Common Risk Factors in Currency Markets*

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Abstract

We identify a 'slope' factor in exchange rates. High interest rate currencies load more on this slope factor than low interest rate currencies. As a result, this factor can account for most of the cross-sectional variation in average excess returns between high and low interest rate currencies. A standard, no-arbitrage model of interest rates with two factors - a country-specific factor and a global factor - can replicate these findings, provided there is sufficient heterogeneity in exposure to the global risk factor. We show that our slope factor is global risk factor. By investing in high interest rate currencies and borrowing in low interest rate currencies, US investors load up on global risk, particularly during bad times.

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Our paper derives novel implications from the moments of exchange rates in the data for dynamic international asset pricing models. We identify a 'slope' factor in exchange rates. We call it a slope factor because high interest rate currencies load more on this factor than low interest rate currencies, and monotonically so. As a result, this factor can account for most of the cross-sectional variation in average excess returns between high and low interest rate currencies. We show that this slope factor is a global risk factor. By investing in high interest rate currencies and borrowing in low interest rate currencies, US investors load up on global risk, particularly during bad times. A standard no-arbitrage model of interest rates with two factors - a country-specific factor and a global factor - can replicate these findings, provided there is sufficient heterogeneity in exposure to the global risk factor. Heterogeneity in exposure to country-specific risk cannot explain cross-sectional loadings of carry trade returns, even though it reproduces the failure of the uncovered interest rate parity (UIP).[1] Heterogeneity in exposure to global risk does both.

We apply Fama and French (1993)'s approach to stocks in currency markets: we identify the common risk factor in the data by building portfolios of currencies sorted on their forward discounts. The forward discount is the difference between log forward rates and log spot rates. Since covered interest rate parity typically holds, forward discounts equal the differences in interest rates between two currencies. As a result, the first portfolio contains the lowest interest rate currencies while the last contains the highest. For each portfolio, we compute the monthly foreign currency excess returns realized by buying or selling one-month forward contracts for all currencies in the portfolio, net of transaction costs. We find that portfolios of currencies with higher interest rates earn higher returns. Between the end of 1983 and the beginning of 2008, US investors earn an annualized log excess return of 4.8 percent by going long currencies in the last portfolio and going short currencies in the first portfolio. The annualized Sharpe ratio on such a strategy is .54.

In the data, the first two principal components of currency portfolio returns account for most of the time series variation in currency returns. The first principal component is a level factor. It is essentially the average excess return on all foreign currency portfolios. We call this average excess return the dollar risk factor RX. The second principal component is a slope factor whose weights decreases monotonically from positive to negative from high to low interest rate currency portfolios. Hence, average returns on these currency portfolios line up with portfolio loadings on this second component. We obtain the same results on exchange rates as on currency returns; these factors do not capture common variation in interest rates, but in exchange rates. Our paper is the first to document this slope factor in exchange rates sorted on interest rates. This common variation in exchange rates is the key ingredient in a risk-based explanation of carry trade returns.

This slope factor in currency portfolio returns is very similar to the return on a zero-cost strategy

[1] According to UIP, expected changes in exchange rates should be equal to interest rate differentials across countries. Usual tests of UIP start off regressions of realized changes in exchange rates on a constant and on interest rate differentials. Assuming rational expectations, UIP implies a slope coefficient of 1.

that goes long in the last portfolio and short in the first portfolio. We label this excess return the carry trade risk factor HML_{FX}, for high interest rate minus low interest rate currencies. The carry trade risk factor HML_{FX} explains the cross-sectional variation in average excess returns on our 6 currency portfolios. The risk price of this carry trade factor that we estimate from the cross-section of currency portfolio returns is roughly equal to its sample mean, consistent with a linear factor pricing model. Low interest rate currencies provide US investors with insurance against HML_{FX} risk, while high interest rate currencies expose investors to more HML_{FX} risk. By ranking currencies into portfolios based on their forward discounts, we find that forward discounts determine currencies' exposure to HML_{FX}, and hence their risk premia.

Building on these findings, we derive conditions that need to be satisfied in a class of exponentially affine asset pricing models commonly used for bond pricing in order to match the currency portfolio returns in the data. Two conditions need to hold. First, we need a common risk factor because it is the only source of cross-sectional variation in currency risk premia. Second, we need sufficient heterogeneity in exposure to the common risk factor. Under these conditions, lower interest rate currencies are typically more exposed to the common risk factor, especially when the price of common risk is high. Hence, by sorting currencies on interest rates, we are really sorting on their exposure to common risk. This result refines the conditions for replicating the forward premium anomaly derived by Backus, Foresi and Telmer (2001) in their seminal paper. We show that heterogeneity in exposure to country-specific risk cannot explain the cross-section of carry trade returns, even though it can generate negative UIP slope coefficients. In related work, Brandt, Cochrane and Santa-Clara (2006) infer the need for a large common component in the SDF from the high Sharpe ratios in equity markets and the low volatility of exchange rates.[2] Our paper infers the need for heterogeneity in loadings on this common component from the Sharpe ratios in the currency carry trade. This heterogeneity is needed to make high interest rate currencies riskier than low interest rate currencies for all investors.

Using the model, we further show that by sorting currencies into portfolios based on interest-rate differentials and constructing HML_{FX}, we isolate the common innovation to stochastic discount factors (SDF). Similarly, we show that the dollar risk factor RX measures home-country-specific innovations to SDFs. As a result, we provide a theoretical foundation for building portfolios of currencies and extracting the risk factors. Obviously, this is harder to accomplish for equities, because they are exposed to cash flow risk.

In our model, currency risk premia are determined by a dollar risk premium that compensates for home country risk and a carry trade risk premium that compensates for global risk. The size of the carry trade risk premium depends on the spread between high and low interest rate currencies in loadings on the common component and on the price of global risk. If there is no

[2]Colacito and Croce (2008) deliver a general equilibrium dynamic asset pricing model with this feature.

spread in loadings, i.e. if low and high interest rate currencies share the same loadings on the common risk factor, then HML_{FX} cannot be a risk factor because the common component does not affect exchange rates. As the price of global risk increases, the spread increases endogenously. This happens because the currencies are sorted on interest rates and interest rates decline more in countries with larger loadings. As a result, the carry trade risk premium goes up. The larger the spread, the riskier high interest rate currencies become relative to low interest rate currencies because the former depreciate more than the latter in case of negative global shocks. In a version of the model that is calibrated to match exchange rate and interest rate moments in the data, we manage to replicate the cross-sectional properties of carry trade portfolios. As predicted by the model, we find that the correlation of carry trade returns with stocks returns increases sharply during times of global volatility, like the recent sub-prime mortgage crisis, which lends plausibility to our interpretation of the slope factor as a global risk factor.

Currency-specific attributes other than interest rates cannot explain our findings because currencies move among low and high interest rate portfolios as their relative interest rates change, which occurs frequently. What about the possibility that some currencies earn high returns merely because they have high interest rates, not because their returns co-vary positively with HML_{FX}? By sorting currencies on interest rate characteristics and using HML_{FX} as a factor, are we simply measuring the effects of interest rate characteristics on currency returns? The data do not seem to support this interpretation. First, the carry trade risk factor has explanatory power for returns on momentum currency portfolios built by ranking currencies on past returns rather than on interest rates. Second, currency portfolios ranked on pre-formation HML_{FX} betas rather than interest rates display a similar pattern in average returns and interest rates. Portfolios with high HML_{FX} exposure do yield high average returns and have high forward discounts. This supports a risk-based rather than a characteristic-based explanation of our findings; a characteristic-based explanation would imply that our risk factor has no explanatory power for currency portfolios not constructed by sorting on interest rates, and that there should be no pattern in currencies sorted on HML_{FX} betas. Third, we split our large sample of developed and emerging countries into two sub-samples. The first sub-sample provides test assets. The second sub-sample provides two risk factors. We find that the risk factors built using currencies that do not belong to test assets can still explain currency excess returns. Fourth, we construct an equity-based volatility measure. The volatility factor measures the average monthly standard deviations of daily changes in foreign country equity indices *in local currencies*. No exchange rate or interest rate information is used. Consistent with the predictions of the model, the low interest rate portfolio has large, positive loadings on innovations to the volatility factor; the high interest rate portfolio has large, negative loadings. We also sort currencies on their volatility loadings and obtain a large spread in returns. These currency portfolios truly seem to have different exposure to aggregate risk.

