should be on average negative and can be thought of as compensation for providing volatility insurance. Thus, we can interpret Portfolio 1 as a portfolio of currencies with low insurance costs and Portfolio 5 as a portfolio of currencies with high insurance costs.

4 Empirical Results

4.1 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 $SW_{t,\tau}$, and volatility risk premium $VRP_{t,\tau} = RV_{t,\tau} - SW_{t,\tau}$ for the one year maturity ($\tau = 1$). $RV_{t,\tau}$ is computed at time t using daily exchange rate returns between times $t - \tau$ and t. $SW_{t,\tau}$ is constructed at time t using τ -period implied volatilities across 5 different deltas as in Jiang and Tian (2005). For the developed countries sample, the volatility risk premium $VRP_{t,\tau}$ is constructed as the difference between $RV_{t,\tau}$ and $SW_{t,\tau}$. The descriptive statistics in Table 1 indicate that, on average across currencies, RV_t equals

¹⁷As described earlier, at time t we compute the volatility risk premium as difference between the lagged realized volatility and the synthetic volatility swap, i.e., $VP_{t,\tau} = RV_{t-\tau,\tau} - SW_{t,\tau}$ for $\tau = 1$.

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 -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 major currencies, as expected, and so is the difference between them (the volatility risk premium, VRP_t), which equals on average -0.92. This is the magnitude of the volatility risk premium that natural hedgers have to pay to satisfy their demand for volatility insurance, on average across the currencies considered.

Table 2 presents the baseline result of the paper. We implement a number of longshort currency strategies using time t-1 information to compare the predictability generated by various alternatives proposed in the literature with the new VRP-based strategy that we propose. We compare the carry trade strategy, which buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differentials over the US interest rate, and the momentum strategy which buys (sells) the top 20% of all currencies with the highest (lowest) lagged 3-month exchange rate return with our VRP-based strategy.¹⁸ In the table, VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) volatility risk premia. We report results for both a sample of developed countries, comprising the 10 most liquid currencies, and for our full sample of 20 currencies (comprising developed and emerging countries).

Panel A of the table shows the results for the portfolio returns generated by the various 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), the carry strategy delivers a very high average excess return, which is also the highest of the 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. Momentum 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

¹⁸Consistent 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.

0.27 for both samples of countries. 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 the developed markets rather than the emerging markets. Finally, note that the Sharpe ratios for all three strategies are statistically significantly different from zero.¹⁹

Panel B of the table introduces the main result of the paper, namely that the lion's share of the returns accruing to the VRP strategy are a result of spot rate predictability. The predictability is twice as large as momentum 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. The exchange rate return from carry is close to zero for both samples, showing that the bulk of the return from this strategy comes from the interest differential. Moreover, the returns from the VRP-strategy display desirable skewness properties as unconditional skewness is positive (albeit small for the full sample), and the maximum drawdown is comparable to that of momentum and far better (i.e., higher) than that of the carry trade. More importantly, the Sharpe ratio for carry applied to the exchange rate component is insignificantly different from zero, whereas the Sharpe ratio for momentum and the VRP-based strategy is statistically significant in all cases considered. Finally, note that the portfolio turnover of the VRP strategy (measured in terms of changes in the composition of the short and long leg of the VRP strategy) is reasonably low, and somewhere in between the very low turnover of the carry strategy and the high turnover of currency momentum.

Table 3 documents the correlation of the VRP-based strategy with carry and momentum, and finds that the strategy tends to be negatively correlated with the carry trade (with correlations of -0.18 and -0.21 for the two samples) and only mildly positively correlated with currency momentum (with correlations of 0.09 and 0.10 for the two samples). Apart

¹⁹We estimate the standard error of the Sharpe ratio using the formula for non-*iid* returns via deltamethod and using a generalized method of moment (GMM) estimator (Lo, 2002). Specifically, the asymptotic distribution of the Sharpe ratio is defined as $\sqrt{T}(\widehat{SR} - SR) \stackrel{a}{\sim} N(0, V)$, 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 Σ_{θ} is the variance-covariance matrix of θ . We estimate θ via GMM and Σ_{θ} using Newey and West (1987).

from showing that the strategy is distinct from those already studied in the literature, this also implies that combining this strategy with carry and momentum may well yield sizable diversification benefits to an investor. It is also useful to note that the correlations for the exchange rate component of the returns from the strategies examined are very close to the correlations for the excess returns.

At this point, we provide further details and statistics to understand the properties of the returns generated by the VRP-based strategy. Table 4 reports summary statistics for the five portfolios that are obtained when sorting on the VRP: specifically, P_L is the long portfolio that buys the top 20% of all currencies with the highest expected volatility premia, 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 ranked by expected volatility premia, and so on till the lowest expected volatility premia. The VRP-based strategy is obtained from buying the currencies in P_L and selling the currencies in P_S , with equal weights, so that $HML = P_L - P_S$. In addition to HML, we also report statistics for the DOL portfolio, which is the average of the five currency portfolios described above.

Looking at the results in Table 4, we note several facts that refine our understanding of the VRP strategy. 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. Second, most of the HML return of the VRP strategy stems from the long portfolio, P_L , signifying that the information content of the VRP is particularly strong to predict the appreciation of high VRP (or low volatility insurance cost) currencies. Also, the return from P_L is basically due fully to prediction of spot rate changes. Third, the turnover in all portfolios is fairly low (e.g., only slightly higher than what is typically recorded in carry strategies), implying that the differences in the VRP across currencies and time and hence the weights in the investment strategy are fairly stable over time or just slightly more volatile than interest rate differentials. The latter point is important because it means that the VRP strategy is likely to perform well also for lower rebalancing periods and that transaction costs – which are known to be relatively small in currency markets – are unlikely to impact significantly on the performance of the VRP strategy.

4.2 The relation between VRP, carry and momentum strategies

While the correlations between carry, momentum and VRP strategies reported in Table 3 suggest that these strategies are not strongly related, we examine more rigorously the relation between them in this section by double sorting the cross-section of currencies on multiple characteristics. Specifically, we carry out independent double-sorted portfolios to measure the performance of each of these three investment strategies net of the performance of each of the others.²⁰

The results are given in Table 4. Starting from the analysis in terms of excess returns, reported in Panel A of the table, the first two columns confirm that momentum and carry strategies contain independent predictive information: for the developed sample the Sharpe ratio of momentum independent of carry is 0.22, and the Sharpe ratio of carry independent of momentum is 0.60; the numbers for the full sample are 0.18 for momentum and 0.66 for carry. This result replicates the result in Menkhoff, Sarno, Schmeling and Schrimpf (2012b) that carry and momentum and largely independent. Turning to the independent predictive power of the VRP as measured by Sharpe ratios, we can see that there is strong and statistically significant predictive power in the VRP independent of both momentum and carry. For the double sorts applied to VRP and carry, we find that carry has more information for future excess returns, whereas for the double sorts applied to VRP and momentum there is more independent information in the VRP over momentum for the developed sample and vice versa in the full sample.

Panel B then reports the double sorted returns for the exchange rate component only. These results indicate that the VRP strategy has the strongest independent information for future exchange rate changes in our cross-section of currencies, followed by momentum, and that carry has no independent information for spot returns at all (i.e., the Sharpe ratio is tiny

²⁰For example, we investigate the incremental information of the VRP strategy relative to the carry strategy using the following double-sorting exercise. We allocate currencies into four buckets by sorting currencies firstly on the basis of the volatility risk premia, and then using the interest rate differential relative to the US dollar. Portfolio 1 (2) contains the currencies with the highest (lowest) volatility risk premia and highest (lowest) interest rate differential. Portfolio 2 (3) contains the currencies with highest (lowest) volatility risk premia but the lowest (highest) interest rate differential. Ultimately, we construct $HML_{VRP} = 0.5 [(P1 + P2) - (P3 + P4)]$, and HML_{FX} as 0.5 [(P1 + P3) - (P2 + P4)]. We use a similar approach for the MOM strategy relative to the carry strategy, and construct $HML_{MOM} = 0.5 [(P1 + P2) - (P3 + P4)]$, and HML_{FX} as 0.5 [(P1 + P3) - (P2 + P4)].

and statistically insignificant). Overall, the results from independent double sorts suggest that the three strategies considered are largely independent of each other, and the predictive information for spot exchange rates that is embedded in the VRP cannot be replicated using common carry and momentum strategies.

We provide a graphical illustration of the differences in the performance of carry, momentum and the VRP-strategy in Figure 1, which plots the one-year rolling Sharpe ratio for the three strategies. The graphs make visually clear the marked difference in the evolution of risk-adjusted returns of the VRP-based strategy relative to carry and momentum. It is also clear that the average Sharpe ratio of the VRP-sorted strategy is not driven entirely or primarily by a particular episode 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 carry and momentum. Finally, in Figure 2 we report cumulative returns over time for the three strategies, for both the sample of developed countries and the full sample. Of particular interest is the decomposition of the cumulative excess return into its two constituents: the exchange rate component (FX) and the interest rate gain component (yield). Both carry and momentum strategies 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 momentum, 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. The VRP-based portfolio returns are very 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 from the VRP-strategy. In short, the VRP-strategy is the only strategy for which the interest rate differential across countries detracts from the full portfolio return, which makes it non-controversial that the VRP contains predictive information only about spot exchange rate fluctuations, not interest rates.

