Carry Trades and Global Foreign Exchange Volatility

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Abstract

We investigate the relation between global foreign exchange volatility and the excess returns to carry trade portfolios. We find a significantly negative return comovement of high interest rate currencies with global volatility, whereas low interest rate currencies provide a hedge against volatility shocks. Our main global foreign exchange volatility proxy accounts for more than 90% of the return spread in five carry trade portfolios. Further analyses show that: (i) liquidity risk also matters for excess returns, but to a lesser degree, and that (ii) excess returns are more strongly related to unexpected components of volatility than to expected components. Our results are robust to different proxies for volatility risk, and extend to other cross-sections such as individual currency returns and (some) momentum portfolios.

JEL-Classification: F31, G12, G15.

Keywords: Carry Trade, Volatility, Liquidity, Forward Premium Puzzle.

1 Introduction

This paper studies the risk-return profile of so-called carry trades, a popular trading strategy in international currency markets. A carry trade strategy invests in currencies which yield high interest rates and funds this investment by borrowing in currencies with low interest rates. According to uncovered interest parity (UIP), exchange rate changes will eliminate this interest rate margin. However, extensive empirical studies show that exchange rate changes do *not* compensate for the interest rate margin. Instead, the opposite holds true empirically: high interest rate currencies tend to appreciate while low interest rate currencies tend to depreciate which yields considerable returns to currency speculation. As a consequence, simple 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 premiums (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 premiums until today.

In the empirical analysis of this paper we follow much of the recent literature (e.g. Burnside et al., 2006; Lustig and Verdelhan, 2007; Lustig et al., 2008) and sort currencies into portfolios according to their relative interest rate differential versus U.S. money market interest rates.[2] This yields a portfolio 1 containing those 20 percent of currencies with the

[1]Since the beginning of the recent global financial crisis, carry trade strategies have made substantial losses. However, these losses are relatively small when compared to the cumulative returns from carry trades of the last 15-20 years (e.g. Brunnermeier et al., 2008).

[2]Originally, the innovation of sorting currencies into portfolios is due to Lustig and Verdelhan (2007) and has been followed by several other papers afterwards.

lowest relative interest rates up to a portfolio 5 containing the highest relative interest rates at each point in time. Investing in portfolio 5 and shorting portfolio 1 therefore results in a carry trade portfolio. This carry trade leads to large and significant unconditional excess returns of more than 5% even after accounting for transaction costs and the recent market crash. These returns cannot be explained by simple measures of risk and seem to offer a free lunch to investors. Guided by theoretical suggestions from ICAPM-type models (Campbell, 1993, 1996) and earlier evidence for stock markets (e.g. Ang et al., 2006b), we test whether the sensitivity of excess returns to global FX volatility can rationalize the returns to these five portfolios in a standard, linear asset pricing framework. We find clear evidence that high interest rate currencies deliver low returns in times of high volatility but that low interest rate currencies provide a hedge against volatility shocks. Therefore, carry trades perform especially poorly during times of market turmoil. 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 et al. (2008), we show that returns to carry trades can be understood by relating them cross-sectionally to two risk factors. Lustig et al. (2008) employ a data-driven approach 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) the return to the carry trade portfolio itself (the "HML_{FX}" factor). Following them, we employ two risk factors to price the cross-section of carry trade returns, one of which is the Dollar risk factor. We differ from them by replacing their data-driven HML_{FX} factor with an intuitively appealing risk factor: global foreign exchange market volatility.[3] We show that global FX volatility is a pervasive risk factor in the cross-section of FX excess returns. Second, Brunnermeier et al. (2008) 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 et al. (2008) we show that liquidity is useful more generally to understand the cross-section of carry trade returns, i.e. also in times when currencies do not crash. We comprehensively document, however,

[3] 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.

that our proxy for global FX volatility is the more powerful factor and that volatility 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 time-varying risk premiums in the cross-section of carry trade returns. The pricing power of volatility furthermore extends to other cross-sections such as (some) FX momentum portfolios as well as to individual currencies' excess returns as well. This finding is in line with results for other markets where it has been shown that volatility is helpful in pricing several asset classes such as stocks, stock options, or corporate bonds (Ang et al., 2006b; Da and Schaumburg, 2008). Reassuringly, we show that FX volatility encompasses several proxies for financial market liquidity such as bid-ask spreads, the TED spread, or the Pastor and Stambaugh (2003) liquidity measure: FX volatility always dominates liquidity proxies in joint asset pricing tests where both factors enter the stochastic discount factor. Again, this finding corroborates evidence for stock markets where e.g. Bandi et al. (2008) show that stock market volatility drives out liquidity in cross-sectional asset pricing exercises. Therefore, results in our paper provide new insights into the behavior of time-varying risk premiums in currency markets in general as well as striking 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. (i) Out of the universe of 48 currencies we take a sub-sample covering only 15 developed countries. (ii) We consider transactions costs by allowing for the bid-ask spread. (iii) We show that sorting currencies on their beta with volatility yields portfolios with a large spread in returns. These portfolios are related, but not identical, to our base test assets of currency portfolios sorted on forward discount. (iv) In order to better understand the economic meaning of volatility we also run the same tests with global illiquidity as a risk factor, where illiquidity is proxied for by (a) the size of the spread in foreign exchange markets, (b) the TED spread, or (c) the Pastor and Stambaugh (2003) liquidity measure for the U.S. equity market. Results show that these measures are related to volatility but that they are inferior and dominated by volatility in our asset pricing tests. (v) Finally, we show that the unexpected component of volatility is the driving force behind our main result, which is less evident for (un)expected components of liquidity.

Moreover, we test the robustness of our results in five directions, again without qualitative changes. (1) We split the sample in half and then estimate our basic model again. (2) We change the volatility proxy by considering the VIX volatility index based on stock options, which leads to a somewhat inferior explanatory power. Moreover, we experiment with weighting schemes of the global FX volatility index. (3) We depart from our base scenario of a U.S. representative investor and run calculations with alternative base currencies (GBP, CHF, JPY). (4) We investigate the explanatory performance of the proposed risk factor for other kinds of test assets. To this end, we use momentum portfolios, i.e. currencies sorted depending on previous excess returns. We find that a standard momentum 12-1-strategy, i.e. a momentum strategy with a formation period of 12 months and an investment period of 1 month, can again be well explained by global FX volatility risk. However, this does not apply to a 1-1 strategy. Returns on these strategies provide a puzzle for us since they hedge against volatility risk and simultaneously earn high returns. (5) As an additional set of test assets, we use the whole cross-section of individual currencies' excess returns and find a smaller but still recognizable relation with volatility in the cross-section.

Our study is closely related to a new strand of literature suggesting explanations for the forward premium puzzle. Important contributions include Burnside et al. (2006), who argue that carry trades may be difficult to implement due to high transaction costs. Brunnermeier et al. (2008) show that carry trades are related to low conditional skewness, indicating that they are subject to crash risk. Related to this, Melvin and Taylor (2009) show that proxies for market stress have some predictive power for carry trade returns. Burnside et al. (2008) 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 et al. (2009) suggest that the forward premium may be due to adverse selection risk. Lustig and Verdelhan (2007) provide evidence that currency risk premiums can be understood in the Durables CCAPM setting of Yogo (2006); Verdelhan (2008) shows how carry trade returns are related to risk arising from consumption habits, and Lustig et al. (2008) use an empirically derived two-factor model which nicely explains the cross-section of currency portfolios and the carry trade, and also partly captures the 1-1 momentum strategy. We also rely on Brunnermeier et al. (2008) in that we confirm some relevance for illiquidity as a risk factor. However, we cannot confirm that transaction costs are prohibitively important (Burnside et al., 2006) or that skewness would be a pervasive proxy for risk in the currency market (Brunnermeier et al., 2008).

The paper is structured into five more sections. First, we shortly review the conceptual role of volatility as a risk measure (Section 2). Section 3 presents data and descriptive statistics. The main results regarding volatility risk are shown in Section 4. Section 5 provides results on the relation of volatility and liquidity risk, robustness tests are presented in Section 6, and conclusions are drawn in Section 7.

2 Volatility as a (Covariance-)Risk Factor in Foreign Exchange

Overall, the idea that volatility has a role in determining asset valuations has long been a cornerstone of finance (Drechsler and Yaron, 2008). Despite its prominence in the stock market literature, there have been hardly any attempts to relate currency risk premiums *cross-sectionally* to currencies' sensitivity to movements in aggregate volatility. When the FX literature dealt with volatility, it was generally seen as a driver of currency risk premiums in a time series setting (see e.g. Bekaert, 1994, 1995, for early contributions). It thus seems quite natural to employ a cross-sectional perspective on the role of (systematic) volatility to help understand currency risk premiums in general, and the forward premium puzzle and carry trades in particular. Therefore, we discuss earlier work in this area which helps motivate our approach.

A useful starting point for our purpose is the thorough survey on the forward premium puzzle by Engel (1996). He covers studies which have assumed rational expectations and attempted to attribute the forward rate bias to a foreign exchange risk premium and concludes that "models of the risk premium have been unsuccessful" (p. 124). These models, which have been empirically unsuccessful in the end, include several time-series tests considering exchange rate volatility as a determinant of the risk premium, such as Bekaert (1994, 1995) or Bekaert and Hodrick (1992). In general, efforts to explain currency risk premiums by relying on (largely idiosyncratic) volatility obtained from analyzing single currencies have not been satisfactory and a different approach seems warranted.

We thus follow another line of literature which was originally developed with stock markets in mind, drawing on Merton's (1973) ICAPM theory. In an intertemporal asset pricing approach, the valuation of financial assets occurs according to their returns' relation to various state variables which characterize the investor's set of future investment opportunities. In this vein, it has recently been analyzed whether the volatility of the market return is a systematic risk factor which should also be priced in the cross-section (Ang et al., 2006b, p. 259). Ang et al. employ changes in the VIX index (from CBOE) to proxy for volatility risk. Indeed, 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 (2008) price several asset classes with a pricing kernel that is linear in the aggregate stock market return and volatility. Their specification is based on the log-linearized discount factor from Campbell (1993) with Epstein-Zin utility. Finally, Bandi et al. (2008) do not only consider volatility, but also liquidity as a further pricing factor.[4] They find that both risk factors are useful for understanding the pricing of U.S. stocks, but that volatility dominates illiquidity when they are considered jointly. In their interpretation they regard both factors as proxies for a more fundamental distress factor so that the relative inferiority of illiquidity underlines the economic meaning and empirical importance of volatility. Summing up these papers on stock pricing, volatility emerges naturally as a state variable in ICAPM-type models (Merton, 1973; Campbell, 1996) where investors hedge against changes in future investment opportunities. This motivates our approach of pricing forward-discount sorted portfolios with a stochastic discount factor (SDF) depending linearly on an aggregate FX market return as well as on aggregate FX market volatility.

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; Ang et al., 2006a, for asset pricing implementations

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

of coskewness).[5] 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 hedge against volatility and should thus earn lower returns. Therefore, this idea is closely related to our setup. Furthermore, Dittmar (2002) uses Taylor approximations of general, nonlinear 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.

All in all there is a wealth of empirical evidence (and theoretical justification) that systematic volatility and stock returns are related cross-sectionally. We show that a similar approach is helpful to understand the cross-section of FX risk premiums as well.

