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Lukas Menkhoff, Lucio Sarno,
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Lukas Menkhoff, Leibniz Universität Hannover
Lucio Sarno, Cass Business School and CEPR
Maik Schmeling, Leibniz Universität Hannover
Andreas Schrimpf, Aarhus University

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Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

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ABSTRACT

Carry Trades and Global Foreign Exchange Volatility*

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. Our proxy for global FX volatility risk captures more than 90% of the cross-sectional excess returns in five carry trade portfolios. In turn, these results provide evidence that there is an economically meaningful risk-return relation in the FX market. Further analysis shows that liquidity risk also matters for expected FX returns, but to a lesser degree than volatility risk. Finally, exposure to our volatility risk proxy also performs well for pricing returns of other cross sections in foreign exchange, U.S. equity, and corporate bond markets.

JEL Classification: F31, G12 and G15
Keywords: carry trade, forward premium puzzle, liquidity and volatility

Lukas Menkhoff
Department of Economics
University of Hannover
Köningsworther Platz 1
D-30167 Hannover
GERMANY

Email: menkhoff@gif.uni-hannover.de

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Lucio Sarno
Finance Faculty
Cass Business School
106 Bunhill Row
EC1Y 8TZ London
UNITED KINGDOM

Email: lucio.sarno@city.ac.uk

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Maik Schmeling
Department of Economics
Leibniz Universität Hannover
Königsworther Platz 1
30167 Hannover
GERMANY

Email:
schmeling@gif.uni-hannover.de

Andreas Schrimpf
Aarhus University
School of Economics and Management
CREATES
Bartholins Allé 10
8000 C Aarhus
Denmark

Email: aschrimpf@creates.au.dk

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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. However, a number of empirical studies show 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 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 are 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 solution for this puzzle is the consideration 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 a compensation for higher risk-exposure by investors. However, the empirical literature has serious problems to convincingly identify risk factors that drive these premia until today.

In our empirical analysis we follow much of the recent literature (Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2010)) 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 and investing in the highest relative interest rate quintile, i.e. portfolio 5, and

[1]Since the beginning of the recent global financial crisis, carry trade strategies have 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]Originally, the innovation of sorting currencies into portfolios is due to Lustig and Verdelhan (2007) and has been followed by other papers afterwards.

shorting the lowest relative interest rate quintile, i.e. portfolio 1, therefore results in a carry trade portfolio. This carry trade leads to large and significant unconditional excess returns of more than 5% p.a. even after accounting for transaction costs and the recent market turmoil. These returns cannot be explained by standard measures of risk (e.g. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006)) and seem to offer a free lunch to investors.

In this paper, we argue that these high returns to currency speculation can indeed be understood as a 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, Hodrick, Xing, and Zhang (2006)), we test whether the sensitivity of excess returns to global FX volatility risk can rationalize the returns to 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 is the major point of our paper and it shows that excess returns to carry trades are indeed a compensation for time-varying risk.

Our paper is closely related to two contributions in the recent literature. First, as in Lustig, Roussanov, and Verdelhan (2010), we show that returns to carry trades can be understood by relating them cross-sectionally to two risk factors. Lustig, Roussanov, and Verdelhan (2010) employ a data-driven approach in line with the Arbitrage Pricing Theory of Ross (1976) and identify two risk factors that are (a) the average currency excess return of a large set of currencies against the USD (which they coin "Dollar risk factor") and (b)

[3]For example, this is a key prediction of the Intertemporal CAPM (Merton (1973), Campbell (1993), Campbell (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.

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. Instead of the HML_{FX} factor of Lustig, Roussanov, and Verdelhan (2010), however, we investigate the empirical performance of a different risk factor: innovations in global FX volatility.[4] This factor is a proxy for unexpected changes in FX market volatility, and is the analogue of the aggregate volatility risk factor used by Ang, Hodrick, Xing, and Zhang (2006) for 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 even more generally, i.e. also in times when currencies do not crash. We comprehensively document, however, that our proxy for global FX volatility is the more powerful risk factor and subsumes the information contained in various liquidity proxies.

Therefore, 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 US corporate bonds, US 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, Hodrick, Xing, and Zhang (2006)). Reassuringly, we find that FX volatility is correlated with several proxies for financial market liquidity such as bid-ask spreads, the TED spread, or the Pastor and Stambaugh (2003) liquidity measure. However, when analyzing carry trade returns, FX volatility always dominates liquidity proxies in joint asset pricing tests where both factors are considered. This finding

[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.

corroborates evidence for stock markets where, e.g. Bandi, Moise, and Russell (2008) show that stock market volatility drives out liquidity in cross-sectional asset pricing exercises. Therefore, the results in our paper 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 various specifications without qualitative changes of 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 forward discount. (ii) We investigate other factors such as liquidity, skewness, or coskewness. (iii) We investigate potential Peso problems using different approaches, such as Empirical Likelihood methods and winsorized volatility series. (iv) We investigate the performance of the proposed risk factor for other test assets, including options, international bonds, US 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 with alternative base currencies (taking the viewpoint of a British, Japanese, or Swiss investor, respectively). We find that our results are robust to these changes and corroborate our core result that volatility risk is a key driver of risk premia in the FX market.

Our study is also closely related to a new strand of literature suggesting explanations for the forward premium puzzle. Important contributions include Burnside, Eichenbaum, Kleshchelski, and Rebelo (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, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009). Related to this, Melvin and Taylor (2009) show that proxies for market stress have some predictive power for carry trade returns. Burnside, Eichenbaum, Kleshchelski, and Rebelo (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, Roussanov, and Verdelhan (2010) use an empirically derived two-factor model which 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, Eichenbaum, Kleshchelski, and Rebelo (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 conclusions are drawn in Section VIII. Details on some of our data and estimation procedures are delegated to an Appendix at the end of the paper. A separate Internet Appendix contains details for robustness tests as well as additional analyses.

[5]With respect to the paper by Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006), it is important to point out that in terms of the bid-ask spread analysis, our results are similar to theirs in the sense that indicative bid-ask spreads generally available from traditional data sources are not large enough to wipe out the profits of carry trade portfolios. However, Burnside, Eichenbaum, Kleshchelski, and Rebelo (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.

I Volatility as a Risk Factor in Foreign Exchange

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, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), Da and Schaumburg (2009)). 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 volatility innovations. This linear pricing kernel implies an expected return-beta representation for excess returns.

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, Hodrick, Xing, and Zhang (2006) employ changes in the VIX index (from CBOE) to proxy for volatility risk, considered as a non-traded 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. They show that each component is priced separately with a negative factor risk price. Moreover, Da and Schaumburg (2009) price several asset classes with a pricing kernel that is linear in the aggregate stock market return and volatility innovations. Christiansen, Ranaldo, and Söderlind (2010) show that volatility matters for the correlation between excess returns of stock markets and currencies. Finally, Bandi, Moise, and Russell (2008) do not only consider volatility, but also liquidity as a further 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.[6]

Summing up these papers on stock pricing, volatility innovations emerge as a state variable and there is a negative price of volatility risk because investors are concerned about changes in future investment opportunities. This motivates our approach of pricing forward-discount sorted portfolios with a SDF depending linearly on two risk factors: (i) an aggregate FX market return, and (ii) aggregate FX market volatility innovations. We show in this paper that this model has a lot to say about returns on carry trades as well as 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 e.g. Harvey and Siddique (1999), Harvey and Siddique (2000), 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, r_m denote the return of a portfolio k and the market benchmark, respectively; and μ and σ denote 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 a high coskewness (i.e. portfolios delivering high returns when market volatility is high) serve as a

[6] Also, see e.g. Acharya and Pedersen (2005), Brunnermeier and Pedersen (2009), Evans and Lyons (2002), and Pastor and Stambaugh (2003) on the role of liquidity for asset prices.

hedge against volatility and should thus earn lower returns. Therefore, this idea is closely related to our setup as well.[7]

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.[8]

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.

Data on spot and forward rates. The data for spot exchange rates and 1-month forward exchange rates versus the US dollar (USD) cover the sample period from November 1983 to August 2009, and are obtained from BBI and Reuters (via Datastream). The empirical analysis is carried out at the monthly frequency, although we start from daily data in order to construct the proxy for volatility risk discussed below.[9] Following the extant literature since Fama (1984), we will work in logarithms of spot and forward rates for ease of exposition and notation. Later in the paper, however, we will use discrete returns (rather than log-returns) for our cross-sectional asset pricing tests.

[7] Furthermore, Dittmar (2002) uses Taylor approximations of general, non-linear pricing kernels to show that the covariance of returns with higher-order moments of returns (such as return variance) theoretically and empirically matters for equilibrium returns.

[8] A number of recent papers suggest theoretical approaches to make sense of the forward premium puzzle and 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 precisely makes 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.

[9] Lustig, Roussanov, and Verdelhan (2010) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) also use these data.

We denote spot and forward rates in logs as s and f, respectively. Our total sample consists of the following 48 countries: 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, Roussanov, and Verdelhan (2010) we also study a smaller sub-sample consisting only of 15 developed countries with a longer data history. This sample includes: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. Since the introduction of the Euro in January 1999, the sample of developed countries covers 10 currencies only.

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 e.g. Akram, Rime, and Sarno (2008)). We re-balance portfolios at the end of each month. This is repeated month by month during the more than 25 years period. Currencies are ranked from low to high interest rates. Portfolio 1 contains currencies with the lowest interest rate (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, say, are computed as

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

As basis 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 bid-ask spread adjusted currency positions (net returns). We employ a setup where bid-ask spreads 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 $rx_{t+1}^{l} = f_t^b - s_{t+1}$ 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 through 5 (investment currencies) are adjusted for transaction costs in long positions. In the paper, we report results for these net returns since transaction costs are available and can be quite high for some currencies (Burnside, Eichenbaum, and Rebelo (2007)). Also, our portfolios have about 30% turnover per month so that transaction costs should play a role.[10]

The return difference between portfolio 5 and portfolio 1 (the long-short portfolio H/L) then is the carry trade portfolio obtained from borrowing money in low interest rate countries and investing in high interest rate countries' money markets, HML_{FX} in the notation of Lustig, Roussanov, and Verdelhan (2010). We also build and report results for a portfolio denoted DOL, which is the average of all five currency portfolios, i.e. the average return of a strategy that borrows money in the U.S. and invests in global money markets outside the U.S. Lustig, Roussanov, and Verdelhan (2010) call this zero-cost portfolio the "Dollar risk factor", hence the abbreviation "DOL".[11]

[10]Results for unadjusted returns are very similar, though, and are reported in the Internet Appendix to this paper. Below, we also provide results for a transaction cost adjustment scheme as in Lustig, Roussanov, and Verdelhan (2010) where we assume 100% portfolio turnover each month.

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

Descriptive statistics for portfolios. Descriptive statistics for the five carry trade portfolios, the DOL and H/L portfolios can be found in Table I. The first 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 for positive return autocorrelation, e.g. 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 also 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 Eq. (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.[12] We find that coskewness does not show a monotone pattern with respect to mean excess returns of the portfolio. We will elaborate on this point below in Section V.C.

TABLE I ABOUT HERE

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

[12] 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.

the 80s and 90s; 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 not have any significant influence on returns. It is only in the last recession – that 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, 2006) seem rather unrelated to the U.S. business cycle. This is consistent with Burnside, Eichenbaum, Kleshchelski, and Rebelo (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 about here

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, i.e. our global FX volatility proxy in month t is 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 a proxy $\sigma_t^{FX,DEV}$ based on the developed country sample's returns.

This proxy has obvious similarities to measures of realized volatility (see e.g. Andersen, Bollerslev, Diebold, and Labys (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, e.g. according to shares in international reserves or trade, but provide robustness on this issue later in the paper.[13] Figure 1, Panel (b), shows a time-series plot of σ_t^{FX}. Several spikes in this series line up with known crisis periods, e.g. the LTCM crisis in 1998 or, most 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 $\Delta\sigma_t^{FX}$), as a non-traded 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 e.g. Ang, Hodrick, Xing, and Zhang (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 that it 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 and do not find that it matters much, and, second, we also present results for simple changes in volatility and basically find the same results as for our volatility innovations based on an AR(1).[14] A plot of these AR(1) based volatility innovations is shown in Figure 1, Panel (b).

Data on currency options. We furthermore 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

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

[14]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, it 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, Hodrick, Xing, and Zhang (2006) on these issues.

one month. For each currency pair we have implied volatilities for at-the-money (ATM) options, 25-Delta (out-of-the-money), and 10-Delta (far out-of-the-money) options.[15]

Currencies with available data are the same as listed above, except for the member countries of the Euro (the EUR is included, though), and, in addition, 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/USD 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 sub-samples depending on the value of global FX volatility innovations. The first sub-sample contains the 25% months with the lowest realizations of the risk factor and the fourth sub-sample contains the 25% months with the highest realizations. We then calculate average excess returns for these sub-samples for the return difference between portfolio 5 and 1. Results are shown in Figure 2. Panel (a) on the left shows results for all countries whereas Panel (b) on the right gives the corresponding results for the smaller sample of 15 developed countries.

[15] 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 for example, whereas a 25-Delta call has a delta of 0.25.

Figure 2 about here

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 when the market is volatile, i.e. 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 (2010) for instance.

We denote excess returns of portfolio i in period $t+1$ by rx^i_{t+1}.[16] The usual no-arbitrage relation applies so that risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$\mathbb{E}[m_{t+1} rx^i_{t+1}] = 0 \tag{5}$$

[16]Note that we follow Lustig, Roussanov, and Verdelhan (2010) 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 $rx^k_{t+1} = \frac{F^k_t - S^k_{t+1}}{S^k_t}$ where F and S are the level of the forward and spot exchange rate respectively.

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

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

for each portfolio i (see e.g. Cochrane (2005)). The relationship between the factor risk prices in Eq. (6) and the SDF parameters in Eq. (5) is given by $\lambda = \Sigma_h b$ such that factor risk prices, comparable to the traditional Fama-MacBeth (FMB) approach, can be easily obtained via the SDF approach as well.