Taken together, the results from the previous analysis and from the double sorting exercise 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 either carry or momentum for exchange rate returns and the predictive information content is largely independent of carry and momentum. This means that a currency manager would benefit greatly from adding the VRP strategy to carry and momentum to enhance risk-adjusted returns, and also that a spot trader interested in forecasting exchange rate fluctuations (as opposed to excess returns) would value the VRP strategy more than carry and momentum.

4.3 Pricing the Returns from VRP-sorted portfolios

In this section we carry out some cross-sectional asset pricing tests to determine whether the returns from the VRP-based strategy can be understood as compensation for systematic risk. The results 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 start 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 that risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$\mathbb{E}[M_{t+1}RX_{t+1}^i] = 0 \tag{9}$$

with a linear SDF $M_t = 1 - b'(H_t - \mu)$ and H denoting a vector of risk factors. b is the vector of SDF parameters and μ denotes factor means. This specification implies a beta pricing model where expected excess returns depend on factor risk prices λ and risk quantities β_i , which are the regression betas of portfolio excess returns on the risk factors:

$$\mathbb{E}\left[RX^{i}\right] = \lambda'\beta_{i} \tag{10}$$

for each portfolio *i* (see e.g., Cochrane, 2005). The relationship between the factor risk prices in Equation (10) and the SDF parameters in Equation (9) is given by $\lambda = \Sigma_H b$ such that factor risk prices, as in the traditional Fama-MacBeth (FMB) approach, can be easily obtained via the SDF approach as well. We estimate parameters of Equation (9) via the generalized method of moments (GMM).²¹

²¹Estimation 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 per se (see Cochrane, 2005; Burnside, 2011).

In our asset pricing tests we consider a two-factor linear model that comprises DOL and one more risk factor (RF), which is one of HML_{FX} , VOL_{FX} , $ILLIQ_{FX}$, and $ILLIQ_{VP}$, which we define below. DOL denotes the average return from borrowing in the US money market and equally investing in foreign money markets. HML_{FX} 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 (see Lustig, Roussanov and Verdelhan, 2011). VOL_{FX} denotes a global FX volatility risk factor constructed as the innovations to global FX volatility. $ILLIQ_{FX}$ is a global FX illiquidity factor constructed as the global bid-ask spread of spot exchange rates. VOL_{FX} and $ILLIQ_{FX}$ are constructed as in Menkhoff, Sarno, Schmeling and Schrimpf (2012a). $ILLIQ_{VP}$ is a global illiquidity factor for FX options constructed exactly like $ILLIQ_{FX}$ except that we use the bid-ask spread of the at-the-money implied volatilities rather than the bid-ask spread of currencies.

In Table 6 we report GMM estimates of b and implied λ s as well as cross-sectional R^2 s and the Hansen-Jagannathan (HJ) distance measure (Hansen and Jagannathan, 1997). Standard errors are based on Newey and West (1987) with optimal lag length selection according to Andrews (1991).²² In assessing our results, we are aware of the statistical problems plaguing standard asset pricing tests, recently emphasized by Lewellen, Nagel and Shanken (2010): specifically, asset-pricing tests are often highly misleading in the sense that they can indicate illusory strong explanatory power in terms of high cross-sectional R^2 and small pricing errors when in fact a risk factor has no or weak pricing power. Given the relatively small crosssection of currencies and time span of our sample, these problems can be severe in our tests. Hence, in 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. Starting from Panel A of Table 6, we can see clearly how none of the risk factors considered enters the

²²Besides the GMM tests, we employ the traditional FMB two-pass OLS methodology 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. We point out, however, that our results are virtually identical when we replace the DOL factor with a constant in the second stage regressions. Since DOL has basically no cross-sectional relation to the carry trade portfolios' returns, it serves the same purpose as a constant that allows for a common mispricing. Also see Lustig and Verdelhan (2007) and Burnside (2011) on the issue of whether to include a constant or not. The FMB results are qualitatively and in most cases also quantitatively identical to the one-step GMM results reported in Table 6, and hence not reported to conserve space.

SDF with a statistically significant risk price λ , and this is the case for both the developed countries and the full sample. The best performing SDF includes DOL and $ILLIQ_{VP}$ which generates some highly respectable cross-sectional R^2 (0.57 and 0.80) but the market price of risk is marginally 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.

Panel B of Table 6 reports asset pricing tests, carried out using the same methods and risk factors as for Panel A, where we attempt to price only the exchange rate component of the returns from the VRP-based strategy. The results are equally disappointing in that all risk factors included in the various SDF specifications are statistically insignificant except $ILLIQ_{VP}$, which enters significantly and an intuitively clear positive sign – higher illiquidity in the options market is associated with higher returns from the VRP strategy. However, even this result is not particularly convincing, as the vector of SDF parameters b is insignificantly different from zero.

Overall, the asset pricing tests in this section reveal that it is not possible to understand the returns from the VRP strategy as compensation for risk using the carry risk factor and global measures of volatility risk and illiquidity in the FX market of the kind used in the literature. While this result is somewhat disappointing, it is also consistent with our earlier results that indicate that the VRP portfolio returns are very different from carry and momentum returns, and hence their source is likely to stem from a different mechanism rather than as a compensation for canonical sources of systematic risk.²³ Therefore, we now turn to examine an alternative mechanism.

4.4 Explaining the Performance of the VRP strategy

A potential explanation for the predictive power of the VRP is that it arises from the interaction between natural hedgers of FX risk and speculators. The explanation has additional testable implications which we test in Table 7. The table presents coefficients from predictive time-series regressions of the exchange rate component of the VRP-sorted portfolio returns

²³In unreported results, we also carried out asset pricing tests where we use the three-factor Fama-French model, and also its four-factor variant that also allows for equity momentum. These equity risk factors are also unable to price the returns from the VRP strategy.

on a number of conditioning factors implied by our proposed mechanism. We report results from the exchange rate component of the VRP returns since we are primarily interested in understanding the predictive power of the VRP for spot exchange rates, but the results for the VRP portfolio returns are, not surprisingly, qualitatively identical and quantitatively very similar.

The first column in both panels shows the univariate regression of the exchange rate component of the VRP portfolio returns on the lagged TED spread. At times when funding liquidity is lower (i.e., times of high capital constraints on speculators), we should find that the expected (exchange rate) return from the VRP strategy should increase, and Table 7 provides strong confirmation for this for developed countries. While the sign of the coefficient on TED is positive for the full sample, it is not statistically significant. In our view, this could be because the TED spread is possibly less useful as a proxy for funding liquidity constraints for emerging markets. The second column shows that when changes in VIX are positive, which we use as a proxy to capture increases in the risk aversion of natural hedgers, the VRP strategy FX return increases, again consistent with the explanation. Again, this result is only significant for the sample of developed countries. The third column 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.

The next two columns use data from CFTC's Commitments of Traders reports, and create measures of hedging demand for the carry trade, a favoured strategy of speculators. The measure we consider is the net short position in Australian dollar futures plus the net long position in the Japanese yen, normalized by total positions. The idea of this measure is that it should capture the risk appetite of speculators – when the measure is high, it suggests that speculators are averse to carry risk, in the sense that they are reluctant to take positions in high interest rate currencies like the Australian dollar, and more inclined to go long futures of safe haven currencies like the yen. We also substitute the Swiss franc for the yen and use this alternative construction as a robustness check in the fifth column of each panel. Table 7 shows that, as predicted, when speculators' risk appetite is diminished, the expected returns to the VRP-sorted strategy increase. This is true for both measures that we consider.

The final columns in the two panels of the table add in measures of capital flows into hedge funds, constructed as the change in assets under management less accrued returns, normalized by lagged assets under management of the combined universe of hedge funds in the TASS, HFR, CISDM, Barclay Hedge and Morningstar databases (with roughly \$2 trillion under management as of end 2012). When capital flows into hedge funds are high, signifying that they experience fewer constraints on their ability to engage in arbitrage transactions and provide insurance, we find that the returns for our VRP-sorted portfolio are lower and vice versa.

The final three rows of Table 7 add in several of the variables described above together to test their joint explanatory power, and individual contributions to the proposed explanation of our results that relies on the interaction between hedgers and speculators in currency markets. 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. We find that all the variables retain their signs and are generally statistically significant in these predictive regressions, offering support to the explanation of our results.

