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Carry Trades and Global Foreign Exchange Volatility

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ABSTRACT

We investigate the relation between global foreign exchange (FX) volatility risk and the cross section of excess returns arising from popular strategies that borrow in low interest rate currencies and invest in high interest rate currencies, so-called "carry trades." We find that high interest rate currencies are negatively related to innovations in global FX volatility, and thus deliver low returns in times of unexpected high volatility, when low interest rate currencies provide a hedge by yielding positive returns. Furthermore, we show that volatility risk dominates liquidity risk and our volatility risk proxy also performs well for pricing returns of other portfolios.

THIS PAPER STUDIES THE risk-return profile of a popular trading strategy that borrows in currencies with low interest rates and invests in currencies with high interest rates. This trading strategy is called "carry trade." According to uncovered interest parity (UIP), if investors are risk neutral and form expectations rationally, exchange rate changes will eliminate any gain arising from the differential in interest rates across countries. A number of empirical studies show, however, that exchange rate changes do *not* compensate for the interest rate differential. Instead, the opposite holds true empirically: high interest rate currencies tend to appreciate, while low interest rate currencies tend to

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depreciate. As a consequence, carry trades form a profitable investment strategy, violate UIP, and give rise to the "forward premium puzzle" (Fama (1984)).

This puzzle and the resulting carry trade strategy have been well documented for at least 25 years (Hansen and Hodrick (1980, 1983), Fama (1984)). Considering the very liquid foreign exchange (FX) markets, the dismantling of barriers to capital flows between countries, and the existence of international currency speculation during this period, it is difficult to understand why carry trades have been profitable for such a long time.[1] A straightforward and theoretically convincing explanation for this puzzle is based on the existence of time-varying risk premia (Engel (1984), Fama (1984)): If investments in currencies with high interest rates deliver low returns during "bad times" for investors, then carry trade profits are merely compensation for investors' higher risk-exposure. Empirically, however, the literature has had serious problems in convincingly identifying risk factors that drive these premia until now.

In our empirical analysis, we follow much of the recent literature (Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2011)) and sort currencies into portfolios according to their forward discount (or, equivalently, their relative interest rate differential versus U.S. money market interest rates) at the end of each month.[2] We form five such portfolios. Investing in the highest relative interest rate quintile (portfolio 5) and shorting the lowest relative interest rate quintile (portfolio 1) therefore results in a carry trade portfolio. This carry trade strategy leads to large and significant unconditional excess returns of more than 5% per annum even after accounting for transaction costs and the recent market turmoil. These returns cannot be explained by standard measures of risk (e.g., Burnside et al. (2006)) and seem to offer investors a free lunch.

In this paper, we show that these high returns to currency speculation can indeed be understood as compensation for risk. Finance theory predicts that investors are concerned about state variables affecting the evolution of the investment opportunities set and wish to hedge against unexpected changes (innovations) in market volatility, leading risk-averse agents to demand currencies that can hedge against this risk.[3] Guided by this insight and earlier evidence for stock markets (e.g., Ang et al. (2006)), we test whether the sensitivity of excess returns to global FX volatility risk can rationalize the returns to

[1] Since the beginning of the recent global financial crisis, carry trade strategies made substantial losses but recovered during 2009. Moreover, these losses are relatively small when compared to the cumulative returns from carry trades of the last 15–20 years (e.g., Brunnermeier, Nagel, and Pedersen (2009)).

[2] The innovation of sorting currencies into portfolios is due to Lustig and Verdelhan (2007) and has been followed by other papers afterward.

[3] For example, this is a key prediction of the Intertemporal CAPM (Merton (1973), Campbell (1993, 1996), Chen (2003)). Also, assets that deliver low returns in times of high volatility add negative skewness to a portfolio. Hence, if investors have preferences over skewness, assets with a highly negative return sensitivity to volatility shocks should demand a higher return in equilibrium. Harvey and Siddique (2000) examine this sort of coskewness risk and find that it matters for stock returns.

currency portfolios in a standard, linear asset pricing framework. We find empirically that high interest rate currencies are negatively related to innovations in global FX volatility, and thus deliver low returns in times of unexpectedly high volatility, when low interest rate currencies provide a hedge by yielding positive returns. In other words, carry trades perform especially poorly during times of market turmoil, and thus their high returns can be rationalized from the perspective of standard asset pricing. This result, which is the major point of our paper, shows that excess returns to carry trades are indeed a compensation for time-varying risk.

Our paper is closely related to two studies in the recent literature. First, as in Lustig, Roussanov, and Verdelhan (2011), we show that returns to carry trades can be understood by relating them cross sectionally to two risk factors. Lustig, Roussanov, and Verdelhan (2011) employ a data-driven approach in line with the Arbitrage Pricing Theory of Ross (1976) and identify two risk factors, namely, the average currency excess return of a large set of currencies against the U.S. dollar (USD) (which they coin "Dollar risk factor") and the return to the carry trade portfolio itself (the "HML_{FX}" factor). In the present paper, we also employ two risk factors to price the cross section of carry trade returns, one of which is the Dollar risk factor. However, instead of the Lustig, Roussanov, and Verdelhan (2011) HML_{FX} factor, we investigate the empirical performance of innovations in global FX volatility.[4] This factor is a proxy for unexpected changes in FX market volatility, and is the analog of the aggregate volatility risk factor used by Ang et al. (2006) in pricing the cross section of stock returns. We show that global FX volatility is indeed a pervasive risk factor in the cross section of FX excess returns and that its pricing power extends to several other test assets. Second, Brunnermeier, Nagel, and Pedersen (2009) find that liquidity is a key driver of currency crashes: when liquidity dries up, currencies crash. Experience from the recent financial market crisis suggests that liquidity is potentially important for understanding the cross section of carry trade excess returns as well. Following Brunnermeier, Nagel, and Pedersen (2009), we show that liquidity is useful to understand the cross section of carry trade returns more generally, that is, also in times when currencies do not crash. However, we document that our proxy for global FX volatility is the more powerful risk factor, as it subsumes the information contained in various liquidity proxies.

To summarize, our main contribution relative to the existing literature is as follows. We show that global FX volatility is a key driver of risk premia in the cross section of carry trade returns. The pricing power of volatility also applies to other cross sections, such as a common FX momentum strategy, individual currencies' excess returns, domestic U.S. corporate bonds, U.S. equity momentum, as well as FX option portfolios and international bond portfolios. This finding is in line with the result that aggregate volatility risk is helpful in pricing some cross sections of stock returns (Ang et al. (2006)). Reassuringly,

[4] Global FX volatility has a correlation of about −30% with the HML_{FX} factor. We therefore do not exchange one factor for an essentially identical factor.

we find that FX volatility is correlated with several proxies for financial market liquidity such as bid–ask spreads (BASs), the TED spread, or the Pástor and Stambaugh (2003) liquidity measure. However, when analyzing carry trade returns, FX volatility always dominates liquidity proxies in joint asset pricing tests in which both factors are considered. This finding corroborates evidence for stock markets where, for example, Bandi, Moise, and Russell (2008) show that stock market volatility drives out liquidity in cross-sectional asset pricing exercises. The results in our paper therefore provide new insights into the behavior of risk premia in currency markets in general as well as similarities between the relation of volatility and cross-sectional excess returns in FX and stock markets.

We examine our main result in the following specifications without qualitative changes in our findings: (i) We show that sorting currencies on their beta with volatility innovations yields portfolios with a large difference in returns. These portfolios are related, but not identical, to our base test assets of currency portfolios sorted on the forward discount. (ii) We investigate other factors such as liquidity, skewness, and coskewness. (iii) We investigate potential Peso problems using different approaches, such as Empirical Likelihood (EL) methods and winsorized volatility series. (iv) We investigate the performance of the proposed risk factor for other test assets, including options, international bonds, U.S. stock momentum, and corporate bonds, as well as individual currency returns. (v) We experiment with other proxies for FX volatility (implied volatility from equity and currency options) or different weighting schemes for individual realized volatility. (vi) We depart from our base scenario of a U.S.-based investor and run calculations using alternative base currencies (taking the viewpoint of a British, Japanese, or Swiss investor, respectively). We find that our results are robust to each of these changes and thus corroborate our core finding that volatility risk is a key driver of risk premia in the FX market.

Our paper is also closely related to a new strand of literature suggesting explanations for the forward premium puzzle. Important contributions include Burnside et al. (2006), who argue that carry trades may be difficult to implement due to high transaction costs. Brunnermeier, Nagel, and Pedersen (2009) show that carry trades are related to low conditional skewness, indicating that they are subject to crash risk, a result confirmed in further analysis by Farhi et al. (2009). Related to this finding, Melvin and Taylor (2009) show that proxies for market stress have some predictive power for carry trade returns. Burnside et al. (2011) carefully document that carry trades are still profitable after covering most of the downside risk through the use of derivatives so that the puzzle basically remains, whereas Burnside, Eichenbaum, and Rebelo (2009) suggest that the forward premium may also be due to adverse selection risk. Lustig and Verdelhan (2007) provide evidence that currency risk premia can be understood in the Durables Consumption CAPM setting of Yogo (2006), Verdelhan (2010) shows how carry trade returns are related to risk arising from consumption habits, and Lustig et al. (2011) use an empirically derived two-factor model that parsimoniously explains the cross section of currency portfolios and the carry trade. We also rely on Brunnermeier, Nagel, and Pedersen (2009) in that we confirm some relevance for illiquidity as a risk factor. However, we cannot confirm that transaction costs are prohibitively important (Burnside et al. (2006)) or that skewness would be a pervasive proxy for risk in the currency market (Brunnermeier, Nagel, and Pedersen (2009)).[5]

The paper is structured as follows. In Section I, we briefly review the conceptual role of volatility as a risk measure. Section II presents data and descriptive statistics. The main results regarding volatility risk are shown in Section III. Section IV provides results on the relation between volatility and liquidity risk. Other possible explanations for our findings are discussed in Section V, whereas results for other test assets are shown in Section VI. We briefly discuss robustness checks in Section VII, and draw conclusions in Section VIII. Details on some of our data and estimation procedures are delegated to the Appendix at the end of the paper. A separate Internet Appendix contains details on robustness tests as well as additional analyses.[6]

I. Volatility as a Risk Factor in FX

Finance theory suggests that there must be a negative volatility risk premium because a positive volatility innovation (i.e., unexpectedly high volatility) worsens the investor's risk-return tradeoff, characterizing a bad state of the world. Moreover, high unexpected volatility typically coincides with low returns so that assets that covary positively with market volatility innovations provide a good hedge and are therefore expected to earn a lower expected return. Motivated by these insights, several recent papers study how exposure to market volatility risk is priced in the cross section of returns on the stock market (Ang et al. (2006), Adrian and Rosenberg (2008), Da and Schaumburg (2008)). In fact, given that volatility is known to exhibit substantial persistence, it is reasonable to consider aggregate volatility innovations as a pricing factor. In empirical research inspired by these considerations, the recent asset pricing literature considers a parsimonious two-factor pricing kernel m (or stochastic discount factor, SDF) with the market excess return and volatility innovations as risk factors:

$$m_{t+1} = 1 - b_1 r^e_{m,t+1} - b_2 \Delta V_{t+1}, \tag{1}$$

where $r^e_{m,t+1}$ is the log market excess return and ΔV_{t+1} denotes the volatility innovations. This linear pricing kernel implies an expected return-beta representation for excess returns.

[5] With respect to the paper by Burnside et al. (2006), it is important to point out that, in terms of the BAS analysis, our results are similar to theirs in the sense that indicative BASs generally available from traditional data sources are not large enough to wipe out the profits of carry trade portfolios. However, Burnside et al. (2006) argue that transaction costs may be an important part of the explanation of carry trade returns if the spreads charged to large trades limit the volume (or total value) of speculation.