We estimate parameters of Eq. (5) via the generalized method of moments (GMM) of Hansen (1982). Estimation is based on a pre-specified weighting matrix and we focus on unconditional moments (i.e. we do not use instruments other than a constant vector of ones) since our interest lies in the performance of the model to explain the cross-section of expected currency excess returns 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 Eq. (5). This one-step approach ensures that potential estimation uncertainty – associated with the fact that factor means and the covariance matrix of factors have to be estimated – is incorporated adequately (see e.g. Burnside (2009)).[17]

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 the test of whether the

[17] In a similar way, 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.

HJ distance is equal to zero.[18]

Besides the GMM tests, we also report results using traditional FMB two-pass 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, i.e. we do not allow a common over- or under-pricing in the cross-section of returns. We point out, however, that our results are virtually identical when we replace the DOL factor with a constant in the second stage regressions. Since DOL has basically no cross-sectional relation to the carry trade portfolios' returns, it seems to serve the same purpose as a constant that allows for a common mispricing.[19] We report standard errors with a Shanken (1992) adjustment as well as GMM standard errors with 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 to 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.

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, i.e. the pricing kernel reads:

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

[18]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).

[19]Also see Burnside (2009) and Lustig and Verdelhan (2007) on the issue of whether to include a constant or not.

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

Table II about here

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 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 and the developed country sample. Estimates of β_{VOL} are large and positive for currencies 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 that produces the large spread in mean excess returns shown in Table I.[20] These results also corroborate our simple graphical exposition (Figure 2) in Section III.A.: Investors demand a high return on the investment currencies in the carry trade (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 they provide them with a hedge in periods of market turmoil.

Finally, we document the fit of our model graphically in Figure 3 which shows 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 (Panel (a)) and the sample of developed countries (Panel (b)).

Figure 3 about here

Factor-mimicking portfolio. Following Breeden, Gibbons, and Litzenberger (1989) and Ang, Hodrick, Xing, and Zhang (2006) we build a factor-mimicking portfolio of volatility innovations. Converting our factor into a return has the advantage of being able 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.

[20] In the Internet Appendix, we also report results using simple volatility changes instead of AR(1)-innovations. Results are very similar. We also estimated 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 above in Section II. Our results are basically unchanged, though. 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, we also show results when using transaction cost adjustments which assume 100% turnover per month as in Lustig, Roussanov, and Verdelhan (2010) in the Internet Appendix. Again, our results are robust to this modification. Finally, we also estimate our baseline specification using log returns instead of discrete returns. Using discrete or log excess returns does not impact our results.

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

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

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 was shown above to provide a hedge against volatility innovations, and has an increasingly negative loading on the portfolios 2 – 5. It also shows that the factor-mimicking portfolio should capture some pricing information in the Lustig, Roussanov, and Verdelhan (2010) 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 (2010) show that HML_{FX} is closely related to the second principal component (PC) of the cross-section of carry trade portfolios and that 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, 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^{FM}_{t+1} in the pricing kernel. As above, we use the five carry trade portfolios as our test assets. Results are shown in Table III and 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 $\overline{rx}^{FM}_{t+1} = -0.107\%$. This result is comforting since it implies that our factor price of risk makes sense economically, that the factor prices itself, and is thus arbitrage-free.[21]

Table III about here

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, 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 necessary information to price this cross-section, but it may raise concerns that our estimated price of volatility risk may be mechanically identical to the mean return on the factor-mimicking portfolio.[22] 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

[21] See Lewellen, Nagel, and Shanken (2010) on the importance to take the magnitude of the cross-sectional slopes, i.e. the factor prices, seriously.

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

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% p.a. (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 about −1.2 to −1.3%, which is close to the estimated value of about −1% for stock markets documented by Ang, Hodrick, Xing, and Zhang (2006).

D. Portfolios Based on Volatility Betas

We now show the explanatory power of volatility risk for carry trade portfolios in another dimension. 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.[23] 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 (2010)), and we re-balance portfolios every six months.[24] Descriptive statistics for portfolio excess returns are shown in Table IV.

Table IV about here

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, i.e. high volatility risk)

[23] Beta sorts are a common means to investigate risk premia in financial markets (see e.g. Pastor and Stambaugh (2003), Ang, Hodrick, Xing, and Zhang (2006), Lustig, Roussanov, and Verdelhan (2010)).

[24] 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.

and portfolio 5 (high volatility beta, i.e. low volatility risk) exceeds 4% p.a. for both the sample of all countries and the sample of developed markets. Moreover, mean excess returns tend to decrease steadily when moving from portfolio 1 to portfolio 5 (there is a twist in mean excess returns for the developed markets sample, though).

The table also shows pre- and post-formation 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 and these volatility beta-sorted portfolios is that they have a very different skewness pattern compared to the forward-discount sorts. Table I showed 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, we find a clear increase in post-sorting 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 so that 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 where assets which offer high payoffs in times of (unexpected) high aggregate volatility – and hence 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 – especially in the case of liquidity – not directly observable. However, it is interesting to examine the contribution of these two proxies of risk for currency investments since Brunnermeier, Nagel, and Pedersen (2009) suggest that liquidity plays an important role in understanding risk premia in foreign exchange. This section therefore relates volatility and liquidity proxies and investigates their relative pricing power.

A. Liquidity Proxies

Global bid-ask spread. As a first measure of global FX liquidity, we resort to a classical measure from market microstructure, the bid-ask spread (BAS). For consistency, we use the same aggregating scheme as for global FX volatility in Eq. (4) to obtain a global bid-ask spread 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 bid-ask spread of currency k on day τ. Higher bid-ask spreads indicate lower liquidity, so that the aggregate measure ψ_t^{FX} can be seen as a global proxy for FX market *illiquidity*.

TED spread. The TED spread is defined as the interest rate difference between 3-month Eurodollar 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 e.g. by Brunnermeier, Nagel, and Pedersen

(2009). We include the TED spread to proxy for illiquidity in the funding market for carry trades.

Pastor/Stambaugh liquidity measure. Pastor and Stambaugh (2003) construct a liquidity measure for the U.S. stock market based on price reversals. The general idea underlying their measure (denoted 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 Pastor 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, i.e. higher values of the PS measure reflect higher liquidity. This contrasts with the other two liquidity proxies which rather 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.

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 bid-ask spread measure (approx. 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. Bid-ask spreads and the TED spread, for instance, are only very mildly correlated (8%) and no correlation coefficient is larger than 30% in absolute value. Similarly, a principal component analysis reveals that the first principal component 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 innovations with innovations of one of the three liquidity factors. Table V shows factor loadings and prices for these models.[25] All three models shown in Panels A to 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 bid-ask spread and marginally significant for the PS measure. None of these three models outperforms the volatility risk factor in terms of R^2s and HJ-distances for both the full and the restricted developed country sample, though.

Table V about here

To address the relative importance of volatility and liquidity as risk factors, we also evaluate specifications where 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 where 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.[26]

The central message of these results is that volatility innovations emerge as the dominant risk factor, corroborating the evidence in Bandi, Moise, and Russell (2008) for the U.S.

[25] 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 to this paper.

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

stock market. Panel A, for example, shows results when jointly including innovations to global FX volatility and global bid-ask spreads: both b_{VOL} and λ_{VOL} are significantly different from zero, whereas the bid-ask spread factor is found to be insignificant in this joint specification. The same result is found 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 which are not captured by our three (il)liquidity proxies.

TABLE VI ABOUT HERE

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 of 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 be potentially 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, had market participants expected less volatility spikes, our estimate of the volatility risk premium may be biased upwards. 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 of all, we winsorize our volatility series at the 99%, 95% and 90% level, i.e. we set the 1%, 5%, or 10% most extreme volatility observations equal to their cutoff levels.[27] When we repeat our benchmark pricing test with these winsorized volatility factors, we obtain very robust results. For instance, we find an estimate for the SDF slope $b = -7.446$ (GMM s.e.: 3.623), volatility risk premium $\lambda = -0.072$ (GMM s.e.: 0.035) and a cross-sectional R^2 of 97% when we exclude the 1% most extreme volatility observations. Similarly, we find $b = -8.334$ (4.043), $\lambda = -0.067$ (0.032) and an R^2 of 97% when excluding the 5% most extreme observations, and estimates of $b = -9.510$ (4.465), $\lambda = -0.062$ (0.029) and an R^2 of 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 Empirical Likelihood (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 the results based on GMM so that Peso problems do not seem to drive our results. We refer to the Internet Appendix of this paper for the exact implementation of the procedure and detailed estimation results.

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

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, Roussanov, and Verdelhan (2010) 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 to the factor-mimicking volatility portfolio. Results are shown in this ordering of specifications in Panels A to D of Table VII.

Table VII about here

As a first result from 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 principal component of the carry trade return cross-section, which accounts for almost all cross-sectional variation in returns. Also, it is clear that a non-return factor (volatility innovations) cannot beat its own factor-mimicking portfolio in a horse race (see e.g. 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 we thus find that the SDF slopes (b) of both factors turn insignificant and that 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 when orthogonalizing 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 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 principal component of the cross-section of returns that is not captured by HML_{FX}. On the contrary, Panel D shows that the orthogonalized component of HML_{FX} is not priced when jointly including it 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 a 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 a HJ-distance of 13% with a p-value of 0.33. Thus, volatility innovations seem 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, i.e. 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, i.e. 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 showed this for the beta-sorted portfolios in Table IV and the developed countries in Table I. Furthermore, we have experimented with aggregate skewness measures (computed similarly to our volatility proxy in Eq. (4) or just as the skewness from the DOL portfolio estimated from daily returns within a given month) and tested 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). Results for these tests are available upon request.

Regarding coskewness (Harvey and Siddique (1999), Harvey and Siddique (2000)) we showed 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 have used the direct coskewness measure $\widehat{\beta}_{SKD}$ as described above in Section II of our paper). 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 Fama-MacBeth procedure can be directly 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.[28]

[28] We can replace our volatility proxy in Eq. (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.

VI Other Test Assets

We have also tested 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, ten U.S. stock momentum portfolios, five 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 that 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 asset noted 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.[29] 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 that 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 description of the test assets' returns, portfolio construction, and empirical estimates of factor models for pricing these cross-sections.

VII Robustness

We have performed a number of additional robustness checks relating to different proxies for volatility, non-linearities in the relation between volatility and carry trade returns, or the use of alternative base currencies (i.e. taking the viewpoint of a British, Japanese, or Swiss investor). Overall, our results are very robust towards all these modifications so we document these tests in the Internet Appendix to this paper in order to conserve space.

[29] In addition, we present additional 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.

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 simultaneously provides an explanation of currency risk premia and helps to understand 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, this 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), 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 idea has proven to be fruitful in empirical research on equity markets and we show that it also works very well in FX markets.

We argue in this paper 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, there is a significantly negative co-movement of high interest rate currencies (carry trade investment currencies) with 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, or 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 a better understanding of these linkages is warranted. In addition, it would be useful to build a structural asset pricing model which 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 for future research.

Appendix

In this Appendix we provide details on the construction of option returns and methodological details 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).[30] We calculate net payoffs to option positions in USD. We term this "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, Eichenbaum, Kleshchelski, and Rebelo (2011)). For example, the net payoff to a long call position in a foreign currency against the USD is given by

$$rx_{t+1}^{L,C} = F_t^{-1}(\max[S_{t+1} - K, 0] - C_t(1 + r_t)) \tag{9}$$

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

$$rx_{t+1}^{S,C} = F_t^{-1}(\min[K - S_{t+1}, 0] + C_t(1 + r_t)) \tag{10}$$

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) denote 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, Eichenbaum, Kleshchelski, and Rebelo (2011) in this respect). For our analysis in the main text, we combine different

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

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 $m_{t+1} = 1 - (h_{t+1} - \mu)$ linear in the k risk factors h_{t+1}. Thus, the basic asset pricing equation in Eq. (5) implies the following moment conditions for the N-dimensional vector of test asset excess returns rx_{t+1}

$$\mathbb{E}\left\{\left[1 - b'(h_{t+1} - \mu)\right] rx_{t+1}\right\} = 0. \tag{11}$$

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 factor means μ have to be estimated.[31] Factor risk prices λ can be easily 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.[32] Following Burnside (2009), the individual elements of $\Sigma_{h,ij}$, $i = 1, \ldots, k$, $j = 1, \ldots, k$ are estimated along with the other model arameters by including an additional set of corresponding moment conditions. Hence, the estimating function takes the following form

$$g(z_t, \theta) = \begin{bmatrix} \left[1 - b'(h_t - \mu)\right] rx_t \\ h_t - \mu \\ \text{vec}((h_t - \mu)(h_t - \mu)') - \text{vec}(\Sigma_h) \end{bmatrix} \tag{12}$$

where θ contains the parameters $(b' \;\; \mu' \;\; \text{vec}(\Sigma_h)')'$ 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 (12), estimation uncertainty – due to the fact that factor means and the covariance matrix of factors are

[31] 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.

[32] Standard errors for λ are obtained by the Delta Method.

estimated – is incorporated in our standard errors of factor risk prices.[33] Our (first-stage) GMM estimation uses a pre-specified 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 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 procedure, with the number of lags in the Bartlett kernel determined optimally by the data-driven approach of Andrews (1991).

Fama-MacBeth two-pass procedure. We additionally employ the traditional Fama-MacBeth (FMB) two-step OLS methodology (Fama and MacBeth (1973)) to estimate factor prices and portfolio betas. Our two-pass procedure is standard (e.g. Ch. 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 onto the time-series betas to estimate factor risk prices λ. There is no constant in the second pass of the regression. To 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)).[34]

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

$$\sigma_t^{FX} = \gamma + \rho\sigma_{t-1}^{FX} + \epsilon_{\sigma;t}^{FX} \tag{13}$$

[33]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 (2009)).

[34]See Cochrane (2005, Ch. 12.2) and Burnside (2009) for further details on the derivation of HAC standard errors in the two-pass cross-sectional regression approach.