There is a large literature that documents the failure of UIP in the time series, starting with the work of Hansen and Hodrick (1980) and Fama (1984): higher than usual interest rates lead to further appreciation, and investors earn more by holding bonds from currencies with interest rates that are *higher than usual* (see e.g. Cochrane (2001)). Backus et al. (2001) show that asymmetries in loadings on country-specific factors are sufficient for replicating the failure of UIP in the time series. Bansal and Dahlquist (2000) conclude from the time series evidence that country-specific attributes are critical to understanding cross-sectional variations in currency risk premia. In this paper, we offer a different perspective. By building portfolios of positions in currency forward contracts sorted on forward discounts, we show that UIP also fails in the cross-section. Hence, investors earn large excess returns simply by holding bonds from currencies with interest rates that are *currently high*, not only *higher than usual*. We derive asymmetries in loadings on a common risk factor as a necessary condition for replicating the failure of UIP in the cross-section and hence for explaining carry trade returns. We obtain this condition in a large class of exponentially affine models that are popular in the term structure literature. These models have been used in international finance by Frachot (1996), Backus et al. (2001), and Brennan and Xia (2006), among others.

We do not attempt to provide a fully specified dynamic asset pricing model that starts from preferences, but instead, we derive novel implications from the moments of exchange rates, interest rates and currency returns for a broad class of international models of dynamic economies, as do Backus et al. (2001) and Brandt et al. (2006). However, we specifically examine the moments of exchange rates after sorting currencies on interest rates, and this sorting yields novel insights. Recent contributions that address for the forward premium puzzle with fully-specified dynamic asset pricing models that start from a complete description of preferences and endowments include the following papers: Lustig and Verdelhan (2007) estimate a consumption-based model with durable goods, following work by Yogo (2003) on stocks; Verdelhan (2009) uses habit preferences in the vein of Campbell and Cochrane (1999), Bansal and Shaliastovich (2008) build on the long run risk model pioneered by Bansal and Yaron (2004), and Farhi and Gabaix (2008) augment the standard consumption-based model with disaster risk following Barro (2006).[3] We show that these models need a common heteroscedastic risk factor with asymmetric loadings to explain the cross-section of carry trade returns; in the context of these models, this means heterogeneity in exposure to global consumption growth risk, global consumption disaster risk, or long run global

[3]Cumby (1988) provides some early evidence that the forward premium is related to conditional covariances with US consumption growth. Hollifield and Yaron (2001) were the first to show that real rather than inflation-related factors help to account for the forward premium puzzle. We also show that HML_{FX} is strongly related to macroeconomic risk; it has a US consumption growth beta between 1 and 1.5, which is consistent with the findings of Lustig and Verdelhan (2007). In recent related work, DeSantis and Fornari (2008) provide more evidence that currency returns compensate investors for systematic, business cycle risk. Brunnermeier, Nagel and Pedersen (2008) show that high interest rate currencies are more subject to crash risk than low interest rate currencies; they attribute this to liquidity drying up in currency markets.

consumption growth risk.

Our paper is organized as follows: we start by describing the data, the method used to build currency portfolios, and the main characteristics of these portfolios. Section 2 shows that a single factor, HML_{FX}, explains most of the cross-sectional variation in foreign currency excess returns. In section 3, we use a no-arbitrage model of exchange rates to interpret these findings. A calibrated version of the model replicates the key moments of the data. Section 4 considers several extensions. We look at beta-sorted portfolios and confirm the same pattern in excess returns. We show that the carry trade risk factor has some explanatory power for momentum currency portfolios. By randomly splitting the sample, we also show that risk factors constructed from currencies not used as test assets still explain the cross-section. Section 5 concludes. All tables and figures are in the appendix. The portfolio data can be downloaded from our web sites and are regularly updated. A separate appendix, available on-line, reports additional results.

1 Currency Portfolios and Risk Factors

We focus on investments in forward and spot currency markets. Compared to Treasury Bill markets, forward currency markets only exist for a limited set of currencies and shorter time-periods. However, forward currency markets offer two distinct advantages. First, the carry trade is easy to implement in these markets, and the data on bid-ask spreads for forward currency markets are readily available. This is not the case for most foreign fixed income markets. Second, these forward contracts are subject to minimal default and counter-party risk. This section describes the properties of monthly foreign currency excess returns from the perspective of a US investor. We consider currency portfolios that include developed and emerging market countries for which forward contracts are traded. We find that currency markets offer Sharpe ratios comparable to the ones measured in equity markets, even after controlling for bid-ask spreads. As in Lustig and Verdelhan (2005, 2007), we sort currencies on their interest rates and allocate them to portfolios. Unlike those papers, which use T-bill yields, our current paper focusses on monthly investment horizons and uses only spot and forward exchange rates to compute returns. These contracts are easily tradable, subject to minimal counter-party risk, and their transaction costs are easily available. As a result, we can account for the bid-ask spreads that investors incur when they trade these spot and forward contracts in currency markets.

1.1 Building Currency Portfolios

We start by setting up some notation. Then, we describe our portfolio building methodology, and we conclude by giving a summary of the currency portfolio returns.

Currency Excess Returns We use s to denote the log of the spot exchange rate in units of foreign currency per US dollar, and f for the log of the forward exchange rate, also in units of foreign currency per US dollar. An increase in s means an appreciation of the home currency. The log excess return rx on buying a foreign currency in the forward market and then selling it in the spot market after one month is simply:

$$rx_{t+1} = f_t - s_{t+1}.$$

This excess return can also be stated as the log forward discount minus the change in the spot rate: $rx_{t+1} = f_t - s_t - \Delta s_{t+1}$. In normal conditions, forward rates satisfy the covered interest rate parity condition; the forward discount is equal to the interest rate differential: $f_t - s_t \approx i_t^\star - i_t$, where $i^\star$ and i denote the foreign and domestic nominal risk-free rates over the maturity of the contract. Akram, Rime and Sarno (2008) study high frequency deviations from covered interest rate parity (CIP). They conclude that CIP holds at daily and lower frequencies. Hence, the log currency excess return approximately equals the interest rate differential less the rate of depreciation:

$$rx_{t+1} \approx i_t^\star - i_t - \Delta s_{t+1}.$$

Transaction Costs Since we have bid-ask quotes for spot and forward contracts, we can compute the investor's actual realized excess return net of transaction costs. The *net* log currency excess return for an investor who goes long in foreign currency is:

$$rx_{t+1}^l = f_t^b - s_{t+1}^a.$$

The investor buys the foreign currency or equivalently sells the dollar forward at the bid price (f^b) in period t, and sells the foreign currency or equivalently buys dollars at the ask price (s_{t+1}^a) in the spot market in period $t+1$. Similarly, for an investor who is long in the dollar (and thus short the foreign currency), the net log currency excess return is given by:

$$rx_{t+1}^s = -f_t^a + s_{t+1}^b.$$

Data We start from daily spot and forward exchange rates in US dollars. We build end-of-month series from November 1983 to March 2008. These data are collected by Barclays and Reuters and available on Datastream. Lyons (2001) reports that bid-ask spreads from Reuters are roughly twice the size of inter-dealer spreads (page 115). As a result, our estimates of the transaction costs are conservative. Lyons (2001) also notes that these indicative quotes track inter-dealer quotes closely, only lagging the inter-dealer market slightly at very high intra-day frequency. This is clearly not an issue here at monthly horizons. Our main data set contains 37 currencies: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, Euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. Some of these currencies have pegged their exchange rate partly or completely to the US dollar over the course of the sample. We keep them in our sample because forward contracts were easily accessible to investors. We leave out Turkey and United Arab Emirates, even if we have data for these countries, because their forward rates appear disconnected from their spot rates. As a robustness check, we also a study a smaller data set that contains only 15 developed countries: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland and United Kingdom. We present all of our results on these two samples.