[6] An Internet Appendix for this article is available online in the "Supplements and Datasets" section at http://afajof.org/supplements.asp.

Regardless of its simplicity and the likely omission of other potential factors, this empirical model has delivered important insights on the relationship between volatility risk and expected stock returns. For example, Ang et al. (2006) employ changes in the VIX index (from CBOE) to proxy for volatility risk as a nontraded risk factor. They find that aggregate volatility is priced in the cross section of U.S. stock returns and that stocks with a higher sensitivity to volatility risk do earn lower returns. Further studies in this line of literature include Adrian and Rosenberg (2008), who decompose market volatility into a long-run and a short-run component and show that each component is priced separately with a negative factor risk price. Da and Schaumburg (2009) price several asset classes with a pricing kernel that is linear in the aggregate stock market return and volatility innovations, and Christiansen, Ranaldo, and Söderlind (2011) show that volatility matters for the correlation between excess returns of stock markets and currencies. Finally, Bandi, Moise, and Russell (2008) consider not only volatility but also liquidity as an additional pricing factor. They find that both risk factors are useful for understanding the pricing of U.S. stocks, but that volatility dominates liquidity when they are considered jointly.[7]

Summarizing these papers on stock pricing, volatility innovations emerge as a state variable and a negative price of volatility risk arises because investors are concerned about changes in future investment opportunities. This motivates our approach of pricing forward discount-sorted portfolios with an SDF depending linearly on two risk factors: (i) an aggregate FX market return and (ii) aggregate FX market volatility innovations. We show that this model has a lot to say about returns on carry trades as well as about other cross sections of asset returns.

In addition to this line of literature, our approach of using the covariance of returns with market volatility as a priced source of risk is also related to the literature on coskewness (see, for example, Harvey and Siddique (1999, 2000), and Ang, Chen, and Xing (2006) for asset pricing implementations of coskewness). Coskewness is given by

$$\text{coskew} = \frac{\mathbb{E}\left[(r_k - \mu_k)(r_m - \mu_m)^2\right]}{\sigma(r_k)\sigma^2(r_m)}, \tag{2}$$

where r_k and r_m denote the return of portfolio k and the market benchmark, respectively, and μ and σ denote the mean and standard deviation, respectively. Applying a covariance decomposition to the numerator above, the covariance of returns with market volatility emerges from this framework as well. The general idea here is that portfolios with high coskewness (i.e., portfolios delivering high returns when market volatility is high) serve as a hedge against volatility and thus should earn lower returns. Therefore, this idea is closely related to our setup as well.[8]

[7] See also Acharya and Pedersen (2005), Brunnermeier and Pedersen (2009), Evans and Lyons (2005), and Pástor and Stambaugh (2003) on the role of liquidity for asset prices.

[8] Furthermore, Dittmar (2002) uses Taylor approximations of general nonlinear pricing kernels

Overall, empirical evidence suggests that volatility innovations matter for understanding the cross section of equity returns. We show that a similar approach is helpful to understand the cross section of FX risk premia as well.[9]

II. Data and Currency Portfolios

This section describes the currency and interest rate data used in the empirical analysis, the construction of portfolios and associated excess returns, our main proxy for global FX volatility risk, and data on currency options. We also provide some basic descriptive statistics.

A. Data on Spot and Forward Rates

The data for spot exchange rates and 1 month forward exchange rates versus the USD cover the sample period from November 1983 to August 2009, and are obtained from Barclays Bank International (BBI) and Reuters (via Datastream). The empirical analysis is carried out at the monthly frequency, although we start from daily data to construct the proxy for volatility risk discussed below.[10] Following the extant literature since Fama (1984), we work in logarithms of spot and forward rates for ease of exposition and notation. Later in the paper, however, we use discrete returns (rather than log-returns) in our cross-sectional asset pricing tests.

We denote spot and forward rates in logs as s and f, respectively. Our full sample consists of the following 48 countries (referred to as our "all countries" sample below): Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. Following Lustig et al. (2011), we also study a smaller subsample consisting only of 15 developed countries (referred to as our "developed countries" sample below) with a longer data history. This sample comprises: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden,

to show that the covariance of returns with higher order moments of returns (such as return variance) matters theoretically and empirically for equilibrium returns.

[9] A number of recent papers suggest theoretical approaches to make sense of the forward premium puzzle. A selected list includes Bacchetta and van Wincoop (2006), Bansal and Shaliastovich (2008), Farhi and Gabaix (2009), Gourinchas and Tornell (2004), and Ilut (2010). However, none of these papers make the prediction that exposure to global volatility shocks should matter for currency risk premia, which is central to our setup and results below. Hence, further theoretical research is needed to pin down the exact reason why currency exposure to volatility innovations is strongly related to cross-sectional return differences.

[10] Lustig, Roussanov, and Verdelhan (2011) and Burnside, Roussanov, and Verdelhan (2011) also use these data.

Switzerland, and the United Kingdom. Since the introduction of the euro in January 1999, the sample of developed countries covers 10 currencies only.

B. Portfolio Construction

At the end of each period t, we allocate currencies to five portfolios based on their forward discounts $f - s$ at the end of period t. Sorting on forward discounts is equivalent to sorting on interest rate differentials since covered interest parity holds closely in the data at the frequency analyzed in this paper (see, for example, Akram, Rime, and Sarno (2008)). We rebalance portfolios at the end of each month. Currencies are ranked from low to high interest rates. Portfolio 1 contains currencies with the lowest interest rates (or smallest forward discounts) and portfolio 5 contains currencies with the highest interest rates (or largest forward discounts). Monthly excess returns for holding foreign currency k are computed as

$$rx_{t+1}^{k} \equiv i_t^k - i_t - \triangle s_{t+1}^{k} \approx f_t^k - s_{t+1}^{k}. \tag{3}$$

For further calculations, we compute the log currency excess return $rx_{i,t+1}$ for portfolio i by taking the (equally weighted) average of the log currency excess returns in each portfolio i (gross returns). We then compute excess returns for BAS adjusted currency positions (net returns). We employ a setup in which BASs are deducted from returns whenever a currency enters and/or exits a portfolio. The net return for a currency that enters a portfolio at time t and exits the portfolio at the end of the month is computed as $rx_{t+1}^{l} = f_t^b - s_{t+1}^a$ for a long position and $rx_{t+1}^{s} = -f_t^a + s_{t+1}^b$ for a short position. A currency that enters a portfolio but stays in the portfolio at the end of the month has a net excess return of $rx_{t+1}^{l} = f_t^b - s_{t+1}$ for a long position and $rx_{t+1}^{s} = -f_t^a + s_{t+1}$ for a short position, whereas a currency that exits a portfolio at the end of month t but already was in the current portfolio the month before $(t-1)$ has an excess return of $rx_{t+1}^{l} = f_t - s_{t+1}^a$ for a long position and $rx_{t+1}^{s} = -f_t + s_{t+1}^b$ for a short position. We assume that the investor has to establish a new position in each single currency in the first month (November 1983) and that he has to sell all positions in the last month (at the end of August 2009). Returns for portfolio 1 (i.e., the funding currencies in the carry trade) are adjusted for transaction costs in short positions, whereas portfolios 2–5 (investment currencies) are adjusted for transaction costs in long positions. In this paper, we report results for these net returns since transaction costs data are available, and these costs can be quite high for some currencies (Burnside, Eichenbaum, and Rebelo (2007)). Moreover, our portfolios have about 30% turnover per month, which implies that transaction costs should play a role.[11]

The return difference between portfolio 5 and portfolio 1 (the long–short portfolio H/L) is the carry trade portfolio obtained from borrowing money in

[11] Results for unadjusted returns are very similar, however, and are reported in the Internet Appendix. Below, we also provide results for a transaction cost adjustment scheme as in Lustig, Roussanov, and Verdelhan (2011) where we assume 100% portfolio turnover each month.

low interest rate countries and investing in high interest rate countries' money markets, HML_{FX} in the notation of Lustig, Roussanov, and Verdelhan (2011). We also build and report results for a portfolio that is the average of all five currency portfolios, that is, the average return of a strategy that borrows money in the United States and invests in global money markets outside the United States. Lustig, Roussanov, and Verdelhan (2011) call this zero-cost portfolio the "Dollar risk factor" and here we refer to the portfolio as the DOL portfolio.[12]

C. Descriptive Statistics for Portfolios

Descriptive statistics for the five carry trade portfolios, the DOL portfolio, and the H/L portfolio can be found in Table I. The top panel shows results for the sample of all 48 currencies, and the lower panel shows results for the sample of 15 developed countries. We report results for net returns (denoted "with b-a").

Average returns monotonically increase when moving from portfolio 1 to portfolio 5 and the H/L portfolio. We also see a monotonically decreasing skewness when moving from portfolio 1 to portfolio 5 and H/L for the sample of all countries, as suggested by Brunnermeier, Nagel, and Pedersen (2009), but a less monotonic pattern for developed countries. A similar pattern emerges for kurtosis. There is no clear pattern, however, for the standard deviation. Furthermore, there is some evidence of positive return autocorrelation among high interest rate currencies (portfolios 3 and 5), the long-short carry trade portfolio H/L (or HML_{FX}), and the DOL portfolio. Finally, we look at coskewness, which is computed by $\beta_{SKD} = E[\epsilon_{i,t+1}\epsilon^2_{M,t+1}]/(E[\epsilon^2_{i,t+1}]^{0.5}E[\epsilon^2_{M,t+1}])$ as in equation (11) of Harvey and Siddique (2000), where ϵ_i denotes a portfolio's (excess) return innovation with respect to a market factor and ϵ_M denotes the market (excess) return innovation.[13] We find that coskewness does not show a monotone pattern with respect to mean excess portfolio returns. We elaborate on this point below in Section V.C.

The unconditional average excess return from holding an equally weighted portfolio of foreign currencies (i.e., the DOL portfolio) is about 2% per annum, which suggests that U.S. investors demand a low but positive risk premium for holding foreign currency.

Figure 1 shows cumulative log returns for the carry trade portfolio H/L for all countries and for the smaller sample of developed countries. Shaded areas correspond to NBER recessions. Interestingly, carry trades among developed countries were more profitable in the 1980s and 1990s; only in the last part of the sample did the inclusion of emerging markets' currencies improve returns to the carry trade. Also, the two recessions in the early 1990s and 2000s did

[12] Equal weights in the DOL portfolio lead to a rebalancing effect and effectively contrarian behavior. We argue below that the DOL portfolio is not crucial to our results, so we do not expect this contrarian effect to be important.

[13] To calculate β_{SKD} for our currency portfolios, we either use the DOL portfolio or the U.S. stock market return (MKT) as the market factor. Since there is evidence of some low autocorrelation in the DOL portfolio, we use unexpected returns from a simple AR(1) to compute the coskewness measure.

Table I

Descriptive Statistics

The table reports mean and median returns, standard deviations (annualized), skewness, and kurtosis of currency portfolios sorted monthly on time $t-1$ forward discounts. We also report annualized Sharpe Ratios, AC(1), the first-order autocorrelation coefficient, and Coskew(·), the Harvey and Siddique (2000) measure of coskewness with respect to either the excess return of a broad currency index (DOL) or the U.S. stock market (MKT, based on CRSP). Portfolio 1 contains the 20% of currencies with the lowest forward discounts, whereas portfolio 5 contains currencies with highest forward discounts. All returns are excess returns in USD. DOL denotes the average return of the five currency portfolios and H/L denotes a long-short portfolio that is long in portfolio 5 and short in portfolio 1. We report excess returns with transaction cost adjustments (with b-a). Returns for portfolio 1 are adjusted for transaction costs that occur in a short position and returns for portfolios 2–5 are adjusted for transaction costs that occur in long positions. Numbers in brackets show Newey and West (1987) HAC t-statistics and numbers in parentheses show p-values. Returns are monthly and the sample period is December 1983 to August 2009.