3 Data and Currency Portfolios

This section describes the data used in the empirical analyses, the construction of portfolios and associated excess returns, and our main proxy for global FX volatility. We also provide some basic descriptive statistics.

Data source and sample currencies. The data for spot exchange rates and 1-month forward exchange rates cover the sample period from November 1983 to November 2008, and are obtained from BBI and Reuters (via Datastream).[6] We denote the 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, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzer-

[5] Coskewness is given by

$$\text{coskew} = \frac{\mathbb{E}\left[(r^k - \mu^k)(r^m - \mu^k)^2\right]}{\sigma(r^k)\sigma^2(r^m)}$$

where r^k, r^m denote the return of a portfolio k and the market benchmark, respectively; and σ denotes standard deviation. Applying a covariance decomposition to the numerator above, the covariance of returns with market volatility naturally emerges from this framework as well.

[6] Lustig et al. (2008) and Burnside et al. (2008) also use these data.

land, Taiwan, Thailand, Ukraine, United Kingdom. Following Lustig et al. (2008) we also study a smaller sub-sample consisting only of 15 developed countries with a longer data history. This sample includes: Australia, Austria, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, Switzerland, United Kingdom.

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 (see e.g. Akram et al., 2008), i.e. $f_t - s_t \simeq i_t^* - i_t$ where i denotes interest rates and stars indicate foreign countries. We re-balance portfolios at the end of each month. Currencies are ranked from low to high interests 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

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

We compute the log currency excess return $rx_{j,t+1}$ for portfolio j by taking the (equally weighted) average of the log currency excess returns in each portfolio j. As in Lustig et al. (2008), we also compute excess returns for bid-ask spread adjusted currency positions. These are computed as $rx_{t+1}^l = f_t^b - s_{t+1}^a$ for long positions and $rx_{t+1}^s = -f_t^a + s_{t+1}^b$ for short positions.

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. We also build and report results for a portfolio denoted DOL which is just 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.[7]

[7]Lustig et al. (2008) call this zero-cost portfolio the "Dollar risk factor", hence the abbreviation "DOL".

Descriptive statistics. Descriptive statistics for the five forward discount portfolios, the DOL and H/L portfolio can be found in Table 1. The first two panels show results for the sample of all 48 countries, and the lower two panels show results for the sample of 15 developed countries. We show results for unadjusted log excess returns (without b-a) and for returns adjusted for bid-ask spread transaction costs (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 et al. (2008), and an almost monotonic pattern for developed countries. A similar pattern emerges for excess kurtosis. There is no such pattern, however, for the standard deviation.

Table 1 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 before transaction costs, which suggests that U.S. investors demand a low but positive risk premium for holding foreign currency.[8]

Figure 1, Panel (a), shows cumulative log returns for the carry trade portfolio H/L for all countries (solid black line) and for the smaller sample of developed countries (broken blue line). As may be expected, carry trade returns are much smoother for the sample of developed countries. Interestingly, carry trades among developed countries were more profitable in 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.

Volatility proxy. We use a straightforward measure to proxy for global FX volatility which is based on daily excess returns. More specifically, we calculate the absolute daily

[8]This premium is almost non-existent after transaction costs, but it should be noted that transaction costs are calculated for an investor who buys and sells a currency each month. The unconditional buy and hold return is not affected by monthly transaction costs, so that the positive DOL return seems to be a risk premium for investing outside the U.S. rather than a compensation for transaction costs.

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

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{|r_\tau^k|}{K_\tau} \right) \right] \tag{2}$$

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 et al., 2001), although we use absolute returns and not squared returns to minimize the impact of outlier returns since our full sample includes several emerging markets. We also do not weight currencies, e.g. according to shares in international reserves or trade, to limit the impact of arbitrary assumptions.[9] 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 market meltdown. Therefore, our proxy seems to capture obvious times of market distress quite well.

FIGURE 1 ABOUT HERE

4 Empirical Results

This section presents our main findings. We briefly show our methodological approach (4.1) and present our main result in a graphical preview (4.2) before formal asset pricing test results are shown (4.3). Finally, we provide additional evidence from portfolios sorted on the basis of volatility betas (4.4).

[9] We provide robustness on this issue later in the paper. The main message is that our results do not change when using sensible weighting schemes.

4.1 Methodology

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

$$\mathbb{E}[m_{t+1} rx^j_{t+1}] = 0 \tag{3}$$

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

$$\mathbb{E}\left[rx^j\right] = \lambda' \beta_j \tag{4}$$

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

We estimate parameters of the above equation via the generalized method of moments (GMM) following Hansen (1982). Estimation is based on a pre-specified weighting matrix and factor means are estimated by an additional moment condition.[10]

In the following tables we report estimates of b and implied λs as well as cross-sectional R^2s and the HJ distance measure (Hansen and Jagannathan, 1997). We also report simulated p-values for the test of whether the HJ distance is equal to zero.[11]

We additionally employ the traditional Fama-MacBeth two-step methodology (Fama and MacBeth, 1973) to estimate factor prices and portfolio betas. Our Fama-MacBeth procedure is standard and we employ first-step time-series regressions of the form

[10] The moment conditions are $\begin{bmatrix} (1 - b'(h_{t+1} - \mu))\, rx^j_{t+1} \\ h_{t+1} - \mu \end{bmatrix}$ with corresponding prespecified weighting matrix $W = \begin{bmatrix} I_N & 0 \\ 0 & p \end{bmatrix}$ so that the five portfolios are given equal weight in the minimization. We set p to have large values in order to pin down the factor means precisely.

[11] 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).

$$rx_{t+1}^j = \alpha_j + \beta_j h_{t+1} + \varepsilon_{t+1}^j \tag{5}$$

to estimate in-sample betas for each portfolio j. These betas are then used in cross-sectional regressions to estimate factor prices λ at each point in time

$$rx_{t+1}^j = \hat{\beta}_j{}' \lambda_{t+1} + \epsilon_{t+1}^j, \;\; j = 1, \ldots, N. \tag{6}$$

Estimates of factor prices λ are then obtained by averaging the λ_t-estimates over time. This is the standard procedure as outlined e.g. in Cochrane (2005). Note that we do not include a constant in the second stage of the Fama-MacBeth 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.[12]

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

We first provide a simple graphical analysis to visualize the relationship between global FX volatility and currency excess returns. To do so, we divide the sample into four samples depending on the value of global FX volatility. 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.

[12] Also see Burnside (2007) and Lustig and Verdelhan (2008) on the issue of whether to include a constant or not.

Figure 2 about here

Bars show the annualized mean returns of the carry trade portfolio. As can be seen from the figure, high interest rate currencies clearly yield higher excess returns when volatility is 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 both the full sample and the smaller sample of developed countries. While this analysis is intentionally simple, it intuitively demonstrates the strong relationship between global FX volatility and returns to carry trade portfolios. Times of high volatility are clearly 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 (i.e. funding currencies) provide a hedge in times of market turmoil.[13] The following sections test this finding more rigorously.

4.3 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.

Table 2 presents results for asset pricing tests based on equations (3) – (5) and using the five currency portfolios detailed above as test assets. As factors we use DOL and global FX volatility (VOL), i.e. the pricing kernel is:

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

Panel A of Table 2 shows cross-sectional pricing results. We are primarily interested in the factor price risk of global FX volatility, 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

[13] We basically find the same result when we look at return differences between portfolios 5 and 3 and portfolios 3 and 1. There is a monotone and negative relationship between volatility and excess returns. Clarida et al. (2009) document a similar feature and relate this to results from Fama UIP regressions.

(right part of the table), and this estimate is significant for both the GMM and FMB estimates (with or without the Shanken adjustment).

The negative factor price estimate directly translates into lower risk premiums for portfolios that co-move positively with volatility (i.e. volatility hedges) whereas portfolios with a negative covariance with volatility 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 and only reach values of 9% and 4% for the full and the developed country sample, respectively.

Now, which portfolios provide insurance against volatility risk and which do not? Panel B of Table 2 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. 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 1. These results also corroborate our graphical exposition (Figure 2) in the previous section.

Table 2 about here

To examine whether these results are driven by transaction costs, Table 2 also shows results for when the test assets' excess returns are bid-ask spread adjusted. The results are very similar to those above, suggesting that transaction costs (measured via bid-ask spreads) do not seem to drive our results. Rather, we find lower (maximum) pricing errors as indicated by the lower HJ-distances for transaction cost adjusted returns in Table 2.

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. Panel A (for the full sample) and Panel B (for the developed country sample) show that our risk factor is able to reproduce the spread in mean returns quite well. This is especially true for the low interest rate portfolio (P1) whose return is matched very closely. We are, however, slightly under-predicting mean excess returns for the other corner portfolio, P5. The difference in the fit between the full and developed country sample appears to be very small.

FIGURE 3 ABOUT HERE

4.4 Beta Sorts: Volatility

We now show the explanatory power of volatility risk for carry trade portfolios in another dimension. If volatility is a priced factor, then it is reasonable to assume that currencies sorted according to their exposure to volatility movements yield a cross-section of portfolios with a significant spread in mean returns.[14] Currencies that hedge against volatility risk should trade at a premium, whereas currencies that yield low returns when volatility is high should demand a higher return in equilibrium, consistent with ICAPM theory (Merton, 1973; Campbell, 1993, 1996).

We therefore sort currencies into five portfolios depending on their past beta with global FX volatility. We use rolling estimates of beta with a rolling window of 36 months (as in Lustig et al., 2008) and we re-balance portfolios every six months. Portfolio excess returns are shown in Table 3. We do not adjust for transaction costs here, since portfolio re-balancing occurs only twice per year. Thus, transaction costs will be small anyway.

TABLE 3 ABOUT HERE

The table shows that the spread between currencies with a high volatility beta (i.e. hedges against volatility risk) and currencies with low betas is clearly positive. Moreover, some

[14] Beta sorts are a common means to investigate risk premiums in financial markets (see e.g. Pastor and Stambaugh, 2003; Ang et al., 2006b; Lustig et al., 2008).

of these portfolios deliver high Sharpe Ratios. Pre- and post-formation forward discounts suggest that these portfolios are similar to the carry trade portfolios. However, a noteworthy feature of these portfolios is that they have a very different skewness pattern compared to the forward discount-sorts. Table 1 shows that excess returns of high interest rate currencies have much lower skewness than low interest rate currencies (also see Brunnermeier et al., 2008). We do not find this pattern here. On the contrary, the H/L portfolios actually tend to be positively skewed (except for a slightly negative skewness for developed countries) which suggests that sorting on volatility betas produces portfolios related to, but not identical to the carry trade portfolios.

All in all, this section has shown that volatility risk – as measured by the covariance of a portfolio's return with aggregate 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 high aggregate volatility – and thus serve as a volatility hedge – trade at a premium in equilibrium and vice versa.