Finally, we examine post-formation portfolio returns. Under our proposed explanation for the spot predictability in the VRP, this predictability cannot be very long-lived. Recall the scenario where speculators face a shock that reduces their available arbitrage capital and limits their ability to provide cheap volatility insurance. Ned demand for volatility insurance increases, making hedging more expensive, as reflected in a lower VRP for currencies. Given the high cost of volatility insurance, 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., a higher VRP and relatively higher returns on the spot currency position. This implies – as a testable implication – reversal in post-formation cumulative returns, which is exactly what we find. In Figure 3, we plot cumulative post-formation excess returns (left) and exchange rate returns (right) over periods of $1, 2, \ldots, 20$ months for the VRP-sorted portfolios, for both samples of countries examined. Specifically we plot returns net of the exposure to carry trade risk, i.e., we use the residuals from a regression of portfolio returns or exchange rate returns on HML_{FX} , so that the returns can be considered as alphas over and above carry trade returns.²⁴ Returns in the post-formation period are overlapping since we form new portfolios each month but track these portfolios for 20 months. Starting from excess returns, there is a clear pattern of increasing returns that peaks after 3 months for the developed countries sample and 4 months for the full sample, and a subsequent period of declining excess returns. Looking at spot exchange rate returns (the FX component of the strategy returns), the peak in cumulative post-formation exchange rate return actually occurs around 4 months for the developed sample and 5-6 months for the full sample. Thus, on the face of it, this evidence looks consistent with the reversal implied by our proposed explanation of the economic source of VRP predictive power.

Overall, taken together, the empirical results in this section lend some support to our proposed explanation for the predictability of spot exchange rates arising from the VRP, and the mechanism considered here is consistent with the growing theoretical and empirical literature that highlights the role of limits to arbitrage and the interaction between hedgers and speculators in asset markets.

5 Conclusions

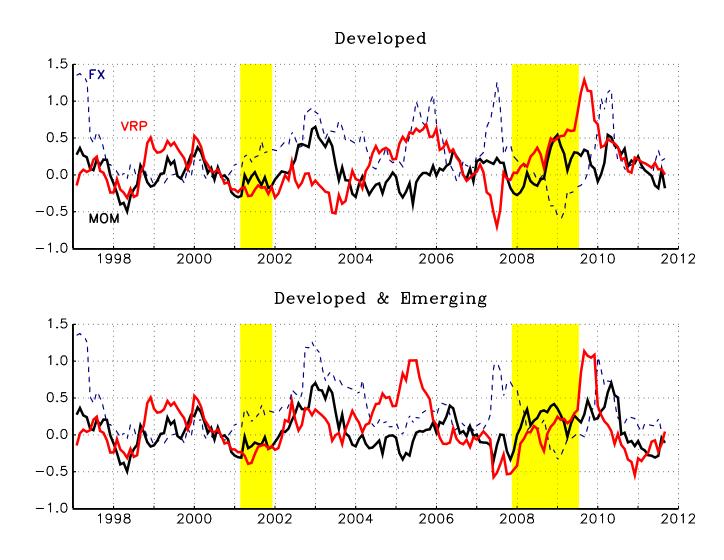
We show that the currency volatility risk premium (VRP) has substantial predictive power for the cross-section of currency returns. Sorting currencies on the VRP generates economically significant returns in a standard multi-currency portfolio setting. This predictive power is specifically related to spot exchange rate returns, not interest rate differentials, and the spot rate predictability is much stronger than that observed from carry and currency momentum strategies. Specifically, currencies for which volatility insurance is relatively cheap tend to predictably appreciate, while currencies for which volatility hedging is relatively expensive tend to predictably depreciate. We also find that the returns from our VRP-sorted strategy are largely uncorrelated with carry and momentum strategies, thus providing a substantial diversification gain to investors. We confirm that double sorting currency portfolios by both the VRP and either carry or momentum does not affect the predictive power of the VRP. Finally, standard risk factors cannot price satisfactorily the returns from portfolios sorted on

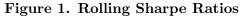
²⁴Using raw portfolio returns or their exchange rate component produces a very similar pattern for the full sample, and a virtually identical pattern for the developed sample, as expected given that we know already from previous analyses that HML_{FX} has almost no pricing power for the VRP-sorted returns.

the VRP, corroborating the notion that this strategy delivers a source of predictable returns that cannot easily be replicated using extant trading strategies.

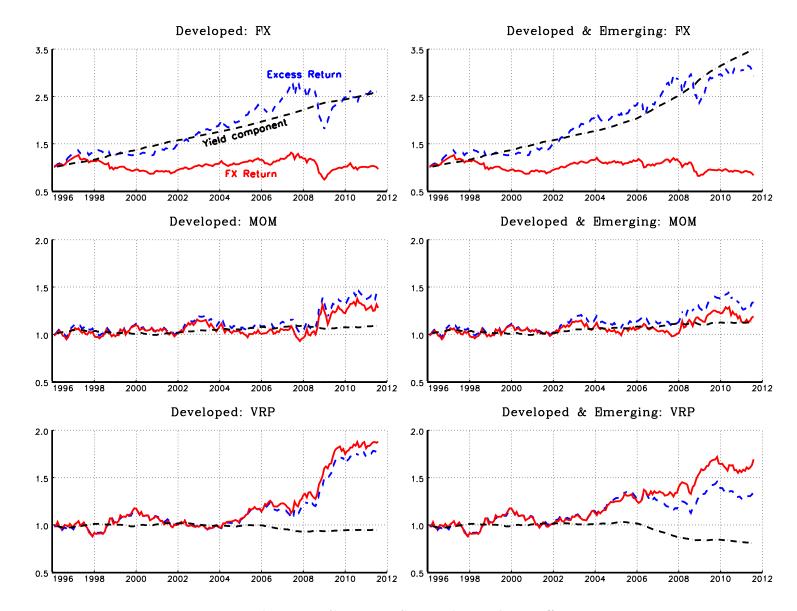
We provide some evidence that the exchange rate predictability embedded in the VRP can be rationalized in terms of the time-variation of limits to arbitrage capital and the incentives of hedgers and speculators in financial markets. Specifically, the returns from the VRP strategy appear to be higher at times when funding liquidity is lower, risk aversion is higher, and there is increasing demand for hedging high-risk currency positions. This seems consistent with the notion 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 expensive volatility protection. The pattern of exchange rate predictability stemming from the VRP appears to be empirically consistent with this simple mechanism.

Overall, the results in this paper provide new insights into the predictability of the crosssection of exchange rate returns and the linkages between the cost of volatility protection and the returns from underlying currencies.





The figure presents the one-year rolling Sharpe ratios on long/short currency strategies formed using time t-1 information. FX is the carry trade strategy that buys (sells) the top 20% of all currencies currencies with the highest (lowest) interest rate differential relative to the US dollar. MOM is the momentum strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia. The Shaded areas are the NBER recession periods for the US. 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.





The figure presents the cumulative payoffs of long/short currency strategies formed using time t-1 information. FX is the carry trade strategy that buys (sells) the top 20% of all currencies currencies with the highest (lowest) interest rate differential relative to the US dollar. MOM is the momentum strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia. 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.

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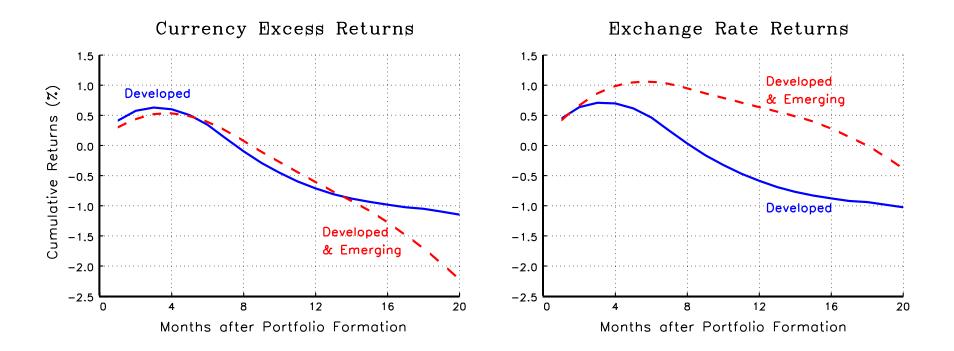


Figure 3. Long-horizon Returns

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 $1, 2, \ldots, 20$ 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.

Table 1. Descriptive Statistics of Volatility Risk Premia

This table presents summary statistics for the annualized average realized volatility $RV_{t,\tau}$ (Panel A), synthetic volatility swap rate $SW_{t,\tau}$ (Panel B), and volatility risk premium $VRP_{t,\tau} = RV_{t,\tau} - SW_{t,\tau}$ (Panel C) where τ , the maturity of the volatility swap, is equal to 1-year. $RV_{t,\tau}$ is computed at time t using daily exchange rate returns between times $t - \tau$ and t. $SW_{t,\tau}$ is constructed at time t using τ -period implied volatilities across 5 different deltas as in Jiang and Tian (2005). The volatility risk premium $VRP_{t,\tau}$ is constructed as the difference between $RV_{t,\tau}$ and $SW_{t,\tau}$. Q_j refers to the j^{th} percentile. AC_{τ} indicates the τ^{th} -order autocorrelation coefficient. 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.