Currency Portfolios At the end of each period t, we allocate all currencies in the sample to six portfolios on the basis of their forward discounts $f-s$ observed at the end of period t. Portfolios are re-balanced at the end of every month. They are ranked from low to high interests rates; portfolio 1 contains the currencies with the lowest interest rate or smallest forward discounts, and portfolio 6 contains the currencies with the highest interest rates or largest forward discounts. We compute the log currency excess return rx_{t+1}^{j} for portfolio j by taking the average of the log currency excess returns in each portfolio j. For the purpose of computing returns net of bid-ask spreads we assume that investors *short* all the foreign currencies in the *first* portfolio and go *long* in all the other foreign currencies.

The total number of currencies in our portfolios varies over time. We have a total of 9 countries at the beginning of the sample in 1983 and 26 at the end in 2008. We only include currencies for which we have forward and spot rates in the current and subsequent period. The maximum number of currencies attained during the sample is 34; the launch of the euro accounts for the subsequent decrease in the number of currencies. The average number of portfolio switches per month is 6.01 for portfolios sorted on one-month forward rates. We define the average frequency as the time-average of the following ratio: the number of portfolio switches divided by the total number of currencies at each date. The average frequency is 29.32 percent, implying that currencies switch portfolios roughly every three months. When we break it down by portfolio, we get the following frequency of portfolio switches (in percentage points): 19.9 for the 1st, 33.8 for the 2nd, 40.7 for the 3rd, 43.4 for the 4th, 42.0 for the 5th, and 13.4 for the 6th. Overall, there is quite some variation in the composition of these portfolios, but there is more persistence in the composition of the corner portfolios. As an example, we consider the Japanese yen. The yen starts off in the fourth portfolio early on in the sample, then gradually ends up in the first portfolio as Japanese interest rates fall in the late eighties and it briefly climbs back up to the sixth portfolio in the early nineties. The yen stays in the first portfolio for the remainder of the sample.

1.2 Returns to Currency Speculation for a US investor

Table 1 provides an overview of the properties of the six currency portfolios from the perspective of a US investor. For each portfolio j, we report average changes in the spot rate Δs^j, the forward discounts $f^j - s^j$, the log currency excess returns $rx^j = -\Delta s^j + f^j - s^j$, and the log currency excess returns net of bid-ask spreads rx^j_{net}. Finally, we also report log currency excess returns on carry trades or high-minus-low investment strategies that go long in portfolio $j = 2, 3 \ldots, 6$, and short in the first portfolio: $rx^j_{net} - rx^1_{net}$. All exchange rates and returns are reported in US dollars and the moments of returns are annualized: we multiply the mean of the monthly data by 12 and the standard deviation by $\sqrt{12}$. The Sharpe ratio is the ratio of the annualized mean to the annualized standard deviation.

The first panel reports the average rate of depreciation for all currencies in portfolio j. According to the standard uncovered interest rate parity (UIP) condition, the average rate of depreciation $E_T(\Delta s^j)$ of currencies in portfolio j should equal the average forward discount on these currencies $E_T(f^j - s^j)$, reported in the second panel. Instead, currencies in the first portfolio trade at an average forward discount of -390 basis points, but they appreciate on average only by almost 100 basis points over this sample. This adds up to a log currency excess return of minus 290 basis points on average, which is reported in the third panel. Currencies in the last portfolio trade at an average discount of 778 basis points but they depreciate only by 188 basis points on average. This adds up to a log currency excess return of 590 basis points on average. A large body of empirical work starting with Hansen and Hodrick (1980) and Fama (1984) reports violations of UIP in the time series. However, our results are different because we only consider whether a currency's interest rate is currently high, not whether it is higher than usual.

The fourth panel reports average log currency excess returns net of transaction costs. Since we rebalance portfolios monthly, and transaction costs are incurred each month, these estimates of net returns to currency speculation are conservative. After taking into account bid-ask spreads, the average return on the first portfolio drops to minus 170 basis points. Note that the first column reports *minus* the actual log excess return for the first portfolio, because the investor is short in these currencies. The corresponding Sharpe ratio on this first portfolio is minus 0.21. The return on the sixth portfolio drops to 314 basis points. The corresponding Sharpe ratio on the last portfolio is 0.34.

The fifth panel reports returns on zero-cost strategies that go long in the high interest rate portfolios and short in the low interest rate portfolio. The spread between the net returns on the first and the last portfolio is 483 basis points. This high-minus-low strategy delivers a Sharpe ratio of 0.54, after taking into account bid-ask spreads. Equity returns provide a natural benchmark. Over the same sample, the (annualized) Fama-French monthly excess return on the US stock market is 7.11 percent, and the equity Sharpe ratio is 0.48. Note that this equity return does not take into account transaction costs.

[Table 1 about here.]

We have documented that a US investor with access to forward currency markets can realize large excess returns with annualized Sharpe ratios that are comparable to those in the US stock market. Table 1 also reports results obtained on a smaller sample of developed countries. The Sharpe ratio on a long-short strategy is 0.39. There is no evidence that time-varying bid-ask spreads can account for the failure of UIP in the data or that currency excess returns are small in developed countries, as suggested by Burnside, Eichenbaum, Kleshchelski and Rebelo (2006). We turn now to the common variation in exchange rates among currencies sorted on interest rates, the key result of our paper.

2 Common Factors in Currency Returns

We show that the sizeable currency excess returns described in the previous section are matched by covariances with risk factors. The riskiness of different currencies can be fully understood in terms of two currency factors that are essentially the first two principal components of the portfolio returns. All portfolios load equally on the first component, which is essentially the average currency excess return. We label it the *dollar risk factor*. The second principal component, which is very close to the difference in returns between the low and high interest rate currencies, explains a large share of the cross-section. We refer to this component as the *carry risk factor*. The risk premium on any currency is determined by the dollar risk premium and the carry risk premium. The carry risk premium depends on which portfolio a currency belongs to, i.e. whether the currency has high or low interest rates, but the dollar risk premium does not.

2.1 Methodology

Linear factor models predict that average returns on a cross-section of assets can be attributed to risk premia associated with their exposure to a small number of risk factors. In the arbitrage pricing theory (APT) of Ross (1976), these factors capture common variation in individual asset returns. A principal component analysis on our currency portfolios reveals that two factors explain more than 80 percent of the variation in returns on these six portfolios. The top panel in table 2 reports the loadings of our currency portfolios on each of the principal components as well as the fraction of the total variance of portfolio returns attributed to each principal component. The first principal component explains 70 percent of common variation in portfolio returns, and can be interpreted as a *level* factor, since all portfolios load equally on it. The second principal component, which is responsible for over 12 percent of common variation, can be interpreted as a *slope* factor, since portfolio loadings increase monotonically across portfolios. The first principal component is indistinguishable from the average portfolio return. The second principal component is essentially the difference between the return on the sixth portfolio and the return on the first portfolio.

As a consequence, we have recovered two candidate risk factors: the average currency excess return, denoted RX, and the difference between the return on the last portfolio and the one on the first portfolio, denoted HML_{FX}. The correlation of the first principal component with RX is .99. The correlation of the second principal component with HML_{FX} is .94. Both factors are computed from net returns, after taking into account bid-ask spreads. The bottom panel confirms that we obtain similar results even when we exclude developing countries from the sample. It is important to point out these components capture common variation in exchange rates, not interest rates. When we redo our principal component analysis on the exchange rates that correspond to the currency portfolios, we get essentially the same results.