Portfolio	1	2	3	4	5	Avg.	H/L
All Countries (with b-a)							
Mean	−1.46	−0.10	2.65	3.18	5.76	2.01	7.23
	[−0.80]	[−0.06]	[1.43]	[1.72]	[2.16]	[1.18]	[3.13]
Median	−2.25	0.77	1.96	4.09	10.17	2.87	11.55
Std. dev.	8.50	7.20	8.11	8.39	10.77	7.39	9.81
Skewness	0.18	−0.23	−0.28	−0.55	−0.66	−0.40	−1.03
Kurtosis	3.77	4.11	4.34	4.78	5.08	3.98	4.79
Sharpe ratio	−0.17	−0.01	0.33	0.38	0.54	0.27	0.74
AC(1)	0.04	0.09	0.14	0.11	0.23	0.14	0.18
	(0.74)	(0.27)	(0.04)	(0.14)	(0.00)	(0.04)	(0.01)
Coskew (DOL)	0.38	−0.07	−0.14	−0.15	−0.06	0.38	−0.21
Coskew (MKT)	0.18	0.03	0.11	0.10	0.04	0.10	−0.12
Developed Countries (with b-a)							
Mean	−0.82	1.55	1.98	2.82	4.90	2.09	5.72
	[−0.40]	[0.68]	[0.97]	[1.38]	[1.95]	[1.07]	[2.50]
Median	−1.13	2.64	2.93	3.11	6.17	3.25	8.18
Std. dev.	9.75	10.02	9.34	9.40	10.82	8.71	10.24
Skewness	0.14	−0.17	−0.14	−0.70	−0.27	−0.23	−0.92
Kurtosis	3.45	3.69	3.91	5.84	4.73	3.60	5.76
Sharpe ratio	−0.08	0.16	0.21	0.30	0.45	0.24	0.56
AC(1)	0.02	0.11	0.12	0.12	0.17	0.12	0.13
	(0.97)	(0.14)	(0.11)	(0.12)	(0.01)	(0.12)	(0.07)
Coskew (DOL)	0.30	−0.14	0.03	−0.33	0.03	0.14	−0.15
Coskew (MKT)	0.24	0.10	0.08	0.05	−0.11	0.08	−0.36

not have any significant influence on returns. It is only in the last recession, which also saw a massive financial crisis, that carry trade returns show some sensitivity to macroeconomic conditions. By and large, most of the major spikes in carry trade returns (e.g., in 1986, 1992, 1997/1998, and 2006) appear to be rather unrelated to the U.S. business cycle. This is consistent with Burnside et al. (2011), who find in a more detailed analysis that standard business cycle risk factors are unable to account for returns to carry trades.

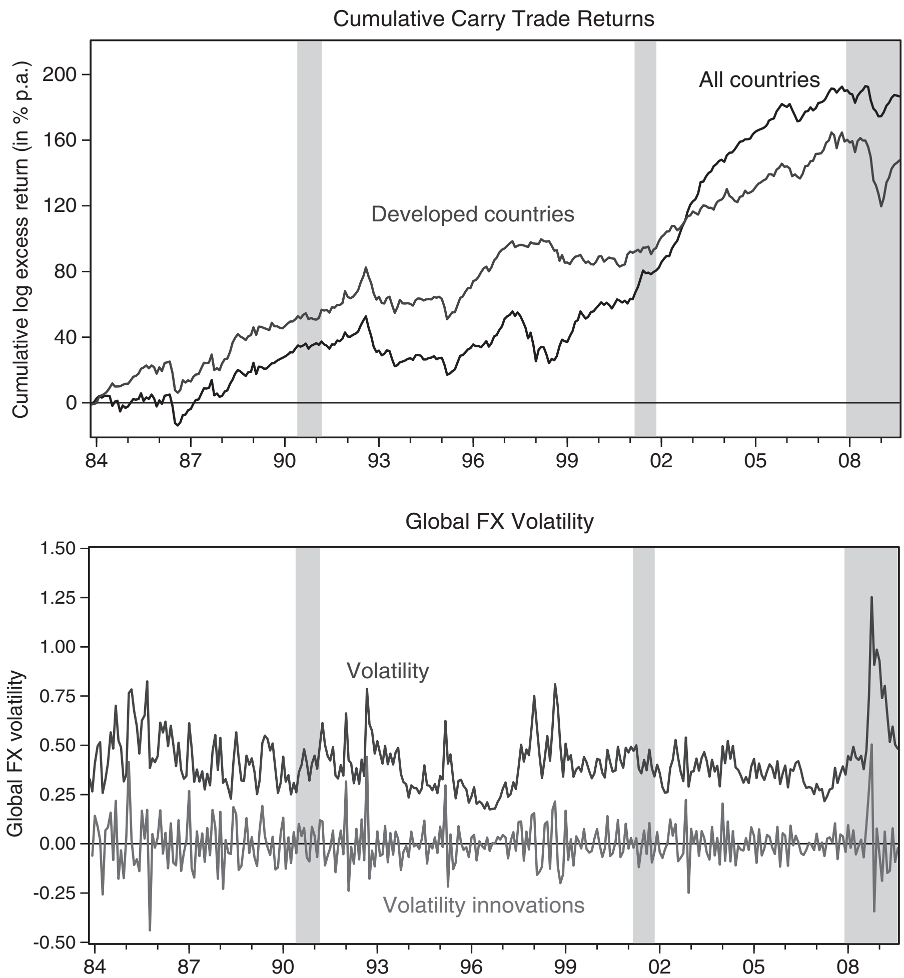

Figure 1. Returns to carry trade portfolios. The upper panel of this figure shows cumulative log excess returns of the carry trade portfolio. The solid black line corresponds to all countries, while the gray line corresponds to our sample of 15 developed countries. The lower panel shows a time-series plot of global FX volatility (upper black line) and volatility innovations (lower gray line). Shaded areas in the figure correspond to NBER recessions. The sample period is November 1983 to August 2009.

D. Volatility Proxy

We use a straightforward measure to proxy for global FX volatility. More specifically, we calculate the absolute daily log return $|r_\tau^k|$ $(= |\triangle s_\tau|)$ for each currency k on each day τ in our sample. We then average over all currencies available on any given day and average daily values up to the monthly frequency. Our global FX volatility proxy in month t is thus given by

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{|r_\tau^k|}{K_\tau} \right) \right], \tag{4}$$

where K_τ denotes the number of available currencies on day τ and T_t denotes the total number of trading days in month t. We also calculate the proxy $\sigma_t^{FX,DEV}$ based on the developed countries' returns.

This proxy has obvious similarities to measures of realized volatility (see, for example, Andersen et al. (2001)), although we use absolute returns and not squared returns to minimize the impact of outlier returns since our full sample includes several emerging markets. We also do not weight currencies, for example, according to shares in international reserves or trade, but provide robustness on this issue later in the paper.[14] The lower panel of Figure 1 shows a time-series plot of σ_t^{FX}. Several spikes in this series line up with known crisis periods, for example, the Long-Term Capital Management crisis in 1998 or, more recently, the current financial markets meltdown. Therefore, our proxy seems to capture obvious times of market distress quite well.

For the empirical analysis, we focus on volatility *innovations* (denoted as $\Delta\sigma_t^{FX}$) as a nontraded risk factor. We tried a number of alternative ways to measure innovations. The simplest way to do this is to take first differences of the volatility series described above (as in, for example, Ang et al. (2006)). We do find, however, that first differences are significantly autocorrelated with a first-order autocorrelation of about -22%. We therefore estimate a simple AR(1) for the volatility level and take the residuals as our main proxy for innovations since the AR(1) residuals are, in fact, uncorrelated with their own lags. The downside of this procedure is that it may induce an errors-in-variables problem and requires estimation on the full sample, preventing pure out-of-sample tests. We deal with this potential problem in two ways. First, we adjust our standard errors for estimation uncertainty. We do not find that the latter matters much. Second, we also present results for simple changes in volatility. We find similar results as for our volatility innovations based on an AR(1).[15] A plot of these AR(1)-based volatility innovations is shown in the lower panel of Figure 1.

[14] See Section VII. The main message is that our results do not change when using sensible weighting schemes.

[15] It is also worth noting that, while $\Delta\sigma_t^{FX}$ is a plausible proxy for innovations in global FX volatility, and, in practice, it would be possible to trade a basket of realized volatilities of the kind defined here using customized over-the-counter volatility derivatives contracts, there are several caveats with respect to considering $\Delta\sigma_t^{FX}$ as observed volatility (Della Corte, Sarno, and Tsiakas (2011)). First, volatility trading in currency markets did not exist for most of our sample period. Second, trading tends to happen on contracts that define volatility using the Garman and Kohlhagen (1983) formula or use implied volatility, as in the case of the JP Morgan VXY Index; see also the discussion of Ang et al. (2006) on these issues.

E. Data on Currency Options

We employ monthly currency option data from JP Morgan for a total of 29 currencies against the USD. Our sample covers the period from 1996 to 2009. The data include quoted implied volatilities for options with a maturity of 1 month. For each currency pair, we have implied volatilities for at-the-money (ATM) options, 25-Delta (out-of-the-money) options, and 10-Delta (far out-of-the-money) options.[16]

Currencies with available data are the same as listed above, except for the member countries of the euro (the EUR is included though) as well as Bulgaria, Croatia, Egypt, Kuwait, Saudi Arabia, and Ukraine. Thus, the data do not include potentially interesting information about several large currencies such as the DEM but still include the major currencies and several important carry trade vehicle currencies, such as the GBP, AUD, or JPY.

Returns to option strategies employed below are obtained by combining returns from being long or short in calls or puts of a certain currency. We detail the calculation of returns to options in the Appendix to this paper.

III. Empirical Results

A. A First Look at the Relation between Volatility and Currency Returns

We first provide a simple graphical analysis to visualize the relationship between innovations to global FX volatility and currency excess returns. To do so, we divide the sample into four subsamples depending on the value of global FX volatility innovations. The first subsample contains the 25% months with the lowest realizations of the risk factor and the fourth subsample contains the 25% of months with the highest realizations. We then calculate average excess returns for these subsamples for the return difference between portfolios 5 and 1. Results are shown in Figure 2. The left panel shows results for all countries, whereas the right panel gives the corresponding results for the smaller sample of 15 developed countries.

Bars show the annualized mean returns of the carry trade portfolio (the long–short portfolio H/L as discussed above). As can be seen from the figure, high interest rate currencies clearly yield higher excess returns when volatility innovations are low and vice versa. Average excess returns for the long–short portfolios decrease monotonically when moving from the low to the high volatility states for the sample of developed countries, and almost monotonically for the full sample of countries. While this analysis is intentionally simple, it intuitively demonstrates a clear relationship between global FX volatility innovations and returns to carry trade portfolios. Times of high volatility innovations are times when the carry trade performs poorly. Consequently, low interest rate currencies perform well compared to high interest rate currencies

[16] The convention in FX markets is to multiply the delta of a put by -100 and the delta of a call by 100. Thus, a 25-Delta put has a delta of -0.25, whereas a 25-Delta call has a delta of 0.25.