	$RV_{t,\tau} \times 100$	$SW_{t,\tau} \times 100$	$VRP_{t,\tau} \times 100$	$RV_{t,\tau} \times 100$	$SW_{t,\tau} \times 100$	$VRP_{t,\tau} \times 100$
		Developed		Dec	veloped & Eme	rging
Mean	10.68	11.31	-0.62	10.82	11.74	-0.92
Sdev	2.88	2.75	1.58	3.10	3.22	1.78
Skew	1.85	1.42	0.54	2.12	2.07	-0.31
Kurt	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
AC_{τ}	0.33	0.53	-0.19	0.27	0.46	-0.17

Table 2. Descriptive Statistics of Currency Strategies

This table presents descriptive statistics of long/short currency strategies formed using time t-1 information. FX 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. MOM is the momentum strategy that buys (sells) the top 20% of all currencies with the highest (lowest) lagged 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia. 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: Currency Excess Returns												
	FX	MOM	VRP	FX	MOM	VRP							
		Developed		Develo	Developed & Emerging								
Mean	6.49	2.58	4.03	7.42	2.22	2.34							
Sdev	10.66	9.55	8.33	9.97	8.30	8.18							
Skew	-0.92	0.35	0.28	-0.92	-0.03	0.12							
Kurt	5.65	3.86	3.47	4.53	2.95	3.26							
SR	0.61	0.27	0.48	0.74	0.27	0.29							
	(0.089)	(0.068)	(0.072)	(0.080)	(0.069)	(0.075)							
SO	0.72	0.50	0.87	0.94	0.47	0.49							
MDD	-0.37	-0.16	-0.18	-0.21	-0.13	-0.18							
AC_1	0.09	0.01	0.04	0.01	-0.09	0.05							
$Freq_L$	0.13	0.48	0.24	0.15	0.49	0.26							
$Freq_S$	0.07	0.43	0.32	0.16	0.46	0.27							
		Pane	l B: Exchai	nge Rate Re	turns								
Mean	0.34	2.03	4.40	-0.65	1.45	3.72							
Sdev	10.66	9.57	8.35	9.99	8.16	8.1'							
Skew	-0.93	0.42	0.28	-1.05	-0.02	0.12							
Kurt	5.82	4.17	3.61	4.84	3.13	3.50							
SR	0.03	0.21	0.53	-0.07	0.18	0.40							
	(0.079)	(0.068)	(0.072)	(0.072)	(0.067)	(0.075)							
SO	0.04	0.40	0.93	-0.08	0.30	0.75							
MDD	-0.43	-0.20	-0.19	-0.35	-0.15	-0.18							
AC_1	0.11	0.01	0.04	0.03	-0.12	0.04							
$Freq_L$	0.13	0.48	0.24	0.15	0.49	0.26							
$Freq_S$	0.07	0.43	0.32	0.16	0.46	0.2'							

Table 3. Sample Correlations of Currency Strategies

This table presents the sample correlations of long/short currency strategies formed using time t-1 information. FX is the carry trade strategy that buys (sells) the top 20% of all currencies currencies with the highest (lowest) interest rate differential relative to the US dollar. MOM is the momentum strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 3-month exchange rate return. VRP denotes a strategy that buys (sells) the top 20% of all currencies with the highest (lowest) 1-year volatility risk premia. *Panel A* displays the overall currency excess return whereas *Panel B* reports only the exchange rate component. 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: Currency Excess Returns												
	FX	MOM	VRP	FX	MOM	VRP							
		Developed		Develo	Developed & Emerging								
FX	1.00			1.00									
MOM	-0.17	1.00		-0.03	1.00								
VRP	-0.18	0.09	1.00	-0.21	0.10	1.00							
		Panel B	: Excha	nge Rate I	Returns								
FX	1.00			1.00									
MOM	-0.17	1.00		-0.04	1.00								
VRP	-0.19	0.10	1.00	-0.22	0.12	1.00							

Table 4. Portfolios Sorted on Volatility Risk Premia

This table presents descriptive statistics of five currency portfolios sorted on the 1-year volatility risk premia VRP at time t - 1. The first (last) 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: Curren	cy Excess R	eturns					
	P_L	P_2	P_3	P_4	P_S	DOL	HML	P_L	P_2	P_3	P_4	P_S	DOL	HML
	Developed									Develo	oped & En	nerging		
Mean	4.70	2.24	1.04	1.78	0.67	2.08	4.03	3.59	1.93	1.34	1.40	1.26	1.90	2.34
Sdev	9.08	9.27	9.76	10.07	9.72	8.14	8.33	9.32	8.68	8.89	10.44	8.81	8.07	8.18
Skew	-0.05	0.19	0.09	-0.17	-0.26	0.00	0.28	-0.09	0.05	-0.21	-0.29	-0.39	-0.25	0.12
Kurt	3.13	5.14	5.80	3.85	3.82	3.95	3.47	3.09	4.79	3.85	4.16	3.73	4.37	3.26
SR	0.52	0.24	0.11	0.18	0.07	0.26	0.48	0.39	0.22	0.15	0.13	0.14	0.24	0.29
	(0.078)	(0.084)	(0.077)	(0.081)	(0.073)	(0.073)	(0.073)	(0.074)	(0.085)	(0.079)	(0.078)	(0.075)	(0.086)	(0.072)
SO	0.85	0.39	0.16	0.27	0.10	0.41	0.87	0.62	0.35	0.22	0.19	0.20	0.34	0.49
MDD	-0.27	-0.36	-0.43	-0.35	-0.32	-0.31	-0.18	-0.27	-0.37	-0.42	-0.35	-0.30	-0.31	-0.18
AC_1	0.10	0.04	0.13	0.15	0.01	0.13	0.04	0.10	0.14	0.15	0.13	0.11	0.16	0.05
Freq	0.24	0.44	0.52	0.48	0.32	0.24	0.32	0.26	0.43	0.53	0.48	0.27	0.26	0.27
						Pane	l B: Excha	nge Rate Re	turns					
Mean	4.93	2.06	1.26	1.60	0.52	2.07	4.40	3.51	1.62	1.37	0.82	-0.21	1.42	3.72
Sdev	9.05	9.24	9.63	9.96	9.64	8.05	8.35	9.26	8.62	8.74	10.31	8.75	7.98	8.17
Skew	-0.12	0.15	0.06	-0.18	-0.26	-0.02	0.28	-0.18	0.00	-0.26	-0.31	-0.47	-0.33	0.12
Kurt	3.17	5.24	5.88	4.06	3.83	3.99	3.61	3.07	4.80	4.02	4.36	3.94	4.56	3.50
SR	0.54	0.22	0.13	0.16	0.05	0.26	0.53	0.38	0.19	0.16	0.08	-0.02	0.18	0.46
	(0.078)	(0.082)	(0.078)	(0.081)	(0.073)	(0.078)	(0.072)	(0.074)	(0.084)	(0.081)	(0.074)	(0.075)	(0.084)	(0.075)
SO	0.87	0.35	0.20	0.25	0.08	0.41	0.93	0.59	0.29	0.23	0.11	-0.03	0.25	0.75
MDD	-0.26	-0.34	-0.38	-0.31	-0.29	-0.27	-0.19	-0.26	-0.34	-0.36	-0.32	-0.30	-0.27	-0.18
AC_1	0.10	0.03	0.11	0.13	-0.01	0.12	0.04	0.10	0.13	0.13	0.10	0.10	0.15	0.04
Freq	0.24	0.44	0.52	0.48	0.32	0.24	0.32	0.26	0.43	0.53	0.48	0.27	0.26	0.27