These currency risk factors have a natural interpretation. HML_{FX} is the return in dollars on a zero-cost strategy that goes long in the highest interest rate currencies and short in the lowest interest rate currencies. RX is the average portfolio return of a US investor who buys all foreign currencies available in the forward market. This second factor is essentially the currency "market" return in dollars available to an US investor, which is driven by the fluctuations of the US dollar against a broad basket of currencies.

[Table 2 about here.]

Before turning to our main asset pricing estimates, we build some intuition for why the second principal component is a good candidate risk factor. Following Cochrane and Piazzesi (2008), we compute the covariance of each principal component with the currency portfolio returns, and we compare these covariances (indicated by triangles) with the average currency excess returns (indicated by squares) for each portfolio. Figure 1 illustrates that the second principal component is the only promising candidate. Its covariance with currency excess returns increases monotonically as we go from portfolio 1 to 6.[4] This is not the case for any of the other principal components. As a result, in the space of portfolio returns, the second principal component is crucial.

[Figure 1 about here.]

Cross-Sectional Asset Pricing We use Rx^j_{t+1} to denote the average excess return on portfolio j in period $t+1$. All asset pricing tests are run on excess returns and not log excess returns. In the absence of arbitrage opportunities, this excess return has a zero price and satisfies the following Euler equation:

$$E_t[M_{t+1}Rx^j_{t+1}] = 0.$$

[4] We thank John Cochrane for suggesting this figure. Figure 1 is the equivalent of figure 6 page 25 of Cochrane and Piazzesi (2008).

We assume that the stochastic discount factor M is linear in the pricing factors f:

$$M_{t+1} = 1 - b(f_{t+1} - \mu),$$

where b is the vector of factor loadings and μ denotes the factor means. This linear factor model implies a beta pricing model: the expected excess return is equal to the factor price λ times the beta of each portfolio β^j:

$$E[Rx^j] = \lambda' \beta^j,$$

where $\lambda = \Sigma_{ff} b$, $\Sigma_{ff} = E(f_t - \mu_f)(f_t - \mu_f)'$ is the variance-covariance matrix of the factor, and β^j denotes the regression coefficients of the return Rx^j on the factors. To estimate the factor prices λ and the portfolio betas β, we use two different procedures: a Generalized Method of Moments estimation (GMM) applied to linear factor models, following Hansen (1982), and a two-stage OLS estimation following Fama and MacBeth (1973), henceforth FMB. In the first step, we run a time series regression of returns on the factors. In the second step, we run a cross-sectional regression of average returns on the factors. We do not include a constant in the second step ($\lambda_0 = 0$).

2.2 Results

Table 3 reports the asset pricing results obtained using GMM and FMB on currency portfolios sorted on forward discounts. The left hand side of the table corresponds to our large sample of developed and emerging countries, while the right hand side focuses on developed countries. We describe first results obtained on our large sample.

[Table 3 about here.]

Cross-sectional regressions The top panel of the table reports estimates of the market prices of risk λ and the SDF factor loadings b, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests (in percentage points). The market price of HML_{FX} risk is 546 basis points *per annum*. This means that an asset with a beta of one earns a risk premium of 5.46 percent per annum. Since the factors are returns, no arbitrage implies that the risk prices of these factors should equal their average excess returns. This condition stems from the fact that the Euler equation applies to the risk factor itself, which clearly has a regression coefficient β of one on itself. In our estimation, this no-arbitrage condition is satisfied. The average excess return on the high-minus-low strategy (last row in Table 3) is 537 basis points. This value differs slightly from the previously reported mean excess return because we use excess returns in *levels* in the asset pricing exercise, but Table 1 reports *log* excess returns to illustrate their link to changes in exchange rates and interest rate differentials. So the estimated risk price is only 9 basis points removed from the point estimate implied by linear factor pricing. The GMM standard error of the risk price is 234 basis points. The FMB standard error is 183 basis points. In both cases, the risk price is more than two standard errors from zero, and thus highly statistically significant.

The second risk factor RX, the average currency excess return, has an estimated risk price of 135 basis points, compared to a sample mean for the factor of 136 basis points. This is not surprising, because all the portfolios have a beta close to one with respect to this second factor. As a result, the second factor explains none of the cross-sectional variation in portfolio returns, and the standard errors on the risk price estimates are large: for example, the GMM standard error is 168 basis points. When we drop the dollar factor, the RMSE rises from 95 to 168 basis points, but the adjusted R^2 is still 76 %. The dollar factor does not explain any of the cross-sectional variation in expected returns, but it is important for the level of average returns. When we include a constant in the 2nd step of the FMB procedure, the RMSE drops to 92 basis points with only HML_{FX} as the pricing factor. Including a constant to the dollar risk factor is redundant because the dollar factor acts like a constant in the cross-sectional regression.

The λ's indicate whether risk is priced, and HML_{FX} risk clearly is in the data. The loadings (b) have a natural interpretation as the regression coefficients in a multiple regression of the SDF on the factors. The t-stats on b_{HML} consistently show that that the carry trade risk factor helps to explain the cross-section of currency returns in a statistically significant way, while the dollar risk factor does not.

Overall, the pricing errors are small. The RMSE is around 95 basis points and the adjusted R^2 is 69 percent. The null that the pricing errors are zero cannot be rejected, regardless of the estimation procedure. Figure 2 plots predicted against realized excess returns for all six currency portfolios. Clearly, the model's predicted excess returns line up rather well with the average excess returns. The predicted excess return in this graph is simply the OLS estimate of the betas times the sample mean of the factors, not the estimated prices of risk. Fitted risk prices would imply an even better fit by construction. These results are robust. They also hold in a smaller sample of developed countries, as shown in the right-hand side of Table 3.

Time Series Regressions The bottom panel of Table 3 reports the constants (denoted α^j) and the slope coefficients (denoted β^j) obtained by running time-series regressions of each portfolio's currency excess returns Rx^j on a constant and risk factors. The returns and α's are in percentage points per annum. The first column reports α's estimates. The fourth portfolio has a large α of 162 basis points per annum, significant at the 10 percent level but not statistically significant at the 5 percent level. The other α estimates are much smaller and not significantly different from zero. The null that the α's are jointly zero cannot be rejected at the 5 or 10 % significance level. Using a linear combination of the portfolio returns as factors entails linear restrictions on the α's. When the two factors HML_{FX} and RX_{FX} are orthogonal, it is easy to check that $\alpha^1 = \alpha^6$, because

$\beta^6_{HML_{FX}} - \beta^1_{HML_{FX}} = 1$ by construction. In this case, the risk prices exactly equal the factor means. This is roughly what we find in the data.

The second column of the same panel reports the estimated βs for the HML_{FX} factor. These βs increase monotonically from -.39 for the first portfolio to .61 for the last currency portfolio, and they are estimated very precisely. The first three portfolios have betas that are negative and significantly different from zero. The last two have betas that are positive and significantly different from zero. The third column shows that betas for the dollar factor are essentially all equal to one. Obviously, this dollar factor does not explain any of the variation in average excess returns across portfolios, but it helps to explain the average level of excess returns. These results are robust and comparable to the ones obtained on a sample of developed countries (reported on the right hand side of the table).

[Figure 2 about here.]

A natural question is whether the unconditional betas of the bottom panel of Table 3 are driven by the covariance between exchange rate changes and risk factors, or between interest rate changes and risk factors. This is important because the conditional covariance between the log currency returns and the carry trade risk factor obviously only depends on the spot exchange rate changes:

$$cov_t\left[rx^j_{t+1}, HML_{FX,t+1}\right] = -cov_t\left[\Delta s^j_{t+1}, HML_{FX,t+1}\right].$$

In Table 4, we report the regression results of the log changes in spot rates for each portfolio on the factors. These conditional betas are almost identical to the unconditional ones (with a minus sign), as expected. Low interest currencies offer a hedge against carry trade risk because they appreciate when the carry return is low, not because the interest rates on these currencies increase. High interest rate currencies expose investors to more carry risk, because they depreciate when the carry return is low, not because the interest rates on these currencies decline. This is exactly the pattern that our no-arbitrage model in section 3 delivers. Our analysis within the context of the model focuses on conditional betas.