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 pre-estimation of volatility innovations) on inference with regard to the estimates of factor risk prices. To do so, we stack in our GMM system the moment conditions implied by OLS estimation of the AR(1) model $\mathbb{E}[\epsilon_{\sigma;t}^{FX} x_t] = 0,\ x_t = (\ 1 \quad \sigma_{t-1}^{FX}\ )'$ with the asset pricing moment conditions (for time-series regressions $\mathbb{E}[(rx_t^i - \alpha_i - \beta_i' h_t)\tilde{h}_t'] = 0, \quad i = 1, \ldots, N, \quad \tilde{h}_t = (\ 1 \quad h_t'\ )'$, and 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 $\tilde{\beta}_i = (\ \alpha_i \quad \beta_i'\ )'$ for asset i and β as the $N \times k$ matrix collecting the betas of the individual test assets. The estimating function then reads

$$g(z_t, \theta) = \begin{bmatrix} \tilde{h}_t(rx_t^1 - \tilde{h}_t'\tilde{\beta}_1) \\ \vdots \\ \tilde{h}_t(rx_t^N - \tilde{h}_t'\tilde{\beta}_N) \\ rx_t - \beta\lambda \\ \epsilon_{\sigma;t}^{FX} \\ \epsilon_{\sigma;t}^{FX}\sigma_{t-1}^{FX} \end{bmatrix}, \tag{14}$$

where $\epsilon_{\sigma;t}^{FX} = \sigma_t^{FX} - \gamma - \rho\sigma_{t-1}^{FX}, \quad h_t = (\ DOL_t \quad \Delta\sigma_t^{FX}\ )'$. Based on the system defined by the $N(k+2)+2$ moment conditions in (14) both volatility innovations $\Delta\sigma_t^{FX}$ and model parameters $\theta = (\ vec(\tilde{\beta})' \quad \lambda' \quad \gamma \quad \rho\ )'$ 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 pre-estimating 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.

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Table I. Descriptive Statistics

The table reports mean and median returns, standard deviations (both annualized), skewness, and kurtosis of currency portfolios sorted monthly on time $t-1$ forward discounts. We also report annualized Sharpe Ratios, AC(1) is the first order autocorrelation coefficient, and Coskew(·) denotes 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 all 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 portfolios 2 – 5 are adjusted for transaction costs that occur in long positions. Numbers in brackets show Newey and West (1987) HAC based t-statistics and numbers in parentheses show p-values. Returns are monthly and the sample period is 12/1983 – 08/2009.

All countries (with b-a)							
Portfolio	1	2	3	4	5	Avg.	H/L
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)							
Portfolio	1	2	3	4	5	Avg.	H/L
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

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 (DOL) factor 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 we 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-West procedure with optimal lag selection according to Andrews (1991). We also report the cross-sectional R^2 and the Hansen-Jagannathan distance (HJ-dist) along with the (simulation-based) p-value for the test 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 (DOL) factor, and global FX volatility innovations (VOL). HAC standard errors (Newey-West with optimal lag selection) are reported in parentheses. The sample period is 12/1983 – 08/2009 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)	

Table III. Cross-Sectional Asset Pricing Results: Factor-mimicking Portfolio

The setup of this table is identical to Table II but 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-West 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 (DOL) factor, and the factor mimicking portfolio of volatility innovations. Robust (HAC) standard errors are reported in parentheses. The sample period is 12/1983 – 08/2009 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)	

Table IV. Portfolios Sorted on Betas with Global Volatility

The table reports statistics for portfolios sorted on volatility betas, i.e. 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 pre-formation (pre-f. $f-s$) and post-formation (post-f. $f-s$) forward discounts for each portfolio (in % p.a.). Pre-formation discounts are calculated at the end of the month just prior to portfolio formation whereas post-formation forward discounts are calculated over the six months following portfolio formation. We also report pre-sorting (pre-β) and post-sorting (pre-β) volatility betas in the last two rows of each panel.

			All countries				
Portfolio	1	2	3	4	5	Avg.	H/L
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				
Portfolio	1	2	3	4	5	Avg.	H/L
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		

Table V. Cross-Sectional Asset Pricing Results: Liquidity Risk

The setup is the same as in Table II but 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 (DOL) factor, and innovations of (i) global average percentage bid-ask spreads denoted as BAS (Panel A), (ii) the TED spread (Panel B), or (iii) the Pastor and Stambaugh (2003) liquidity measure denoted as PS (Panel C).

Panel A: Factor Prices – Global bid-ask spreads

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 – Pastor/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)		

Table VI. Cross-Sectional Asset Pricing Results: Volatility and Liquidity Risk

The setup is the same as in Table V. As test assets we use excess returns to the five carry trade portfolios based on all countries. Factors are the dollar risk (DOL) factor, FX volatility innovations (VOL), and innovations to (i) global average percentage bid-ask spreads denoted as BAS (Panel A), (ii) the TED spread (Panel B), or (iii) the Pastor 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)		

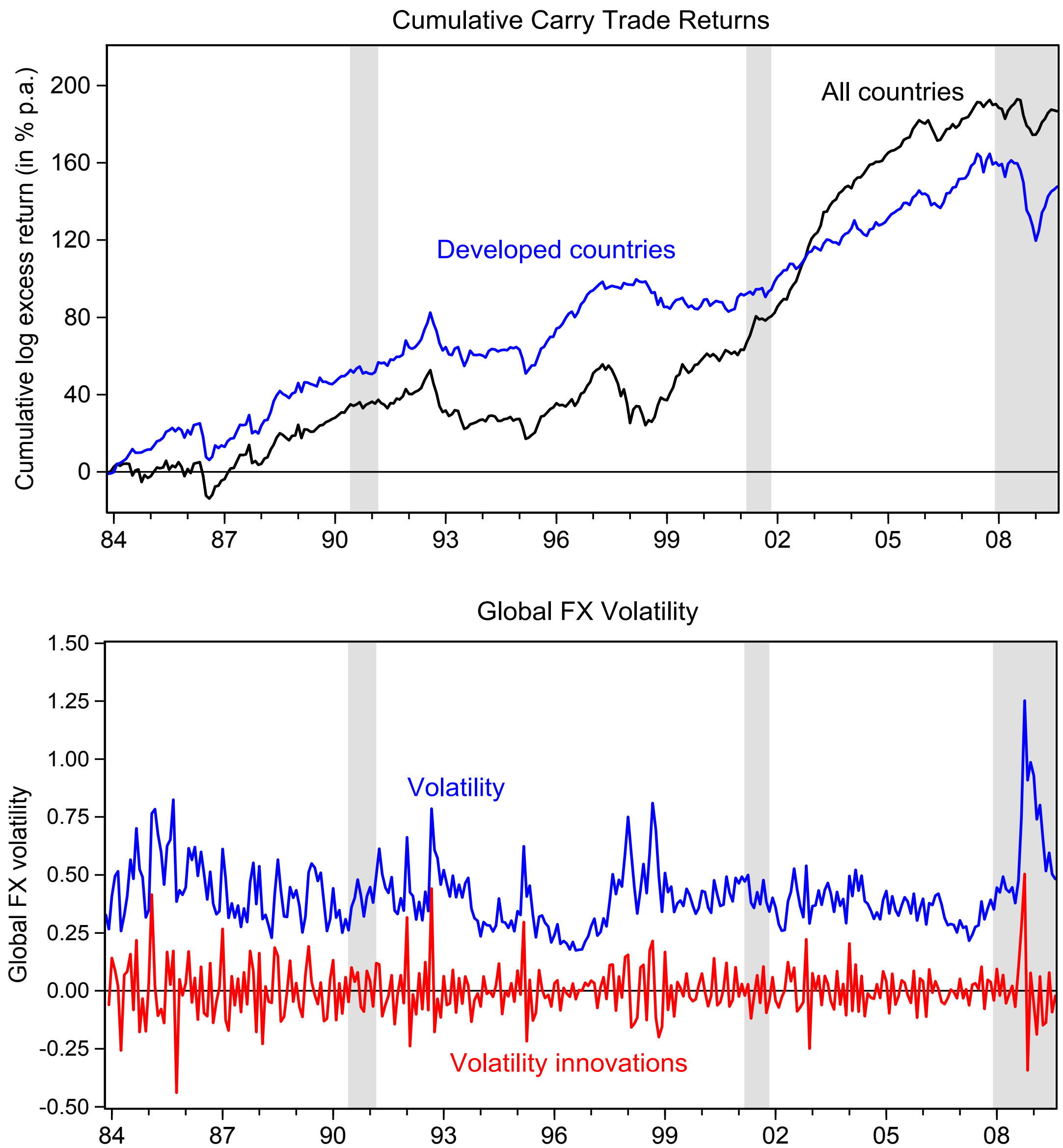
Table VII. Cross-Sectional Asset Pricing Results: Volatility and HML_{FX}

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 using volatility innovations, Panel B for the factor-mimicking portfolio of volatility innovations (VOL_{FM}), Panel C shows results for the factor-mimicking portfolio orthogonalized with respect to HML_{FX}, denoted $\text{VOL}_{FM}^{Orth.}$, and HML_{FX}, whereas Panel D reverses the last setup and shows results for using the factor-mimicking portfolio for volatility VOL_{FM} and HML_{FX} orthogonalized with respect to volatility, denoted $HML_{FX}^{Orth.}$. The sample period is 11/1983 – 08/2009.

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	$\text{VOL}_{FM}^{Orth.}$	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)		

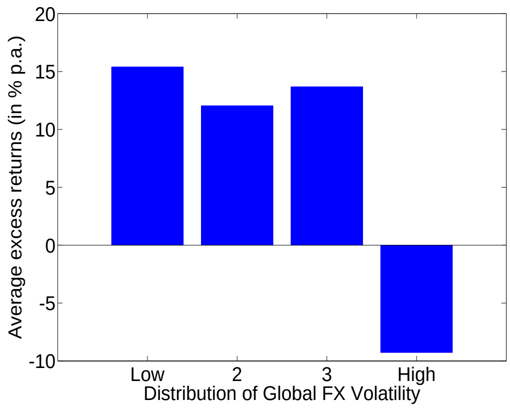
Figure 1. Returns to Carry Trade Portfolios



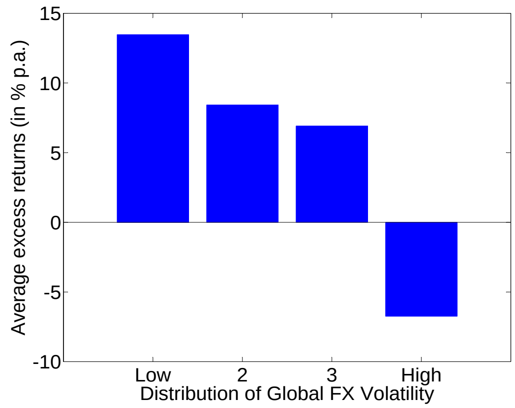
The upper panel of this figure shows cumulative log excess returns of the carry trade. The black line corresponds to all countries, while the blue line corresponds to a subset of 15 developed countries. The lower panel shows a time-series plot of global FX volatility (blue line) and volatility innovations (red line). Shaded areas in the figure correspond to NBER recessions. The sample period is 11/1983 – 08/2009.

Figure 2. Excess Returns and Volatility

(a) All Countries



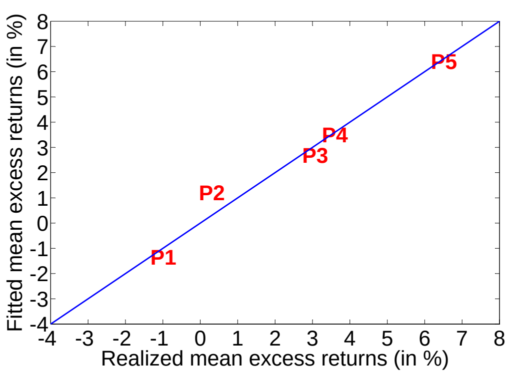
(b) Developed Countries



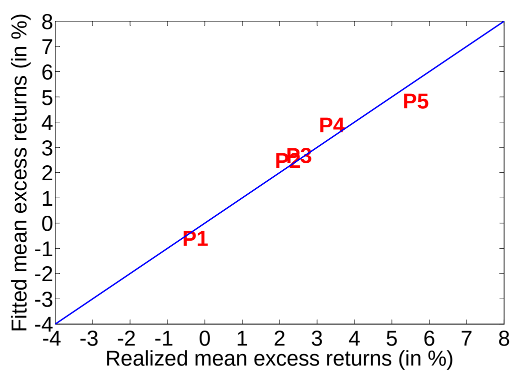
The figure shows mean excess returns for carry trade portfolios conditional on global FX volatility innovations being within the lowest to highest quartile of its sample distribution (four categories from "lowest" to "highest" shown on the x-axis of each panel). The bars show average excess returns for being long in portfolio 5 (largest forward discounts) and short in portfolio 1 (lowest forward discounts). Panel (a) shows results for all countries, while Panel (b) shows results for developed countries. The sample period is 11/1983 – 08/2009.

Figure 3. Pricing Error Plots

(a) All Countries



(b) Developed Countries



The figure shows pricing errors for asset pricing models with global volatility as risk factor. The sample period is 11/1983 – 08/2009.

Internet Appendix for
Carry Trades and Global Foreign Exchange Volatility

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

I Empirical Likelihood estimates

In order to further account for the possibility of Peso problems, we adopt an Empirical Likelihood (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). As in their paper, we employ both a conventional EL estimator (see e.g. Owen (2001) or Kitamura (2006) for overviews of EL methodology) as well as the blockwise EL procedure of Kitamura (1997), where we use blocks of observations to preserve information about dependence in the data in a nonparametric way.

First, we briefly outline how we estimate our asset pricing models by Empirical Likelihood (EL).[1] From a methodological perspective, EL and the traditional GMM framework share many common features. Both methods rely on moment restrictions for estimation and they both require only relatively mild assumptions, e.g. no specification of a parametric likelihood function is necessary. However, GMM essentially weights different observations equally when computing sample moments (by taking means of the estimating functions), whereas EL allows probabilities attached to different observations to differ across states of the economy (and from their observed frequencies in the data) in an endogenous fashion.[2] This is an attractive feature of EL and renders the method more robust to problems caused by rare events or potential Peso problems (see e.g. Ghosh and Julliard (2010)).

[1] The discussion here is intentionally simple and only presents the major ideas and basic setup of EL estimation. For more details, see Owen (2001) or Kitamura (2006).

[2] Besides this appealing property, several recent papers have shown that the statistical properties of EL are often superior as those of GMM (see e.g. Newey and Smith (2004), Kitamura (2006)).