5 Relating Volatility and Liquidity Risk

As noted in the beginning of this paper, it is hard to disentangle volatility and liquidity effects, since both concepts are closely related and – especially in the case of liquidity – not directly observable. However, it is clearly interesting to examine the contribution of these two proxies of risk for currency investments since Brunnermeier et al. (2008) suggest that liquidity is potentially crucial to understanding risk premiums in foreign exchange. This section therefore relates volatility and liquidity proxies and investigates their relative pricing power. We start with a short overview of liquidity measures employed in this paper (5.1) and then move on to present empirical results for the explanatory power of liquidity factors (5.2) and the pricing information contained in expected and unexpected components of volatility and liquidity factors (5.3).

5.1 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 equation (2) to obtain our global bid-ask spread measure ψ^{FX}:

$$\psi_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{\psi_\tau^k}{K_\tau} \right) \right]. \tag{7}$$

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 our 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-months Eurodollar interbank deposits (LIBOR) and 3-months T-Bills. Differences between these rates reflect among other things the willingness of banks to provide funding in the interbank market; thus a large spread should be related to lower liquidity. Hence, the TED spread serves as an illiquidity measure, as used e.g. by Brunnermeier et al. (2008). We include the TED spread to proxy for illiquidity in global money markets.

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 mean higher liquidity. This contrasts with our other three liquidity measures which rather measure *illiquidity*. We include it as a proxy for global stock market liquidity.

Relations among volatility and liquidity factors. Table 4 shows correlation coefficients and principal components for the three liquidity proxies and global FX volatility. We multiply the PS measure by minus 1 to make results more easily interpretable here. The upper panel shows correlation coefficients and it can be seen that our FX volatility proxy is positively correlated with all three illiquidity measures, which is not surprising. However, the relation between the three illiquidity measures is far from perfect. Bid-ask spreads and the TED spread, for instance, are negatively correlated and the other correlations are close to zero.

Table 4 about here

The lower panel of Table 4 also shows a principal components analysis which serves to investigate different dimensions of volatility and liquidity. The first principal components only explain about 35% of the total variation, which corroborates results from the correlation analysis and shows that global volatility and illiquidity have several dimensions. The first PC can be seen as the common component of all four proxies, whereas the second PC contrasts the FX-based measures from the money and equity markets. The third PC further contrasts the TED spread and the PS factor, whereas the fourth PC still explains about 14% of the total variation and mainly captures differences between FX volatility and bid-ask spreads.

5.2 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 but replace the volatility factor with one of the three liquidity factors. Table 5 shows factor loadings and prices for these models. All three models shown in Panels A to C perform quite well and are not rejected by the HJ distance specification tests or the χ^2 test with Shanken adjustment. Moreover, factor prices λ have the expected sign – negative for illiquidity (BAS, TED) and positive for liquidity (PS) – and are significantly different from zero (except for the PS factor in the sample of all 48 countries). None of these three models clearly outperforms the volatility risk factor in terms of R^2s and HJ-distances for both the full and the restricted developed country sample.

Table 5 about here

To address the relative importance of volatility and liquidity as risk factors, we also evaluated several specifications where we include volatility and one of the liquidity factors (or, alternatively, that part of liquidity not explained by contemporaneous volatility) jointly in the discount factor. Here, we report results for the full country sample without transaction costs for the case where both volatility and one of the three liquidity factors are included. Results are shown in Table 6.[15]

The central message of these results is that volatility is the dominant factor, corroborating evidence in Bandi et al. (2008) for the U.S. stock market. Panel A, for example, shows results for jointly including global volatility and global bid-ask spreads and both b_{VOL} and λ_{VOL} are significantly different from zero (at 10% and 5%, respectively), whereas the bid-ask spread factor is found to be insignificant in this joint specification. The same result is basically found for the TED spread (Panel B) and Pastor and Stambaugh's 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, of course.

Table 6 about here

[15] Results for developed countries and results with bid-ask spread adjusted returns are very similar. Also, using one of the four principal components shown in Table 4 does not yield additional insights. The first principal component captures the cross-section of returns quite well but is clearly inferior to using global volatility alone. Results for the other principal components are typically worse. Therefore, combining volatility and liquidity information does not increase the cross-sectional fit compared to using only volatility.

5.3 Expected versus Unexpected Components of Volatility and Liquidity

We also look at pricing information contained in expected and unexpected parts of our volatility and (il)liquidity risk factors. Looking at expected and unexpected components seems sensible, since the effect of volatility risk is best understood in an ICAPM framework (see Campbell, 1993, 1996). In this framework, investors want to hedge against *changes* in future investment opportunities so that innovations in volatility or liquidity *may* be more important than the level of these variables.

As in Bandi et al. (2008), we employ time-series methods to decouple expected and unexpected factor components. For consistency, we estimate simple ARMA(1,1) models for *all* four factors (volatility, bid-ask spreads, TED spread, and the Pastor/Stam-baugh liquidity factor). Estimation results (not shown for the sake of brevity) suggest that serial correlation in the factors is effectively removed by this parsimonious specification. We use expected (EXP) and unexpected factor components (UNEXP) jointly in our asset pricing exercises. Our pricing kernel thus reads:

$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_E(h^E_{t+1} - \mu_E) - b_U(h^U_{t+1} - \mu_U)$$

where h is one of the four factors.

Figure 4 shows estimates for first-stage time-series estimates of β_E (solid, red line) and β_U (dashed, blue line) for the five forward discount-sorted portfolios. Panel (a) shows that betas to the unexpected component of volatility monotonically decrease when moving from portfolio 1 to portfolio 5. This pattern is inversely related to the monotonically increasing average excess returns to the five portfolios. However, we do not find this pattern for the expected volatility component so that the cross-sectional pricing power of volatility stems from the unexpected part of volatility which is in line with earlier results for equity markets (see e.g. Ang et al., 2006b).

Figure 4 about here

Looking at results for the liquidity proxies, we find a similar result for global bid-ask spreads (Panel (b)) which suggests a tight relation between the volatility and illiquidity measures in foreign exchange. The TED spread in Panel (c) shows a different behavior, though. Here, both betas for expected and unexpected factor components decrease monotonically, so that both components seem to carry the same pricing information. Finally, Panel (d) shows betas for the expected and unexpected part of the Pastor/Stambaugh liquidity factor (the vertical axis is inverted to make results comparable to the other *illiquidity* factors). Betas of the unexpected component show the same pattern as above but we find a completely reversed pattern for the expected component, which seems puzzling. A higher sensitivity of a currency portfolio to expected liquidity in stock markets is associated with lower returns.

Finally, Table 7 shows cross-sectional test results. Corroborating the findings discussed above, we find that the unexpected components of volatility and bid-ask spread are significantly priced (with a negative λ), respectively, whereas expected components do not matter. This is also confirmed by our estimates of b_{UNEXP}, which can be used to test for whether factors are marginally priced relative to the other factors.[16] Evidence for the TED spread and Pastor/Stambaugh factor components is less convincing. This is unsurprising for the TED spread since the two factor components seem to carry the same pricing information, which is also evident from the identical factor price estimates. The unexpected part of the Pastor/Stambaugh factor has the intuitively expected sign but is (marginally) not significant. Economically, this may be due to the fact that U.S. stock market liquidity is less relevant for global FX markets than liquidity factors from money markets (TED spread) or direct FX measures (FX volatility and bid-ask spreads).

Table 7 about here

Summing up, we find that using unexpected components does not uniformly enhance the empirical fit of our models. While there is clear evidence that unexpected volatility seems

[16] The λ_U estimates are indeed statistically significant with (Shanken-adjusted) t-statistics of -2.6 (unexpected volatility) and -2.3 (unexpected bid-ask spreads). Also, t-statistics for b_U estimates are -1.97 (unexpected volatility) and -2.1 (unexpected bid-ask spreads), respectively. This is difficult to see in Table 7 due to the two-digit rounding of numbers.

to be the driving force behind our main result (consistent with theoretical arguments in Campbell, 1993, 1996), there is less evidence for expected versus unexpected components of il(liquidity).

6 Robustness Issues

This section presents evidence on the robustness of our results by investigating the sensitivity of estimation results for different sub-samples, an alternative proxy for volatility (the options-based VIX), alternative base currencies, and different cross-sections, namely momentum portfolios and the cross-section of individual currencies.

Sub-sample analysis. We estimate our basic model with DOL and VOL as risk factors on two sub-samples covering (a) the period 1983 – 1995 and (b) the period 1996 – 2008. This split yields roughly equal sample sizes. It also serves to divide our sample into an earlier period where the FX market was dominated by trading bilaterally and over-the-counter and a more recent period that has seen the advent of electronic trading systems (e.g. EBS, Reuters) that dominate FX markets today.

Results are shown in Table 8. Factor price estimates for volatility are significantly negative in both periods. Regarding the empirical fit of our model, we find that the first subperiod from 1983 to 1995 provides a somewhat better fit in terms of the cross-sectional R^2 and pricing errors as measured by the HJ-distance. Factor prices are larger and more precisely estimated in the second sub-sample, though. All in all, our main result regarding volatility risk is robust to using different sub-samples.

Table 8 about here

Other proxies for volatility. We repeat our main asset pricing setup but use the VIX volatility index (CBOE), based on stock options, instead of the global FX volatility proxy proposed in this paper (e.g. Ang et al., 2006b, also use the VIX). We expect to see very similar results, since periods of market turmoil or distress are often visible across asset classes and not specific to one certain group of assets, e.g. only equities or only FX markets. Table 9 shows results when using the VIX (the sample starts in 1986) as volatility proxy. As with our FX volatility proxy, we find that the covariance of returns with volatility is significantly priced and that factor prices are negative. Here, results indicate a somewhat worse fit compared to the FX volatility proxy.

Table 9 about here

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 reservers in a given year (data is available from the International Monetary Fund) but did not find any interesting differences in our results. The main reason seems to be that using σ_t^{FX} or $\sigma_t^{FX,DEV}$ does not produce different results in the first place, so that other convex weighting schemes of currency volatilities do not change our findings either.

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 have re-estimated our main result regarding the pricing power of global volatility for alternative investors.[17] More specifically, we have converted 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 A.2 in the Appendix. 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 A.1 in

[17] This is a common robustness check and has been applied by other authors as well, see e.g. the robustness appendix to Lustig et al. (2008).

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.[18] These differences in cross-sectional excess returns and volatility seem to make tests based on these alternative currencies an interesting robustness check.

Cross-sectional test results are shown in Table 10. As is evident from these results, volatility is a significant cross-sectional determinant of returns to carry trade portfolios, no matter which base currency is used. Estimates of factor prices are very similar across currencies at about -0.11 which is very similar to the U.S. results shown in Table 2. We also find the same monotonic decline in time-series VOL-betas. We therefore conclude that our results documented above are not specific to employing the perspective of a U.S. investor.

Table 10 about here

Momentum portfolios. It is also instructive to test a risk factor on different cross-sections of test assets to see whether it prices other excess returns as well. Here, we employ excess returns to currency momentum strategies. We consider two different versions. A momentum strategy with a one-month formation and a holding period as in Lustig et al. (2008) and the more familiar strategy from equity markets with a 12-months formation and a one-month holding period.[19]

Table 11 shows descriptive statistics for momentum portfolios' excess returns and the H/L values for both sets of parameters. Both momentum strategies in foreign exchange are profitable; the 1-1 strategy yields higher Sharpe ratios than the 12-1 strategy.