[Table 4 about here.]

Principal Components as Factors Alternatively, we can use the two first principal components themselves as factors. We re-scaled these principal component coefficients to obtain zero cost investment strategies, and we use $w^c_j, j = 1, \ldots, 6$ to denote these weights. For the second component, these portfolio weights are:

$$w^c = \begin{bmatrix} -0.757 & -0.472 & -0.479 & -0.100 & 0.203 & 1.501 \end{bmatrix}.$$

Since the factors are orthogonal, we know that $\sum_{j=1}^{6} w_j^i \beta_i^j = 1$ for each risk factor $i = c, d$, and hence we know that $\sum_{j=1}^{6} w_j^i \alpha_0^j = 0$ by construction. These results are reported in Table 15. This investment strategy involves borrowing 75 cents in currencies in the first portfolio, 47 cents in the currencies in the second portfolio, etc, and finally investing \$1.50 in currencies in the last portfolio. This is a risky strategy. The risk price of the carry factor (the second principal component) is 7.42 % per annum and the risk price of the dollar factor (the first principal component) is 1.37 % per annum. The risk-adjusted return on HML_{FX} is only 35 basis points per annum. The only portfolio with a statistically significant positive risk-adjusted return is the fourth one. However, the null that the α's are jointly zero cannot be rejected. All of the statistics of fit are virtually identical to those that we obtained we when we used HML_{FX} and RX_{FX} as factors.

[Table 5 about here.]

We have shown in this section that currency excess returns are compensations for HML_{FX} risk. To check that a currency's interest rate relative to that of other currencies truly measures its exposure to the carry risk factor, section 4.1 sorts currencies into portfolios based on their carry-risk-betas. We recover a similar pattern in the forward discounts and in the excess returns.

Foreign Investors We have also checked the Euler equation of foreign investors in the UK, Japan and Switzerland. To do so, we construct the new asset pricing factors (HML_{FX} and RX) in local currencies, and we use the local currency returns as test assets. HML_{FX} is essentially the same risk factor in all currencies, if we abstract from bid-ask spreads. For all countries, the estimated market price of HML_{FX} risk is less than 70 basis points removed from the sample mean of the factor. The HML_{FX} risk price is estimated at 5.54 percent in the UK, 5.50 percent in Japan and 5.79 percent in Switzerland. These estimates are statistically different from zero in all three cases. The two currency factors explain between 47 and 71 percent of the variation (after adjusting for degrees of freedom). The mean squared pricing error is 95 basis points for the UK, 116 basis points for Japan and 81 basis points for Switzerland. The null that the underlying pricing errors are zero cannot be rejected except for Japan, for which the p-values are smaller than 10 percent.[5]

To interpret these currency portfolio returns and the risk factors that we have constructed, the next section introduces a standard no-arbitrage model of the term structure.

3 A No-Arbitrage Model of Exchange Rates

We use a standard affine model of interest rates to show that, by constructing currency portfolios, we measure the common innovation to the stochastic discount factor (henceforth SDFs). In

[5]These results are available in a separate appendix.

addition, we derive conditions under which a model that belongs to this class can explain carry trade returns. These conditions are different from the ones needed to generate negative UIP slope coefficients. We show inside the model how sorting currencies based on interest rates is indeed equivalent to sorting these currencies on their exposure to the global risk factor. Finally, we show that a reasonably calibrated version of the model can replicate the moments of carry trade returns in the data.

Our model falls in the essentially-affine class and therefore shares some features with the models proposed by Frachot (1996) and Brennan and Xia (2006), as well as Backus et al. (2001). Like these authors, we do not specify a full economy complete with preferences and technologies; instead we posit a law of motion for the SDFs directly. We consider a world with N countries and currencies. Following Backus et al. (2001), we assume that in each country i, the logarithm of the SDF m^i follows a two-factor Cox, Ingersoll and Ross (1985)-type process:

$$-m_{t+1}^i = \lambda^i z_t^i + \sqrt{\gamma^i z_t^i} u_{t+1}^i + \tau^i z_t^w + \sqrt{\delta^i z_t^w} u_{t+1}^w.$$

There is a common global factor z_t^w and a country-specific factor z_t^i. The currency-specific innovations u_{t+1}^i and global innovations u_{t+1}^w are *i.i.d* gaussian, with zero mean and unit variance; u_{t+1}^w is a world shock, common across countries, while u_{t+1}^i is country-specific. The country-specific volatility component is governed by a square root process:

$$z_{t+1}^i = (1-\phi^i)\theta^i + \phi^i z_t^i + \sigma^i \sqrt{z_t^i} v_{t+1}^i,$$

where the innovations v_{t+1}^i are uncorrelated across countries, *i.i.d* gaussian, with zero mean and unit variance. The world volatility component is also governed by a square root process:

$$z_{t+1}^w = (1-\phi^w)\theta^w + \phi^w z_t^w + \sigma^w \sqrt{z_t^w} v_{t+1}^w,$$

where the innovations v_{t+1}^w are also standard normal. In this model, the conditional market price of risk has a domestic component $\sqrt{\gamma^i z_t^i}$ and a global component $\sqrt{\delta^i z_t^w}$.[6] Brandt et al. (2006), Colacito (2008), Bakshi, Carr and Wu (2008), and Colacito and Croce (2008) emphasize the importance of a large common component in stochastic discount factors to make sense of the high volatility of SDF's and the 'low' volatility of exchange rates. In addition, there is a lot evidence that much of the stock return predictability around the world is driven by variation in the global risk price, starting with the work of Harvey (1991) and Campbell and Hamao (1992). A major

[6]The real interest rate investors earn on currency i is given by:

$$r_t^i = \left(\lambda - \frac{1}{2}\gamma\right) z_t^i + \left(\tau - \frac{1}{2}\delta^i\right) z_t^w.$$

difference between our model and that proposed by Backus et al. (2001) is that we allow the loadings δ^i on the common component to differ across currencies. This will turn out to be critically important.

Complete Markets We assume that financial markets are complete, but that some frictions in the goods markets prevent perfect risk-sharing across countries. As a result, the change in the real exchange rate Δq^i between the home country and country i is:

$$\Delta q^i_{t+1} = m_{t+1} - m^i_{t+1},$$

where q^i is measured in country i goods per home country good. An increase in q^i means a real appreciation of the home currency. For the home country (the US), we drop the superscript. The expected excess return in levels (i.e. corrected for the Jensen term) consists of two components:

$$E_t[rx^i_{t+1}] + \frac{1}{2}Var_t[rx^i_{t+1}] = \sqrt{\delta^i}\left(\sqrt{\delta} - \sqrt{\delta^i}\right) z^w_t + \gamma z_t.$$

The risk premium has a global and a dollar component. $\left(\sqrt{\delta} - \sqrt{\delta^i}\right)$ is the loading of the return on currency i on the common shock, and z^w_t is the risk price. The loading on the dollar shock is one for all currencies, and z_t is the risk price for dollar shocks. So, the expected return on currency i has a simple beta representation: $E_t[rx^i_{t+1}] + \frac{1}{2}Var_t[rx^i_{t+1}] = \beta^i \lambda_t$ with $\beta^i = \delta^i \left[\delta^i(\sqrt{\delta} - \sqrt{\delta^i}), 1\right]$ and $\lambda_t = [z^w_t, \gamma z_t]'$. The risk premium is *independent* of the foreign country-specific factor z^i_t and the foreign country-specific loading γ^i.[7] Hence, we need asymmetric loadings on the common component as a source of variation across currencies. While asymmetric loadings on the country-specific component can explain the negative UIP slope coefficients in time series regression (as Backus et al. (2001) show), these asymmetries cannot account for any variation in risk premia across different currencies. As a consequence, and in order to simplify the analysis, we impose more symmetry on the model with the following assumption:

Assumption. *All countries share the same loading on the domestic component γ. The home country has the average loading on the global component δ: $\sqrt{\delta} = \overline{\sqrt{\delta}}$.*

[7] The expected log currency excess return does depend on the foreign factor; it equals the interest rate difference plus the expected rate of appreciation:

$$\begin{aligned} E_t[rx^i_{t+1}] &= -E_t[\Delta q^i_{t+1}] + r^i_t - r_t, \\ &= \frac{1}{2}[\gamma z_t - \gamma^i z^i_t + \left(\delta - \delta^i\right) z^w_t]. \end{aligned}$$

3.1 Building Currency Portfolios to Extract Factors

As in the data, we sort currencies into portfolios based on their forward discounts. We use H to denote the set of currencies in the last portfolio and L to denote the currencies in the first portfolio. The carry trade risk factor HML_{FX} and the dollar risk factor $\overline{rx}$ are defined as follows:

$$
\begin{aligned}
hml_{t+1} &= \frac{1}{N_H}\sum_{i\in H} rx^i_{t+1} - \frac{1}{N_L}\sum_{i\in L} rx^i_{t+1}, \\
\overline{rx}_{t+1} &= \frac{1}{N}\sum_{i} rx^i_{t+1},
\end{aligned}
$$

where lower letters denote logs. We let $\overline{\sqrt{\delta^j_t}}$ denote the average $\sqrt{\delta^i}$ of all currencies (indexed by i) in portfolio j. Note that the portfolio composition changes over time, and in particular, it depends on the global risk price z^w_t.

In this setting, the carry trade and dollar risk factors have a very natural interpretation. The first one measures the common innovation, while the second one measures the country-specific innovation. In order to show this result, we appeal to the law of large numbers, and we assume that the country-specific shocks average out within each portfolio.

Proposition 3.1. *The innovation to the HML_{FX} risk factor only measures exposure to the common factor u^w_{t+1}, and the innovation to the dollar risk factor only measures exposure to the country-specific factor u_{t+1}:*

$$
\begin{aligned}
hml_{t+1} - E_t[hml_{t+1}] &= \left(\overline{\sqrt{\delta^L_t}} - \overline{\sqrt{\delta^H_t}}\right)\sqrt{z^w_t}\,u^w_{t+1}, \\
\overline{rx}_{t+1} - E_t[\overline{rx}_{t+1}] &= \sqrt{\gamma}\sqrt{z_t}\,u_{t+1}.
\end{aligned}
$$

When currencies share the same loading on the common component, there is no HML_{FX} risk factor. This is the case considered by Backus et al. (2001). However, if lower interest rate currencies have different exposure to the common volatility factor - $\overline{\sqrt{\delta^L}} \neq \overline{\sqrt{\delta^H}}$ - then the innovation to HML_{FX} measures the common innovation to the SDF. As a result, the return on the zero-cost strategy HML_{FX} measures the stochastic discount factors' exposure to the common shock u^w_{t+1}.

Proposition 3.2. *The HML_{FX} betas and the RX_{FX} betas of the returns on currency portfolio j:*

$$
\begin{aligned}
\beta^j_{hml,t} &= \frac{\sqrt{\delta} - \sqrt{\delta^j_t}}{\sqrt{\delta^L_t} - \sqrt{\delta^H_t}}, \\
\beta^j_{rx,t} &= 1.
\end{aligned}
$$

The betas for the dollar factor are all one. Not so for the carry trade risk factor. If the sorting of currencies on interest rate produces a monotonic ranking of δ on average, then the HML_{FX} betas will increase monotonically as we go from low to high interest rate portfolios. As it turns out the model with asymmetric loadings automatically delivers this if interest rates decrease when global risk increases. This case is summarized in the following condition:

Condition 3.1. *The precautionary effect of global volatility the real short rate dominates iff:*

$$0 < \tau < \frac{1}{2}\delta^i.$$

This condition naturally holds in most standard consumption-based pricing models: as the conditional volatility of consumption growth increases, interest rates decline.

The real short rate depends both on country-specific factors and on a global factor. The only sources of cross-sectional variation in interest rates are the shocks to the country-specific factor z^i_t, and the heterogeneity in the SDF loadings δ^i on the world factor z^w. As a result, as z^w increases, on average, the currencies with the high loadings δ will tend to end up in the lowest interest rate portfolios, and the gap $\left(\sqrt{\delta^L_t} - \sqrt{\delta^H_t}\right)$ increases. This implies that in bad times the spread in the loadings increases. We provide below a calibrated version of the model that illustrates these effects. As shown above, in our model economy, the currency portfolios recover the two factors that drive innovations in the pricing kernel. Therefore, these two factors span the mean-variance efficient portfolio, and it comes as no surprise that these two factors can explain the cross-sectional variation in average currency returns.

3.2 Risk Premia in No-Arbitrage Currency Model

In our model, the risk premium on individual currencies consists of two parts: a dollar risk premium and a carry trade risk premium. Our no-arbitrage model also delivers simple closed-form expression for these risk premia.

Proposition 3.3. *The carry trade risk premium and the dollar risk premium are:*

$$\begin{aligned} E_t[hml_{t+1}] &= \frac{1}{2}\left(\overline{\delta_t^L} - \overline{\delta_t^H}\right) z_t^w, \\ E_t[\overline{rx}_{t+1}] &= \frac{1}{2}\gamma\left(z_t - \overline{z_t}\right). \end{aligned} \tag{3.1}$$

The carry trade risk premium is driven by the global risk factor. The size of the carry trade risk premium is governed by the spread in the loadings (δ) on the common factor between low and high interest rate currencies, and by the global price of risk. When this spread doubles, the carry trade risk premium doubles. However, the spread itself also increases when the global Sharpe ratio is high. As a result, the carry trade risk premium increases non-linearly when global risk increases. The dollar risk premium is driven only by the US risk factor, if the home country's exposure to global risk factor equals to the average δ.

The risk premia on the currency portfolios have a dollar risk premium and a carry trade component:

$$rp_t^j = \frac{1}{2}\gamma\left(z_t - \overline{z_t^j}\right) + \frac{1}{2}\left(\delta - \overline{\delta^j}\right) z_t^w. \tag{3.2}$$

The first component is the dollar risk premium part. The second component is the carry trade part. The highest interest rate portfolios load more on the carry trade component, because their loadings are smaller than the home country's δ, while the lowest interest rate currencies have a negative loading on the carry trade premium, because their loadings exceed the home country's δ. Note that $\overline{z^j}$ is constant in the limit $N \to \infty$ by the law of large numbers.

In a reasonably specified model, the US-specific component of the risk price, z_t, and hence the dollar risk premium, should be counter-cyclical -with respect to the US-specific component of the business cycle-, and the global component z_t^w, and hence the carry risk premium, should be counter-cyclical with respect to the global business cycle. We now turn to a calibrated version of this no-arbitrage model. We show that it can match the key moments of currency returns in the data, while also matching the usual moments of interest rates and inflation.

3.3 Calibration

We calibrate the model at monthly frequency by targeting annualized moments of monthly data. In this calibration, we focus on developed countries over the 1983-2008 sample. The calibration proceeds in two stages. In a first stage, we calibrate the real side of the model by targeting moments of the real variables. In the second stage, we turn to the nominal SDFs by matching some moments of inflation.