As with GMM, estimation via EL starts from moment conditions of the form

$$\mathbb{E}[g(z_t, \theta_0)] = \int g(z, \theta_0) d\mu = 0 \tag{IA.1}$$

where $g(\cdot)$ is a J-dimensional moment function, z_t represents a vector of data, and θ_0 denotes the true parameter value. Consistent estimates $\widehat{\theta}_{EL}$ can be obtained provided that the data are either *i.i.d.* or weakly dependent. Central to EL estimation is the concept of an empirical (nonparametric) log likelihood which is defined as

$$\mathcal{L}_{EL}(\pi_1, \ldots, \pi_T) = \sum_{t=1}^{T} \ln \pi_t. \tag{IA.2}$$

The probabilities attached to observations at different points in time are denoted as π_t and are constrained by the usual restrictions $0 < \pi_t < 1$ and $\Sigma_{t=1}^{T} \pi_t = 1$. EL estimation of the parameters of the model solves the following constrained maximization problem:

$$\underset{\theta, \pi_1, \ldots, \pi_T}{\text{argmax}} \sum_{t=1}^{T} \ln \pi_t$$

$$\text{subject to} \quad \sum_{t=1}^{T} \pi_t g(z_t, \theta) = 0, \quad \sum_{t=1}^{T} \pi_t = 1.$$

In words, the model's parameters $\begin{pmatrix} \theta' & \pi_1, \ldots, \pi_T \end{pmatrix}'$ are estimated by maximizing the empirical likelihood subject to the constraints imposed by (i) the (probability weighted) moment conditions (which are given by the economic model), and (ii) the normalizing condition on the probabilities. EL estimators behave equivalently to GMM estimators in terms of first-order[3] asymptotics and the limiting distribution of the EL estimator is given

[3] Newey and Smith (2004) find, however, that EL estimators outperform GMM in terms of second order bias, which should also be reflected in good finite-sample properties of the estimator.

by

$$\sqrt{T}(\widehat{\theta}_{EL} - \theta_0) \xrightarrow{d} N(0, (D'S^{-1}D)^{-1}), \tag{IA.3}$$

where $D = E[\partial g(z, \theta_0)/\partial \theta']$ and $S = E[g(z, \theta_0)g(z, \theta_0)']$.

Blockwise Empirical Likelihood. Standard EL requires that the data are *i.i.d.* or weakly dependent to obtain consistent estimates. In the presence of serial correlation, however, inference based on the asymptotic result in (IA.3) may not be valid (see Kitamura (2006, p. 35)). Returns scaled by the SDF should typically be close to a martingale-difference series, as also noted by Ghosh and Julliard (2010). However, as mentioned in the main paper, there is evidence of some (albeit low) autocorrelation in our test asset returns (but not in the risk factor). For robustness, we therefore also estimate the model using the blockwise EL approach of Kitamura (1997) and Kitamura and Stutzer (1997). Instead of $g(z_t, \theta_0)$, blockwise EL uses the "smoothed" estimating function

$$\tilde{g}(z_t, \theta_0) = \frac{1}{2K+1} \sum_{s=-K}^{K} g(z_{t+s}, \theta_0) \tag{IA.4}$$

in the constrained maximization problem above and by doing so preserves information on dependence in the data in a non-parametric way. The limiting distribution of the blockwise EL estimator is then

$$\sqrt{T}(\widehat{\theta}_{BEL} - \theta_0) \xrightarrow{d} N(0, (D'S^{-1}D)^{-1}), \tag{IA.5}$$

where $D = \mathbb{E}[\partial g(z, \theta_0)/\partial \theta']$ and $S = \sum_{j=-\infty}^{\infty} \mathbb{E}[g(z_t, \theta_0)g(z_{t-j}, \theta_0)']$. We estimate the long-run covariance matrix of moment conditions S in the blockwise EL approach using the Newey-West procedure. We choose K to be two (implying a window size for the smoothed estimating function of five), whereas the lag length in the Newey-West approach is set to five. Our results are robust to sensible modifications of this choice.

We estimate the model via EL and blockwise EL exploiting the same asset pricing moment conditions as for the GMM approach discussed in Section III of the paper. Results from this exercise are shown in Table IA.1 and confirm the robustness of our main result. For the sample of all countries, we find a factor price of volatility risk of $\lambda_{VOL} = -0.07$, and $\lambda_{VOL} = -0.06$ for the sample of developed countries. We find it comforting that the estimated factor prices are basically unchanged when using this setup which endogenously reduces the impact of extreme values in the volatility series. We thus conclude that our core results are unlikely to be driven entirely by a Peso story.

II Other Test Assets

A. FX Momentum Portfolios

We first look at a cross-section of currency momentum portfolios and sort individual currencies into five portfolios depending on their excess returns over the past 12 months.[4] We rely on a 12 months formation period and one month investment horizon since Moskowitz and Grinblatt (1999) show that this 12-1 momentum strategy yields much larger returns than e.g. the 6-6 strategy of Jegadeesh and Titman (1993, 2001) and has become the benchmark strategy in equity markets. For this reason, we also employ this momentum variant here. It should be mentioned, though, that other combinations of formation and holding period naturally give rise to different return cross-sections which are not necessarily (highly) correlated with the cross-section investigated here. Hence, our results are best viewed as being specific to the particular momentum strategy under study here but not as general evidence that volatility innovations are useful for pricing *any* possible currency momentum cross-section.

This yields a cross-section of portfolios with increasing mean excess returns that range

[4] Jegadeesh and Titman (1993, 2001) document momentum strategies in equity markets.

from 0.35% p.a. for low return currencies to 6.9% p.a. for high return currencies (see Table IA.2 for descriptive statistics).

Cross-sectional pricing results using DOL and volatility innovations are shown in the left part of Table IA.3. We find a negative factor price of -0.07, which is in line with the estimate for our carry trade portfolios in Table II of the main paper. Also, we find that the factor price is more imprecisely estimated and borderline significant with a cross-sectional R^2 of roughly 60% and an insignificant HJ-distance. This is an interesting result since momentum and carry trade portfolios are far from being perfectly correlated. For example, the correlation between the long-short portfolio (portfolio 5 minus portfolio 1) for the carry trade cross-section (i.e. HML_{FX}) and the momentum cross-section is basically zero. Therefore, it seems that FX volatility has some pricing power for other currency cross-sections as well.[5] Also, it seems important to point out that HML_{FX} does not price this cross-section (see the left part of Table IA.5).

B. US portfolios: Equity Momentum and Corporate Bonds

As a further pricing exercise, we rely on domestic U.S. assets whose returns clearly do not directly contain a currency component. We employ the ten U.S. equity momentum portfolios (from Kenneth French's web site) and six portfolios of U.S. corporate bonds. We still employ the DOL factor and volatility innovations in our tests but note that using the U.S. stock market excess return – which would seem natural in this case – instead of DOL gives very similar results and is inconsequential for our conclusions below.

Results for excess returns to the U.S. stock momentum cross-section are shown in the middle part of Table IA.3. We find a larger (in absolute terms) risk price estimate of $\lambda = -0.13$ (compared to -0.07 on the carry trade cross-section) with a GMM t-statistic of -1.97 and a cross-sectional R^2 of about 41%. While the risk price estimate here is clearly lower than our benchmark estimate, the standard errors are fairly large so that there is still considerable overlap between the confidence intervals from our estimates based on stock

[5] We do not claim, however, that volatility innovations price *any* cross-section of currencies, of course.

returns and the carry trade cross-section. In any case, our FX volatility innovation factor provides a fairly good cross-sectional fit, which is especially noteworthy when compared to other pricing factors. For example, we find that traditional models of equity asset pricing, such as a standard CAPM or the Fama-French three-factor model, do not provide better results than our two-factor model with FX volatility innovations employed here.[6] Moreover, HML_{FX} is not significantly priced and has a negative R^2 on this cross-section (see the middle part of Table IA.5 in the Internet Appendix). In short, our factor captures part of the spread in U.S. stock momentum returns, and the estimated factor price of risk is consistent with our baseline estimate on the carry trade cross-section.

Next, we follow Da and Schaumburg (2009) and also investigate a cross-section of six corporate bond portfolios (one portfolio for each available rating category from AAA to BA) based on the corporate bond indices from Lehman Brothers.[7] The available sample runs from April 1990 to August 2009. Pricing results for corporate bond excess returns are shown in the right part of Table IA.3. We find a reasonable factor risk price estimate of -0.10, a high cross-sectional R^2 of 93%, and a HJ distance measure of 0.14 which is not significantly different from zero. Despite this good cross-sectional fit, the risk price estimate is significant only with FMB Shanken standard errors but becomes insignificant once we correct for autocorrelation in the cross-sectional regressions or use GMM standard errors. This finding is identical to Da and Schaumburg (2009) and can be understood through a combination of the relatively small sample size and the higher return volatility of lower-rated bonds during the recent financial market turmoil. Despite this lack of statistical significance, we find it reassuring that the factor risk price estimate is close to our estimate of -0.07 on the carry trade cross-section and that the factor provides a good cross-sectional fit in this out-of-sample test since this is a purely domestic US cross-section. Finally, when we replace volatility innovations by HML_{FX} we find a much lower cross-sectional R^2 of

[6] Table IA.6 documents these results. A CAPM with a single market factor produces a negative R^2 and clear rejections in all specification tests (χ^2 and HJ distance). The three-factor model produces a cross-sectional R^2 of 50% which is only slightly higher than in our setup (although we are using only two factors) and yields insignificant but *negative* risk price estimates for HML and SMB which are clearly not sensible. However, the fact that these models fail on U.S. momentum returns is well known from papers such as Fama and French (1996) or Jegadeesh and Titman (2001).

[7] As in Da and Schaumburg (2009), we duration-adjust corporate bond returns.

only 27% and a significant HJ distance (see the right part of Table IA.5).

C. Individual Currencies

Next, we test our volatility risk factor on individual currencies. When dealing with individual currencies, we face an unbalanced panel of data and highly idiosyncratic return series for less traded currencies. To accommodate these features in our pricing tests, we rely on robust regressions, where outlier observations are weighed down by an iterative procedure.[8] More specifically, we run FMB regressions using robust regressions in the first (estimate of in-sample betas) and second stage (cross-sectional estimation of risk prices). Since we have an unbalanced panel and we deal with a generated factor (volatility residuals from an AR(1)) we rely on a bootstrap approach to generate critical values for our test statistics which we detail next.

Individual currencies – bootstrap approach. We first generate our volatility innovations by estimating an AR(1) for global FX volatility. We run the FMB regressions on the cross-section of individual currencies using robust regressions in both steps as noted above.

For the simulations, we then bootstrap the *changes* of the volatility series (i.e. *not* the residuals from the AR(1)-model) and the DOL factor using blocks of five observations. We apply a block bootstrap to the volatility changes to account for the mild autocorrelation we find in volatility changes (as discussed in Section II above). We then form a new volatility series in levels by summing over the bootstrapped volatility changes. Next, we estimate an AR(1) on the simulated volatility series and use the residuals as our pricing factor. We impose the null of no relation between our factors and currency returns by separately block-bootstrapping the matrix of individual currency returns (to account for potential autocorrelation in excess returns of individual currencies) again using blocks of

[8]The regression is first estimated via OLS. Outlier observations (based on OLS residuals) are weighed down and the regression is again estimated by OLS. This procedure continues until outliers do not impact the results any more.

five observations. We then run FMB on the simulated cross-section of returns, using the simulated DOL and volatility innovation series in order to conduct inference on the model's parameters.

Results. Results are shown in Table IA.4. The first rows show coefficient estimates and t-statistics from the cross-sectional regression. Numbers in parentheses show bootstrap p-values based on the distribution of simulated t-statistics. We find a significantly negative estimate for $\lambda_{VOL} = -0.05$, which is close to the estimate of -0.07 that we found for the carry trade portfolios. Furthermore, we find a R^2 of about 31%, which is lower than the R^2 found for the carry trade portfolios, as one would expect since individual excess returns are far more noisy than the portfolio returns in our benchmark analysis. Still, we find that volatility risk is significantly negatively priced even after taking into account outliers in returns and estimation uncertainty regarding the volatility innovations.

The second specification in Table IA.4 adds an interaction term of the volatility beta with a dummy variable indicating an emerging market. We use this specification to test whether factor prices are equal across developed and emerging markets. The results are mixed. We find a highly negative estimate for the interaction term (i.e. the factor price is -0.11 for emerging markets instead of -0.05) but the estimate is very imprecise and not significantly different from zero.

As a final examination we are interested to learn about the merits of our global FX volatility factor and the HML_{FX} factor. Thus, in the third specification volatility innovations are replaced by the HML_{FX} factor, resulting in a rather low cross-sectional R^2 of 10% and an insignificant factor risk price for HML_{FX}.[9]

[9] In a final specification, we include both volatility innovations and HML_{FX} and find that volatility innovations are still priced whereas HML_{FX} is not. It thus seems that volatility innovations contain information about the cross-section of individual currencies not included in HML_{FX}.

D. International Bond Portfolios

As an additional set of test assets, we look at international bond portfolios. To this end, we sort bonds of different maturities (1-3y, 3-5y, 5-7y, 7-10y, >10y) and for 19 countries into five portfolios depending on their redemption yield. We rely on all available data and total return indices (in USD) from Datastream and consider a sample ranging from 1983 to 2009.[10] This yields a cross-section of monotonically increasing excess returns (in excess of the U.S. risk-free rate) with an annualized excess return of about 2% for low yield bonds to 9% p.a. for high yield bonds. Testing our main result on this cross-section seems natural since this "bond carry trade" also operates on international yield differentials but extends the dimension to longer-term maturities instead of relying solely on short-term money markets. Descriptive statistics are shown in Panel A, Table IA.7; we stress here, however, that the bond portfolios and carry trade portfolios are not perfectly correlated. For example, the correlation between HML_{FX} and the return to the long-short international bond portfolio (long in portfolio 5, short in portfolio 1) is about 50%.

We show pricing results using the DOL factor and innovations to global FX volatility in the left part of Table IA.9. We find a negative estimate of $\lambda_{VOL} = -0.09$ which is significantly different from zero at the 5% (FMB) or 10% (GMM) level, respectively. That is, the factor price is somewhat more imprecisely estimated than for the FX carry trade portfolios in Table II of the main paper, but the estimated factor price of volatility risk is reasonably close to the estimate of -0.07 on the carry trade cross-section. Also, we find a reasonable cross-sectional R^2 of almost 70% but that the HJ-distance is significantly different from zero at the 10% (but not the 5%) level.