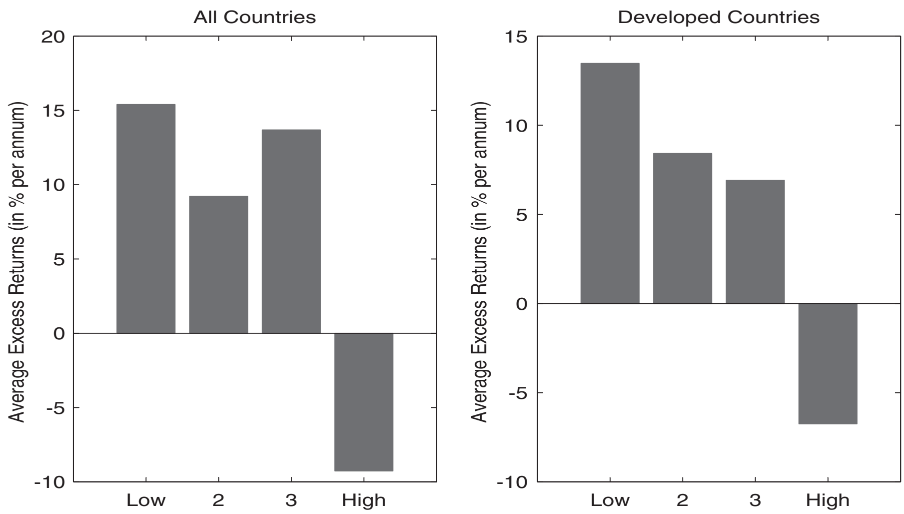

Figure 2. Excess returns and volatility. The figure shows mean excess returns for carry trade portfolios conditional on global FX volatility innovations being within the lowest to highest quartile of its sample distribution (four categories from "Low" to "High" shown on the x-axis of each panel). The bars show average excess returns for being long in portfolio 5 (largest forward discounts) and short in portfolio 1 (lowest forward discounts). The left panel shows results for all countries, while the right panel shows results for developed countries. The sample period is November 1983 to August 2009.

when the market is volatile, that is, low interest rate currencies (or funding currencies) provide a hedge in times of market turmoil. The following sections test this finding more rigorously.

B. Methods

This section briefly summarizes our approach to cross-sectional asset pricing. The benchmark results rely on a standard SDF approach (Cochrane (2005)), which is also used in Lustig, Roussanov, and Verdelhan (2011), for instance.

We denote excess returns of portfolio i in period $t+1$ by rx_{t+1}^{i}.[17] The usual no-arbitrage relation applies so that risk-adjusted currency excess returns have a price of zero and satisfy the basic Euler equation

$$\mathbb{E}\left[m_{t+1} rx_{t+1}^{i}\right] = 0, \tag{5}$$

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

[17] Note that we follow Lustig, Roussanov, and Verdelhan (2011) and employ discrete returns (and not log returns as above) in all our pricing exercises below to satisfy the Euler equation, which is for levels of returns and not logs. Discrete returns for currency k are defined as $rx_{t+1}^{k} = \frac{F_t^k - S_{t+1}^k}{S_t^k}$, where F and S are the level of the forward and spot exchange rate, respectively.

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:

$$\mathbb{E}[rx^i] = \lambda' \beta_i, \tag{6}$$

for each portfolio i (see, for example, Cochrane (2005)). The relationship between the factor risk prices in equation (6) and the SDF parameters in equation (5) is given by $\lambda = \Sigma_h b$ such that, similar to the traditional Fama–MacBeth (FMB) approach (Fama and MacBeth (1973)), factor risk prices can easily be obtained via the SDF approach.

We estimate the parameters of equation (5) via the Generalized Method of Moments (GMM) of Hansen (1982). Estimation is based on a prespecified 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 ability of the model to explain the cross section of expected currency excess returns per se. Factor means and the individual elements of the covariance matrix of risk factors Σ_h are estimated simultaneously with the SDF parameters by adding the corresponding moment conditions to the asset pricing moment conditions implied by equation (5). This one-step approach ensures that we adequately incorporate estimation uncertainty associated with the fact that factor means and the factor covariance matrix have to be estimated (see, for example, Burnside (2011)).[18]

In the following tables, we report estimates of b and implied λs as well as cross-sectional R^2s 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). We also report simulated p-values for tests of whether the HJ distance is equal to zero.[19]

Besides the GMM tests, we also report results using traditional FMB two-pass ordinary least squares (OLS) methodology (Fama and MacBeth (1973)) to estimate portfolio betas and factor risk prices. Note that we do not include a constant in the second stage of the FMB regressions, that is, we do not allow a common over- or underpricing in the cross section of returns. However, our results are virtually identical when we replace the DOL factor with a constant in the second-stage regressions. Since DOL has basically no cross-sectional relation with the carry trade portfolios' returns, it effectively serves

[18] We also estimate a version where we account for uncertainty induced by the estimation of volatility innovations by stacking the corresponding moment conditions of the AR(1) model for our volatility series with the remaining asset pricing moment conditions. We then use the estimated volatility innovations in the pricing kernel such that estimation uncertainty is incorporated directly in the estimation of factor prices and model parameters. We provide details of this approach in the Appendix.

[19] Simulations are based on weighted $\chi^2(1)$-distributed random variables. For more details on the computation of the HJ distance and the respective tests, see Jagannathan and Wang (1996) and Parker and Julliard (2005).

the same purpose as a constant that allows for a common mispricing.[20] We report standard errors with a Shanken (1992) adjustment as well as GMM standard errors with a Newey and West (1987) adjustment and automatic lag length determination according to Andrews (1991). More details on the FMB procedure, computation of GMM and FMB standard errors, and the exact moment conditions used in the GMM estimation are provided in the Appendix of this paper.

C. Asset Pricing Tests

This section presents our main result that excess returns to carry trade portfolios can be understood by their covariance exposure with global FX volatility innovations.

C.1. Volatility Innovations

Table II presents results of our asset pricing tests using the five currency portfolios detailed above as test assets. As factors we use DOL and innovations to global FX volatility (VOL, or $\triangle\sigma_{t+1}^{FX}$ in the regressions below) based on the residuals of an AR(1) for global volatility. The pricing kernel is thus given by

$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{VOL}\triangle\sigma_{t+1}^{FX}.$$

Panel A of Table II shows cross-sectional pricing results. We are primarily interested in the factor risk price of global FX volatility innovations. As theoretically expected, we find a significantly negative estimate for λ_{VOL}. In fact, λ_{VOL} is estimated to be negative both for the full sample (left part of the table) and for the developed country sample (right part of the table). The estimated factor price is -0.07 for the full sample and -0.06 for the developed country sample.

The negative factor price estimate directly translates into lower risk premia for portfolios whose returns co-move positively with volatility innovations (i.e., volatility hedges), whereas portfolios with a negative covariance with volatility innovations demand a risk premium. We also find that the volatility factor yields a nice cross-sectional fit with R^2s of more than 90%, and we cannot reject the null that the HJ distance is equal to zero. The values of the distance measure (i.e., the maximum pricing errors per one unit of the payoff norm) are also quite small in economic terms, both for the full sample and the developed country sample.

Now, which portfolios of currencies provide insurance against volatility risk and which do not? Panel B of Table II shows time-series beta estimates for the five forward discount-sorted portfolios based on the full sample and the developed country sample. Estimates of β_{VOL} are large and positive for currencies

[20] Also see Burnside (2011) and Lustig and Verdelhan (2007) on the issue of whether to include a constant.

Table II

Cross-sectional Asset Pricing Results: Volatility Risk

The table reports cross-sectional pricing results for the linear factor model based on the dollar risk factor (DOL) and global FX volatility innovations (VOL). The test assets are excess returns to five carry trade portfolios based on currencies from all countries (left panel) or developed countries (right panel). Panel A shows coefficient estimates of SDF parameters b and factor risk prices λ obtained by GMM and FMB cross-sectional regression. We use first-stage GMM and do not use a constant in the second-stage FMB regressions. Standard errors (s.e.) of coefficient estimates are reported in parentheses and are obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). We also report the cross-sectional R^2 and the HJ distance (HJ dist) along with the (simulation-based) p-value for the test of whether the HJ distance is equal to zero. The reported FMB standard errors and χ^2 test statistics (with p-values in parentheses) are based on both the Shanken (1992) adjustment (Sh) or the Newey–West approach with optimal lag selection (NW). Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), and global FX volatility innovations (VOL). HAC standard errors (Newey–West with optimal lag selection) are reported in parentheses. The sample period is December 1983 to August 2009 and we use monthly transaction cost adjusted returns.

Panel A: Factor Prices

All Countries (with b-a)					Developed Countries (with b-a)				
GMM	DOL	VOL	R^2	HJ dist	GMM	DOL	VOL	R^2	HJ dist
b	0.00	−7.15	0.97	0.08	b	0.02	−4.38	0.94	0.06
s.e.	(0.05)	(2.96)		(0.79)	s.e.	(0.03)	(2.73)		(0.89)
λ	0.21	−0.07			λ	0.22	−0.06		
s.e.	(0.25)	(0.03)			s.e.	(0.22)	(0.04)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.21	−0.07	1.35	0.94	λ	0.22	−0.06	0.95	0.83
(Sh)	(0.15)	(0.02)	(0.72)	(0.82)	(Sh)	(0.16)	(0.02)	(0.81)	(0.84)
(NW)	(0.13)	(0.03)			(NW)	(0.15)	(0.03)		

Panel B: Factor Betas

All Countries (with b-a)					Developed Countries (with b-a)				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	−0.29	1.01	4.34	0.76	1	−0.23	0.94	4.52	0.71
	(0.08)	(0.04)	(0.70)			(0.09)	(0.05)	(1.42)	
2	−0.15	0.84	1.00	0.74	2	−0.05	1.05	0.43	0.82
	(0.06)	(0.04)	(0.59)			(0.07)	(0.04)	(0.89)	
3	0.05	0.97	−0.30	0.79	3	−0.02	1.01	0.01	0.88
	(0.06)	(0.04)	(0.63)			(0.05)	(0.03)	(0.64)	
4	0.09	1.02	−1.06	0.83	4	0.07	0.96	−1.94	0.82
	(0.06)	(0.04)	(0.71)			(0.07)	(0.03)	(0.97)	
5	0.30	1.15	−3.98	0.67	5	0.24	1.04	−3.02	0.73
	(0.11)	(0.06)	(1.20)			(0.10)	(0.05)	(1.09)	

with a low forward discount (i.e., with low interest rates), whereas countries with a high forward discount co-move negatively with global FX volatility innovations. There is a strikingly monotone decline in betas when moving from the first to the fifth portfolio and it is precisely this monotone relationship

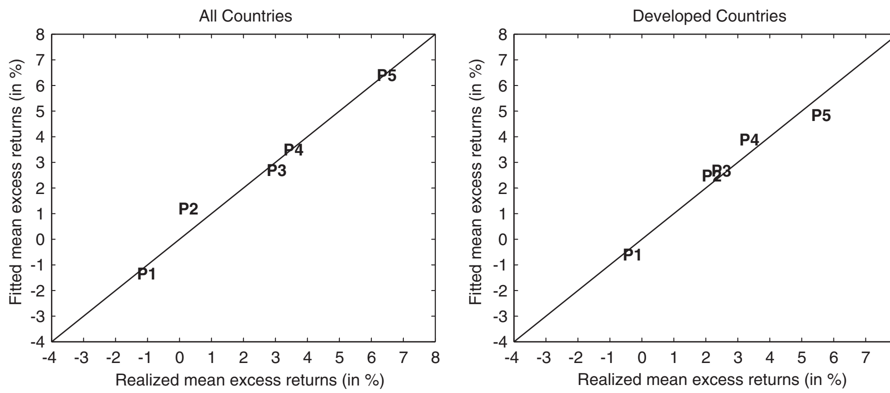

Figure 3. Pricing error plots. The figure shows pricing errors for asset pricing models with global volatility as the risk factor. The sample period is November 1983 to August 2009.

that produces the large spread in mean excess returns as shown in Table I.[21] These results also corroborate our simple graphical illustration (Figure 2) in Section III.A: Investors demand a high return on the investment currencies in the carry trade portfolio (high interest rate currencies) since they perform particularly poorly in periods of unexpected high volatility, whereas investors are willing to accept low returns on carry trade funding currencies (low interest rate currencies) since these currencies provide a hedge against periods of market turmoil.