We start by calibrating a completely symmetric version of the model, and then we introduce enough heterogeneity in the SDF loadings on the global shock across countries to match the carry trade risk premium. There are 7 parameters in the model: 4 parameters govern the countries' SDFs (λ, γ, τ and δ) and 3 parameters describe the evolution of the country-specific and global state variables. We choose these parameters to match 7 key moments in the data: the mean, standard deviation and autocorrelation of real risk-free rates, the average conditional variance of changes in real exchange rates, the mean and standard deviation of the maximal conditional Sharpe ratio and the UIP slope coefficient. Panel I of Table 6 lists all of these moments and panel II lists the parameter choices. These moments were generated by drawing $10,000$ observations from a model with 40 currencies. The simulated model produces a real risk-free rate with a mean of 1.2 percent, a standard deviation of 0.2 percent and an autocorrelation of 0.7 (on annual basis). The mean and autocorrelation of the real interest rate fall within the range of empirical estimates for the post-war U.S. data (e.g. Campbell (2003)). The average (annualized) standard deviation of real exchange rates is about 10 percent and the average regression coefficient of exchange rate changes on interest rate differentials is around -1, roughly consistent with our data. Our model produces an average conditional maximum Sharpe ratio for the domestic investor with a mean of 0.32 and a standard deviation of 0.04, in annual units.

Next, we set the heterogeneity in the loadings on the common risk factor by choosing the range of parameters δ^i to match the mean of the carry trade risk factor. Setting the range for countries' global risk loadings to be within 40 percent of the home country's loading leads to a mean carry factor HML_{FX} of 5 percent per annum, which is broadly consistent with our empirical results for developed countries. Expanding the range of global shock loadings allows us to match the higher average return obtained using all countries in our sample, but also increases the average exchange rate volatility.

[Table 6 about here.]

We add inflation to the model in order to match moments of nominal interest rates and exchange rates. The log of the nominal pricing kernel in country i is simply given by the real pricing kernel less the rate of inflation π^i:

$$m_{t+1}^{i,\$} = m_{t+1}^{i} - \pi_{t+1}^{i}.$$

We assume that inflation is composed of a country-specific component and a global component. The bottom panel of Table 6 lists the moments of inflation processes used in calibration; the details of the calibration are in the appendix.

The calibrated version of our multi-country model delivers reasonable interest rates and exchange rates. The annualized average real one-period yields are between -1 and 10 percent. The mean nominal one-period interest rate is between 2 and 6 percent, with an average 4.2 across countries, and average standard deviation of about 2 percent. The annualized standard deviations of changes in the real and nominal exchanges rates are between 9 and 15 percent.

3.4 Currency Portfolio Returns

We simulate a version of the model with $N = 40$ countries over 10,000 periods. We build currency portfolios starting from the simulated data in the same way as for the actual data. Table 7 reports summary statistics on these portfolios and estimates of the market prices of risk associated with the two factors, RX and HML_{FX}. The model delivers a sizable cross-section of currency excess returns. The spread between the first and last portfolio is 5 percent per annum, implying an annualized Sharpe ratio of 0.44. In the cross-sectional asset pricing tests, the market price of the carry trade factor HML_{FX} is 5 percent per annum, very close to the sample mean. The price of the aggregate market return RX is close to zero and not statistically significant. This is not surprising; with a large number of periods, the mean of RX should be zero according to equation (3.1) as long as the home country SDF has an "average" loading on the global risk factor. At the same time, due to the cross-sectional heterogeneity in the loadings on the world risk factor, our model is able to reproduce the variation in average returns on currency portfolios, and in particular the large average return on the carry trade factor.

[Table 7 about here.]

The simulated market price of carry risk varies for two reasons. First, it is high when the world risk factor z^w is high. Second, this effect is amplified by changes in portfolio composition: higher world risk price drives the selection of low-global risk countries into high interest rate portfolios, and vice versa. Thus, in "bad times," when z^w is high, the spread between the average δ in the first and the last portfolio increases.[8]

3.5 Volatility risk

Despite the low unconditional market beta of the carry trade in the data, the carry risk factor HML_{FX} is very highly correlated with the stock market during periods of increased market volatility. The recent sub-prime mortgage crisis offers a good example. Between July 2007 and March 2008, the correlation between US stock returns and HML_{FX} was .78. This pattern is consistent with the model. In the two-factor affine model, the conditional correlation of HML_{FX} and the SDF in the home country is:

$$corr_t\left(hml_{t+1}, m_{t+1}\right) = \frac{\sqrt{\delta z_t^w}}{\sqrt{\delta z_t^w} + \sqrt{\gamma z_t}}. \tag{3.3}$$

As the global component of the conditional market price of risk z_t^w increases, the conditional correlation between the stochastic discount factor at home and the carry trade returns HML_{FX}

[8]Figure 8 in the separate appendix illustrates this second effect.

increases. We find strong evidence for this type of increased correlation of carry trade returns with US stock returns in crisis episodes (e.g. LTCM crisis and the Tequila crisis). For example, the US stock market beta of HML_{FX} increases to 1.14 in the run-up to the Russian default in 1998, implying that high interest rate currencies depreciate on average by 1.14 percent relative to low interest rate currencies when the stock market goes down by one percent. The market beta of the high-minus-low strategy increases dramatically in times when the price of global risk is high[9]. This evidence suggests that our global risk interpretation is consistent with the data.

Volatility as a Risk Factor In a reasonable model, global volatility should increase in bad times for global investors. If innovations to the common component of marginal utility growth u^w are indeed correlated with innovations to global volatility z^w, then volatility innovations could proxy for HML_{FX} innovations. We show that this is the case in the data and in the model.

We introduce equity in the model by defining country i's total stock market portfolio as a claim to the aggregate dividend stream of that country, D_t^i. We model each country's dividend process as a random walk with a drift for the logarithm $d_t^i = \log D_t^i$:

$$\Delta d_{t+1}^i = d_{t+1}^i - d_t^i = g^{Di} + \sigma^{Di} w_{t+1}^{Di},$$

where the w^D innovations are i.i.d. and normally distributed. In order to command a risk premium, the dividend growth innovations must be correlated with the SDF. In particular, we specify the conditional correlations of the dividend growth process with both the world and country-specific innovations to the SDF:

$$\rho^{Dw} = corr\left(w^{Di}, u^w\right) \text{ and } \rho^{Di} = corr\left(w^{Di}, u^i\right).$$

We choose the standard deviation of log dividend growth σ^{Di} to be 10 percent per annum, and we simply choose the correlations with the two SDF shocks $\rho^{Dw} = \rho^{Di} = 0.7$, since it is *a priori* reasonable that aggregate dividends are equally affected by global and country-specific shocks. The resulting stock market return process has an empirically plausible annualized monthly Sharpe ratio of 0.29, although both the equity premium and the stock return volatility are low, at about 3 percent and just over 10 percent, respectively. This is because the amount of variation in expected stock returns generated by the model is too small.

In the model, we estimate volatility risk by computing the 12-month rolling window standard deviations of equity returns. The equity volatility series is multiplied by the square root of 12 to obtain an annualized measure, and first differences of this series are used as a measure of volatility innovations. Betas are estimated by matching the mid-point of the rolling window with the month

[9]See Table 30 in the separate appendix for detailed evidence

over which the corresponding currency return is calculated. The calibration is the same as described above, except that we choose the innovations to the global factor v^w to be perfectly (negatively) correlated with the global SDF innovation u^w, in order to maximize the degree to which global volatility risk can be priced in the model. This leaves the other features of the model reported above virtually unchanged. We then calculate equity market returns as before and simulate a series of 1000 monthly returns, using these to estimate rolling standard deviations.

In the data, our volatility measure is the average volatility of stock returns in local currency across all currencies in our sample. To build our volatility factor, we compute the standard deviation over one month of daily MSCI changes for each currency. In order to obtain our final monthly measure of equity volatility, we compute the cross-sectional mean of these volatility series. We multiply the volatility factor by $\sqrt{252}$ in order to annualize it. To maximize the distance between our risk factor and test assets, we build our volatility measure using foreign equity returns measured in local currencies. As a result, this new factor is not directly influenced by exchange rate or interest rate fluctuations.