Table 5. 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: Curren	cy Excess R	eturns				
	=	\Rightarrow \Rightarrow			=	⇒	=	⇒	=	⇒	=	\Rightarrow
	MOM	FX	VRP	FX	VRP	MOM	MOM	FX	VRP	FX	VRP	MOM
	Developed							Develo	oped & Eme	erging	ring	
Mean	1.43	3.28	2.38	3.34	2.02	1.64	1.03	3.33	1.08	4.27	0.84	2.1
Sdev	6.42	5.51	4.73	5.68	4.80	5.65	5.73	5.08	4.76	5.67	4.80	5.0
Skew	0.09	-0.59	-0.33	-0.69	-0.03	0.11	-0.37	-0.84	0.03	-1.00	0.20	-0.1
Kurt	4.54	5.09	3.42	4.15	3.29	3.66	3.87	4.17	3.78	4.63	3.79	4.3
SR	0.22	0.60	0.50	0.59	0.42	0.29	0.18	0.66	0.23	0.75	0.18	0.42
	(0.073)	(0.078)	(0.067)	(0.082)	(0.072)	(0.071)	(0.074)	(0.074)	(0.072)	(0.085)	(0.072)	(0.070)
SO	0.33	0.77	0.77	0.78	0.70	0.50	0.25	0.84	0.37	0.99	0.30	0.6
MDD	-0.16	-0.15	-0.13	-0.18	-0.14	-0.11	-0.16	-0.10	-0.15	-0.17	-0.15	-0.0
AC_1	0.04	-0.05	-0.07	0.03	0.05	0.05	0.07	-0.06	-0.02	0.14	0.03	-0.0
$Freq_L$	0.36	0.36	0.27	0.27	0.47	0.47	0.38	0.38	0.27	0.27	0.43	0.4
$Freq_S$	0.38	0.38	0.31	0.31	0.47	0.47	0.38	0.38	0.29	0.29	0.42	0.4
				Pane	el B: Exchan	ge Rate Re	eturns					
Mean	0.22	0.32	1.97	0.38	2.08	1.19	0.17	-0.57	1.52	0.32	1.54	1.5
Sdev	6.42	5.52	4.74	5.71	4.83	5.65	5.67	5.11	4.81	5.73	4.85	5.0
Skew	0.18	-0.58	-0.40	-0.72	-0.08	0.17	-0.31	-0.92	-0.01	-1.10	0.19	-0.0
Kurt	4.84	5.16	3.42	4.24	3.33	3.95	3.92	4.33	3.90	4.98	3.95	4.6
SR	0.03	0.06	0.42	0.07	0.43	0.21	0.03	-0.11	0.32	0.06	0.32	0.3
	(0.073)	(0.076)	(0.067)	(0.080)	(0.072)	(0.073)	(0.073)	(0.058)	(0.072)	(0.086)	(0.072)	(0.073)
SO	0.05	0.07	0.61	0.09	0.71	0.35	0.04	-0.14	0.51	0.07	0.55	0.4
MDD	-0.25	-0.20	-0.15	-0.21	-0.14	-0.14	-0.23	-0.19	-0.15	-0.20	-0.15	-0.1
AC_1	0.03	-0.04	-0.07	0.04	0.05	0.05	0.05	-0.04	-0.01	0.16	0.03	-0.0
$Freq_L$	0.36	0.36	0.27	0.27	0.56	0.56	0.38	0.38	0.27	0.27	0.43	0.4
$Freq_S$	0.38	0.38	0.31	0.31	0.58	0.58	0.38	0.38	0.29	0.29	0.42	0.4

Table 6. Asset Pricing Tests

This table reports asset pricing results for a linear factor model that includes DOL and RF as risk factors. Our risk factors includes HML_{FX} , VOL_{FX} , $ILLIQ_{FX}$, and $ILLIQ_{VP}$. The test assets are currency excess returns (*Panel A*) and exchange rate returns (*Panel B*) to five portfolios sorted on the 1-year volatility risk premia available at time t - 1. DOL denotes the average return from borrowing in the US money market and equally investing in foreign money markets. HML_{FX} 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. VOL_{FX} denotes the global FX volatility risk factor constructed as the innovations to the average exchange rate volatility across currencies. $ILLIQ_{FX}$ is the illiquidity risk factor constructed using the average bid-ask spreads across our spot exchange rates. $ILLIQ_{VP}$ is the illiquidity risk factor constructed using the average bid-ask spreads across our spot exchange rates. $ILLIQ_{VP}$ is the illiquidity risk factor constructed using the average bid-ask spreads across our spot exchange rates. $ILLIQ_{VP}$ is the illiquidity risk factor constructed using the average bid-ask spreads across our spot exchange rates. $ILLIQ_{VP}$ is the illiquidity risk factor constructed using the average bid-ask spreads of the at-the-money implied volatilities. The table reports one-stage GMM estimates of the factor loadings b, and the market price of risk λ . The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parenthesis. The *p-values* are reported in brackets. Returns are expressed in percentage per annum. 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 M

						Panel	A: Curre	ency Exce	ss Returns							
RF	b_{DOL}	b_{RF}	λ_{DOL}	λ_{RF}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{RF}	λ_{DOL}	λ_{RF}	R^2	RMSE	χ^2	HJ
Developed											D	eveloped	& Emerge	ing		
HML_{FX}	0.42	-0.47	0.02	-0.05	-0.07	3.29	4.35	0.16	0.24	0.01	0.02	0.01	-0.14	2.09	1.93	0.11
	(0.36)	(0.55)	(0.02)	(0.07)			[0.23]	[0.20]	(0.35)	(0.51)	(0.02)	(0.06)			[0.59]	[0.59]
VOL_{FX}	0.52	0.36	0.02	0.57	0.26	2.74	3.02	0.13	0.48	0.16	0.02	0.29	-0.07	2.04	2.31	0.11
	(0.32)	(0.23)	(0.02)	(0.37)			[0.39]	[0.44]	(0.72)	(0.43)	(0.02)	(0.78)			[0.51]	[0.55]
$ILLIQ_{FX}$	0.32	0.40	0.02	0.02	0.03	2.59	3.81	0.13	0.74	4.50	0.02	0.21	0.26	2.62	3.58	0.15
	(0.59)	(2.62)	(0.02)	(0.13)			[0.28]	[0.39]	(0.66)	(5.87)	(0.02)	(0.16)			[0.31]	[0.53]
$ILLIQ_{VP}$	0.83	14.78	0.02	0.10	0.57	2.10	1.23	0.11	0.18	5.63	0.02	0.10	0.80	0.87	0.32	0.05
	(0.71)	(11.72)	(0.02)	(0.06)			[0.75]	[0.87]	(0.32)	(5.33)	(0.02)	(0.07)			[0.96]	[0.96]
						Pane	l B: Excl	ange Rat	e Returns							
HML_{FX}	0.43	-0.50	0.02	-0.06	-0.05	3.46	5.23	0.17	0.30	-0.44	0.01	-0.05	0.13	2.54	3.12	0.13
	(0.36)	(0.52)	(0.02)	(0.07)			[0.16]	[0.14]	(0.34)	(0.47)	(0.02)	(0.05)			[0.37]	[0.37]
VOL_{FX}	0.58	0.42	0.02	0.65	0.35	2.74	2.74	0.13	0.94	0.48	0.02	0.94	0.26	2.34	2.47	0.12
	(0.33)	(0.25)	(0.02)	(0.38)			[0.43]	[0.47]	(0.87)	(0.49)	(0.02)	(0.76)			[0.48]	[0.55]
$ILLIQ_{FX}$	0.37	0.77	0.02	0.04	0.05	2.54	3.87	0.13	0.74	5.08	0.01	0.24	0.39	2.28	2.07	0.13
	(0.67)	(3.31)	(0.02)	(0.15)			[0.28]	[0.37]	(0.61)	(5.42)	(0.02)	(0.14)			[0.56]	[0.65]
$ILLIQ_{VP}$	0.77	14.77	0.02	0.10	0.53	2.33	1.61	0.12	0.14	6.42	0.02	0.13	0.77	1.32	0.71	0.08
	(0.66)	(11.36)	(0.02)	(0.05)			[0.66]	[0.83]	(0.36)	(5.52)	(0.02)	(0.07)			[0.87]	[0.90]

Table 7. Risk Factors: Liquidity and Hedging

This table presents least squares estimates of predictive regressions. The dependent variable is the monthly exchange rate component of the VRP strategy at time t. This strategy is 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 include the TED spread, the VIX index, the hedgers net position on carry trade strategies, proxied as net short futures position on Australian dollar A\$ and net long futures position on the Japanese Yen Ψ (Swiss franc SFr), and the changes in the number of speculators measured as net flow of new funds to hedge funds, scaled by the lagged assets under management. Newey and West (1987) standard errors are reported in parenthesis. The superscripts a, b, and c indicate statistical significance at 10%, 5%, and 1%, respectively. Returns are expressed in percentage per annum. Exchange rates are from *Datastream*, implied volatility quotes are from JP Morgan, hedging positions are from the US Commodity Futures Trading Commission (CFTC), hedge fund flows are from Patton and Ramadorai (2013), whereas all other data are from Bloomberg.