Finally, we present results on the fit of our model in Figure 3, which plots realized mean excess returns along the horizontal axis and fitted mean excess returns implied by our model along the vertical axis. The main finding is that volatility risk is able to reproduce the spread in mean returns quite well, both in the full sample (left panel) and in the sample of developed countries (right panel).

C.2. Factor-Mimicking Portfolio

Following Breeden, Gibbons, and Litzenberger (1989) and Ang et al. (2006), we build a factor-mimicking portfolio of volatility innovations.

[21] In the Internet Appendix, we also report results using simple volatility changes instead of AR(1) innovations. Results are very similar. We also estimate the AR(1) parameters jointly with the rest of the model's parameters by stacking AR(1) moment conditions and asset pricing moment conditions imposing cross-equation restrictions. This avoids potential errors-in-variables problems as noted in Section II. Our results are basically unchanged, however. For example, the standard error of λ_{VOL} is 0.031 when we estimate the AR(1)-based volatility innovations within the system of moments. This result is not too surprising since volatility is rather persistent and the AR(1) coefficients are estimated with high precision in our sample. Furthermore, in the Internet Appendix, we also show results using transaction cost adjustments that assume 100% turnover per month as in Lustig, Roussanov, and Verdelhan (2011). Again, our results are robust to this modification. Finally, we estimate our baseline specification using log returns instead of discrete returns. Using discrete or log excess returns does not impact our results.

Converting our factor into a return has the advantage of allowing us to scrutinize the factor price of risk in a natural way. If the factor is a traded asset, then the risk price of this factor should be equal to the mean return of the traded portfolio so that the factor prices itself and no-arbitrage is satisfied.

To obtain the factor-mimicking portfolio, we regress volatility innovations on the five carry trade portfolio *excess* returns

$$\triangle\sigma_{t+1}^{FX} = a + \mathbf{b}'\mathbf{rx_{t+1}} + u_{t+1}, \tag{7}$$

where rx_{t+1} is the vector of excess returns of the five carry trade portfolios. The factor-mimicking portfolio's excess return is then given by $rx_{t+1}^{FM} = \widehat{\mathbf{b}}'\mathbf{rx_{t+1}}$. The average excess return to this mimicking portfolio is -1.28% per annum. It is also instructive to look at the weights $\widehat{b}$ of this portfolio given by

$$rx_{t+1}^{FM} = 0.202rx_{t+1}^1 - 0.054rx_{t+1}^2 - 0.063rx_{t+1}^3 - 0.068rx_{t+1}^4 - 0.071rx_{t+1}^5,$$

which shows, as one would expect, that the factor-mimicking portfolio for volatility innovations loads positively on the return to portfolio 1. This portfolio provides a hedge against volatility innovations and has an increasingly negative loading on portfolios 2–5. The portfolio weights also show that the factor-mimicking portfolio should capture some pricing information in the Lustig et al. (2011) HML_{FX} factor, which is long in portfolio 5 and short in portfolio 1. Indeed, our factor-mimicking portfolio has a correlation of roughly -85% with HML_{FX}. This result is not surprising. Lustig, Roussanov, and Verdelhan (2011) show that HML_{FX} is closely related to the second principal component (PC) of the cross section of carry trade portfolios and this second PC captures basically all the necessary cross-sectional pricing information. Since volatility innovations as a pricing factor also lead to a very high cross-sectional fit (as shown above), it is natural to expect that the factor-mimicking portfolio of the five carry trade portfolios is closely related to this second PC (correlation with the factor-mimicking portfolio: 80%) and thus to HML_{FX}. We find that this is the case.

Finally, we test the pricing ability of the factor-mimicking portfolio and replace volatility innovations with rx_{t+1}^{FM} in the pricing kernel. As above, we use the five carry trade portfolios as our test assets. The results, reported in Table III, reveal a significantly negative factor price of $\lambda_{VOL} = -0.102\%$, which can be compared to the average monthly excess return of the factor-mimicking portfolio of $\overline{rx}_{t+1}^{FM} = -0.107\%$. This result is comforting since it implies that our factor price of risk makes sense economically, and the factor prices itself and thus is arbitrage-free.[22]

C.3. Zero-Beta Straddle

While the analysis in Breeden, Gibbons, and Litzenberger (1989) calls for using the test assets as the base assets to construct the factor-mimicking portfolio,

[22] See Lewellen, Nagel, and Shanken (2010) on the importance of taking the magnitude of the cross-sectional slopes, that is, the factor prices, seriously.

Table III

Cross-sectional Asset Pricing Results: Factor-Mimicking Portfolio

The setup of this table is identical to Table II except we replace volatility innovations by the factor-mimicking portfolio of volatility innovations (VOL_{FM}). Test assets are the five carry trade portfolios (excess returns) based on all countries or the 15 developed countries. Panel A reports SDF parameter estimates b and factor prices λ obtained by GMM and FMB cross-sectional regression. Standard errors (s.e.) of coefficient estimates (Newey and West (1987) with optimal lag selection) are reported in parentheses, as well as p-values for the Hansen–Jagannathan distance (HJ dist) and the χ^2 test statistics for the null that all pricing errors are jointly equal to zero. FMB standard errors and pricing error statistics are based on the Shanken (1992) adjustment (Sh) or the Newey–West approach with optimal lag selection (NW). Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), and the factor-mimicking portfolio of volatility innovations. Robust (HAC) standard errors are reported in parentheses. The sample period is December 1983 to August 2009 and we use monthly net returns.

Panel A: Factor Prices

All Countries (with b-a)					Developed Countries (with b-a)				
GMM	DOL	VOL	R^2	HJ dist	GMM	DOL	VOL	R^2	HJ dist
b	0.00	−0.71	0.97	0.08	b	0.01	−0.58	0.97	0.06
s.e.	(0.03)	(0.23)		(0.64)	s.e.	(0.03)	(0.26)		(0.86)
λ	0.21	−0.10			λ	0.22	−0.08		
s.e.	(0.15)	(0.03)			s.e.	(0.16)	(0.04)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.21	−0.10	1.89	4.59	λ	0.22	−0.09	0.90	0.81
(Sh)	(0.13)	(0.02)	(0.60)	(0.20)	(Sh)	(0.15)	(0.03)	(0.83)	(0.85)
(NW)	(0.13)	(0.03)			(NW)	(0.14)	(0.03)		

Panel B: Factor Betas

All Countries (with b-a)					Developed Countries (with b-a)				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	−0.01	1.21	3.63	1.00	1	0.02	1.05	3.08	0.84
	(0.01)	(0.00)	(0.02)			(0.08)	(0.04)	(0.26)	
2	−0.08	0.89	0.85	0.76	2	0.04	1.09	1.09	0.84
	(0.06)	(0.04)	(0.21)			(0.07)	(0.04)	(0.18)	
3	0.03	0.96	−0.24	0.79	3	−0.04	1.00	−0.29	0.88
	(0.06)	(0.05)	(0.19)			(0.06)	(0.03)	(0.16)	
4	0.02	0.98	−0.88	0.84	4	−0.03	0.92	−1.16	0.84
	(0.06)	(0.04)	(0.24)			(0.08)	(0.04)	(0.28)	
5	0.04	0.96	−3.36	0.79	5	0.01	0.94	−2.71	0.81
	(0.09)	(0.05)	(0.30)			(0.09)	(0.04)	(0.30)	

as we have done above, we empirically find that the resulting factor-mimicking portfolio is very close to the second PC of the carry trade cross section. This shows that volatility innovations contain all the information necessary to price this cross section, but it may also raise concerns that our estimated price of volatility risk may be mechanically identical to the mean return on the factor-mimicking portfolio.[23] Hence, we complement the analysis above by constructing a zero-beta straddle along the lines of Coval and Shumway (2002) based on our FX option data (described in Section III above).

To this end, we form an equally weighted portfolio of long calls and long puts of all available currencies to obtain a time series of average excess returns to holding call and put positions. We then combine these two portfolio excess returns to obtain a straddle portfolio that has zero correlation with the "market risk" factor (the *DOL* factor in our case). This portfolio delivers high returns in times of high volatility by construction, and hence loads on volatility risk but has no market risk.

Empirically, the zero-beta straddle has a weight on long calls of roughly 52% and a weight on long puts of 48% in order for it to be uncorrelated with the *DOL* factor. More importantly, the straddle portfolio yields a significantly negative mean return of -1.22% per annum (with a t-statistic of -2.77), which is very close to our price of volatility risk estimated above. Also, the straddle return has a correlation of about 40% with our factor-mimicking portfolio. Hence, our risk price estimate from above is validated by the zero-beta straddle return and has a magnitude of approximately -1.2% to -1.3%, which is close to the estimated value of about -1% for stock markets documented by Ang et al. (2006).

D. Portfolios Based on Volatility Betas

We now explore the explanatory power of volatility risk for carry trade portfolios from another perspective. If volatility risk is a priced factor, then it is reasonable to assume that currencies sorted according to their exposure to volatility innovations yield a cross section of portfolios with a significant spread in mean returns.[24] Currencies that hedge against volatility risk should trade at a premium, whereas currencies that yield low returns when volatility is high should yield a higher return in equilibrium.

We therefore sort currencies into five portfolios depending on their past beta with innovations to global FX volatility. We use rolling estimates of beta with a rolling window of 36 months (as in Lustig, Roussanov, and Verdelhan (2011)), and we rebalance portfolios every 6 months.[25] Descriptive statistics for portfolio excess returns are shown in Table IV.

The table shows that investing in currencies with high volatility beta (i.e., hedges against volatility risk) leads to a significantly lower return than investing in low volatility beta currencies. The spread between portfolio 1 (low volatility beta, that is, high volatility risk) and portfolio 5 (high volatility beta, that is, low volatility risk) exceeds 4% per annum for both the sample of all

[23] We thank an anonymous referee for pointing this out.

[24] Beta sorts are a common means to investigate risk premia in financial markets (see, for example, Pástor and Stambaugh (2003), Ang et al. (2006), Lustig, Roussanov, and Verdelhan (2011)).

[25] We do not employ returns from the first 36 months of our sample for this analysis since we would have to rely on in-sample estimated betas for this period.

Table IV

Portfolios Sorted on Betas with Global Volatility

The table reports statistics for portfolios sorted on volatility betas, that is, currencies are sorted according to their beta in a rolling time-series regression of individual currencies' excess returns on volatility innovations. Portfolio 1 contains currencies with the lowest betas, whereas portfolio 5 contains currencies with the highest betas. The remaining notation follows Table I. We report average preformation (pre-f. $f-s$) and post formation (post-f. $f-s$) forward discounts for each portfolio (in % per annum). Preformation discounts are calculated at the end of the month just prior to portfolio formation, whereas post formation forward discounts are calculated over the 6 months following portfolio formation. We also report presorting (pre-β) and post sorting (post-β) volatility betas in the last two rows of each panel.