Table 11 about here

[18] Some largely idiosyncratic volatility spikes can be found e.g. for the GBP during the Pound crisis in 1992 or for the JPY during the Asian crisis in 1997/1998.

[19] See Jegadeesh and Titman (1993, 2001) for momentum strategies in equity markets. Moskowitz and Grinblatt (1999) show that a 12-1 momentum strategy yields much larger returns than e.g. the 6-6 strategy of Jegadeesh and Titman.

Table 12 shows asset pricing tests for these investment strategies. Both sets of test assets yield significant estimates for λ_{VOL} and an HJ-distance measure insignificantly different from zero. However, while λ_{VOL} is estimated to be negative for the 12-1 momentum strategy (as suggested theoretically), we find a very puzzling result for the 1-1 momentum strategy. Returns to the latter momentum portfolios produce a positive coefficient estimate for λ_{VOL} and thus suggest that the portfolio of winner currencies earns high excess returns while simultaneously providing a hedge against volatility risk. We have no explanation for this puzzling result and leave its further investigation to future research.

Table 12 about here

Individual currencies. As an additional set of test assets, we employ the whole cross-section of individual currencies' excess returns. Figure 5 shows some instructive cross-plots with volatility betas along the horizontal axis and mean excess returns (in %) on the vertical axis. Panel (a) shows the sample of all countries whereas Panel (b) shows the smaller developed country sample. The figures include a fitted regression line obtained from regressing mean returns cross-sectionally on volatility betas. Since there are several emerging market currencies with a very short sample length, we employ robust regression (which is similar to a quantile regression for the conditional median) instead of OLS, which is vulnerable to outliers.

Both panels of the figure show a negative relation between volatility betas and average excess returns for most countries except for some emerging markets outliers. These outliers are indicated in Panel (a) and correspond to minor currencies with short sample periods, such as Iceland (ISK), Ukraine (UAH), or South Korea (KRW). Also indicated in Panel (a) are some major currencies with long data histories such as the GB Pound, the Euro, or the Hong Kong Dollar. The general finding from this exercise is that volatility betas tend to matter for excess returns even when looking at single currencies which are known to have large idiosyncratic return components.

Panel (b) only shows results for the 15 developed countries and we also find a negative relation between volatility betas and excess returns (again, based on a robust regression techniques), although the relation is not as strong as in the full sample. A major outlier here is the Belgian Franc. However, we only have two years of data for this currency so that this particular case should not be overstated. It is, however, interesting to see the high volatility beta of the Japanese Yen and the low beta of the Australian Dollar. The JPY is a classic funding currency for carry trade strategies, whereas the AUD usually serves as an investment currency. It can be seen from this graph that the Yen is a hedge against volatility risk whereas the AUD yields higher returns when volatility is low. This is directly in line with findings for carry trade portfolio returns.

Figure 5 about here

7 Conclusion

This study examines the risk-return profile of carry trades. Carry trades are the consequent trading strategy derived from the forward premium puzzle. The major avenue of research to solve this puzzle is the search for appropriate time-varying risk premiums. Hence, dealing with a risk-based explanation for carry trades simultaneously provides an explanation of currency risk premiums and the forward premium puzzle.

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 premiums; unfortunately without a satisfying result. However, this earlier use of volatility in modeling currency risk premiums has applied a time-series perspective on single exchange rates. In contrast to this approach, we rely on asset pricing theory and methods well-established in the stock market literature where aggregate volatility serves as a systematic risk factor for the cross-section of portfolio returns. This idea – drawing on the ICAPM theory – has proven to be fruitful in empirical research on equity markets and we show that it also works very well in foreign exchange markets.

We argue in this paper that global FX volatility is 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 foreign exchange volatility as a systematic risk factor. Interestingly, there is a significantly negative return co-movement of high interest rate currencies with global FX volatility whereas low interest rate currencies provide a hedge against volatility shocks. The covariance of excess returns with volatility is so strong that our main global FX volatility proxy accounts for more than 90% of the spread in five carry trade portfolios. Further analyses show that (i) liquidity risk also matters for excess returns, albeit to a lesser degree, and that (ii) excess returns are more strongly related to unexpected components of volatility and liquidity than to expected components. Our results are robust to different proxies for volatility and liquidity risk and extend to other cross-sections such as individual currency returns and (some) momentum portfolios.

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Table 1. Descriptive Statistics

The table reports mean returns, standard deviations (both annualized), skewness, and (excess) kurtosis of currency portfolios sorted monthly on time $t-1$ forward discounts. SR denotes (annualized) Sharpe Ratios. 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 and without transaction cost adjustments. The former is done by accounting for bid-ask spreads when buying and selling currencies. Panels with transaction cost adjustments (with b-a) show returns for being long in the five portfolios and the DOL portfolio. The H/L portfolio, however, is adjusted for being long in portfolio 5 and short in portfolio 1. Returns are monthly and the sample period is 11/1983 – 11/2008.

	All countries (without b-a)						
Portfolio	1	2	3	4	5	DOL	H/L
mean	-2.06	-0.05	2.74	3.53	5.92	2.02	7.99
std	8.40	7.04	7.90	8.14	10.71	7.23	9.74
skew	0.18	-0.22	-0.30	-0.55	-0.69	-0.43	-0.99
kurt	0.95	1.28	1.53	1.96	2.26	1.13	1.67
SR	-0.25	-0.01	0.35	0.43	0.55	0.28	0.82
	All countries (with b-a)						
Portfolio	1	2	3	4	5	DOL	H/L
mean	-3.39	-1.19	1.23	1.70	2.43	0.16	3.14
std	8.41	7.04	7.87	8.15	10.66	7.22	9.70
skew	0.17	-0.23	-0.31	-0.57	-0.77	-0.45	-1.04
kurt	0.92	1.27	1.54	2.01	2.33	1.12	1.71
SR	-0.40	-0.17	0.16	0.21	0.23	0.02	0.32
	Developed countries (without b-a)						
Portfolio	1	2	3	4	5	DOL	H/L
mean	-1.13	1.50	1.93	2.77	4.32	1.88	5.45
std	9.61	9.93	9.06	8.93	10.39	8.48	9.72
skew	0.06	-0.20	-0.25	-0.63	-0.36	-0.26	-1.02
kurt	0.37	0.80	1.06	2.88	1.40	0.64	3.06
SR	-0.12	0.15	0.21	0.31	0.42	0.22	0.56
	Developed countries (with b-a)						
Portfolio	1	2	3	4	5	DOL	H/L
mean	-2.20	0.35	0.68	1.40	2.45	0.54	2.48
std	9.61	9.93	9.05	8.93	10.37	8.48	9.73
skew	0.05	-0.20	-0.25	-0.64	-0.38	-0.27	-1.02
kurt	0.35	0.80	1.06	2.84	1.35	0.63	3.03
SR	-0.23	0.04	0.08	0.16	0.24	0.06	0.26

Table 2. Cross-Sectional Pricing Results: Volatility Risk

The left panel reports results for all countries whereas the right panel reports results for developed countries. Panel A shows Factor Prices and Loadings from GMM and Fama-MacBeth procedures. b denotes coefficient estimates for the pricing kernel whereas λ denotes factor prices. 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 in parentheses, as well as p-values for the Hansen-Jagannathan Distance measure (HJ-dist) and p-values for the χ^2 test statistic which is based on the null that all pricing errors are jointly equal to zero. (Sh) denotes the Shanken (1992) adjustment. Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk (DOL) factor of Lustig et al. (2008), and global FX volatility (VOL). Robust standard errors are reported in parentheses. The sample period is 11/1983 – 11/2008 and we use monthly returns.

Panel A: Factor Prices and Loadings

All countries (without b-a)					Developed countries (without b-a)				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	-0.01	-5.89	0.93	0.09	b	0.01	-3.16	0.98	0.04
s.e.	(0.06)	(2.38)		(0.79)	s.e.	(0.04)	(2.18)		(0.94)
λ	0.21	-0.10			λ	0.20	-0.06		
s.e.	(0.31)	(0.04)			s.e.	(0.24)	(0.03)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)	FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.21	-0.10	3.04	1.52	λ	0.20	-0.06	0.60	0.47
s.e.	(0.12)	(0.02)	(0.39)	(0.68)	s.e.	(0.14)	(0.02)	(0.90)	(0.93)
(Sh)	(0.15)	(0.03)			(Sh)	(0.15)	(0.02)		

Panel B: Factor Betas

All countries (without b-a)					Developed countries (without b-a)				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-1.87	1.03	3.76	0.77	1	-2.13	0.97	4.66	0.73
	(0.20)	(0.04)	(0.54)			(0.45)	(0.05)	(1.17)	
2	-0.58	0.84	1.07	0.73	2	-0.37	1.08	0.82	0.84
	(0.18)	(0.04)	(0.42)			(0.24)	(0.04)	(0.58)	
3	0.59	0.95	-1.30	0.78	3	0.14	1.00	-0.35	0.88
	(0.25)	(0.05)	(0.65)			(0.19)	(0.03)	(0.49)	
4	0.76	1.00	-1.56	0.82	4	0.92	0.92	-2.07	0.80
	(0.19)	(0.04)	(0.49)			(0.28)	(0.03)	(0.71)	
5	1.11	1.18	-1.97	0.66	5	1.44	1.03	-3.06	0.75
	(0.39)	(0.06)	(1.05)			(0.29)	(0.04)	(0.75)	

Table 3. Portfolios Sorted on Betas with Global Volatility

The table reports mean excess returns and other descriptive 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. The rolling estimation window is 36 months and portfolios are rebalanced every six months. Portfolio 1 contains currencies with the lowest betas whereas portfolio 5 contains currencies with the highest betas. Avg. denotes the average of all five portfolios. H/L is a long-short portfolio; long in portfolio 1 and short in portfolio 5. We report results for all countries in the upper panel and for developed countries in the lower panel. Means, standard deviations, skewness, and (excess) kurtosis are shown first. SR denotes Sharpe Ratios. The last two rows in each panel show average pre-formation (pre-f. $f - s$) and post-formation (post-f. $f - s$) forward discounts for each portfolio. 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. Both forward discounts are annualized and in percent. The sample period is 11/1983 – 11/2008 and returns are monthly.

All countries							
Portfolio	1	2	3	4	5	Avg.	H/L
mean	4.35	3.80	1.32	0.90	-0.90	1.89	5.26
std	8.48	6.80	7.07	7.56	8.56	6.51	8.47
skew	-0.02	0.13	-0.42	-0.30	-0.14	-0.30	0.08
kurt	1.01	1.77	2.20	1.49	0.20	0.70	0.65
SR	0.51	0.56	0.19	0.12	-0.11	0.29	0.62
pre-f. $f - s$	3.78	1.55	1.40	0.64	-0.05	1.46	
post-f. $f - s$	4.14	1.72	1.13	0.53	-0.20	1.47	
Developed countries							
Portfolio	1	2	3	4	5	Avg.	H/L
mean	4.05	3.46	2.14	0.85	0.30	2.16	3.75
std	8.60	8.70	8.83	9.67	9.63	7.95	8.42
skew	-0.10	0.00	-0.23	-0.35	-0.02	-0.21	0.05
kurt	0.72	0.30	0.36	0.81	0.35	0.30	1.19
SR	0.47	0.40	0.24	0.09	0.03	0.27	0.45
pre-f. $f - s$	2.44	1.02	1.02	0.05	-0.50	0.81	
post-f. $f - s$	2.59	1.02	0.75	0.03	-0.51	0.78	

Table 4. Volatility and Liquidity Factors

This table shows correlation coefficients (upper panel) and principal components for global FX volatility (VOL), global FX bid-ask spreads (BAS), the TED spread, and Pastor and Stambaugh's liquidity factor.