			$TED \times$	Hedging	Position	Hedge Fund					$TED \times$	Hedging	g Position	Hedge Fund	
α	TED	ΔVIX	ΔVIX	A\$/¥	A\$/SFr	Flows	$\overline{R}^2_{(\%)}$	α	TED	ΔVIX	ΔVIX	A	A\$/SFr	Flows	$\overline{R}^2_{(\%)}$
			D e	eveloped							Develope	ed & Emer	ging		
-0.301 (0.278)	$1.326^b\ (0.570)$						3.0	$\begin{array}{c} 0.043 \\ (0.286) \end{array}$	$\begin{array}{c} 0.530 \\ (0.548) \end{array}$						0.1
0.350^b (0.172)		0.004^{a} (0.002)					1.4	$\begin{array}{c} 0.297^{a} \ (0.171) \end{array}$		0.003 (0.002)					0.7
$0.258 \\ (0.160)$			$\begin{array}{c} 0.007^c \ (0.001) \end{array}$				4.7	$0.234 \\ (0.166)$			$0.005^c \ (0.002)$				2.1
0.385^b (0.182)				$\begin{array}{c} 0.130^c \ (0.016) \end{array}$			1.5	0.327^a (0.176)				$\begin{array}{c} 0.119^c \ (0.017) \end{array}$			1.2
0.388^b (0.182)					$egin{array}{c} 0.130^c \ (0.022) \end{array}$		1.5	$\begin{array}{c} 0.330^{a} \ (0.177) \end{array}$					$\begin{array}{c} 0.121^c \ (0.022) \end{array}$		1.3
$0.458^b \\ (0.204)$						$egin{array}{c} -0.125^a \ (0.065) \end{array}$	2.4	$\begin{array}{c} 0.379^{a} \ (0.193) \end{array}$						${-0.095^a} \ (0.061)$	1.2
-0.074 (0.335)	1.023^a (0.609)			$\begin{array}{c} 0.119^c \ (0.015) \end{array}$		-0.079 (0.061)	4.8	$\begin{array}{c} 0.268 \ (0.330) \end{array}$	$\begin{array}{c} 0.229 \\ (0.57) \end{array}$			$\begin{array}{c} 0.110^c \ (0.018) \end{array}$		-0.079 (0.062)	1.8
0.442^b (0.191)		$0.003 \\ (0.002)$		$\begin{array}{c} 0.118^c \ (0.015) \end{array}$		-0.098^a (0.058)	4.0	$\begin{array}{c} 0.369^b \ (0.186) \end{array}$		$0.002 \\ (0.002)$		$\begin{array}{c} 0.110^{c} \ (0.017) \end{array}$		-0.073 (0.057)	2.3
$\begin{array}{c} 0.348^{a} \\ (0.182) \end{array}$			0.006^{c} (0.001)	$\begin{array}{c} 0.118^c \ (0.015) \end{array}$		-0.080 (0.053)	6.6	$\begin{array}{c} 0.306^{a} \ (0.185) \end{array}$			$\begin{array}{c} 0.004^{c} \ (0.002) \end{array}$	$0.110^{c}\ (0.017)$		-0.062 (0.056)	3.5

Table A1. Descriptive Statistics of the 1-Year Volatility Swaps

This table presents summary statistics for the volatility risk premium (Panel A) and realized volatility premium (Panel B). The τ -period volatility risk premium is constructed as difference between the lagged realized volatility $RV_{t-\tau,\tau}$ and the synthetic volatility swap rate $SW_{t,\tau}$, whereas the realized volatility premium is computed as difference between the ex-post realized volatility $RV_{t,\tau}$ and SW_t . The synthetic volatility swap rate constructed using τ -year implied volatilities across 5 different deltas as in Jiang and Tian (2005). τ denotes the maturity of volatility swap and is equal to 1-year. Q_j refer to j^{th} percentile. AC_{τ} indicates the τ^{th} -order autocorrelation coefficient. The sample period comprises daily data from January 1996 to August 2012. Exchange rates are from Datastream whereas implied volatility quotes are proprietary data from JP Morgan.

	Par	nel A: Vo	latility I	Risk Prer	nium (R	$V_{t-\tau,t} - S$	$(W_{t,\tau}) \times (W_{t,\tau})$	100	Pan	el B: Rea	alized Vo	olatility I	Premium	$(RV_{t,\tau} -$	$\overline{SW_t}$ ×	100
	Mean	Med	Sdev	Skew	Kurt	Q_5	Q_{95}	AC_{τ}	 Mean	Med	Sdev	Skew	Kurt	Q_5	Q_{95}	AC_{τ}
AUD	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
CAD	-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
CHF	-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
DKK	-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
EUR	-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
GBP	-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
JPY	-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
NOK	-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
NZD	-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
SEK	-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
BRL	-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
CZK	-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
HUF	-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
KRW	-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
MXN	-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
PLN	-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
SGD	-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
TRY	-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
TWD	-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
ZAR	-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
Mean	-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 A2. Asset Pricing Tests I

This table reports asset pricing results. The linear factor model includes the dollar (DOL) and the slope (HML_{FX}) risk factors. HML_{FX} 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. The test assets are currency excess returns (*Panel A*) and exchange rate returns (*Panel B*) to five portfolios sorted on the 1-year volatility risk premia (VRP) available at time t - 1. The table reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ , and least squares estimates of time series slopes β . The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection and Shanken (1992) standard errors (sh) are reported in parenthesis. The *p*-values are reported in brackets. Excess returns are expressed in percentage per annum. 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.

						Pane	el A: Cui	rency Ex	cess Retur	rns						
								Factor	Prices							
	b_{DOL}	b_{HML}	λ_{DOL}	λ_{HML}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{HML}	λ_{DOL}	λ_{HML}	R^2	RMSE	χ^2	HJ
					loped						D	eveloped	び Emerg	ing		
GMM_1	0.42	-0.47	0.02	-0.05	-0.07	3.29	4.35	0.16	0.24	0.01	0.02	0.01	-0.14	2.09	1.93	0.11
	(0.36)	(0.55)	(0.02)	(0.07)			[0.23]	[0.20]	(0.35)	(0.51)	(0.02)	(0.06)			[0.59]	[0.59]
GMM_2	0.35	-0.37	0.02	-0.03	-0.09	3.32	4.30		0.24	0.09	0.02	0.02	-0.15	2.10	1.90	
	(0.36)	(0.54)	(0.02)	(0.07)			[0.23]		(0.35)	(0.50)	(0.02)	(0.06)			[0.59]	
FMB	0.42	-0.47	0.02	-0.05	-0.07	3.29	4.35		0.24	0.01	0.02	0.01	-0.14	2.09	1.93	
	(0.37)	(0.58)	(0.02)	(0.07)			[0.23]		(0.34)	(0.52)	(0.02)	(0.06)			[0.59]	
(sh)	(0.34)	(0.61)	(0.02)	(0.08)					(0.30)	(0.53)	(0.02)	(0.06)			2 3	
								Factor	· Betas							
		α	β_{DOL}	β_{HML}	R^2	χ^2				α	β_{DOL}	β_{HML}	R^2	χ^2		
P_L		0.03	0.89	-0.04	0.62	8.75	-			0.02	0.96	-0.02	0.69	3.10	-	
		(0.02)	(0.06)	(0.07)		[0.12]				(0.01)	(0.04)	(0.05)		[0.68]		
P_2		0.01	0.94	0.04	0.71					0.01	0.96	-0.02	0.79			
		(0.01)	(0.08)	(0.05)						(0.01)	(0.04)	(0.04)				
P_3		-0.01	1.00	0.05	0.72					0.01	1.00	-0.08	0.80			
0		(0.01)	(0.05)	(0.05)						(0.01)	(0.04)	(0.04)				
P_4		0.01	1.15	-0.15	0.81					0.01	1.20	-0.09	0.84			
- 4		(0.01)	(0.05)	(0.05)	0.01					(0.01)	(0.05)	(0.06)	0.01			
P_S		-0.02	1.03	0.08	0.79					-0.02	0.87	0.17	0.75			
- 5		(0.01)	(0.04)	(0.05)	0.15					(0.01)	(0.05)	(0.05)	0.10			

						Pane	el B: Exc	hange Ra	te Return	s						
								Factor	Prices							
	b_{DOL}	b_{HML}	λ_{DOL}	λ_{HML}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{HML}	λ_{DOL}	λ_{HML}	R^2	RMSE	χ^2	HJ
				Deve	eloped						De	$veloped \ \mathcal{E}$	d Emer	ging		
GMM_1	0.43	-0.50	0.02	-0.06	-0.05	3.46	5.23	0.17	0.30	-0.44	0.01	-0.05	0.13	2.54	3.12	0.13
	(0.36)	(0.52)	(0.02)	(0.07)			[0.16]	[0.14]	(0.34)	(0.47)	(0.02)	(0.05)			[0.37]	[0.37]
GMM_2	0.32	-0.36	0.02	-0.03	-0.07	3.50	5.12		0.24	-0.37	0.01	-0.03	0.12	2.56	3.08	
	(0.35)	(0.52)	(0.02)	(0.07)			[0.16]		(0.33)	(0.46)	(0.02)	(0.05)			[0.38]	
FMB	0.43	-0.50	0.02	-0.06	-0.05	3.46	5.22		0.29	-0.44	0.01	-0.05	0.13	2.54	3.12	
	(0.36)	(0.58)	(0.02)	(0.07)			[0.16]		(0.33)	(0.48)	(0.02)	(0.05)			[0.37]	
(sh)	(0.34)	(0.61)	(0.02)	(0.08)					(0.30)	(0.52)	(0.02)	(0.06)				
		. ,						Factor	Betas		. ,	. ,				
		α	β_{DOL}	β_{HML}	R^2	χ^2				α	β_{DOL}	β_{HML}	R^2	χ^2		
P_L		0.03	0.89	-0.04	0.62	5.07	-			0.02	0.96	-0.02	0.69	9.44	-	
		(0.02)	(0.06)	(0.07)		[0.41]				(0.01)	(0.04)	(0.05)		[0.09]		
P_2		0.01	0.93	0.04	0.70					0.01	0.95	-0.02	0.78			
		(0.01)	(0.08)	(0.05)						(0.01)	(0.04)	(0.04)				
P_3		-0.01	0.97	0.06	0.71					0.01	0.98	-0.08	0.80			
- 5		(0.01)	(0.05)	(0.05)						(0.01)	(0.04)	(0.04)				
P_4		0.01	1.13	-0.14	0.80					-0.01	1.18	-0.09	0.83			
14		(0.01)	(0.05)	(0.05)	0.00					(0.01)	(0.05)	(0.06)	0.00			
D		. ,	` '	. ,	0.79					. ,	· /	· /	0.74			
P_S		-0.02	1.01	0.08	0.78					-0.03	0.86	0.18	0.74			
		(0.01)	(0.04)	(0.05)						(0.01)	(0.04)	(0.05)				

 Table A2. Asset Pricing Test I (continued)

Table A3. Asset Pricing Tests II

This table reports asset pricing results. The linear factor model includes the dollar (DOL) and the foreign exchange volatility (VOL_{FX}) risk factors. VOL_{FX} is constructed as the innovations to the global foreign exchange volatility. The test assets are currency excess returns (Panel A) and exchange rate returns (Panel B) to five portfolios sorted on the 1-year volatility risk premia (VRP) available at time t-1. The table reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ , and least squares estimates of time series slopes β . The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection and Shanken (1992) standard errors (sh) are reported in parenthesis. The *p*-values are reported in brackets. Excess returns are expressed in percentage per annum. 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.