Portfolio	1	2	3	4	5	Avg.	H/L
All Countries							
Mean	4.28	2.76	2.19	0.69	0.17	2.02	4.11
	[2.05]	[1.36]	[1.37]	[0.39]	[0.09]	[0.98]	[1.91]
Std. dev.	9.58	8.43	7.22	7.35	8.19	6.93	8.88
Skewness	−0.63	−0.67	−0.61	−0.41	−0.01	−0.48	−0.23
Kurtosis	5.17	5.23	6.75	4.06	3.30	4.22	3.29
AC(1)	17.47	11.69	3.26	5.34	3.84	12.15	0.33
	(0.00)	0.00	0.20	0.07	0.15	0.00	0.85
Coskew (DOL)	−0.14	0.11	−0.10	0.06	0.27	−0.47	−0.23
Coskew (MKT)	0.12	0.11	0.22	0.16	0.13	0.17	0.01
pre-f. $f-s$	0.23	0.22	0.11	0.06	0.01		
post-f. $f-s$	0.25	0.27	0.11	0.02	0.00		
pre-β	−9.49	−3.58	−0.75	2.11	5.77		
post-β	−4.30	0.65	−0.51	0.99	3.18		
Developed Countries							
Mean	3.77	1.99	1.46	1.76	−0.43	1.71	4.20
	[1.25]	[0.88]	[0.64]	[1.20]	[−0.17]	[0.87]	[1.69]
Std. dev.	8.93	9.59	9.83	10.43	9.08	8.39	8.68
Skewness	−1.02	−0.32	−0.40	−0.18	0.06	−0.35	−0.38
Kurtosis	7.78	4.33	4.07	3.57	3.48	3.77	4.58
AC(1)	12.10	5.41	4.53	2.10	2.04	7.92	0.68
	0.00	0.07	0.10	0.35	0.36	0.02	0.71
Coskew (DOL)	−0.38	−0.07	0.09	0.02	0.25	−0.25	−0.37
Coskew (MKT)	0.03	0.13	0.12	0.29	0.06	0.15	−0.03
pre-f. $f-s$	0.09	0.08	0.05	0.07	0.04		
post-f. $f-s$	0.10	0.07	0.05	0.05	0.03		
pre-β	−12.74	4.05	15.30	26.47	44.26		
post-β	−2.20	−1.15	1.17	0.67	2.06		

countries and the sample of developed markets. Moreover, mean excess returns tend to decrease steadily when moving from portfolio 1 to portfolio 5 (although there is a twist in mean excess returns for the developed markets sample).

The table also shows pre- and postformation forward discounts for the five portfolios. The results suggest that these portfolios are similar to the carry trade portfolios in that forward discounts monotonically decline when moving from high return portfolios (portfolio 1) to low return portfolios (portfolio 5). Thus, sorting on volatility risk is similar to sorting on interest rate differentials and hence the carry trade portfolios themselves.

However, a noteworthy difference between the carry trade portfolios and these volatility beta-sorted portfolios is that they have a very different skewness pattern compared to the forward discount sorts. Table I shows that excess returns of high interest rate currencies have much lower skewness than low interest rate currencies (also see Brunnermeier, Nagel, and Pedersen (2009)). We do not find this pattern here. On the contrary, the H/L portfolios actually tend to have higher skewness than portfolio 1, which suggests that sorting on volatility betas produces portfolios related to but not identical to the carry trade portfolios. Furthermore, we also do not find patterns in kurtosis or coskewness that line up well with average excess returns. Related to this finding, we find a clear increase in postsorting time-series volatility betas when moving from portfolio 1 to portfolio 5, just as for the carry trade portfolios documented in Table I. However, the increase is not completely monotonic, and, thus, our beta sorts do not reproduce the carry trade cross section completely.

Overall, this section shows that volatility risk, as measured by the covariance of a portfolio's return with innovations to global FX volatility, matters for understanding the cross section of currency excess returns. This empirical relation is in line with theoretical arguments that assets offering high payoffs in times of (unexpected) high aggregate volatility, and hence that serve as a volatility hedge, trade at a premium in equilibrium and vice versa.

IV. Relating Volatility and Liquidity Risk

As noted at the beginning of this paper, it is hard to disentangle volatility and liquidity effects since these concepts are closely related and, particularly in the case of liquidity, not directly observable. However, it is interesting to examine the contribution of these two proxies for currency investment risk since Brunnermeier, Nagel, and Pedersen (2009) suggest that liquidity plays an important role in understanding risk premia in FX. This section therefore relates volatility and liquidity proxies and investigates their relative pricing power.

A. Liquidity Proxies

A.1. Global Bid-Ask Spread

As a first measure of global FX liquidity, we resort to a classical measure from market microstructure, the BAS. For consistency, we use the same aggregating scheme as for global FX volatility in equation (4) to obtain a global BAS measure ψ^{FX}:

$$\psi_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{\psi_\tau^k}{K_\tau} \right) \right], \tag{8}$$

where ψ_τ^k is the percentage BAS of currency k on day τ. Higher BASs indicate lower liquidity so that the aggregate measure ψ_t^{FX} can be seen as a global proxy for FX market *illiquidity*.

A.2. TED Spread

The TED spread is defined as the interest rate difference between 3 month euro interbank deposits (LIBOR) and 3 month Treasury bills. Differences between these rates reflect, among other things, the willingness of banks to provide funding in the interbank market; a large spread should be related to lower liquidity. Hence, the TED spread serves as an illiquidity measure, as used, for example, by Brunnermeier, Nagel, and Pedersen (2009). We include the TED spread to proxy for illiquidity in the funding market for carry trades.

A.3. Pástor-Stambaugh Liquidity Measure

Pástor and Stambaugh (2003) construct a liquidity measure for the U.S. stock market based on price reversals. The general idea underlying their measure (denoted as PS here) is that stocks with low liquidity should be characterized by a larger price impact of order flow. Liquidity-induced movements of asset prices have to be reversed eventually such that stronger price reversals indicate lower liquidity. We refer to Pástor and Stambaugh (2003) for more details on the construction of this measure and simply note here that they scale their measure to be a liquidity proxy, that is, higher values of the PS measure reflect higher liquidity. This contrasts with the other two liquidity proxies, which instead measure *illiquidity*. Since it seems reasonable to assume that liquidity risk is correlated across assets to a certain extent, we include the PS measure to proxy for liquidity risk in the home market of our baseline U.S. investor.

A.4. Relations among Volatility and Liquidity Factors

How strongly are volatility and liquidity factors related? We find that innovations of our FX volatility proxy are positively correlated with innovations of the BAS (20%) and the TED spread (19%), and negatively correlated with innovations of the PS measure (−21%). Not surprisingly, the relation between the three liquidity measures and FX volatility is far from perfect. The BAS and the TED spread measures, for instance, are only mildly correlated (8%) and no correlation coefficient is larger than 30% in absolute value. Similarly, a PC analysis reveals that the first PC explains less than 30% of the total variance. Overall, volatility and liquidity are statistically significantly correlated, but the magnitudes of correlations are not impressive quantitatively.

B. Empirical Results for Liquidity Factors

To shed more light on the role of liquidity risk for currency returns, we run the same asset-pricing exercises as above in Section III, but replace volatility

Table V

Cross-Sectional Asset Pricing Results: Liquidity Risk

The setup is the same as in Table II except this table shows factor prices for three different models. We only report results based on GMM. As test assets we use excess returns to the five carry trade portfolios based on all countries or the 15 developed countries. Factors are the dollar risk factor (DOL), and innovations of (i) the global average percentage bid-ask spread denoted as BAS (Panel A), (ii) the TED spread (Panel B), or (iii) the Pástor and Stambaugh (2003) liquidity measure denoted as PS (Panel C).

Panel A: Factor Prices—Global Bid-Ask Spread

All Countries (with b-a)					Developed Countries (with b-a)				
GMM	DOL	BAS	R^2	HJ dist	GMM	DOL	BAS	R^2	HJ dist
b	0.00	−54.06	0.74	0.19	b	0.02	−36.68	0.58	0.13
s.e.	(0.05)	(26.48)		(0.16)	s.e.	(0.03)	(22.63)		(0.36)
λ	0.21	−0.03			λ	0.22	− 0.02		
s.e.	(0.24)	(0.01)			s.e.	(0.21)	(0.01)		

Panel B: Factor Prices and Loadings—TED Spread

All Countries (with b-a)					Developed Countries (with b-a)				
GMM	DOL	TED	R^2	HJ dist	GMM	DOL	TED	R^2	HJ dist
b	0.04	−4.38	0.73	0.13	b	0.03	−2.44	0.81	0.66
s.e.	(0.07)	(3.35)		(0.53)	s.e.	(0.04)	(2.06)		(0.16)
λ	0.21	−0.36			λ	0.22	−0.20		
s.e.	(0.30)	(0.28)			s.e.	(0.24)	(0.17)		

Panel C: Factor Prices and Loadings—Pástor/Stambaugh Liquidity Measure

All Countries (with b-a)					Developed Countries (with b-a)				
GMM	DOL	PS	R^2	HJ dist	GMM	DOL	PS	R^2	HJ dist
b	0.06	12.89	0.70	0.19	b	0.05	12.24	0.97	0.05
s.e.	(0.05)	(8.29)		(0.09)	s.e.	(0.04)	(9.05)		(0.94)
λ	0.18	0.05			λ	0.18	0.05		
s.e.	(0.22)	(0.03)			s.e.	(0.23)	(0.03)		

innovations with innovations of one of the three liquidity factors. Table V shows factor loadings and prices for these models.[26] All three models shown in panels A–C perform quite well with R^2s ranging from 70% to almost 100% and are not rejected by the HJ distance specification tests or the χ^2 test (except for the PS measure on the sample of all countries). Moreover, the factor prices λ have the expected sign—that is, negative for illiquidity (BAS, TED) and positive for liquidity (PS)—and are significantly different from zero for the BAS and marginally significant for the PS measure. However, none of these three

[26] We only report GMM results in Table V (and all future tables in the paper) to conserve space. Results based on the two-pass FMB method are available in the Internet Appendix of this paper.

Table VI

Cross-sectional Asset Pricing Results: Volatility and Liquidity Risk

The setup is the same as in Table II. As test assets we use excess returns to the five carry trade portfolios based on all countries. Factors are the dollar risk factor (DOL), FX volatility innovations (VOL), and innovations to (i) the global average percentage bid-ask spread denoted as BAS (Panel A), (ii) the TED spread (Panel B), or (iii) the Pástor and Stambaugh (2003) liquidity measure denoted as PS (Panel C). The latter three measures of liquidity risk are orthogonalized with respect to volatility innovations.

Panel A: Volatility and Global Bid-Ask Spreads

GMM	DOL	BAS	VOL	R^2	HJ dist
b	0.01	18.23	−8.11	0.98	0.06
s.e.	(0.07)	(36.08)	(4.24)		(0.82)
λ	0.21	0.01	−0.08		
s.e.	(0.31)	(0.02)	(0.04)		

Panel B: Volatility and TED Spread

GMM	DOL	TED	VOL	R^2	HJ dist
b	0.01	−1.03	−6.17	0.98	0.07
s.e.	(0.05)	(2.94)	(3.28)		(0.66)
λ	0.21	−0.08	−0.06		
s.e.	(0.25)	(0.24)	(0.03)		

Panel C: Volatility and P/S Liquidity Measure

GMM	DOL	PS	VOL	R^2	HJ dist
b	−0.01	−1.65	−7.46	0.97	0.08
s.e.	(0.07)	(10.36)	(3.82)		(0.65)
λ	0.18	−0.01	−0.08		
s.e.	(0.29)	(0.04)	(0.04)		

models outperform the volatility risk factor in terms of R^2s and HJ distances for either the full sample or developed country sample.

To address the relative importance of volatility and liquidity as risk factors, we also evaluate specifications in which we include volatility innovations and innovations of one of the liquidity factors (or, alternatively, that part of liquidity not explained by contemporaneous volatility) jointly in the SDF. Since volatility and liquidity are somewhat correlated, leading to potential multicollinearity and identification issues, we report results for the full country sample for the case in which volatility innovations and the orthogonalized component (orthogonalized with respect to volatility innovations) of one of the three liquidity factors are included. Results are shown in Table VI.[27]

The central message of these results is that volatility innovations emerge as the dominant risk factor, corroborating the evidence in Bandi, Moise, and

[27] Results for developed countries and results for not orthogonalizing liquidity innovations are very similar.