[10] Countries with available data are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Portugal, Singapore, Spain, Sweden, Switzerland, U.K., and the U.S.

E. Currency Options

We show implied volatility patterns (volatility smiles or skews) for portfolios sorted on lagged forward discounts and for portfolios sorted on lagged volatility betas. The implied volatility patterns suggest that risk associated with these portfolios is priced in option markets. Furthermore, we price a cross-section of option portfolios with our benchmark factor model.

We first report differences between implied volatilities of puts and calls for different moneyness groups. Table IA.10, Panel A, shows the difference between log implied volatilities for 25-Delta puts and 25-Delta calls (OTM options) and for the log difference between 10-Delta puts and calls for our five carry trade portfolios sorted on lagged forward discounts.[11] Panel B shows the same statistics but for the five portfolios sorted on lagged volatility betas. It can be seen from this table that portfolios with high returns (high forward discounts, low volatility betas) also have higher implied volatilities for puts than for calls, i.e. buying portfolio insurance for these high risk and return currencies is more expensive. However, we find a symmetric result for low return portfolios (low forward discounts, high volatility betas). Here, premia for buying calls, i.e. portfolio insurance for funding currencies, are higher than for buying puts. For example, buying 10-Delta calls for funding currencies in portfolio 1 of the carry trade cross-section is 7.96% more expensive than buying 10-Delta puts, whereas buying puts for the high interest rate currencies in portfolio 5 is about 26% more expensive than buying calls. Therefore, it seems that risk in the carry trade and volatility-beta sorted portfolios is priced in the option market as well. Furthermore, we do not find that only downside risk is priced but that option prices reflect downside and upside risk depending on whether currencies tend to appreciate or depreciate in times of high volatility.

Next, we test our model on a set of option portfolios constructed from the implied volatility data used above. To this end, we consider returns to three strategies, i.e. risk reversals (long 25-Delta Put, short 25-Delta calls), bull spreads (long ATM calls, short

[11] Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009) document similar results.

25-Delta calls), and bear spreads (long ATM puts, short 25-Delta puts). For each option strategy, we form four portfolios by sorting underlyings of the option strategy on their lagged forward discounts (we only form four portfolios since we have a smaller cross-section and shorter time-series for option data). Excess returns to the option strategies are such that we scale the option bets to have the size of one USD for each currency.

Descriptive statistics for these 12 option portfolios can be found in Table IA.8. To summarize, Figure IA.2 shows average excess returns and Sharpe Ratios for these portfolios. It can be seen that the three cross sections differ in terms of Sharpe Ratios and mean return patterns. For example, the Bull spreads have a rather flat pattern for portfolios 2 and 3, whereas the bear spreads have a non-monotonic pattern in Sharpe Ratios. In sum, the three cross-sections are related but far from being identical. We thus use these 12 portfolios in a joint pricing exercise.

Pricing results for the 12 option portfolios as test assets and the DOL factor and volatility innovations as risk factors are shown in the right part of Table IA.9. We find a highly significant factor risk price of -0.08, which is reasonably close to the estimate we found for the five carry trade portfolios. We also find a somewhat lower, but comparable, cross-sectional R^2 of about 90% and an insignificant HJ-distance.

III Additional Results for Fama-MacBeth Regressions

Tables IA.11 to IA.13 report additional results for Fama-MacBeth regressions that were left out of the main paper where we only showed GMM results. We report these results for completeness only.

IV Additional Robustness Tests

Descriptive statistics for unadjusted returns. Table IA.14 reports results for currency excess returns not adjusted for transaction costs. Clearly, average excess returns are more extreme and the carry trade appears quite a bit more profitable without adjusting for bid-ask spreads.

Pricing tests with full transaction cost adjustments. Table IA.15 reports pricing results for our baseline specification. As can be seen, results are very similar so that our exact transaction cost adjustment procedure does not seem to drive our results.

Other proxies for volatility. We first re-estimate our benchmark model but use simple changes in volatility instead of AR(1)-residuals as a proxy for volatility innovations. Results are shown in Table IA.16 and it can be seen that our results are not affected by using simple changes.

Next, we repeat our main asset pricing setup but use the JP Morgan Implied Volatility Index for the G-7 currencies (the "JPM G-7 VIX") and the VIX volatility index from the CBOE, based on stock options, instead of the global FX volatility proxy proposed in this paper (e.g. Ang, Hodrick, Xing, and Zhang (2006) also use the VIX). We expect to see somewhat similar results, since periods of market turmoil or distress are often visible across asset classes rather than specific to one certain group of assets, e.g. only equities or only FX markets.

For example, Table IA.17 shows results when using innovations to the JPM G-7 VIX (left panel) or innovations to the CBOE VIX (right panel) as volatility proxies.[12] As with our FX volatility proxy, we find the same monotonically declining pattern in the time-series betas of returns with volatility and that factor prices are negative.

We also experimented with different weighting schemes for our global FX volatility proxy. For example, we weighted the volatility contribution of different currencies by their share in international currency reserves in a given year (data are available from the International Monetary Fund) but did not find any interesting differences in our results.

[12] We employ simple changes to the implied volatility index to obtain innovations (as in Ang, Hodrick, Xing, and Zhang (2006)). Using more elaborate ways to extract innovations does not change our findings reported below.

Alternative base currencies. Up to now we have taken the perspective of a U.S. investor by calculating excess returns, the DOL and global volatility factor against the USD. As a robustness check, we test the pricing power of innovations to global FX volatility for alternative investors.[13] Specifically, we convert returns into three alternative currencies, namely the GBP, the JPY, and the CHF. The DOL factor and volatility factors are also based on quoted rates against these base currencies, respectively.

We provide descriptive statistics for these alternative portfolios in Table IA.18. The H/L portfolio has the same mean return by construction for all three alternative base currencies. However, the level of average returns for the five currency portfolios (and the DOL factor) obviously differs across countries.

We also present time-series plots of global FX volatility factors for the three alternative base currencies in Figure IA.1 in the Appendix. It can be seen from this graph that there is much common movement in these volatility series but that these series are far from being perfectly correlated.[14] These differences in cross-sectional excess returns and volatility seem to make tests based on these alternative currencies an interesting robustness check.

Time-series results and cross-sectional test results are shown in Table IA.19. We find the same declining pattern in time-series volatility betas for all three base currencies and this pattern is identical to our U.S. benchmark results. Furthermore, volatility innovations have significant cross-sectional pricing power for returns to carry trade portfolios, no matter which base currency is used. Estimates of factor prices for the GBP ($\lambda_{VOL} = -0.08$) and CHF ($\lambda_{VOL} = -0.10$) are close to the U.S. results where the factor price of $\lambda_{VOL} = -0.07$. We find a much lower factor price of $\lambda_{VOL} = -0.36$ for the JPY. This lower factor price seems surprising at first glance, but may indeed be the result of a potential Peso problem as discussed above. Figure IA.1 shows that the volatility series (and, thus, volatility innovations) for the JPY is quite smooth and has fewer spikes. In case the market has expected more volatility spikes than have actually occurred so far, we would expect to

[13] This is a common robustness check and has been applied by other authors as well, see e.g. the robustness appendix to Lustig, Roussanov, and Verdelhan (2010).

[14] Some largely idiosyncratic volatility spikes can be found e.g. for the GBP during the Exchange Rate Mechanism crisis in 1992 or for the JPY during the Asian crisis in 1997-1998.

see exactly the result documented above, namely a much lower factor price than for the other currencies.

Overall, we find the same patterns in volatility betas as for the U.S. and we find a significantly negative factor price for volatility risk in the cross section. Thus, we conclude that our results are not specific to a U.S. investor.

Non-Linearities. We have also experimented with non-linearities in our risk factor such that time-series betas and/or the price of risk depend on the sign of volatility innovations or whether volatility innovations are large or small in absolute magnitude. We did not find any noteworthy effects, though. Volatility risk seems to be priced in all regions of the volatility distribution.

In Table IA.20 we document some representative estimates. The left part shows results when we only use positive values of volatility innovations (which have a mean of zero) and the right part shows results when we only use the negative values of volatility innovations. The results suggest that the estimated factor risk prices do not differ much; we have the same monotone pattern in volatility time-series betas, the HJ-distance is small and not significantly different from zero, and the cross-sectional fit is good.

Sub-samples. We also examined sub-samples of our total sample, namely the periods 1983 – 1995 and 1996 – 2009. Results are shown in Table IA.21. Regarding the economics of our results, the estimated factor prices are negative for both periods (-0.05 for the first and -0.08 for the second sub-sample) and thus well within the confidence interval around the point estimate of the full sample. We also find the same monotonically declining pattern in volatility time-series betas such that low interest rate currencies are a hedge against volatility shocks, whereas high interest rate currencies perform poorly in times of high (unexpected) volatility. In terms of statistical significance, results are stronger for the second sub-sample, where we have more data (since many countries only enter the sample in the 90s).[15] Given that our economic finding is qualitatively identical across the two periods, we are not too concerned about statistical significance, which varies naturally when changing the sample size.

[15] We find basically the same pattern in statistical significance when using HML_{FX} instead of volatility innovations in our pricing exercise.

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Table IA.1. Cross-Sectional Asset Pricing Results: Empirical Likelihood

The setup of this Table is similar to Table II in the main paper but we estimate the linear factor model via Empirical Likelihood (EL) instead of GMM. As test assets we use (excess returns to) the five carry trade portfolios based on all countries or the 15 developed countries. The left part of the table shows results for a standard EL approach, whereas the right part shows results for the blockwise EL approach of Kitamura (1997). The block length in block-wise EL is set to five and standard errors of block-wise EL estimates are based on Newey-West estimation of the spectral density matrix with five lags. The OIR test (OIR χ^2) is equivalent to a J-test in the GMM framework and tests for the validity of the overidentifying restrictions.

Panel A: All countries									
	EL estimates				Blockwise – EL estimates				
	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}		b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}
coeff.	0.01	-6.79	0.25	-0.07	coeff	0.01	-6.53	0.24	-0.07
s.e.	(0.05)	(2.52)	(0.24)	(0.03)	s.e.	(0.05)	(2.54)	(0.27)	(0.03)
OIR χ^2	1.33				OIR χ^2	3.37			
p-value	(0.72)				p-value	(0.34)			
Panel B: Developed countries									
	EL estimates				Blockwise – EL estimates				
	b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}		b_{DOL}	b_{VOL}	λ_{DOL}	λ_{VOL}
coeff.	0.03	-5.32	0.28	-0.06	coeff	0.02	-5.27	0.27	-0.06
s.e.	(0.04)	(3.09)	(0.21)	(0.03)	s.e.	(0.04)	(3.08)	(0.24)	(0.04)
OIR χ^2	0.76				OIR χ^2	5.55			
p-value	(0.86)				p-value	(0.14)			

Table IA.2. Descriptive Statistics for Other Test Assets

The table reports mean excess returns, standard deviations (both annualized), and Sharpe Ratios (all annualized) for five FX momentum portfolios, ten US momentum equity portfolios, and six corporate bond portfolios.

	FX momentum			Stock momentum			Corp. bonds		
Portfolio	MEAN	STD	SR	MEAN	STD	SR	MEAN	STD	SR
1	0.35	9.64	0.04	1.95	31.43	0.06	3.58	6.71	0.53
	[0.17]			[0.29]			[3.11]		
2	2.17	8.39	0.26	9.39	23.19	0.40	2.50	4.58	0.55
	[1.16]			[1.92]			[2.66]		
3	3.12	8.50	0.37	10.68	19.57	0.55	2.35	4.52	0.52
	[1.67]			[2.59]			[2.44]		
4	4.71	8.83	0.53	11.47	17.07	0.67	2.58	9.85	0.26
	[2.38]			[3.22]			[1.49]		
5	6.89	8.48	0.81	10.35	15.83	0.65	5.46	7.10	0.77
	[3.48]			[3.12]			[3.01]		
6				10.36	15.49	0.67	5.15	8.53	0.60
				[3.25]			[3.24]		
7				11.37	14.94	0.76			
				[4.11]					
8				13.24	14.61	0.91			
				[4.42]					
9				11.54	16.08	0.72			
				[3.47]					
10				15.91	21.51	0.74			
				[3.44]					
Av.	3.45	7.22	0.48	10.62	16.70	0.64	3.60	6.42	0.56
	[2.07]			[3.02]			[2.94]		
H/L	6.54	10.39	0.63	13.96	28.02	0.50	1.57	3.70	0.42
	[3.19]			[2.43]			[1.89]		

Table IA.3. Cross-Sectional Pricing Results: Other Test Assets

The setup is the same as in Table II in the main paper but here we show cross-sectional pricing results for three different sets of test assets: five currency momentum portfolios, ten US stock momentum portfolios (from Kenneth French's web page), and six corporate bond portfolios (one for each available rating category from AAA to BA, based on Lehman Brothers bond index data). The six bond portfolios are adjusted for durations as in Da and Schaumburg (2009) and the five currency momentum portfolios are based on sorting individual currencies into quintile portfolios based on their lagged 12-months return. The sample period is 11/1983 – 08/2009 for stock and FX momentum and 04/1990 – 08/2009 for corporate bonds.

Factor Prices														
5 Currency Momentum Portfolios					US stock momentum					US corporate bonds				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.05	-6.36	0.59	0.18	b	-0.33	-13.79	0.41	0.35	b	-0.39	-12.33	0.93	0.14
s.e.	(0.05)	(4.69)		(0.10)	s.e.	(0.54)	(7.07)		(0.01)	s.e.	(0.34)	(8.38)		(0.81)
λ	0.36	-0.07			λ	-1.12	-0.13			λ	-0.93	-0.10		
s.e.	(0.27)	(0.05)			s.e.	(2.38)	(0.07)			s.e.	(1.31)	(0.08)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.36	-0.07	6.79	14.35	λ	-1.12	-0.13	12.96	11.77	λ	-0.93	-0.10	1.91	1.64
(Sh)	(0.15)	(0.03)	(0.08)	(0.00)	(Sh)	(1.84)	(0.05)	(0.11)	(0.16)	(Sh)	(1.08)	(0.04)	(0.75)	(0.89)
(NW)	(0.15)	(0.04)			(NW)	(2.27)	(0.06)			(NW)	(1.30)	(0.07)		

Table IA.4. Individual Currencies

The table reports pricing results for individual currencies' excess returns. We run a Fama-MacBeth two-step procedure with robust regressions in the first and second step to account for outliers in individual currency excess returns. We report t-statistics and bootstrapped p-values for our estimates of factor risk prices. The "p-value" for the cross-sectional R^2 is based on the number of simulated R^2s exceeding the R^2 in the original regression. Simulated p-values are based on a block-bootstrap with 10,000 repetitions. Risk factors employed in various specifications are the average currency excess return against the USD (the DOL factor), innovations to global FX volatility (VOL), and the HML_{FX} factor of Lustig, Roussanov, and Verdelhan (2010). We also include a dummy VOL_{EM} in one specification that equals one for currencies of emerging markets (i.e. we use an interaction term of the VOL-beta with this dummy in the second stage regression).