						Pan	el A: Cu	rrency E	xcess Retu	irns						
								Facto	or Prices							
	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}	R^2	RMSE	χ^2	HJ
				Deve	loped							eveloped	& Emerg	ing		
GMM_1	0.52	0.36	0.02	0.57	0.26	2.74	3.02	0.13	0.48	0.16	0.02	0.29	-0.07	2.04	2.31	0.11
	(0.32)	(0.23)	(0.02)	(0.37)			[0.39]	[0.44]	(0.72)	(0.43)	(0.02)	(0.78)			[0.51]	[0.55]
GMM_2	0.44	0.29	0.02	0.52	0.25	2.75	2.91		0.30	0.04	0.02	0.08	-0.10	2.06	2.22	
	(0.32)	(0.23)	(0.02)	(0.37)			[0.41]		(0.70)	(0.41)	(0.02)	(0.78)			[0.53]	
FMB	0.52	0.36	0.02	0.57	0.26	2.74	3.02		0.48	0.16	0.02	0.29	-0.07	2.04	2.31	
	(0.36)	(0.23)	(0.02)	(0.37)			[0.39]		(0.66)	(0.39)	(0.02)	(0.78)			[0.51]	
(sh)	(0.33)	(0.27)	(0.02)	(0.43)					(0.71)	(0.43)	(0.02)	(0.86)				
								Facto	or Betas							
		α	β_{DOL}	β_{VOL}	R^2	χ^2				α	β_{DOL}	β_{VOL}	R^2	χ^2	_	
P_L		0.03	0.90	0.02	0.62	10.01				0.02	0.97	0.01	0.69	2.94		
		(0.01)	(0.06)	(0.02)		[0.07]				(0.01)	(0.05)	(0.01)		[0.71]		
P_2		0.01	0.94	-0.02	0.71					0.01	0.95	0.01	0.79			
		(0.01)	(0.08)	(0.01)						(0.01)	(0.05)	(0.01)				
P_3		-0.01	1.02	0.01	0.71					-0.01	0.99	0.01	0.79			
		(0.01)	(0.06)	(0.02)						(0.01)	(0.04)	(0.01)				
P_4		-0.01	1.10	0.01	0.78					-0.01	1.19	0.01	0.83			
т		(0.01)	(0.06)	(0.01)						(0.01)	(0.05)	(0.01)				
P_S		-0.02	1.04	-0.02	0.78					-0.01	0.91	-0.01	0.71			
- 5		(0.01)	(0.04)	(0.01)	0.10					(0.01)	(0.05)	(0.01)	0.11			

						Pan	el B: Ex	change R	ate Returi	ns						
								Factor	· Prices							
	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}	R^2	RMSE	χ^2	HJ
				Deve	loped						De	veloped ℓ	3 Emer	ging		
GMM_1	0.58	0.42	0.02	0.65	0.35	2.74	2.74	0.13	0.94	0.48	0.02	0.94	0.26	2.34	2.47	0.12
	(0.33)	(0.25)	(0.02)	(0.38)			[0.43]	[0.47]	(0.87)	(0.49)	(0.02)	(0.76)			[0.48]	[0.55]
GMM_2	0.51	0.34	0.02	0.61	0.34	2.75	2.64		0.65	0.27	0.02	0.68	0.24	2.38	2.21	
	(0.33)	(0.23)	(0.02)	(0.38)			[0.45]		(0.83)	(0.46)	(0.02)	(0.76)			[0.53]	
FMB	0.57	0.41	0.02	0.65	0.35	2.74	2.75		0.94	0.48	0.02	0.94	0.26	2.34	2.48	
	(0.36)	(0.24)	(0.02)	(0.38)			[0.43]		(0.66)	(0.38)	(0.02)	(0.76)			[0.48]	
(sh)	(0.34)	(0.28)	(0.02)	(0.45)					(0.84)	(0.50)	(0.02)	(1.01)				
								Factor	r Betas							
		α	β_{DOL}	β_{VOL}	R^2	χ^2				α	β_{DOL}	β_{VOL}	R^2	χ^2	_	
P_L		0.03	0.89	0.02	0.62	5.39				0.02	0.96	0.01	0.69	7.68		
		(0.01)	(0.06)	(0.02)		[0.37]				(0.01)	(0.04)	(0.01)		[0.17]		
P_2		0.01	0.93	-0.02	0.70					0.01	0.94	-0.01	0.78			
		(0.01)	(0.08)	(0.01)						(0.01)	(0.05)	(0.01)				
P_3		-0.01	1.00	0.01	0.70					-0.01	0.97	0.01	0.79			
÷		(0.01)	(0.06)	(0.02)						(0.01)	(0.04)	(0.01)				
P_4		-0.01	1.08	0.01	0.78					-0.01	1.17	0.01	0.82			
7		(0.01)	(0.06)	(0.01)						(0.01)	(0.04)	(0.01)				
P_S		-0.02	1.03	-0.02	0.78					-0.02	0.89	-0.01	0.70			
- 5		(0.01)	(0.04)	(0.01)	0.10					(0.01)	(0.04)	(0.01)	0.10			

 Table A3. Asset Pricing Tests II (continued)

Table A4. Asset Pricing Tests III

This table reports asset pricing results. The linear factor model includes the dollar (DOL) and the foreign exchange liquidity $(ILLIQ_{FX})$ risk factors. $ILLIQ_{FX}$ is constructed using the global average bid-ask spread of the spot exchange rates. The test assets are currency excess returns (Panel A) and exchange rate returns (Panel B) to five portfolios sorted on the 1-year volatility risk premia (VRP) available at time t - 1. The table reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ , and least squares estimates of time series slopes β . The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection and Shanken (1992) standard errors (sh) are reported in parenthesis. The *p*-values are reported in brackets. Excess returns are expressed in percentage per annum. 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.

						Pane	l A: Cui	rency Ex	cess Retur	ms						
								Factor	· Prices							
	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ
				Develo	ped						De	$veloped \ {\ensuremath{\mathfrak{C}}}$	Emerg	ing		
GMM_1	0.32	0.40	0.02	0.02	0.03	2.59	3.81	0.13	0.74	4.50	0.02	0.21	0.26	2.62	3.58	0.15
	(0.59)	(2.62)	(0.02)	(0.13)			[0.28]	[0.39]	(0.66)	(5.87)	(0.02)	(0.16)			[0.31]	[0.53]
GMM_2	0.53	0.95	0.02	0.04	0.02	2.60	3.59		0.88	6.83	0.02	0.26	0.25	2.64	3.26	
	(0.51)	(2.35)	(0.02)	(0.13)			[0.31]		(0.60)	(4.73)	(0.02)	(0.16)			[0.35]	
FMB	0.32	0.40	0.02	0.02	0.03	2.59	3.81		0.73	4.48	0.02	0.21	0.26	2.62	3.59	
	(0.47)	(2.35)	(0.02)	(0.13)			[0.28]		(0.43)	(3.3)	(0.02)	(0.16)			[0.31]	
(sh)	(0.49)	(2.32)	(0.02)	(0.12)					(0.59)	(4.66)	(0.02)	(0.22)				
								Factor	r Betas							
		α	β_{DOL}	β_{ILLIQ}	R^2	χ^2				α	β_{DOL}	β_{ILLIQ}	R^2	χ^2		
P_L		0.08	0.93	-0.08	0.64	6.28				0.01	0.96	0.01	0.69	0.85	-	
		(0.06)	(0.08)	(0.07)		[0.28]				(0.06)	(0.05)	(0.05)		[0.97]		
P_2		-0.04	1.03	0.05	0.78					-0.01	1.03	0.02	0.82			
		(0.04)	(0.06)	(0.05)						(0.05)	(0.04)	(0.04)				
P_3		0.01	0.95	-0.02	0.75					0.06	1.00	-0.07	0.78			
0		(0.04)	(0.05)	(0.05)						(0.07)	(0.04)	(0.06)				
P_4		0.01	1.06	0.01	0.71					-0.02	0.97	0.03	0.68			
÷ 4		(0.06)	(0.06)	(0.07)	0.11					(0.08)	(0.06)	(0.06)	0.00			
P_S		0.01	1.02	-0.04	0.69					-0.04	1.03	0.01	0.75			
1 5		(0.01)	(0.08)	(0.06)	0.09					(0.06)	(0.05)	(0.01)	0.10			