	Correlation coefficients			
	VOL	BAS	TED	-PS
VOL	1.000	0.365	0.357	0.116
BAS		1.000	-0.034	0.062
TED			1.000	0.097
-PS				1.000
	Principal Components			
	1^{st}	2^{nd}	3^{rd}	4^{th}
VOL	0.663	-0.191	-0.039	-0.723
BAS	0.608	-0.425	0.076	0.666
TED	0.325	0.613	-0.699	0.174
-PS	0.292	0.638	0.710	0.061
% variance	0.376	0.254	0.226	0.144

Table 5. Cross-Sectional Pricing Results: Illiquidity Risk

The setup is the same as in Table 2 but this table only shows factor prices and loadings for three different models. Factors are the dollar risk (DOL) factor of Lustig et al. (2008), and (i) global average percentage bid-ask spreads (Panel A), (ii) the TED spread (Panel B), or (iii) the Pastor and Stambaugh (2003) liquidity measure (Panel C).

Panel A: Factor Prices and Loadings – Global bid-ask spreads

All countries (without b-a)					Developed countries (without b-a)				
GMM	DOL	BAS	R^2	HJ-dist	GMM	DOL	BAS	R^2	HJ-dist
b	0.07	-31.14	0.63	0.16	b	0.04	-21.96	0.96	0.06
s.e.	(0.05)	(15.56)		(0.59)	s.e.	(0.03)	(12.98)		(0.91)
λ	0.21	-0.06			λ	0.20	-0.04		
s.e.	(0.24)	(0.03)			s.e.	(0.20)	(0.03)		
FMB	DOL	BAS	χ^2	χ^2 (Sh)	FMB	DOL	BAS	χ^2	χ^2 (Sh)
λ	0.21	-0.06	10.04	6.23	λ	0.20	-0.04	1.02	0.52
s.e.	(0.12)	(0.01)	(0.02)	(0.10)	s.e.	(0.14)	(0.02)	(0.80)	(0.91)
(Sh)	(0.21)	(0.02)			(Sh)	(0.20)	(0.02)		

Panel B: Factor Prices and Loadings – TED spread

All countries (without b-a)					Developed countries (without b-a)				
GMM	DOL	TED	R^2	HJ-dist	GMM	DOL	TED	R^2	HJ-dist
b	-0.06	-2.13	0.98	0.07	b	0.00	-1.03	0.85	0.10
s.e.	(0.07)	(1.08)		(0.89)	s.e.	(0.03)	(0.80)		(0.55)
λ	0.20	-0.66			λ	0.20	-0.33		
s.e.	(0.32)	(0.34)			s.e.	(0.22)	(0.25)		
FMB	DOL	TED	χ^2	χ^2 (Sh)	FMB	DOL	TED	χ^2	χ^2 (Sh)
λ	0.20	-0.66	1.49	0.60	λ	0.20	-0.32	2.43	2.16
s.e.	(0.12)	(0.15)	(0.68)	(0.90)	s.e.	(0.14)	(0.12)	(0.49)	(0.54)
(Sh)	(0.19)	(0.23)			(Sh)	(0.16)	(0.14)		

Panel C: Factor Prices and Loadings – Pastor/Stambaugh liquidity measure

All countries (without b-a)					Developed countries (without b-a)				
GMM	DOL	PS	R^2	HJ-dist	GMM	DOL	PS	R^2	HJ-dist
b	0.15	55.37	0.79	0.19	b	0.07	26.39	0.85	0.13
s.e.	(0.11)	(56.42)		(0.51)	s.e.	(0.05)	(18.70)		(0.53)
λ	0.25	0.16			λ	0.24	0.08		
s.e.	(0.43)	(0.17)			s.e.	(0.28)	(0.06)		
FMB	DOL	PS	χ^2	χ^2 (Sh)	FMB	DOL	PS	χ^2	χ^2 (Sh)
λ	0.25	0.16	0.53	4.07	λ	0.24	0.08	4.64	1.21
s.e.	(0.12)	(0.03)	(0.91)	(0.25)	s.e.	(0.14)	(0.02)	(0.20)	(0.75)
(Sh)	(0.39)	(0.11)			(Sh)	(0.25)	(0.04)		

Table 6. Cross-Sectional Pricing Results: Volatility and Illiquidity

The setup is the same as in Table 2 but this table shows factor prices and loadings for three different models. Factors are the dollar risk (DOL) factor of Lustig et al. (2008), our global volatility measure (VOL), and (i) global average percentage bid-ask spreads (Panel A), (ii) the TED spread (Panel B), or (iii) the Pastor and Stambaugh (2003) liquidity measure (Panel C).

Panel A: Volatility and global bid-ask spreads					
GMM	DOL	VOL	BAS	R^2	HJ-dist
b	-0.04	-8.33	18.65	0.97	0.08
s.e.	(0.08)	(4.81)	(26.83)		(0.62)
λ	0.20	-0.10	0.02		
s.e.	(0.31)	(0.04)	(0.04)		
FMB				χ^2	χ^2 (Sh)
λ	0.20	-0.10	0.02	2.56	1.47
s.e.	(0.12)	(0.02)	(0.03)	(0.28)	(0.48)
(Sh)	(0.18)	(0.03)	(0.04)		

Panel B: Volatility and TED spread					
GMM	DOL	VOL	TED	R^2	HJ-dist
b	-0.05	-1.82	-1.53	0.99	0.05
s.e.	(0.08)	(4.07)	(1.83)		(0.85)
λ	0.20	-0.07	-0.52		
s.e.	(0.30)	(0.04)	(0.48)		
FMB				χ^2	χ^2 (Sh)
λ	0.20	-0.07	-0.52	0.69	0.36
s.e.	(0.12)	(0.02)	(0.27)	(0.71)	(0.84)
(Sh)	(0.17)	(0.03)	(0.38)		

Panel C: Volatility and P/S liquidity measure					
GMM	DOL	VOL	PS	R^2	HJ-dist
b	0.08	-6.16	13.25	0.90	0.11
s.e.	(0.09)	(3.95)	(34.27)		(0.54)
λ	0.25	-0.10	0.04		
s.e.	(0.26)	(0.04)	(0.10)		
FMB				χ^2	χ^2 (Sh)
λ	0.25	-0.10	0.04	3.67	1.69
s.e.	(0.12)	(0.02)	(0.05)	(0.16)	(0.43)
(Sh)	(0.18)	(0.04)	(0.08)		

Table 7. Cross-Sectional Pricing Results: Expected versus Unexpected Factor Components

The setup is the same as in Table 2 but this table only shows factor prices and loadings. Factors are the expected (EXP) and unexpected (UNEXP) part of volatility, bid-ask spreads, the TED spread, and the Pastor/Stambaugh (2003) liquidity measure. Factor decompositions are based on ARMA(1,1) models.

Panel A: Volatility					
GMM	DOL	EXP	UNEXP	R^2	HJ-dist
b	-0.01	-0.15	-8.00	0.98	0.06
s.e.	(0.06)	(6.55)	(4.07)		(0.76)
λ	0.21	0.00	-0.08		
s.e.	(0.27)	(0.05)	(0.04)		
FMB	DOL	EXP	UNEXP	χ^2	χ^2 (Sh)
λ	0.21	0.00	-0.08	0.96	0.65
s.e.	(0.12)	(0.03)	(0.03)	(0.62)	(0.72)
(Sh)	(0.15)	-0.04	(0.03)		

Panel B: Bid-ask spreads					
GMM	DOL	EXP	UNEXP	R^2	HJ-dist
b	0.02	-12.58	-66.17	0.98	0.11
s.e.	(0.06)	(20.37)	(31.55)		(0.62)
λ	0.21	-0.02	-0.03		
s.e.	(0.28)	(0.03)	(0.02)		
FMB	DOL	EXP	UNEXP	χ^2	χ^2 (Sh)
λ	0.21	-0.02	-0.03	1.21	0.55
s.e.	(0.12)	(0.01)	(0.01)	(0.55)	(0.76)
(Sh)	(0.22)	(0.02)	(0.02)		

Panel C: TED spread					
GMM	DOL	EXP	UNEXP	R^2	HJ-dist
b	-0.08	-2.67	-2.67	0.98	0.07
s.e.	(0.11)	(3.03)	(3.03)		(0.79)
λ	0.21	-0.55	-0.55		
s.e.	(0.36)	(0.62)	(0.62)		
FMB	DOL	EXP	UNEXP	χ^2	χ^2 (Sh)
λ	0.20	-0.55	-0.55	8.27	0.90
s.e.	(0.12)	(0.35)	(0.35)	(0.02)	(0.64)
(Sh)	(0.20)	(0.57)	(0.57)		

Panel D: Pastor/Stambaugh					
GMM	DOL	EXP	UNEXP	R^2	HJ-dist
b	0.11	-5.76	39.63	0.86	0.86
s.e.	(0.07)	(72.39)	(30.51)		(0.28)
λ	0.25	0.00	0.11		
s.e.	(0.32)	(0.01)	(0.09)		
FMB	DOL	EXP	UNEXP	χ^2	χ^2 (Sh)
λ	0.25	0.00	0.11	7.17	1.09
s.e.	(0.12)	(0.00)	(0.03)	(0.03)	(0.58)
(Sh)	(0.29)	(0.01)	(0.07)		

Table 8. Cross-Sectional Pricing Results: Sub-samples

The left panel reports results for the sample period 1983–1995 whereas the right panel reports results for the period 1996–2008. Panel A shows Factor Prices and Loadings from GMM and Fama-MacBeth procedures. b denotes coefficient estimates for the pricing kernel whereas λ denotes factor prices. 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 in parentheses, as well as p-values for the Hansen-Jagannathan Distance measure (HJ-dist) and p-values for the χ^2 test statistic, which is based on the null that all pricing errors are jointly equal to zero. (Sh) denotes the Shanken (1992) adjustment. Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk (DOL) factor of Lustig et al. (2008), and global FX volatility (VOL). Robust standard errors are reported in parentheses. The sample period is 11/1983 – 11/2008 and we use monthly returns.