	DOL	VOL	VOL_{EM}	HML_{FX}	R^2
λ	0.25	-0.05			0.31
t-stat	[2.08]	[-3.19]			
BS p-val	(0.25)	(0.05)			(0.01)
λ	0.26	-0.05	-0.06		0.26
t-stat	[2.07]	[-2.56]	[-0.74]		
BS p-val	(0.25)	(0.09)	(0.64)		(0.01)
λ	0.29			0.67	0.10
t-stat	[2.40]			[2.67]	
BS p-val	(0.16)			(0.12)	(0.79)
λ	0.25	-0.05		0.33	0.27
t-stat	[2.01]	[-2.84]		[1.09]	
BS p-val	(0.23)	(0.08)		(0.51)	(0.01)

Table IA.5. Cross-Sectional Pricing Results: Other Test Assets and HML_{FX}

The setup is the same as in Table IA.3 but here we show cross-sectional pricing results when using DOL and HML_{FX} (Lustig, Roussanov, and Verdelhan (2010)) as pricing factors instead of DOL and volatility innovations.

Factor Prices				
5 Currency Momentum Portfolios				
GMM	DOL	HML_{FX}	R^2	HJ-dist
b	0.07	0.03	0.01	0.18
s.e.	(0.04)	(0.05)		(0.06)
λ	0.32	0.26		
s.e.	(0.16)	(0.42)		
FMB	DOL	HML_{FX}	χ^2_{SH}	χ^2_{NW}
λ	0.32	0.26	10.03	13.91
(Sh)	(0.12)	(0.40)	(0.02)	(0.00)
(NW)	(0.14)	(0.41)		
US stock momentum				
GMM	DOL	HML_{FX}	R^2	HJ-dist
b	-1.22	0.71	-1.26	0.37
s.e.	(1.72)	(0.85)		(0.00)
λ	-4.91	4.60		
s.e.	(7.13)	(5.46)		
FMB	DOL	HML_{FX}	χ^2_{SH}	χ^2_{NW}
λ	-4.91	4.60	4.78	5.58
(Sh)	(5.60)	(3.51)	(0.78)	(0.69)
(NW)	(6.90)	(5.08)		
US corporate bonds				
GMM	DOL	HML_{FX}	R^2	HJ-dist
b	-0.41	0.48	0.27	0.28
s.e.	(0.29)	(0.49)		(0.01)
λ	-0.79	2.93		
s.e.	(1.21)	(3.58)		
FMB	DOL	HML_{FX}	χ^2_{SH}	χ^2_{NW}
λ	-0.79	2.93	7.22	7.99
(Sh)	(1.15)	(3.10)	(0.13)	(0.09)
(NW)	(1.16)	(3.46)		

Table IA.6. Other Test Assets and Classical Models of Equity Asset Pricing

The setup is the same as in Table IA.3 but here we only look at U.S. stock momentum returns and use a CAPM (left part) and the Fama French 3-factor model (right part) as pricing models.

Factor Prices									
US stock momentum: CAPM				US stock momentum: 3-factor model					
GMM	MKTRF	R^2	HJ-dist	GMM	MKTRF	SMB	HML	R^2	HJ-dist
b	0.05	-1.21	0.33	b	0.03	-0.30	-0.28	0.50	0.31
s.e.	(0.02)		(0.00)	s.e.	(0.04)	(0.18)	(0.22)		(0.02)
λ	0.81			λ	1.12	-2.01	-1.86		
s.e.	(0.36)			s.e.	(0.43)	(1.25)	(1.52)		
FMB	MKTRF	χ^2_{SH}	χ^2_{NW}	FMB	MKTRF	SMB	HML	χ^2_{SH}	χ^2_{NW}
λ	0.81	37.41	39.22	λ	1.12	-2.01	-1.86	15.68	16.58
(Sh)	(0.27)	(0.00)	(0.00)	(Sh)	(0.28)	(0.84)	(0.98)	(0.03)	(0.01)
(NW)	(0.30)			(NW)	(0.29)	(1.14)	(1.42)		

Table IA.7. Descriptive Statistics for International Bond Portfolios

The table reports descriptive statistics for excess returns to five international bond portfolios (where we sort bonds of different maturities from different countries into portfolios depending on their lagged redemption yield. Excess returns are in USD and with respect to the U.S. risk-free rate. Returns are monthly and the sample period is 12/1983 – 08/2009.

Panel A: International Bond Portfolios							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	2.18	3.59	4.24	5.76	9.09	4.97	6.91
	[0.99]	[1.67]	[2.09]	[2.69]	[4.22]	[2.52]	[3.64]
Median	1.52	2.99	4.66	5.10	9.38	4.99	8.66
Std. Dev.	10.20	9.93	9.94	9.98	10.20	9.26	9.01
Skewness	0.17	0.06	0.12	-0.09	-0.22	0.08	-0.54
Kurtosis	3.12	3.21	3.35	3.42	4.32	3.22	5.03
SR	0.21	0.36	0.43	0.58	0.89	0.54	0.77
AC(1)	0.08	0.10	0.06	0.10	0.09	0.10	0.00
	(0.38)	(0.19)	(0.54)	(0.18)	(0.29)	(0.21)	(1.00)
Coskew (DOL)	0.45	0.26	0.25	0.11	0.19		-0.14
Coskew (MKT)	0.31	0.16	0.20	0.21	0.01	0.19	-0.35

Table IA.8. Descriptive Statistics: Option Portfolios

This table reports descriptive statistics as in Table I in the main paper but for twelve option portfolios. Option strategies considered are risk reversals (long 25-Delta put, short 25-Delta call), bull spreads (long ATM call, short 25-Delta calls), and bear spreads (long ATM put, short 25-Delta puts). For each of the three strategies, we form four portfolios where the underlying currencies are sorted into portfolios according to their lagged forward discount. Portfolio 1 is the equal-weighted average of returns to an option strategy implemented on the 25% of all currencies with the lowest forward discounts, whereas Portfolio 4 runs these strategies on currencies with the highest forward discounts. Returns are monthly and the sample is 02/1996 – 08/2009.

	Risk Reversals				Bull Spreads				Bear Spreads			
Portfolio	1	2	3	4	1	2	3	4	1	2	3	4
Mean	1.45	-0.74	-1.40	-5.11	-1.99	-0.05	0.09	2.15	0.67	-0.46	-1.55	-2.19
	[1.43]	[-0.65]	[-1.00]	[-2.18]	[-3.50]	[-0.07]	[0.12]	[2.27]	[0.90]	[-0.71]	[-2.21]	[-2.06]
Median	0.77	-0.21	-0.80	-5.30	-3.95	-2.11	-0.65	2.10	-0.79	-2.04	-2.60	-4.04
Std. Dev.	3.31	3.74	4.14	6.80	1.98	2.28	2.28	3.02	2.24	2.08	2.23	3.30
Skewness	0.00	0.26	0.41	0.55	0.91	0.63	0.05	0.29	0.44	0.69	0.39	0.42
Kurtosis	4.85	7.28	6.97	8.92	3.67	3.52	3.52	5.60	2.43	4.01	5.27	6.05
SR	0.44	-0.20	-0.34	-0.75	-1.00	-0.02	0.04	0.71	0.30	-0.22	-0.69	-0.66
AC(1)	0.16	0.09	0.28	0.34	0.09	0.06	0.18	0.13	0.20	0.12	0.16	0.14
	(0.12)	(0.51)	(0.00)	(0.00)	(0.52)	(0.74)	(0.08)	(0.25)	(0.04)	(0.29)	(0.13)	(0.19)
Coskew (DOL)	-0.37	0.08	0.11	0.13	0.49	0.52	0.36	0.33	0.01	0.35	0.46	0.11
Coskew (MKT)	0.10	0.29	0.17	0.04	0.07	0.04	0.02	0.26	-0.04	-0.01	0.04	-0.12

Table IA.9. Cross-Sectional Pricing Results: International Bonds and FX Options

The setup is the same as in Table II in the main paper but here we show cross-sectional pricing results for five portfolios based on international bond returns and twelve FX option portfolios. The five bond portfolios are based on international bonds of different maturities and are sorted into portfolios based on their redemption yield. The option portfolios consist of four 25-Delta risk reversals, four 25-Delta Bull Spreads, and four 25-Delta Bear spreads. The sample period is 11/1983 – 08/2009 for the bond and 02/1996 – 08/2009 for the option portfolios.

5 International Bond Portfolios					12 Option portfolios				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.06	-8.57	0.68	0.20	b	-0.08	-9.18	0.91	0.36
s.e.	(0.04)	(5.57)		(0.07)	s.e.	(0.08)	(5.20)		(0.38)
λ	0.46	-0.09			λ	0.15	-0.08		
s.e.	(0.31)	(0.05)			s.e.	(0.44)	(0.04)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.46	-0.09	7.32	5.91	λ	0.15	-0.08	14.28	7.44
(Sh)	(0.21)	(0.03)	(0.06)	(0.12)	(Sh)	(0.20)	(0.02)	(0.16)	(0.68)
(NW)	(0.16)	(0.05)			(NW)	(0.19)	(0.03)		

Table IA.10. Implied Volatility Differences across Portfolios

The table reports volatility smiles (or skews) for the five carry trade portfolios (Panel A) and portfolios sorted on their lagged volatility beta (Panel B). For each of the five portfolios, we report the difference between the (log of) implied volatility of 25-Delta puts and 25-Delta calls (OTM options) as well as the difference between the (log of) implied volatility of 10-Delta puts and 10-Delta calls (for OTM options). Numbers shown are for average implied volatilities across currencies in a specific portfolios and log differences are multiplied by 100 so that differences are in percent. The last column ("5 − 1") shows the average difference between portfolio 5 and portfolio 1. Numbers in squared brackets are t-statistics based on HAC standard errors.

Panel A: Carry Trade Portfolios						
Portfolio	1	2	3	4	5	5-1
25-Delta Put – 25-Delta Call	4.07	2.57	2.54	3.47	6.17	2.10
	[2.53]	[2.59]	[3.96]	[3.14]	[4.16]	[1.11]
10-Delta Put – 10-Delta Call	-7.96	2.20	5.07	15.85	26.17	34.12
	[-3.91]	[1.47]	[1.77]	[5.50]	[9.47]	[10.11]
Panel B: Portfolios based on Volatility Betas						
Portfolio	1	2	3	4	5	5-1
25-Delta Put – 25-Delta Call	5.90	5.20	3.06	0.45	-0.99	-6.90
	[4.45]	[3.50]	[1.32]	[0.25]	[-0.80]	[-3.65]
10-Delta Put – 10-Delta Call	10.53	9.61	7.42	1.67	-1.19	-11.72
	[4.99]	[4.00]	[1.67]	[0.52]	[-0.56]	[-3.75]

Table IA.11. FMB Estimates: Liquidity Risk

The setup is identical to Table V in the main paper but here we report results based on FMB two-pass estimation.

Panel A: Factor Prices – Global bid-ask spreads

All countries (with b-a)					Developed countries (with b-a)				
FMB	DOL	BAS	χ^2_{SH}	χ^2_{NW}	FMB	DOL	BAS	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.03	4.42	2.85	λ	0.22	-0.02	2.96	2.96
(Sh)	(0.20)	(0.01)	(0.22)	(0.42)	(Sh)	(0.19)	(0.01)	(0.40)	(0.40)
(NW)	(0.15)	(0.02)			(NW)	(0.17)	(0.01)		

Panel B: Factor Prices – TED spread

All countries (with b-a)					Developed countries (with b-a)				
FMB	DOL	TED	χ^2_{SH}	χ^2_{NW}	FMB	DOL	TED	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.36	2.03	2.31	λ	0.22	-0.20	1.72	1.16
(Sh)	(0.12)	(0.16)	(0.57)	(0.51)	(Sh)	(0.14)	(0.09)	(0.63)	(0.76)
(NW)	(0.15)	(0.20)			(NW)	(0.17)	(0.13)		

Panel C: Factor Prices – Pastor/Stambaugh liquidity measure

All countries (with b-a)									
FMB	DOL	PS	χ^2_{SH}	χ^2_{NW}	FMB	DOL	PS	χ^2_{SH}	χ^2_{NW}
λ	0.18	0.05	6.65	11.48	λ	0.18	0.05	0.51	0.80
(Sh)	(0.12)	(0.02)	(0.08)	(0.01)	(Sh)	(0.14)	(0.02)	(0.92)	(0.85)
(NW)	(0.15)	(0.03)			(NW)	(0.17)	(0.03)		

Table IA.12. FMB Estimates: Volatility and Liquidity Risk

The setup is identical to Table VI in the main paper but here we report results based on FMB two-pass estimation.

Panel A: Volatility and global bid-ask spreads					
FMB	DOL	BAS	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.21	0.01	-0.08	0.65	0.81
(Sh)	(0.17)	(0.02)	(0.03)	(0.72)	(0.81)
(NW)	(0.15)	(0.02)	(0.04)		
Panel B: Volatility and TED spread					
FMB	DOL	TED	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.08	-0.06	1.00	0.64
(Sh)	(0.12)	(0.18)	(0.03)	(0.61)	(0.73)
(NW)	(0.15)	(0.26)	(0.03)		
Panel C: Volatility and P/S liquidity measure					
FMB	DOL	PS	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.18	-0.01	-0.08	1.18	1.00
(Sh)	(0.12)	(0.03)	(0.03)	(0.55)	(0.61)
(NW)	(0.15)	(0.04)	(0.03)		

Table IA.13. FMB Estimates: Volatility and HML_{FX}

The setup is identical to Table The setup is identical to Table VI in the main paper but here we report results based on FMB two-pass estimation.