						Pan	el B: Ex	change R	ate Returi	ns						
								Factor	· Prices							
	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ
				Develo	ped						De	veloped &	Emerg	ing		
GMM_1	0.37	0.77	0.02	0.04	0.05	2.54	3.87	0.13	0.74	5.08	0.01	0.24	0.39	2.28	2.07	0.13
	(0.67)	(3.31)	(0.02)	(0.15)			[0.28]	[0.37]	(0.61)	(5.42)	(0.02)	(0.14)			[0.56]	[0.65]
GMM_2	0.53	0.84	0.02	0.04	0.05	2.54	3.61		0.76	5.93	0.01	0.26	0.39	2.29	2.01	
	(0.53)	(2.83)	(0.02)	(0.15)			[0.31]		(0.59)	(4.71)	(0.02)	(0.14)			[0.57]	
FMB	0.37	0.76	0.02	0.04	0.05	2.54	3.87		0.73	5.05	0.01	0.24	0.39	2.28	2.08	
	(0.49)	(2.79)	(0.02)	(0.15)			[0.28]		(0.39)	(2.93)	(0.02)	(0.14)			[0.56]	
(sh)	(0.52)	(2.79)	(0.02)	(0.15)					(0.57)	(4.48)	(0.02)	(0.22)				
								Factor	r Betas							
		α	β_{DOL}	β_{ILLIQ}	R^2	χ^2				α	β_{DOL}	β_{ILLIQ}	R^2	χ^2		
P_L		0.04	0.91	-0.04	0.63	7.16	-			-0.02	0.94	0.01	0.68	3.38	_	
		(0.06)	(0.08)	(0.07)		[0.21]				(0.06)	(0.05)	(0.05)		[0.64]		
P_2		-0.06	1.02	0.07	0.78					-0.03	1.02	0.03	0.82			
		(0.04)	(0.06)	(0.05)						(0.05)	(0.04)	(0.04)				
P_3		-0.02	0.95	0.01	0.75					0.06	0.99	-0.07	0.78			
		(0.04)	(0.05)	(0.05)						(0.07)	(0.04)	(0.06)				
P_4		-0.02	1.06	0.05	0.71					-0.02	0.96	0.03	0.67			
		(0.06)	(0.06)	(0.07)						(0.08)	(0.06)	(0.06)				
P_S		-0.01	1.01	0.01	0.69					-0.03	1.02	0.01	0.75			
5		(0.06)	(0.08)	(0.06)						(0.06)	(0.05)	(0.05)				

 Table A4. Asset Pricing Test III (continued)

Table A5. Asset Pricing IV

This table reports asset pricing results. The linear factor model includes the dollar (DOL) and the foreign exchange option liquidity $(ILLIQ_{VP})$ risk factors. $ILLIQ_{VP}$ is constructed using the global average bid-ask spread of the at-the-money implied volatilities. The test assets are currency excess returns (Panel A) and exchange rate returns (Panel B) to five portfolios sorted on the 1-year volatility risk premia (VRP) available at time t - 1. The table reports GMM and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk λ , and least squares estimates of time series slopes β . The χ^2 and the Hansen-Jagannathan distance are test statistics for the null hypothesis that all pricing errors are jointly zero. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection and Shanken (1992) standard errors (sh) are reported in parenthesis. The *p*-values are reported in brackets. Excess returns are expressed in percentage per annum. 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.

						Pane	l A: Cur	rency Ex	cess Retur	ns						
								Factor	Prices							
	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ
				Develo	ped						De	$veloped \ {\ensuremath{\mathfrak{C}}}$	Emerg	ing		
GMM_1	0.83	14.78	0.02	0.10	0.57	2.10	1.23	0.11	0.18	5.63	0.02	0.10	0.80	0.87	0.32	0.05
	(0.71)	(11.72)	(0.02)	(0.06)			[0.75]	[0.87]	(0.32)	(5.33)	(0.02)	(0.07)			[0.96]	[0.96]
GMM_2	0.69	11.92	0.02	0.09	0.56	2.12	1.16		0.15	4.98	0.02	0.09	0.79	0.90	0.29	
	(0.68)	(11.18)	(0.02)	(0.06)			[0.76]		(0.32)	(5.08)	(0.02)	(0.07)			[0.96]	
FMB	0.82	14.70	0.02	0.10	0.57	2.10	1.23		0.18	5.60	0.02	0.10	0.80	0.87	0.32	
	(0.45)	(7.98)	(0.02)	(0.06)			[0.74]		(0.30)	(3.93)	(0.02)	(0.07)			[0.96]	
(sh)	(0.56)	(12.84)	(0.02)	(0.09)					(0.27)	(5.05)	(0.02)	(0.09)				
								Factor	· Betas							
		α	β_{DOL}	β_{ILLIQ}	R^2	χ^2				α	β_{DOL}	β_{ILLIQ}	R^2	χ^2	_	
P_L		-0.05	0.88	0.19	0.62	4.79				-0.05	0.96	0.13	0.69	3.46		
		(0.06)	(0.07)	(0.13)		[0.44]				(0.05)	(0.04)	(0.08)		[0.63]		
P_2		0.05	0.95	-0.11	0.70					-0.04	0.95	0.07	0.79			
		(0.07)	(0.07)	(0.16)						(0.05)	(0.05)	(0.08)				
P_3		0.01	1.01	-0.05	0.71					0.02	0.98	-0.05	0.79			
		(0.09)	(0.06)	(0.24)						(0.05)	(0.03)	(0.09)				
P_4		-0.03	1.10	0.06	0.78					0.06	1.18	-0.12	0.83			
		(0.07)	(0.05)	(0.17)						(0.05)	(0.04)	(0.09)				
P_S		0.04	1.05	-0.13	0.78					0.01	0.92	-0.04	0.71			
		(0.07)	(0.04)	(0.18)						(0.06)	(0.04)	(0.11)				·· · · · · · · · · · · · · · · · · · ·

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						Pan	el B: Ex	change R	ate Returi	ns						
								Factor	· Prices							
	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ	b_{DOL}	b_{ILLIQ}	λ_{DOL}	λ_{ILLIQ}	R^2	RMSE	χ^2	HJ
				Develo	ped						De	$veloped \ \mathcal{E}$	Emerge	ing		
GMM_1	0.77	14.77	0.02	0.10	0.53	2.33	1.61	0.12	0.14	6.42	0.02	0.13	0.77	1.32	0.71	0.08
	(0.66)	(11.36)	(0.02)	(0.05)			[0.66]	[0.83]	(0.36)	(5.52)	(0.02)	(0.07)			[0.87]	[0.90]
GMM_2	0.65	12.36	0.02	0.09	0.52	2.35	1.56		0.09	5.46	0.02	0.11	0.75	1.37	0.65	
	(0.64)	(10.99)	(0.02)	(0.05)			[0.67]		(0.35)	(5.37)	(0.02)	(0.07)			[0.88]	
FMB	0.76	14.69	0.02	0.10	0.53	2.33	1.62		0.14	6.39	0.02	0.13	0.77	1.32	0.71	
	(0.41)	(7.61)	(0.02)	(0.05)			[0.66]		(0.29)	(3.66)	(0.02)	(0.07)			[0.87]	
(sh)	(0.50)	(12.39)	(0.02)	(0.09)					(0.27)	(4.99)	(0.02)	(0.10)				
								Factor	r Betas							
		α	β_{DOL}	β_{ILLIQ}	R^2	χ^2				α	β_{DOL}	β_{ILLIQ}	R^2	χ^2	_	
P_L		-0.07	0.88	0.23	0.62	7.30				-0.02	0.95	0.06	0.69	20.96		
		(0.06)	(0.07)	(0.13)		[0.20]				(0.05)	(0.04)	(0.07)		[<.01]		
P_2		0.04	0.94	-0.09	0.69					-0.03	0.95	0.04	0.78			
		(0.07)	(0.07)	(0.16)						(0.05)	(0.04)	(0.08)				
P_3		-0.02	1.00	0.02	0.70					0.05	0.96	-0.09	0.79			
		(0.09)	(0.06)	(0.23)						(0.04)	(0.03)	(0.07)				
P_4		-0.05	1.08	0.11	0.78					0.07	1.16	-0.15	0.83			
-		(0.07)	(0.05)	(0.16)						(0.05)	(0.04)	(0.08)				
P_S		0.01	1.04	-0.07	0.77					0.06	0.91	-0.14	0.71			
5		(0.08)	(0.04)	(0.19)						(0.05)	(0.04)	(0.09)				

 Table A5. Asset Pricing IV (continued)

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