Panel A: Factor Prices and Loadings									
All countries (without b-a): 1983-1995					All countries (without b-a): 1996-2008				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.06	-3.57	0.90	0.09	b	-0.16	-8.18	0.67	0.25
s.e.	(0.05)	(2.30)		(0.85)	s.e.	(0.13)	(3.12)		(0.26)
λ	0.34	-0.06			λ	0.10	-0.14		
s.e.	(0.29)	(0.04)			s.e.	(0.46)	(0.06)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)	FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.34	-0.06	1.28	3.43	λ	0.10	-0.14	10.72	5.15
s.e.	(0.20)	(0.03)	(0.74)	(0.33)	s.e.	(0.14)	(0.03)	(0.01)	(0.16)
(Sh)	(0.22)	(0.03)			(Sh)	(0.21)	(0.04)		

Panel B: Factor Betas									
All countries (without b-a): 1983-1995					All countries (without b-a): 1996-2008				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-2.02	1.06	4.31	0.80	1	-1.60	0.96	2.89	0.69
	(0.35)	(0.05)	(0.94)			(0.23)	(0.05)	(0.56)	
2	-0.27	0.82	0.40	0.72	2	-0.88	0.87	1.73	0.75
	(0.31)	(0.06)	(0.71)			(0.20)	(0.05)	(0.50)	
3	0.69	0.99	-1.46	0.81	3	0.64	0.88	-1.52	0.72
	(0.29)	(0.06)	(0.66)			(0.41)	(0.08)	(1.15)	
4	0.78	1.03	-1.50	0.82	4	0.85	0.94	-1.93	0.82
	(0.32)	(0.06)	(0.80)			(0.23)	(0.04)	(0.59)	
5	0.82	1.10	-1.75	0.71	5	0.99	1.35	-1.18	0.64
	(0.53)	(0.07)	(1.37)			(0.53)	(0.12)	(1.52)	

Table 9. Cross-Sectional Pricing Results: the VIX

The left panel reports results for all countries whereas the right panel reports results for developed countries. Panel A shows Factor Prices and Loadings from GMM and Fama-MacBeth procedures. b denotes coefficient estimates for the pricing kernel whereas λ denotes factor prices. 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 in parentheses, as well as p-values for the Hansen-Jagannathan Distance measure (HJ-dist) and p-values for the χ^2 test statistic, which is based on the null that all pricing errors are jointly equal to zero. (Sh) denotes the Shanken (1992) adjustment. Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk (DOL) factor of Lustig et al. (2008), and the VXO index. Robust standard errors are reported in parentheses. The sample period is 02/1986 – 11/2008 and we use monthly returns.

Panel A: Factor Prices and Loadings

All countries (without b-a)					Developed countries (without b-a)				
GMM	DOL	VIX	R^2	HJ-dist	GMM	DOL	VIX	R^2	HJ-dist
b	0.12	-6.36	0.86	0.19	b	0.09	-4.91	0.89	0.12
s.e.	(0.05)	(2.78)		(0.14)	s.e.	(0.04)	(2.55)		(0.51)
λ	0.27	-0.18			λ	0.27	-0.14		
s.e.	(0.18)	(0.08)			s.e.	(0.19)	(0.07)		
FMB	DOL	VIX	χ^2	χ^2 (Sh)	FMB	DOL	VIX	χ^2	χ^2 (Sh)
λ	0.27	-0.18	14.60	4.63	λ	0.27	-0.14	3.44	2.17
s.e.	(0.12)	(0.04)	(0.00)	(0.20)	s.e.	(0.15)	(0.04)	(0.33)	(0.54)
(Sh)	(0.18)	(0.06)			(Sh)	(0.19)	(0.06)		

Panel B: Factor Betas

All countries (without b-a)					Developed countries (without b-a)				
PF	α	DOL	VIX	R^2	PF	α	DOL	VIX	R^2
1	-0.38	1.00	1.77	0.71	1	-0.32	1.00	1.70	0.74
	(0.09)	(0.06)	(0.46)			(0.09)	(0.05)	(0.55)	
2	-0.19	0.81	0.37	0.69	2	-0.04	1.10	0.97	0.83
	(0.07)	(0.05)	(0.29)			(0.08)	(0.04)	(0.41)	
3	0.08	1.00	0.59	0.78	3	0.00	1.01	0.27	0.88
	(0.06)	(0.05)	(0.58)			(0.05)	(0.03)	(0.26)	
4	0.12	1.00	-0.52	0.79	4	0.16	0.92	-1.34	0.77
	(0.07)	(0.05)	(0.33)			(0.08)	(0.04)	(0.43)	
5	0.36	1.18	-2.20	0.63	5	0.20	0.98	-1.60	0.70
	(0.12)	(0.08)	(0.69)			(0.10)	(0.05)	(0.53)	

Table 10. Cross-Sectional Pricing Results: Volatility and other Base Currencies

The setup is the same as in Table 2 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, no bid-ask spread adjustment) but are converted to one of the three alternative currencies and the global volatility risk factor is 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 the global volatility factor calculated from daily global currency returns against the GBP. The sample period is 11/1983 – 11/2008 and we use monthly returns.

Panel A: Factor Prices and Loadings

All countries (without b-a): GBP				
GMM	DOL	VOL	R^2	HJ-dist
b	0.12	-5.74	0.99	0.04
s.e.	(0.07)	(2.21)		(0.98)
λ	0.19	-0.11		
s.e.	(0.23)	(0.04)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.19	-0.11	0.40	0.25
s.e.	(0.11)	(0.02)	(0.94)	(0.97)
(Sh)	(0.14)	(0.03)		

All countries (without b-a): JPY				
GMM	DOL	VOL	R^2	HJ-dist
b	0.04	-6.41	0.97	0.06
s.e.	(0.02)	(2.43)		(0.93)
λ	0.59	-0.11		
s.e.	(0.44)	(0.04)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.59	-0.11	0.98	0.57
s.e.	(0.28)	(0.02)	(0.81)	(0.90)
(Sh)	(0.36)	(0.03)		

All countries (without b-a): CHF				
GMM	DOL	VOL	R^2	HJ-dist
b	0.02	-5.34	0.95	0.07
s.e.	(0.02)	(2.17)		(0.86)
λ	0.50	-0.10		
s.e.	(0.51)	(0.04)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.50	-0.10	1.63	1.07
s.e.	(0.30)	(0.02)	(0.65)	(0.78)
(Sh)	(0.37)	(0.03)		

Panel B: Factor Betas

All countries (without b-a), GBP				
PF	α	DOL	VOL	R^2
1	-1.85	1.03	3.72	0.76
	(0.20)	(0.04)	(0.53)	
2	-0.78	1.03	1.47	0.76
	(0.20)	(0.04)	(0.48)	
3	0.48	0.89	-1.01	0.72
	(0.23)	(0.04)	(0.61)	
4	0.74	0.95	-1.51	0.77
	(0.20)	(0.04)	(0.51)	
5	1.40	1.11	-2.67	0.57
	(0.43)	(0.09)	(1.21)	

All countries (without b-a), JPY				
PF	α	DOL	VOL	R^2
1	-1.77	1.08	3.46	0.96
	(0.21)	(0.02)	(0.57)	
2	-0.82	0.95	1.65	0.95
	(0.19)	(0.02)	(0.46)	
3	0.54	0.97	-1.16	0.95
	(0.23)	(0.03)	(0.61)	
4	0.75	0.98	-1.53	0.96
	(0.19)	(0.02)	(0.50)	
5	1.31	1.02	-2.43	0.87
	(0.42)	(0.03)	(1.16)	

All countries (without b-a), CHF				
PF	α	DOL	VOL	R^2
1	-1.87	1.04	3.76	0.96
	(0.20)	(0.02)	(0.54)	
2	-0.69	0.95	1.31	0.95
	(0.18)	(0.02)	(0.42)	
3	0.55	1.00	-1.23	0.96
	(0.25)	(0.02)	(0.67)	
4	0.74	1.00	-1.53	0.97
	(0.19)	(0.02)	(0.49)	
5	1.27	1.00	-2.31	0.89
	(0.43)	(0.03)	(1.18)	

Table 11. Descriptive Statistics for Momentum Portfolios

The table reports mean returns, standard deviations (both annualized), skewness, and (excess) kurtosis of currency momentum portfolios sorted monthly on past 12-months or past one-month returns. SR denotes Sharpe Ratios, which are also annualized. Portfolio 1 contains the 20% of all available currencies at a given point in time with the lowest past return whereas Portfolio 5 contains currencies with highest past returns (f denotes the formation period, h denotes the holding period). All returns are excess returns from the viewpoint of a U.S. investor. H/L denotes a long-short portfolio that is long in Portfolio 5 and short in Portfolio 1. Panels with transaction cost adjustments (with b-a) show returns for being long in the five portfolios. The H/L portfolio, however, is adjusted for being long in portfolio 5 and short in portfolio 1. Returns are monthly and the sample period is 11/1983 – 11/2008.

	Momentum, f=12, h=1 (without b-a)					
Portfolio	1	2	3	4	5	H/L
mean	-0.49	1.63	2.76	4.60	6.58	7.07
std	9.36	8.23	8.21	8.74	8.66	10.42
skew	0.06	0.59	-0.40	-0.29	-0.47	-0.32
kurt	6.26	4.34	1.70	1.84	1.84	1.86
SR	-0.05	0.20	0.34	0.53	0.76	0.68
	Momentum, f=12, h=1 (with b-a)					
Portfolio	1	2	3	4	5	H/L
mean	-2.87	0.36	1.10	2.90	4.70	2.97
std	9.54	8.01	8.29	8.69	8.66	10.75
skew	-0.19	0.44	-0.43	-0.38	-0.47	-0.45
kurt	5.18	4.69	1.71	1.77	1.87	1.50
SR	-0.30	0.05	0.13	0.33	0.54	0.28
	Momentum, f=1, h=1 (without b-a)					
Portfolio	1	2	3	4	5	H/L
mean	-3.65	0.98	1.99	3.21	6.94	10.59
std	9.52	8.32	8.78	8.25	8.56	10.00
skew	-0.89	-0.66	-0.70	0.10	0.21	0.33
kurt	3.85	3.91	3.33	1.01	0.56	2.51
SR	-0.38	0.12	0.23	0.39	0.81	1.06
	Momentum, f=1, h=1 (with b-a)					
Portfolio	1	2	3	4	5	H/L
mean	-5.75	-0.52	0.26	1.51	4.98	6.46
std	9.65	8.27	8.36	8.46	8.43	10.07
skew	-0.95	-0.68	-0.38	-0.06	0.19	0.15
kurt	3.62	4.05	1.92	1.12	0.42	2.26
SR	-0.60	-0.06	0.03	0.18	0.59	0.64

Table 12. Cross-Sectional Pricing Results: Momentum

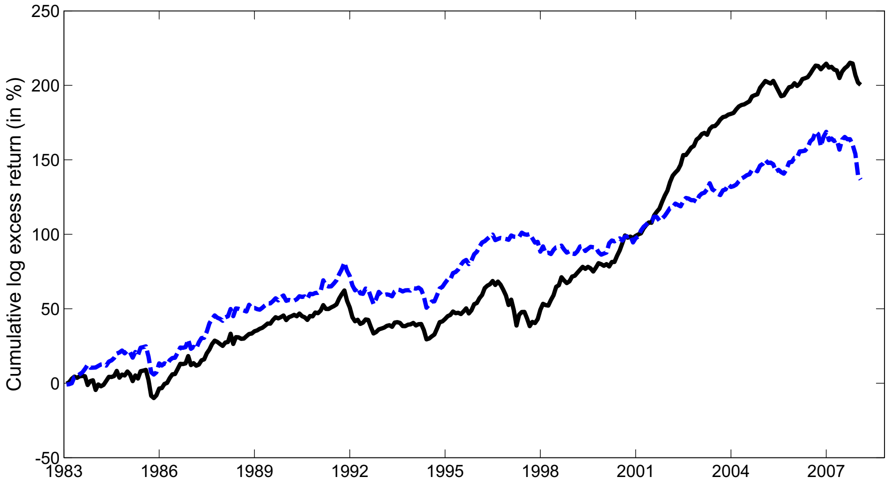
Notes: The left panel reports results for momentum excess returns based on a 12 months formation period whereas the right panel shows results for momentum returns based on a formation period of one month. Panel A shows Factor Prices and Loadings from GMM and Fama-MacBeth procedures. b denotes coefficient estimates for the pricing kernel whereas λ denotes factor prices. 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 in parentheses, as well as p-values for the Hansen-Jagannathan Distance measure (HJ-dist) and p-values for the χ^2 test statistic, which is based on the null that all pricing errors are jointly equal to zero. (Sh) denotes the Shanken (1992) adjustment. Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk (DOL) factor of Lustig et al. (2008), and global FX volatility (VOL). Robust standard errors are reported in parentheses. The sample period is 11/1983 – 11/2008 and we use monthly returns.