Panel A: Volatility innovations and HML_{FX}						Panel B: Factor-mimicking portfolio and HML_{FX}					
FMB	DOL	VOL	HML_{FX}	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL_{FM}	HML_{FX}	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.07	0.65	1.31	0.59	λ	0.17	-0.04	0.59	1.09	0.18
(Sh)	(0.15)	(0.04)	(0.20)	(0.52)	(0.59)	(Sh)	(0.12)	(0.01)	(0.17)	(0.58)	(0.91)
(NW)	(0.13)	(0.05)	(0.17)			(NW)	(0.15)	(0.01)	(0.20)		
Panel C: Factor-mimicking portfolio (orth.) and HML_{FX}						Panel D: Factor-mimicking portfolio and HML_{FX} (orth.)					
FMB	DOL	$\text{VOL}_{FM}^{Orth.}$	HML_{FX}	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL_{FM}	$HML_{FX}^{Orth.}$	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.02	0.65	1.78	0.64	λ	0.21	-0.10	0.07	1.78	0.64
(Sh)	(0.12)	(0.01)	(0.16)	(0.41)	(0.73)	(Sh)	(0.12)	(0.02)	(0.83)	(0.41)	(0.73)
(NW)	(0.15)	(0.01)	(0.20)			(NW)	(0.15)	(0.03)	(0.87)		

Table IA.14. Descriptive Statistics: Unadjusted Returns

The setup of this table is identical to Table I in the main paper but we show results for returns without transaction cost adjustments.

All countries (without b-a)							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	-1.73	0.34	3.25	3.88	6.29	2.41	8.02
	[-0.95]	[0.22]	[1.75]	[2.11]	[2.37]	[1.41]	[3.50]
Median	-2.15	1.22	2.67	4.74	10.80	3.11	12.04
Std. Dev.	8.45	7.25	8.13	8.36	10.75	7.39	9.78
Skewness	0.18	-0.20	-0.28	-0.51	-0.64	-0.38	-1.04
Kurtosis	3.80	4.08	4.33	4.72	5.09	3.97	4.83
SR	-0.21	0.05	0.40	0.46	0.59	0.33	0.82
AC(1)	0.04	0.09	0.14	0.11	0.23	0.14	0.17
	(0.75)	(0.27)	(0.04)	(0.15)	(0.00)	(0.05)	(0.01)
Coskew (DOL)	0.36	-0.06	-0.15	-0.13	-0.05		-0.20
Coskew (MKT)	0.18	0.03	0.12	0.11	0.04	0.11	-0.12
Developed countries (without b-a)							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	-0.97	1.97	2.41	3.31	5.18	2.38	6.15
	[-0.48]	[0.87]	[1.19]	[1.62]	[2.07]	[1.22]	[2.70]
Median	-1.43	2.92	3.75	3.62	6.17	3.50	8.75
Std. Dev.	9.75	10.02	9.34	9.39	10.80	8.71	10.21
Skewness	0.14	-0.17	-0.14	-0.67	-0.26	-0.22	-0.92
Kurtosis	3.44	3.68	3.92	5.79	4.75	3.60	5.78
SR	-0.10	0.20	0.26	0.35	0.48	0.27	0.60
AC(1)	0.02	0.11	0.12	0.12	0.17	0.12	0.13
	(0.96)	(0.14)	(0.11)	(0.12)	(0.01)	(0.12)	(0.08)
Coskew (DOL)	0.30	-0.14	0.03	-0.32	0.03		-0.14
Coskew (MKT)	0.24	0.10	0.08	0.06	-0.11	0.08	-0.36

Table IA.15. Cross-Sectional Asset Pricing Results: Full Transaction Costs

The setup of this table is identical to Table II in the main paper but here we adjust excess returns for transaction costs that would occur under 100% portfolio turnover each month as in Lustig, Roussanov, and Verdelhan (2010).

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.	(0.06)	(3.51)		(0.82)	s.e.	(0.03)	(3.15)		(0.89)
λ	0.21	-0.07			λ	0.22	-0.06		
s.e.	(0.28)	(0.03)			s.e.	(0.23)	(0.04)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.22	-0.06	0.95	2.18	λ	0.22	-0.06	0.95	1.63
(Sh)	(0.16)	(0.02)	(0.81)	(0.54)	(Sh)	(0.16)	(0.02)	(0.81)	(0.65)
(NW)	(0.12)	(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	-0.29	1.01	4.34	0.76	1	-0.23	0.94	4.85	0.71
	(0.08)	(0.05)	(0.71)			(0.09)	(0.05)	(1.59)	
2	-0.15	0.84	1.00	0.74	2	-0.05	1.05	0.84	0.82
	(0.07)	(0.05)	(0.59)			(0.07)	(0.04)	(0.86)	
3	0.05	0.97	-0.30	0.79	3	-0.02	1.01	-0.11	0.88
	(0.06)	(0.05)	(0.58)			(0.05)	(0.03)	(0.67)	
4	0.09	1.02	-1.06	0.83	4	0.07	0.96	-2.41	0.82
	(0.07)	(0.05)	(0.71)			(0.07)	(0.03)	(1.07)	
5	0.30	1.15	-3.98	0.67	5	0.24	1.04	-3.18	0.72
	(0.12)	(0.07)	(1.17)			(0.10)	(0.05)	(1.06)	

Table IA.16. Cross-Sectional Asset Pricing Results: Simple Volatility Changes

The setup of this table is identical to Table II in the main paper but here we use simple volatility innovations (i.e. first differences of our proxy for global foreign exchange volatility, $\sigma_{t+1}^{FX} - \sigma_t^{FX}$) instead of residuals from an AR(1). The sample period is 12/1983 – 08/2009.

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	0.01	-7.57	0.91	0.12	b	0.02	-4.38	0.94	0.06
s.e.	(0.05)	(3.42)		(0.56)	s.e.	(0.03)	(2.73)		(0.89)
λ	0.21	-0.09			λ	0.22	-0.06		
s.e.	(0.24)	(0.04)			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	-0.09	2.47	3.86	λ	0.22	-0.06	0.95	0.83
(Sh)	(0.16)	(0.03)	(0.48)	(0.28)	(Sh)	(0.16)	(0.02)	(0.81)	(0.84)
(NW)	(0.12)	(0.04)			(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	-0.29	1.00	2.93	0.75	1	-0.23	0.94	4.52	0.71
	(0.08)	(0.05)	(0.72)			(0.09)	(0.05)	(1.42)	
2	-0.15	0.84	0.56	0.74	2	-0.05	1.05	0.43	0.82
	(0.06)	(0.04)	(0.57)			(0.07)	(0.04)	(0.89)	
3	0.05	0.98	0.33	0.79	3	-0.02	1.01	0.01	0.88
	(0.06)	(0.04)	(0.58)			(0.05)	(0.03)	(0.64)	
4	0.09	1.03	-0.26	0.82	4	0.07	0.96	-1.94	0.82
	(0.06)	(0.04)	(0.64)			(0.07)	(0.03)	(0.97)	
5	0.31	1.15	-3.56	0.66	5	0.24	1.04	-3.02	0.73
	(0.11)	(0.06)	(1.08)			(0.10)	(0.05)	(1.09)	

Table IA.17. Cross-Sectional Asset Pricing Results: Implied Volatility

The setup of this table is similar to Table II in the main paper but we only consider net returns for the All countries sample. The left part shows results for using innovations to the JP Morgan currency VIX for the G-7 countries and the right part shows results for using innovations to the S&P500 VIX index. The samples start in 1992:06 for the JP Morgan currency VIX and in 1986:02 for the S&P 500 VIX, respectively.

Panel A: Factor Prices

All countries (with b-a), JPM G-7 VIX				
GMM	DOL	$\triangle VIX$	R^2	HJ-dist
b	-0.03	-0.59	0.92	0.15
s.e.	(0.09)	(0.33)		(0.49)
λ	0.11	-0.71		
s.e.	(0.36)	(0.40)		
FMB	DOL	$\triangle VIX$	χ^2_{SH}	χ^2_{NW}
λ	0.11	-0.70	3.48	0.25
(Sh)	(0.16)	(0.24)	(0.32)	(0.97)
(NW)	(0.16)	(0.32)		

All countries (with b-a), S&P500 VIX				
GMM	DOL	$\triangle VIX$	R^2	HJ-dist
b	0.00	-0.18	0.90	0.15
s.e.	(0.08)	(0.11)		(0.37)
λ	0.21	-4.01		
s.e.	(0.33)	(2.42)		
FMB	DOL	$\triangle VIX$	χ^2_{SH}	χ^2_{NW}
λ	0.21	-4.01	3.79	0.32
(Sh)	(0.16)	(1.37)	(0.29)	(0.96)
(NW)	(0.14)	(1.63)		

Panel B: Factor Betas

All countries (with b-a), JPM G-7 VIX				
PF	α	DOL	$\triangle VIX$	R^2
1	-0.31	0.90	0.48	0.69
	(0.09)	(0.06)	(0.11)	
2	-0.15	0.85	0.12	0.73
	(0.07)	(0.05)	(0.06)	
3	0.07	1.00	0.03	0.77
	(0.07)	(0.05)	(0.06)	
4	0.03	1.02	-0.16	0.80
	(0.07)	(0.05)	(0.08)	
5	0.37	1.24	-0.46	0.67
	(0.13)	(0.10)	(0.14)	

All countries (with b-a), S&P500 VIX				
PF	α	DOL	$\triangle VIX$	R^2
1	-0.31	0.97	0.07	0.71
	(0.09)	(0.05)	(0.01)	
2	-0.17	0.84	0.01	0.73
	(0.06)	(0.04)	(0.01)	
3	0.07	1.02	0.01	0.81
	(0.06)	(0.04)	(0.02)	
4	0.07	1.05	-0.02	0.83
	(0.06)	(0.04)	(0.02)	
5	0.34	1.13	-0.09	0.65
	(0.12)	(0.07)	(0.03)	

Table IA.18. Descriptive Statistics: Other Base Currencies

This table reports descriptive statistics for currency portfolios as in Table I in the main paper but portfolio returns are measured in GBP, JPY, or CHF, respectively. Also, in this table, coskewness is measured with respect to the average global currency excess return against the respective base currency and not the USD so that we denote it by Coskew (Avg.).

Base currency: GBP							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	-1.80	-0.44	2.31	2.84	5.42	1.67	7.23
	[-0.97]	[-0.26]	[1.59]	[1.90]	[2.77]	[1.23]	[3.13]
Median	-3.92	-0.25	4.52	3.10	6.83	2.09	11.55
Std. Dev.	8.42	8.10	7.23	7.38	9.73	6.85	9.81
Skewness	0.91	0.30	-0.06	0.40	-0.40	0.40	-1.03
Kurtosis	6.40	5.86	6.29	6.64	4.98	5.84	4.79
SR	-0.21	-0.05	0.32	0.39	0.56	0.24	0.74
AC(1)	0.15	0.09	0.04	0.06	-0.01	0.03	0.18
	(0.03)	(0.26)	(0.80)	(0.58)	(0.99)	(0.86)	(0.01)
Coskew (Avg.)	0.45	0.07	-0.24	0.11	-0.27		-0.38
Base currency: JPY							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	-5.01	-3.65	-0.89	-0.36	2.22	-1.54	7.23
	[-3.03]	[-1.62]	[-0.37]	[-0.14]	[0.73]	[-0.71]	[3.13]
Median	-1.38	-1.56	4.94	4.84	10.23	2.40	11.55
Std. Dev.	7.97	9.96	11.01	11.10	13.34	9.82	9.81
Skewness	-1.13	-0.78	-1.59	-1.01	-0.94	-1.08	-1.03
Kurtosis	8.11	5.71	10.23	6.67	4.86	6.90	4.79
SR	-0.63	-0.37	-0.08	-0.03	0.17	-0.16	0.74
AC(1)	0.03	0.10	0.09	0.12	0.12	0.09	0.18
	(0.90)	(0.21)	(0.32)	(0.09)	(0.10)	(0.26)	(0.01)
Coskew (Avg.)	-0.14	0.19	-0.56	0.00	0.30		0.28
Base currency: CHF							
Portfolio	1	2	3	4	5	Avg.	H/L
Mean	-4.19	-2.83	-0.08	0.45	3.03	-0.72	7.23
	[-3.21]	[-1.83]	[-0.05]	[0.29]	[1.24]	[-0.53]	[3.13]
Median	-5.57	0.00	2.44	1.61	3.52	0.46	11.55
Std. Dev.	6.37	7.70	7.11	7.51	11.41	6.84	9.81
Skewness	0.46	-0.39	-0.61	-0.30	-0.75	-0.38	-1.03
Kurtosis	5.47	4.54	4.13	3.70	4.23	3.71	4.79
SR	-0.66	-0.37	-0.01	0.06	0.27	-0.11	0.74
AC(1)	0.04	0.01	0.01	0.06	0.06	0.00	0.18
	(0.77)	(0.99)	(0.99)	(0.59)	(0.61)	(1.00)	(0.01)
Coskew (Avg.)	0.39	0.08	-0.18	-0.01	-0.21		-0.32

Table IA.19. Cross-Sectional Asset Pricing Results: Other Base Currencies

The setup is the same as in Table II in the main paper but here we show cross-sectional pricing results for alternative base currencies: GBP, JPY, and CHF. The test assets are the five portfolios from above (all countries, with bid-ask spread adjustment) but are converted to one of the three alternative currencies and volatility innovations also calculated based on currencies quoted against these three alternative currencies. For example, results for the GBP are based on five portfolios' excess returns in GBP, the DOL factor (average excess return against the GBP) and innovations to global FX volatility are calculated from a volatility level series based on daily global currency returns against the GBP. The sample period is 11/1983 – 08/2009 and we employ monthly returns.