Russell (2008) for the U.S. stock market. Panel A, for example, shows results when jointly including innovations to global FX volatility and global BASs: both b_{VOL} and λ_{VOL} are significantly different from zero, whereas the BAS factor is found to be insignificant in this joint specification. The same result obtains for the TED spread (panel B) and the PS liquidity factor (panel C). Volatility remains significantly priced, whereas liquidity factors always become insignificant when jointly included with volatility. We therefore conclude that volatility is more important than each of the three single liquidity factors. However, we cannot rule out an explanation based on volatility just being a summary measure of various dimensions of liquidity that are not captured by our three (il)liquidity proxies.

V. Alternative Explanations for Our Findings

This section discusses alternative explanations for our findings beyond liquidity risk.

A. Peso Problems

The estimate of the price of global volatility risk is statistically significant but small in magnitude (−0.07% per unit of volatility beta). Given these small estimates, one alternative explanation for our findings may be a Peso problem. By construction, the factor-mimicking portfolio does well when global FX volatility displays a large positive innovation. The small negative mean of the excess returns in the factor-mimicking portfolio of −0.107% per month may potentially be due to having observed a smaller number of volatility spikes than the market expected ex ante.

Therefore, one explanation for our findings could be that market participants expected more spikes in volatility than have actually occurred over our sample period. Put another way, since the factor price of volatility is negative (or, equivalently, the factor-mimicking portfolio has a negative average excess return), a few more large volatility innovations may suffice to wipe out the negative risk premium estimate in our benchmark specifications in Tables II and III. Similarly, if market participants expected less volatility spikes, our estimate of the volatility risk premium may be biased upward. It is clear that extreme observations in our volatility factor could thus drive our results.

We provide some indicative evidence on the robustness of our findings with respect to the above issue. First, we winsorize our volatility series at the 99%, 95%, and 90% levels, that is, we set the 1%, 5%, or 10% most extreme volatility observations equal to their cutoff levels.[28] When we repeat our benchmark pricing test with these winsorized volatility factors, we obtain very robust results. For instance, we find estimates for the SDF slope, volatility risk premium, and cross-sectional R^2 of $b = -7.446$ (GMM s.e.: 3.623), $\lambda = -0.072$ (GMM s.e.: 0.035), and $R^2 = 0.97\%$ when we exclude the 1% most extreme volatility

[28] We thank an anonymous referee for suggesting this exercise.

observations. Similarly, we find $b = -8.334$ (4.043), $\lambda = -0.067$ (0.032), and $R^2 = 97\%$ when excluding the 5% most extreme observations, and estimates of $b = -9.510$ (4.465), $\lambda = -0.062$ (0.029), and $R^2 = 95\%$ when excluding the 10% most extreme observations. It seems fair to conclude that our main result, as reported in Tables II and III, is not driven by outliers in our volatility proxy.

Second, we adopt an EL approach to estimate the moment conditions implied by our baseline specification. EL shares many similarities with traditional GMM and is particularly attractive here since it endogenously allows the probabilities attached to the states of the economy to differ from their sample frequencies (which is the nature of Peso problems). It is thus more robust under Peso problems or rare events as argued, for example, by Ghosh and Julliard (2010). The results from this exercise are very similar to those based on GMM, and thus Peso problems do not seem to drive our results. In the Internet Appendix of this paper, we discuss the exact implementation of the procedure and provide detailed estimation results.

B. Horse Races between Volatility and HML_{FX}: A First Look

We run horse races between our volatility risk factor and the HML_{FX} factor of Lustig et al. (2011) in four different specifications. First, we simply include DOL, volatility innovations, and HML_{FX} jointly in the SDF; second, we include DOL, the factor-mimicking portfolio for volatility innovations, and HML_{FX}; third, we include all three factors but orthogonalize the factor-mimicking portfolio for volatility innovations with respect to HML_{FX}; and fourth, we include all three factors but orthogonalize HML_{FX} with respect to the factor-mimicking volatility portfolio. Results are shown in this ordering of specifications in Panels A–D of Table VII.

In Panel A, it is clear that HML_{FX} dominates volatility innovations when HML_{FX} and volatility innovations are included jointly in the SDF. This result is not too surprising since HML_{FX} is close to the factor-mimicking portfolio of global FX volatility and the second PC of the carry trade return cross section, which accounts for almost all cross-sectional variation in returns. Also, it is clear that a nonreturn factor (volatility innovations) cannot beat its own factor-mimicking portfolio in a horse race (see, for example, chapter 7 in Cochrane (2005)). We find exactly this result in our first test in Panel A.

Panel B shows results when including both the factor-mimicking portfolio for volatility innovations and HML_{FX}. These two factors are highly correlated, and thus we find that the SDF slopes (b) of both factors become insignificant and both λs are significant so that results here cannot be seen as decisive due to multicollinearity issues.

Perhaps, more interestingly, Panels C and D show results when we orthogonalize either the factor-mimicking portfolio with respect to HML_{FX} (Panel C) or HML_{FX} with respect to the factor-mimicking portfolio of volatility innovations (Panel D). These are more reliable results since, by testing whether the orthogonal component of either factor is priced, we avoid the statistical

Table VII

Cross-sectional Asset Pricing Results: Volatility and HML_{FX}

The setup is the same as in Table II, but this table shows factor prices for models where we jointly include the DOL factor, HML_{FX}, and different variants of global FX volatility factors (VOL). We only report results based on GMM. As test assets we use (excess returns to) the five carry trade portfolios based on all countries or the 15 developed countries. Panel A shows results for volatility innovations, Panel B for the factor-mimicking portfolio of volatility innovations (VOL_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to HML_{FX}, denoted as $VOL_{FM}^{Orth.}$, and HML_{FX}, and Panel D for the factor-mimicking portfolio for volatility VOL_{FM} and HML_{FX} orthogonalized with respect to volatility, denoted as $HML_{FX}^{Orth.}$. The sample period is November 1983 to August 2009.

Panel A: Volatility Innovations and HML_{FX}						Panel B: Factor-Mimicking Portfolio and HML_{FX}					
GMM	DOL	VOL	HML_{FX}	R^2	HJ dist	GMM	DOL	VOL_{FM}	HML_{FX}	R^2	HJ dist
b	0.01	−6.60	0.01	0.97	0.08	b	0.06	−2.54	−0.06	0.98	0.06
s.e.	(0.06)	(6.06)	(0.07)		(0.63)	s.e.	(0.05)	(1.52)	(0.09)		(0.69)
λ	0.21	−0.07	0.65			λ	0.17	−0.04	0.59		
s.e.	(0.27)	(0.06)	(0.33)			s.e.	(0.18)	(0.01)	(0.27)		
Panel C: Factor-Mimicking Portfolio (orth.) and HML_{FX}						Panel D: Factor-Mimicking Portfolio and HML_{FX} (orth.)					
GMM	DOL	$VOL_{FM}^{Orth.}$	HML_{FX}	R^2	HJ dist	GMM	DOL	VOL_{FM}	$HML_{FX}^{Orth.}$	R^2	HJ dist
b	0.00	−6.67	0.08	0.97	0.08	b	0.00	−0.70	0.01	0.97	0.08
s.e.	(0.04)	(4.34)	(0.03)		(0.46)	s.e.	(0.04)	(0.27)	(0.06)		(0.51)
λ	0.21	−0.02	0.65			λ	0.21	−0.10	0.07		
s.e.	(0.16)	(0.01)	(0.24)			s.e.	(0.19)	(0.04)	(1.09)		

inference problems that plague the earlier results. It can be seen from Panel C that the orthogonalized component of the factor-mimicking portfolio still has a significantly negative factor price in the joint specification (the GMM t-statistic is -2.03), presumably due to the fact that the factor-mimicking portfolio picks up some part of the second PC of the cross section of returns that is not captured by HML_{FX}. In contrast, Panel D shows that the orthogonalized component of HML_{FX} is not priced when it is jointly included with the factor-mimicking portfolio of volatility innovations, whereas the latter is highly significantly priced.

Finally, we also compare models with either DOL and volatility innovations or DOL and HML_{FX} in terms of their economic significance. From Table II above, we see that DOL and volatility innovations result in a cross-sectional R^2 of 97% (for the sample of all countries) and an HJ distance of 8% (maximum pricing errors in terms of the payoff norm) with a p-value of 0.79. When we estimate the same model using HML_{FX} instead of volatility innovations, we find a cross-sectional R^2 of 88% and an HJ distance of 13% with a p-value of 0.33. Thus, volatility innovations appear to outperform HML_{FX} in terms of (smaller) pricing errors.

Summing up, it seems fair to conclude that when HML_{FX} and volatility innovations are considered jointly in the SDF, HML_{FX} outperforms volatility innovations in the cross section of carry trade portfolios in terms of statistical significance. However, volatility innovations dominate HML_{FX} in economic terms, that is, by delivering lower pricing errors. This finding is quite remarkable since volatility innovations are not a traded (return-based) risk factor. Importantly, when we convert our risk factor into a return, that is, the factor-mimicking portfolio, and thus level the playground for both factors, we find that the factor-mimicking portfolio prices the cross section at least as well as HML_{FX} and contains some additional information not captured by the latter.

C. Skewness and Coskewness

We also test the pricing ability of skewness and coskewness. With respect to skewness, we do not find that the skewness of a portfolio is robustly related to average excess returns. We show this for the beta-sorted portfolios in Table IV and the developed countries in Table I. Furthermore, we experiment with aggregate skewness measures (computed similarly to our volatility proxy in equation (4) or as the skewness from the DOL portfolio estimated from daily returns within a given month) and test whether the sensitivity of portfolio returns to aggregate skewness (i.e., co-kurtosis) is priced in the cross section of returns. While we find a negative factor price estimate for (sensitivity to) skewness, we do not find it to be significant and the cross-sectional explanatory power is typically low (less than 50% in the cross section of carry trade portfolios).

Regarding coskewness (Harvey and Siddique (1999, 2000)) we show in Table I that the relationship with returns to carry trade portfolios is not particularly strong since the coskewness pattern is not monotone across portfolios. When we test this more formally, we find rather low cross-sectional R^2s of about 50%–60%. We note, however, that this result depends on the specific coskewness measure employed (we use the direct coskewness measure $\widehat{\beta}_{SKD}$ as described above in Section II). In fact, as noted in Section I of the paper, coskewness can alternatively be measured in terms of the sensitivity of returns to market volatility in a time-series regression of excess returns on a market factor and market volatility (see Harvey and Siddique (2000)). Measured in this way, the time-series volatility betas obtained in the first step of our FMB procedure can directly be interpreted as measures of coskewness, and we have shown that the covariance with volatility is significantly priced in the cross section of carry trade returns.[29]

VI. Other Test Assets

We also test the pricing power of global FX volatility as a risk factor for a number of other test assets, which include a cross section of 5 FX momentum returns, 10 U.S. stock momentum portfolios, 5 U.S. corporate bond portfolios (based on ratings), and all 48 individual currencies in our sample. Our results indicate that global FX volatility is priced in these cross sections and we obtain a similar factor price of risk for volatility innovations compared to our benchmark specification in Table II above. These results are interesting since the other test assets above are not highly correlated with the carry trade portfolios and thus serve as an out-of-sample test of the pricing power of volatility innovations.[30] Furthermore, we find that volatility innovations do a much better job of pricing these cross sections than HML_{FX}, lending support to the view that volatility innovations contain additional information and the two factors are not identical.

In short, results based on these out-of-sample tests indicate that our factor is priced in other cross sections and not just in currency carry trades. To conserve space, however, we refer to the Internet Appendix of this paper for a detailed discussion of the test assets' returns, portfolio construction, and empirical estimates of factor models for pricing these cross sections.