Panel A: Factor Prices and Loadings

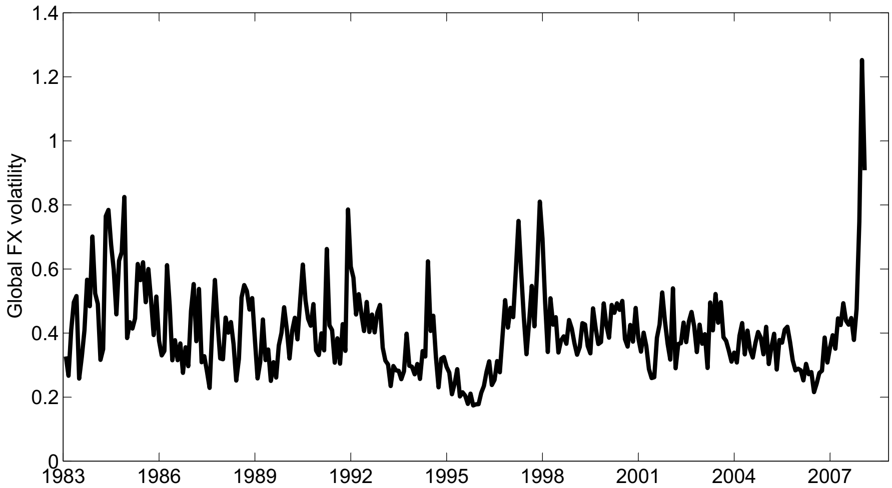
Momentum, f=12, h=1 (without b-a)					Momentum, f=1, h=1 (without b-a)				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	0.02	-7.31	0.56	0.17	b	0.23	19.65	0.94	0.14
s.e.	(0.10)	(4.97)		(0.33)	s.e.	(0.11)	(14.47)		(0.81)
λ	0.36	-0.13			λ	0.16	0.33		
s.e.	(0.38)	(0.08)			s.e.	(0.62)	(0.25)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)	FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.36	-0.13	6.90	2.96	λ	0.16	0.33	7.55	0.74
s.e.	(0.12)	(0.04)	(0.08)	(0.40)	s.e.	(0.12)	(0.06)	(0.06)	(0.86)
(Sh)	(0.17)	(0.06)			(Sh)	(0.33)	(0.17)		

Panel B: Factor Betas

Momentum, f=12, h=1 (without b-a)					Momentum, f=1, h=1 (without b-a)				
PF	α	DOL	VOL	R^2	PF	α	DOL	VOL	R^2
1	-0.53	0.91	0.80	0.45	1	0.10	1.01	-1.33	0.62
	(0.57)	(0.10)	(1.55)			(0.31)	(0.06)	(0.82)	
2	-0.99	0.98	2.30	0.67	2	-0.11	0.98	0.15	0.73
	(0.40)	(0.07)	(1.06)			(0.30)	(0.06)	(0.78)	
3	-0.11	1.06	0.32	0.83	3	0.09	1.08	-0.18	0.80
	(0.24)	(0.04)	(0.62)			(0.20)	(0.04)	(0.56)	
4	-0.13	1.11	0.73	0.78	4	-0.12	0.99	0.63	0.74
	(0.27)	(0.05)	(0.72)			(0.32)	(0.05)	(0.84)	
5	0.88	0.94	-1.28	0.60	5	-0.03	0.93	1.20	0.59
	(0.28)	(0.06)	(0.72)			(0.39)	(0.07)	(1.01)	



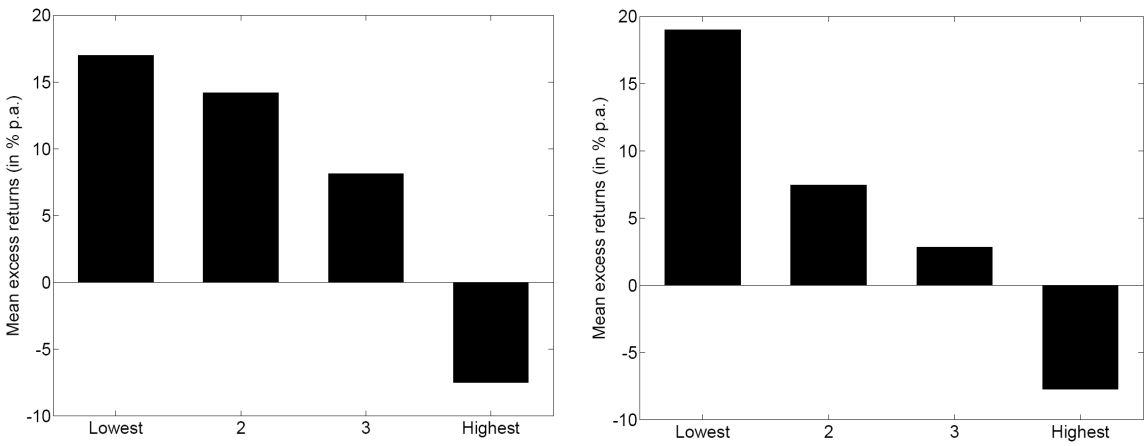
(a) Cumulative Carry Trade Returns



(b) Global FX volatility

Figure 1. Returns to Carry Trade Portfolios

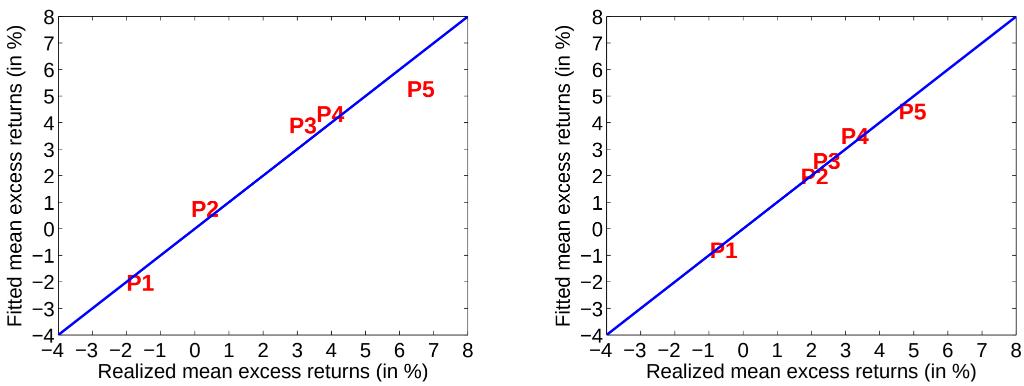
Panel (a) of this figure shows cumulative log excess returns of the carry trade. The solid black line corresponds to all countries, while the broken blue line corresponds to a subset of 15 developed countries. Panel (b) shows a time-series plot of global FX volatility. The sample period is 11/1983 – 11/2008.



(a) All Countries (b) Developed Countries

Figure 2. Excess Returns and Volatility

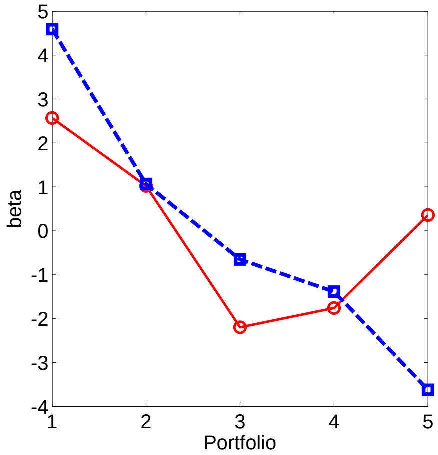
The figure shows mean excess returns for carry trade portfolios conditional on global FX volatility being within the lowest to highest quartile of its sample distribution (four categories from "lowest" to "highest" shown on the x-axis of each panel). The bars show average excess returns for being long 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 – 11/2008.



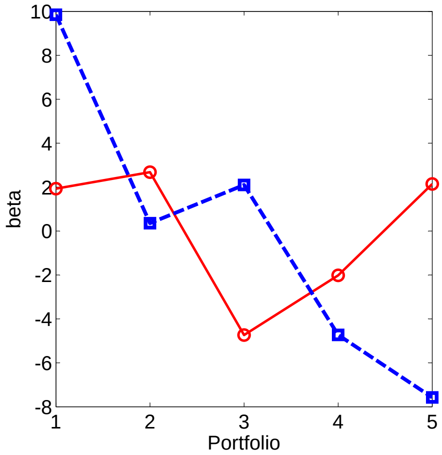
(a) All Countries (b) Developed Countries

Figure 3. Pricing Error Plots

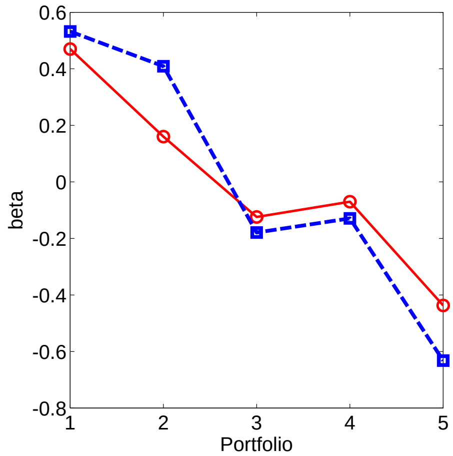
The figure shows pricing errors for asset pricing models with global volatility as risk factor. The sample period is 11/1983 – 11/2008.