Panel A: Factor Prices

GBP: All countries (with b-a)					JPY: All countries (with b-a)					CHF: All countries (with b-a)				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.10	-6.85	0.94	0.10	b	-0.40	-16.05	0.96	0.10	b	-0.20	-9.39	0.80	0.14
s.e.	(0.06)	(3.56)		(0.72)	s.e.	(0.21)	(7.60)		(0.95)	s.e.	(0.09)	(4.43)		(0.56)
λ	0.17	-0.08			λ	-0.07	-0.36			λ	-0.01	-0.10		
s.e.	(0.24)	(0.04)			s.e.	(0.98)	(0.17)			s.e.	(0.26)	(0.05)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.17	-0.08	2.03	2.74	λ	-0.07	-0.36	0.45	0.25	λ	-0.01	-0.10	3.16	2.17
(Sh)	(0.14)	(0.03)	(0.57)	(0.43)	(Sh)	(0.41)	(0.18)	(0.93)	(0.97)	(Sh)	(0.16)	(0.03)	(0.37)	(0.54)
(NW)	(0.12)	(0.04)			(NW)	(0.18)	(0.16)			(NW)	(0.11)	(0.04)		

Panel B: Factor Betas

All countries (with b-a), GBP					All countries (with b-a), JPY					All countries (with b-a), CHF				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-0.29	1.02	3.83	0.76	1	-0.33	0.75	0.83	0.80	1	-0.31	0.80	3.17	0.64
	(0.08)	(0.04)	(0.65)			(0.06)	(0.03)	(0.38)			(0.08)	(0.07)	(0.67)	
2	-0.18	1.03	1.09	0.78	2	-0.18	0.95	0.58	0.85	2	-0.18	1.01	1.61	0.76
	(0.07)	(0.04)	(0.61)			(0.07)	(0.02)	(0.36)			(0.07)	(0.05)	(0.70)	
3	0.06	0.90	-0.05	0.74	3	0.06	1.05	0.01	0.89	3	0.04	0.86	-1.37	0.74
	(0.06)	(0.04)	(0.61)			(0.06)	(0.04)	(0.37)			(0.06)	(0.04)	(0.77)	
4	0.10	0.96	-0.71	0.78	4	0.10	1.07	-0.45	0.90	4	0.09	0.93	-1.75	0.79
	(0.07)	(0.04)	(0.65)			(0.06)	(0.03)	(0.39)			(0.06)	(0.04)	(0.65)	
5	0.31	1.09	-4.16	0.58	5	0.36	1.19	-0.96	0.79	5	0.35	1.40	-1.67	0.75
	(0.12)	(0.08)	(1.34)			(0.12)	(0.06)	(0.63)			(0.11)	(0.07)	(1.25)	

Table IA.20. Cross-Sectional Asset Pricing Results: Non-Linearities

The setup of this table is similar to Table II in the main paper but we only look at the five carry trade portfolios for the all countries sample and we investigate non-linearities in the relationship of volatility innovations and carry trade returns. The left part of the table shows results where we only use positive volatility innovations and the right part of the table shows results where we only use negative volatility innovations.

Panel A: Factor Prices

All countries (with b-a), Δ VOL > 0					All countries (with b-a), Δ VOL < 0				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	-0.01	-9.78	0.98	0.06	b	0.03	-25.58	0.91	0.13
s.e.	(0.06)	(5.07)		(0.91)	s.e.	(0.05)	(11.30)		(0.52)
λ	0.21	-0.05			λ	0.21	-0.06		
s.e.	(0.31)	(0.03)			s.e.	(0.22)	(0.03)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.21	-0.05	0.84	1.17	λ	0.21	-0.06	2.19	3.50
(Sh)	(0.15)	(0.02)	(0.84)	(0.76)	(Sh)	(0.19)	(0.02)	(0.53)	(0.32)
(NW)	(0.15)	(0.02)			(NW)	(0.15)	(0.03)		

Panel B: Factor Betas

All countries (with b-a), Δ VOL > 0					All countries (with b-a), Δ VOL < 0				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-0.52	1.02	6.08	0.76	1	-0.08	0.99	5.69	0.74
	(0.08)	(0.04)	(1.09)			(0.10)	(0.05)	(1.19)	
2	-0.22	0.85	1.76	0.74	2	-0.13	0.84	0.46	0.74
	(0.07)	(0.04)	(0.81)			(0.08)	(0.04)	(1.21)	
3	0.08	0.97	-0.74	0.79	3	0.07	0.98	0.39	0.79
	(0.06)	(0.04)	(0.87)			(0.09)	(0.04)	(1.29)	
4	0.14	1.02	-1.33	0.83	4	0.02	1.03	-1.79	0.83
	(0.06)	(0.04)	(1.11)			(0.08)	(0.04)	(0.98)	
5	0.52	1.14	-5.77	0.67	5	0.12	1.17	-4.75	0.65
	(0.11)	(0.06)	(1.85)			(0.15)	(0.06)	(1.87)	

Table IA.21. Cross-Sectional Asset Pricing Results: Sub-Samples

The setup of this table is similar to Table II in the main paper but we only look at the five carry trade portfolios for the all countries sample and we split the whole sample into two subsamples. The left part of the table shows results for the sample period 1983 – 1995, whereas the right part shows results for the period 1996 – 2009.

Panel A: Factor Prices

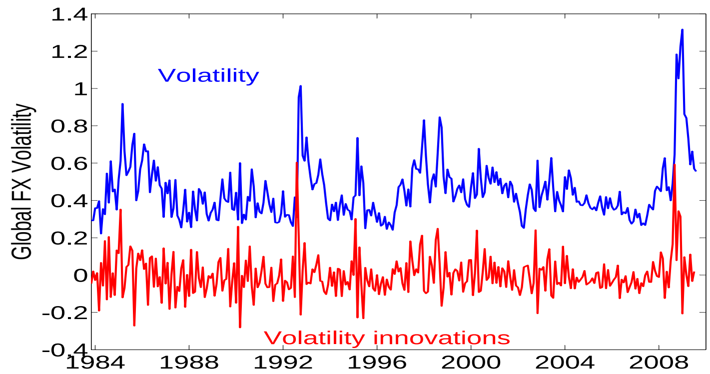
All countries (with b-a), 1983 – 1995					All countries (with b-a), 1996 – 2009				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.05	-3.72	0.75	0.10	b	-0.10	-10.16	0.97	0.14
s.e.	(0.05)	(3.92)		(0.78)	s.e.	(0.10)	(5.19)		(0.76)
λ	0.32	-0.05			λ	0.11	-0.08		
s.e.	(0.28)	(0.05)			s.e.	(0.46)	(0.05)		
FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}	FMB	DOL	VOL	χ^2_{SH}	χ^2_{NW}
λ	0.32	-0.05	1.26	6.12	λ	0.11	-0.08	1.72	2.27
(Sh)	(0.21)	(0.04)	(0.74)	(0.11)	(Sh)	(0.20)	(0.03)	(0.63)	(0.52)
(NW)	(0.22)	(0.05)			(NW)	(0.19)	(0.03)		

Panel B: Factor Betas

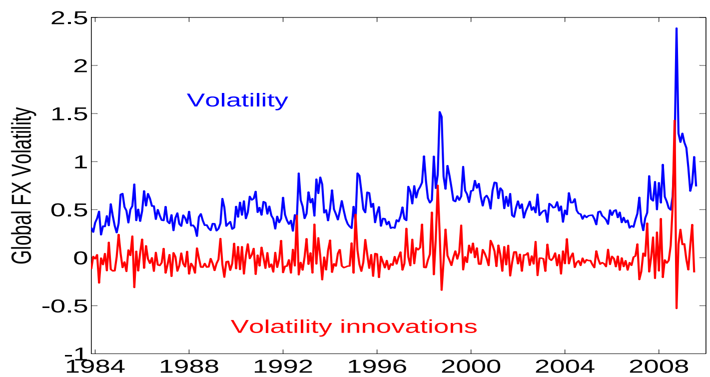
All countries (with b-a), 1983 – 1995					All countries (with b-a), 1996 – 2009				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-0.17	1.06	3.62	0.78	1	-0.41	0.95	4.91	0.73
	(0.12)	(0.06)	(1.01)			(0.09)	(0.04)	(0.81)	
2	-0.09	0.82	0.04	0.71	2	-0.20	0.89	2.45	0.78
	(0.10)	(0.06)	(0.92)			(0.07)	(0.04)	(0.63)	
3	0.05	0.99	-0.78	0.81	3	0.05	0.96	0.22	0.75
	(0.09)	(0.06)	(0.84)			(0.08)	(0.06)	(1.05)	
4	0.13	1.05	-0.69	0.82	4	0.05	0.98	-1.75	0.83
	(0.10)	(0.06)	(1.06)			(0.07)	(0.05)	(0.91)	
5	0.07	1.09	-2.19	0.69	5	0.52	1.22	-5.84	0.66
	(0.15)	(0.07)	(1.49)			(0.15)	(0.11)	(2.04)	

Figure IA.1. Global FX Volatility for Alternative Base Currencies

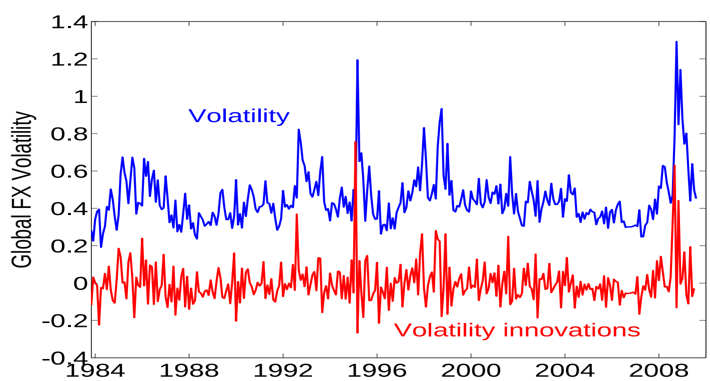
(a) Base Currency: GBP



(b) Base Currency: JPY

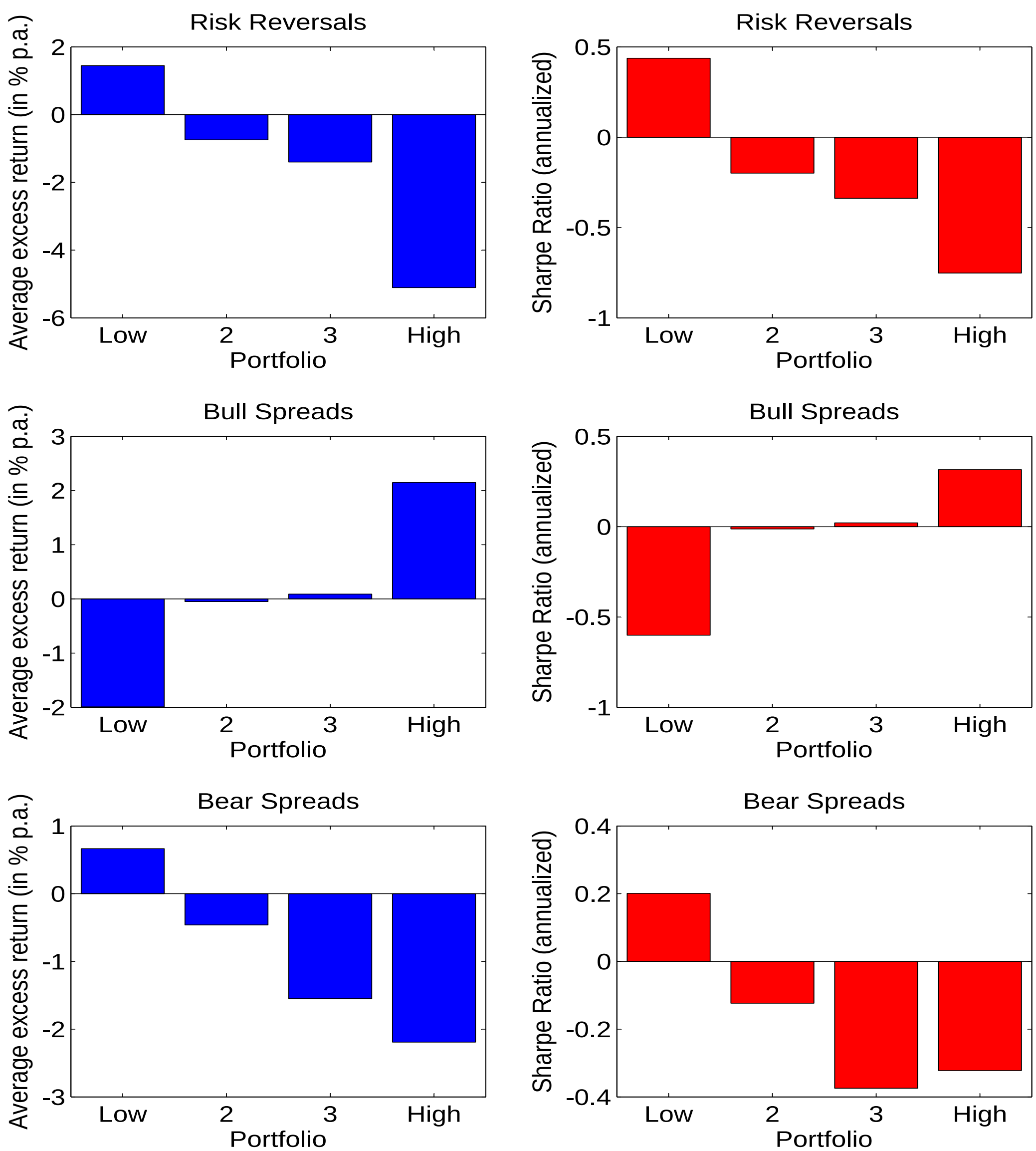


(c) Base Currency: CHF



This figure shows our proxy for global FX volatility for other base currencies. Base currencies are the Great Britain Pound (Panel (a)), the Japanese Yen (Panel (b)), and the Swiss Franc (Panel (c)). The upper (blue) line shows volatility levels whereas the lower (red) line shows volatility innovations.

Figure IA.2. Option Portfolios



The figure shows annualized average excess returns (left panel) and annualized Sharpe Ratios (right panel) for option portfolios. Option strategies considered are risk reversals (long 25-Delta put, short 25-Delta call), bull spreads (long ATM call, short 25-Delta calls), and bear spreads (long ATM put, short 25-Delta puts). For each of the three strategies, we form four portfolios where the underlying currencies are sorted into portfolios according to their lagged forward discount. Returns are monthly and the sample is 02/1996 – 08/2009.