VII. Robustness

We perform a number of additional robustness checks related to different proxies for volatility, nonlinearities in the relation between volatility and carry trade returns, and the use of alternative base currencies (i.e., taking the viewpoint of a British, Japanese, or Swiss investor). Overall, our results are robust

[29] We can replace our volatility proxy in equation (4) by squared market returns and still obtain very similar results. Thus, the analysis of Harvey and Siddique (2000) more or less directly applies to our findings as well.

[30] In addition, we present evidence supporting these results for international bond returns and FX option portfolios. These results also support the estimated level of our factor risk price, but the portfolio returns are correlated with the baseline carry trade portfolios.

to all of these modifications, so to conserve space we document these tests in the Internet Appendix.

VIII. Conclusion

This study empirically examines the risk-return profile of carry trades. Carry trades are the consequent trading strategy derived from the forward premium puzzle, that is, the tendency of currencies trading at a positive forward premium (high interest rate) to appreciate rather than depreciate. The major avenue of research to understand this puzzle is the search for appropriate time-varying risk premia. Hence, dealing with a risk-based explanation for carry trades helps explain currency risk premia, while also shedding light on why trading on the forward premium puzzle is no free lunch.

This issue is a long-standing and largely unresolved problem in international finance. Clearly, the consideration of volatility is not new, as the 1990s brought about many studies examining the role of volatility in explaining time-varying risk premia, unfortunately without a satisfactory result. However, the earlier use of volatility in modeling currency risk premia has applied a time-series perspective on single exchange rates (e.g., Bekaert and Hodrick (1992) and Bekaert (1994)). In contrast, we rely on asset pricing methods well-established in the stock market literature where aggregate volatility innovations serve as a systematic risk factor for the cross section of portfolio returns. This approach has proven to be fruitful in empirical research on equity markets and we show that it works very well in FX markets.

In this paper, we argue that global FX volatility innovations are an empirically powerful risk factor in explaining the cross section of carry trade returns. We employ a standard asset pricing approach and introduce a measure of global FX volatility innovations as a systematic risk factor. Interestingly, we find a significantly negative comovement between high interest rate currencies (carry trade investment currencies) and global FX volatility innovations, whereas low interest rate currencies (carry trade funding currencies) provide a hedge against unexpected volatility changes. The covariance of excess returns with volatility is such that our global FX volatility proxy accounts for more than 90% of the spread in five carry trade portfolios. Further analysis shows that liquidity risk also matters for the cross section of currency returns, albeit to a lesser degree. These results are robust to different proxies for volatility and liquidity risk and extend to other cross sections of asset returns such as individual currency returns, equity momentum, and corporate bonds.

The strong link between exposure to volatility shocks and average currency excess returns should also stimulate further theoretical and empirical research aimed at better understanding the drivers of volatility innovations and their link with currency risk premia. It seems plausible that innovations in volatility capture a broad set of shocks to state variables that are relevant to investors and the evolution of their risk-return tradeoff, and hence a better understanding of these linkages is warranted. In addition, it would be useful to build a structural asset pricing model that allows for a direct role of currency volatility risk so that the magnitude of the price of volatility risk can be evaluated more thoroughly. Having established the main results motivating such extensions, we leave these topics for future research.

Appendix

In the Appendix, we provide details on the construction of option returns and on the asset pricing tests conducted in this paper.

Option Returns

To construct returns to option positions, we rely on the currency version of Black and Scholes (1973), introduced by Garman and Kohlhagen (1983).[31] We calculate net payoffs to option positions in USD. We refer to this as the "net payoff" (or "excess return") since we adjust option payoffs for the price (and interest rate loss) of acquiring the option position (see, for instance, Burnside et al. (2011)). For example, the net payoff to a long call position in a foreign currency against the USD is given by

$$rx_{t+1}^{L,C} = F_t^{-1}(\max[S_{t+1} - K, 0] - C_t(1 + r_t)), \tag{A1}$$

and, similarly, that to a long put position is given by $rx_{t+1}^{L,P} = F_t^{-1}(\max[0, K - S_{t+1}] - P_t(1 + r_t))$. Short call positions yield net payoffs of

$$rx_{t+1}^{S,C} = F_t^{-1}(\min[K - S_{t+1}, 0] + C_t(1 + r_t)), \tag{A2}$$

and short puts yield $rx_{t+1}^{S,P} = F_t^{-1}(\min[S_{t+1} - K, 0] + C_t(1 + r_t))$.

Here, C (P) denotes the call (put) price, K denotes the strike, and S (F) denotes the spot and forward rate in USD per foreign currency units (we use American quotation here for ease of exposition). We scale by the current forward rate F_t so that payoffs correspond to a position with a size of one USD (we follow Burnside et al. (2011) in this respect). For our analysis in the main text, we combine different long and short positions for different moneyness groups (i.e., ATM, Delta-25, or Delta-10) of currency options to obtain net payoffs to option strategies such as risk reversals, bull spreads, and bear spreads.

Generalized Method of Moments

The empirical tests in this paper are based on a stochastic discount factor $m_{t+1} = 1 - (h_{t+1} - \mu)$ that is linear in the k risk factors h_{t+1}. Thus, the basic asset pricing equation in (5) implies the following moment conditions for the

[31] The JP Morgan data provide implied volatilities and deltas, but not prices directly. Hence, we infer strike prices from information about deltas and implied volatilities. These can be used, in turn, to compute option prices and holding period returns (since options expire after exactly 1 month).

N-dimensional vector of test asset excess returns rx_{t+1}:

$$\mathbb{E}\{[1 - b'(h_{t+1} - \mu)]rx_{t+1}\} = 0. \tag{A3}$$

In addition to these N moment restrictions, our set of GMM moment conditions also includes k moment conditions $\mathbb{E}[h_t - \mu] = 0$, accounting for the fact that the factor means μ have to be estimated.[32] Factor risk prices λ can easily be obtained from our GMM estimates via the relation $\lambda = \Sigma_h b$, where $\Sigma_h = \mathbb{E}[(h_t - \mu)(h_t - \mu)']$ is the factor covariance matrix.[33] Following Burnside (2011), the individual elements of $\Sigma_{h,ij},\ i = 1, \ldots, k,\ j = 1, \ldots, k$ are estimated along with the other model parameters by including an additional set of corresponding moment conditions. Hence, the estimating function takes the form

$$g(z_t, \theta) = \begin{bmatrix} [1 - b'(h_t - \mu)]rx_t \\ h_t - \mu \\ \mathrm{vec}((h_t - \mu)(h_t - \mu)') - \mathrm{vec}(\Sigma_h) \end{bmatrix}, \tag{A4}$$

where θ contains the parameters $(b'\mu'\mathrm{vec}(\Sigma_h)')'$ and z_t represents the data (rx_t, h_t). By exploiting the $N + k(1 + k)$ moment conditions $\mathbb{E}[g(z_t, \theta)] = 0$ defined by equation (A4), estimation uncertainty (due to the fact that factor means and the factor covariance matrix are estimated) is incorporated in our standard errors of factor risk prices.[34] Our (first-stage) GMM estimation uses a prespecified weighting matrix W_T based on the identity matrix I_N for the first N asset pricing moment conditions and a large weight assigned to the additional moment conditions (for precise estimation of factor means and the factor covariance matrix). Standard errors are computed based on a heteroscedasticity and autocorrelation consistent (HAC) estimate of the long-run covariance matrix $S = \sum_{j=-\infty}^{\infty} \mathbb{E}[g(z_t, \theta)g(z_{t-j}, \theta)']$ by the Newey–West (1987) procedure, with the number of lags in the Bartlett kernel determined optimally by the data-driven approach of Andrews (1991).

FMB Two-Pass Procedure

We additionally employ the traditional FMB two-step OLS methodology (Fama and MacBeth (1973)) to estimate factor prices and portfolio betas. Our two-pass procedure is standard (e.g., chapter 12 in Cochrane (2005)) and we employ a first-step time-series regression to obtain in-sample betas for each portfolio i. These betas are then used in the (second step) cross-sectional regression of average excess returns on the time-series betas to estimate factor risk prices λ. There is no constant in the second pass of the regression. To

[32] This applies mainly to the DOL portfolio and the liquidity risk factors, which are not mean zero by construction as our series of global FX volatility innovations are.

[33] Standard errors for λ are obtained by the Delta method.

[34] Moreover, point estimates of factor risk premia λ obtained in this way are identical to those obtained by a traditional two-pass OLS approach (as described in Burnside (2011)).

account for the fact that betas are estimated, we report standard errors with the Shanken (1992) adjustment and HAC standard errors based on Newey and West (1987) with automatic lag length selection (Andrews (1991)).[35]

Estimation Uncertainty When Using Volatility Innovations

Our main tests are based on volatility innovations obtained from fitting a simple AR(1) model to the aggregate global FX volatility series

$$\sigma_t^{FX} = \gamma + \rho\sigma_{t-1}^{FX} + \epsilon_{\sigma;t}^{FX}, \tag{A5}$$

and taking the residuals $\Delta\sigma_t^{FX} \equiv \widehat{\epsilon}_{\sigma;t}^{FX} = \sigma_t^{FX} - \hat{\gamma} - \hat{\rho}\sigma_{t-1}^{FX}$ as our series of unexpected volatility.

In our robustness analyses, we also checked the role of potential estimation uncertainty (due to the preestimation of volatility innovations) on inference with regard to the estimates of factor risk prices. To do so, we stack the moment conditions implied by OLS estimation of the AR(1) model $\mathbb{E}[\epsilon_{\sigma;t}^{FX} x_t] = 0,\ x_t = (\,1\ \sigma_{t-1}^{FX}\,)'$, with the asset pricing moment conditions (for time-series regressions $\mathbb{E}[(rx_t^i - \alpha_i - \beta_i' h_t)\tilde{h}_t'] = 0,\quad i = 1, \ldots, N,\quad \tilde{h}_t = (\,1\ h_t'\,)'$, and for cross-sectional regression, $\mathbb{E}[rx_t^i - \beta_i'\lambda] = 0$). Hence, both volatility innovations and model parameters are estimated simultaneously in one step. Define the $(k+1)$-dimensional vector $\tilde{\beta}_i = (\,\alpha_i\ \beta_i'\,)'$ for asset i and β as the $N \times k$ matrix collecting the betas of the individual test assets. The estimating function is then

$$g(z_t, \theta) = \begin{bmatrix} \tilde{h}_t\left(rx_t^1 - \tilde{h}_t'\tilde{\beta}_1\right) \\ \vdots \\ \tilde{h}_t\left(rx_t^N - \tilde{h}_t'\tilde{\beta}_N\right) \\ rx_t - \beta\lambda \\ \epsilon_{\sigma;t}^{FX} \\ \epsilon_{\sigma;t}^{FX}\sigma_{t-1}^{FX} \end{bmatrix}, \tag{A6}$$

where $\epsilon_{\sigma;t}^{FX} = \sigma_t^{FX} - \gamma - \rho\sigma_{t-1}^{FX}$ and $h_t = (\,DOL_t\ \Delta\sigma_t^{FX}\,)'$. Based on the system defined by the $N(k+2)+2$ moment conditions in (A6), both volatility innovations $\Delta\sigma_t^{FX}$ and model parameters $\theta = (\,\mathrm{vec}(\tilde{\beta})'\ \lambda'\ \gamma\ \rho\,)'$ are estimated simultaneously by GMM imposing cross-equation restrictions. This ensures that estimation uncertainty regarding volatility innovations is accounted for when conducting inference on the model parameters. It turns out, as mentioned in the main text, that estimation uncertainty due to preestimating volatility innovations is negligible. This is due to the fact that the AR(1) parameter ρ is quite precisely estimated in samples of our size.

[35] See Cochrane (2005, chapter 12.2) and Burnside (2011) for further details on the derivation of HAC standard errors in the two-pass cross-sectional regression approach.

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