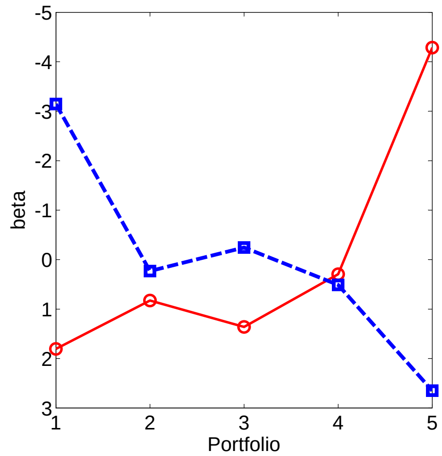
(a) Volatility



(b) Bid-Ask Spread



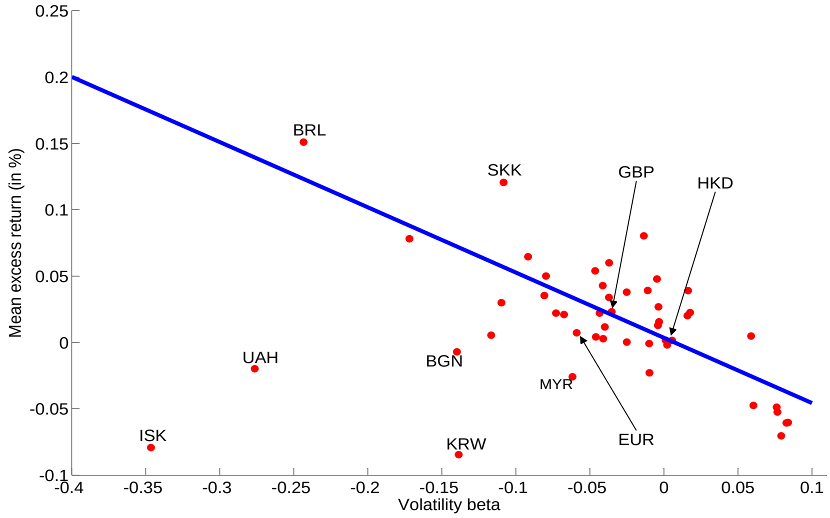
(c) TED Spread



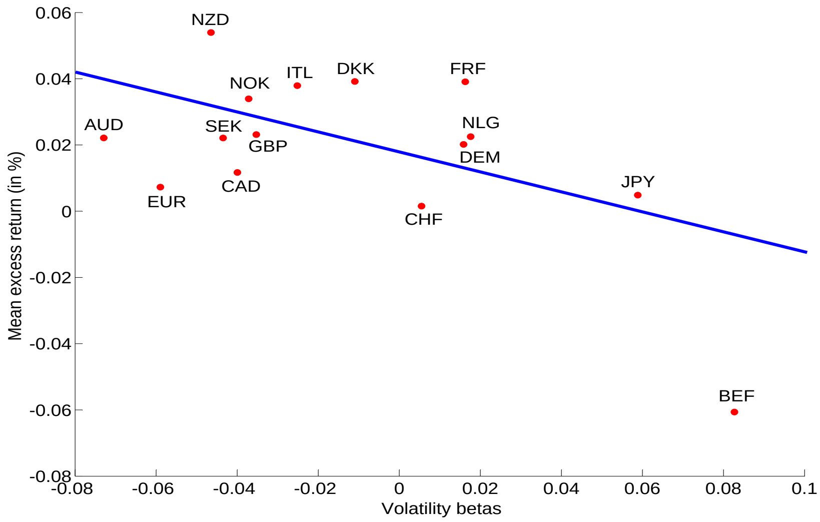
(d) Pastor/Stambaugh

Figure 4. Beta Estimates for Expected and Unexpected Factor Components

The figure shows betas from regressions of portfolio excess returns on a constant, DOL, expected, and unexpected volatility/illiquidity factors. The solid red line (circles) shows betas to the expected component of a factor and the dashed blue line (squares) shows betas to the unexpected component of the factor. Expected and unexpected factor components are obtained by ARMA(1,1) models. Panel (a) shows results for the volatility factor, Panel (b) for precentage bid-ask spreads, (c) for the TED spread, and (d) for the Pastor/Stambaugh liquidity factor. The horizontal axis indicates the five forward discount-sorted portfolios and the vertical axis shows betas. Note that the vertical axis in Panel (d) is inverted since the Pastor/Stambaugh factor measures liquidity whereas the other factors measure illiquidity. The sample period is 11/1983 – 11/2008 for volatility, bid-ask spreads, and TED spread and 11/1983 – 12/2006 for the Pastor/Stambaugh measure.



(a) All Countries



(b) Developed Countries

Figure 5. Individual Currencies

This figure cross-plots individual currencies' volatility betas (horizontal axis) against mean excess returns (vertical axis). Panel (a) shows all countries whereas Panel (b) only shows developed countries. The blue line shows the linear relation between betas and returns from a robust regression of returns on betas. Returns and betas for each currency are calculated over the full available sample for the respective currency.

Appendix

Table A.1. Cross-Sectional Pricing Results: Volatility (after transaction costs)

Notes: The left panel reports results for all countries whereas the right panel reports results for developed countries. Excess returns are adjusted for transaction costs. Panel A shows Factor Prices and Loadings from GMM and Fama-MacBeth procedures. b denotes coefficient estimates for the pricing kernel whereas λ denotes factor prices. 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 in parentheses, as well as p-values for the Hansen-Jagannathan Distance measure (HJ-dist) and p-values for the χ^2 test statistic which is based on the null that all pricing errors are jointly equal to zero. (Sh) denotes the Shanken (1992) adjustment. Panel B reports results for time-series regressions of excess returns on a constant (α), the dollar risk (DOL) factor of Lustig et al. (2008), and global FX volatility (VOL). Robust standard errors are reported in parentheses. The sample period is 11/1983 – 11/2008 and we use monthly returns.

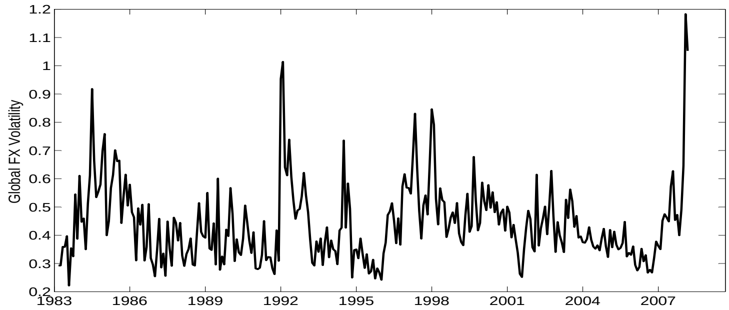
Panel A: Factor Prices and Loadings									
All countries (with b-a)					Developed countries (with b-a)				
GMM	DOL	VOL	R^2	HJ-dist	GMM	DOL	VOL	R^2	HJ-dist
b	-0.04	-4.69	0.99	0.03	b	0.00	-2.74	0.98	0.03
s.e.	(0.06)	(2.07)		(0.99)	s.e.	(0.03)	(1.96)		(0.97)
λ	0.05	-0.08			λ	0.08	-0.05		
s.e.	(0.26)	(0.04)			s.e.	(0.22)	(0.03)		
FMB	DOL	VOL	χ^2	χ^2 (Sh)	FMB	DOL	VOL	χ^2	χ^2 (Sh)
λ	0.04	-0.08	0.19	0.83	λ	0.08	-0.05	0.33	0.28
s.e.	(0.12)	(0.02)	(0.98)	(0.84)	s.e.	(0.14)	(0.02)	(0.95)	(0.97)
(Sh)	(0.14)	(0.02)			(Sh)	(0.15)	(0.02)		

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	-1.89	1.04	3.93	0.77	1	-2.12	0.97	4.69	0.73
	(0.20)	(0.04)	(0.54)			(0.45)	(0.05)	(1.16)	
2	-0.60	0.84	1.20	0.73	2	-0.37	1.08	0.87	0.84
	(0.18)	(0.04)	(0.42)			(0.24)	(0.04)	(0.58)	
3	0.59	0.95	-1.25	0.78	3	0.13	1.00	-0.30	0.88
	(0.24)	(0.05)	(0.65)			(0.19)	(0.03)	(0.49)	
4	0.73	1.00	-1.49	0.82	4	0.92	0.92	-2.08	0.80
	(0.20)	(0.04)	(0.49)			(0.28)	(0.03)	(0.71)	
5	1.17	1.17	-2.39	0.67	5	1.45	1.03	-3.18	0.75
	(0.38)	(0.06)	(1.04)			(0.29)	(0.04)	(0.73)	

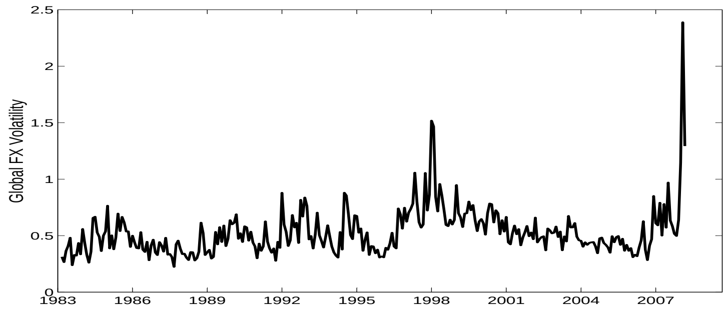
Table A.2. Descriptive Statistics: Other Base Currencies

This table reports descriptive statistics for currency portfolios as in Table 1 but portfolio returns are measured in GBP, JPY, or CHF, respectively.

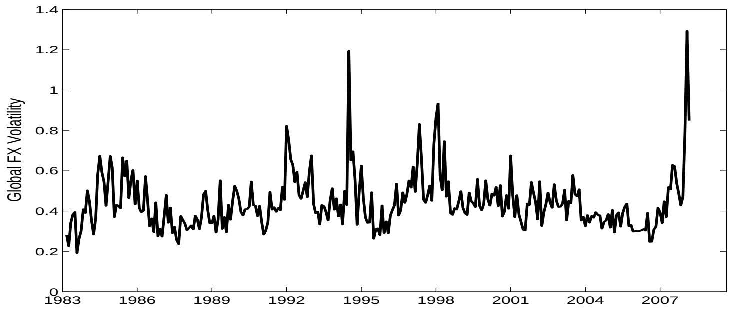
	Base currency: GBP						
Portfolio	1	2	3	4	5	DOL	H/L
mean	-2.16	-0.15	2.65	3.43	5.83	1.92	7.99
std	8.15	7.83	6.85	7.08	9.61	6.56	9.74
skew	0.85	0.18	-0.33	0.17	-0.36	0.20	-0.99
kurt	3.53	2.87	2.83	2.95	1.98	2.51	1.67
SR	-0.26	-0.02	0.39	0.48	0.61	0.29	0.82
	Base currency: JPY						
Portfolio	1	2	3	4	5	DOL	H/L
mean	1.51	3.52	6.32	7.10	9.50	5.59	7.99
std	18.43	16.25	16.39	16.49	17.81	16.49	9.74
skew	0.35	0.20	0.09	0.22	0.30	0.23	-0.99
kurt	0.89	1.09	0.43	0.52	1.50	0.70	1.67
SR	0.08	0.22	0.39	0.43	0.53	0.34	0.82
	Base currency: CHF						
Portfolio	1	2	3	4	5	DOL	H/L
mean	0.19	2.20	5.00	5.78	8.18	4.27	7.99
std	19.21	17.54	18.50	18.50	19.26	18.06	9.74
skew	0.17	-0.11	-0.07	-0.16	-0.23	-0.08	-0.99
kurt	0.29	0.19	0.42	0.47	0.73	0.23	1.67
SR	0.01	0.13	0.27	0.31	0.42	0.24	0.82



(a) Base Currency: GBP



(b) Base Currency: JPY



(c) Base Currency: CHF

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

This figure shows our proxy for global FX volatility as in Figure 1, Panel (b), for other base currencies.