The top panel in Table 8 reports the loadings of different portfolio returns on the first difference in the equity volatility factor. The left and middle panel report the results for the data. The panel on the right reports result for the model. These loadings confirm our intuition. In the data, the loadings on the volatility innovations decrease monotonically from the first to the last portfolio from 0.41 to -0.74 in the full sample (reported in the left panel), and from .4 to -.62 in the case of developed countries (reported in the middle panel). High interest rate countries tend to offer low returns when equity volatility increases. Low interest rate countries, on the contrary, offer high returns when volatility goes up. In the model, the loadings decrease monotonically across portfolios from 2.2 to -3. Hence, the spread in betas in the model is larger.

We also ran cross-sectional regression to compute the implied price of volatility risk in the model and the data. Given the larger spread in betas in the model, the implied risk price is only -1.7, compared to the empirical estimate of -2.8 in the sample of developed currencies and -4.3 on the entire sample. So, the compensation for volatility innovations in the data seems high compared to that in our model, but not implausible, especially when we take the large sampling error into consideration. The estimate for developed countries is less than one standard error removed from the model-implied estimate. [10]

[Table 8 about here.]

While the equity volatility risk factor does not use any information on exchange rates, it has explanatory power for the cross-section of currency excess returns, as predicted by our model.

[10] We also compared the currency price of equity volatility risk to estimates from equity market data. Using 10 Fama-French industry portfolios, we obtained a price of volatility risk that is -2.9. Using 25 book-to-market and size Fama-French portfolios, we obtained a price of volatility risk of -1.5.

However, it cannot replace HML_{FX} as the pricing factor. In a horse race between these two risk factors, HML_{FX} drives out innovations to the volatility factor.[11] Following our model's insights, we also build several other measures of volatility risk, using daily equity returns in US dollars, daily currency returns, and monthly HML_{FX} returns over 12 month rolling windows. To save space, we report the corresponding results in a separate appendix. In contemporaneous work, Menkho, Sarno, Schmeling and Schrimpf (2009) independently find that a volatility factor (in levels) obtained from average daily changes in exchange rates, when combined with our dollar risk factor RX, explains the cross-section of currency excess returns. They find that their volatility risk factor drives out liquidity measures as explanations of carry trade returns.

4 Robustness

We conduct a series of robustness checks to confirm that high interest rate currencies earn large returns because they co-vary with HML_{FX}, not simply because they have high interest rates. To do so, we use other test assets and other factors. In the first exercise, in subsection 4.1, we sort on HML_{FX} betas, not on interest rates, and we find a similar patter in average returns and interest rates. In the second exercise in subsection 4.2, we split the sample, constructing the factors from currencies that are not in the portfolios used as test assets. In the third exercise, in subsection 4.3, we show that the carry trade risk factor has explanatory power for the cross-section of momentum currency returns.

4.1 Other Test Assets: Beta-Sorted Portfolios

To show that the sorting of currencies on forward discounts really does measure the currency's exposure to the risk factor, we build portfolios based on each currency's exposure to aggregate currency risk as measured by HML_{FX}. For each date t, we first regress each currency i log excess return rx^i on a constant and HML_{FX} using a 36-month rolling window that ends in period $t-1$. This gives us currency i's exposure to HML_{FX}, and we denote it $\beta_t^{i,HML}$. Note that it only uses information available at date t. We then sort currencies into six groups at time t based on these slope coefficients $\beta_t^{i,HML}$. Portfolio 1 contains currencies with the lowest βs. Portfolio 6 contains currencies with the highest βs. Table 9 reports summary statistics on these portfolios. The first panel reports average changes in exchange rates. The second panel shows that average forward discounts increase monotonically from portfolio 1 to portfolio 6. Thus, sorts based on forward discounts and sorts based on betas are clearly related, which implies that the forward discounts convey information about riskiness of individual currencies. The third panel reports the average log

[11]The volatility factor does not explain much of the momentum portfolios that we explore in the last section, while HML_{FX} does.

excess returns. They are monotonically increasing from the first to the last portfolio, even though it is smaller than the spread created by ranking directly on interest rates. Clearly, currencies that co-vary more with our risk factor - and are thus riskier - provide higher excess returns. The last panel reports the post-formation betas. They vary monotonically from $-.31$ to $.38$. This finding is quite robust. When we estimate betas using a 12-month rolling window, we also obtain a 300 basis point spread between the first and the last portfolio.

[Table 9 about here.]

As a robustness check, we run the same experiment using our volatility risk factor. We sort countries on their volatility betas (as we did for HML_{FX} betas). For each date t, we first regress each currency i log change in exchange rate Δs^i on a constant and Vol_{Equity} using a 36-month rolling window that ends in period $t-1$. This gives us currency i's exposure to Vol_{Equity}, and we denote it $\beta_t^{i,Vol}$. It only uses information available at date t. We then sort currencies into six groups at time t based on these slope coefficients $\beta_t^{i,Vol}$. In constructing these portfolios, we do not use any information on interest rates. The first portfolio contains currencies with the lowest βs. The last portfolio contains currencies with the highest βs. Table 10 reports summary statistics on these portfolios. The first panel reports average changes in exchange rates. The second panel shows that average forward discounts increase monotonically from the first portfolio to the last portfolio. Again, we have not used any information on exchange rates or interest rates to obtain these portfolios. Yet, they deliver a clear cross-section of interest rates. The third panel reports the average log excess returns. In our large sample of developed and emerging countries, they are almost monotonically increasing across portfolios, with the exception of the last one which is lower. In our sample of developed countries, they are perfectly monotone. The last panel reports the post-formation betas. These betas are not significant, across portfolios and for both samples. Pre-formation betas (obtained over short windows) are more volatile than the post-formation betas (obtained over the entire sample). Nonetheless, using HML_{FX}, however, the post-formation betas that we obtain over the entire sample are significant, and we recover a monotonic cross-section. Countries that load more on global volatility offer higher excess returns because they bear more HML_{FX} risk.

[Table 10 about here.]

4.2 Other Factors: Splitting Samples

To guard against a mechanical relation between the returns and the factors, we randomly split our large sample of developed and emerging countries into two sub-samples. The first sub-sample provides test assets. The second sub-sample provides two risk factors: the average return RX and the return on a long-short strategy HML_FX. We find that the risk factors built using currencies that do not belong to test assets can still explain currency excess returns.

Because of the smaller number of currencies in each sample, we consider only four portfolios and start in May 1984 (first date with 8 forward contracts in our dataset). Table 11 reports summary statistics for these portfolios. Despite the low number of countries in each sample, we still obtain a monotonic cross-section of gross excess returns in both cases. However, the second sample delivers an average return on the long short strategy that is lower than the one obtained on the full sample.

[Table 11 about here.]

Table 12 reports market prices of risk and factor betas. Clearly, risk factors built using currencies that do not belong to the portfolios used as test assets can still explain currency excess returns. The market price of risk appears higher and less precisely estimated than on the full sample, and thus further from its sample mean. However, portfolio betas are precisely estimated and increase monotonically from the first to the last portfolio, showing that common risk factors are at work on currency markets.

[Table 12 about here.]

4.3 Other Test Assets: Momentum Portfolios

One potential concern we have already mentioned is that by sorting currencies into portfolios based on interest rates, we might be picking up the effects of the characteristics of currencies rather than the true exposure to risk (Daniel and Titman (2005)). To address this concern, we exploit a different source of variation in currency returns: momentum. We show that the carry risk factor can account for at least 50 % of the cross-sectional variation in momentum-driven currency returns, even though the momentum portfolios are constructed on the basis of past returns, not interest rate differentials.

Table 13 reports the momentum returns. The momentum portfolios are constructed by sorting currencies at time t into portfolios based on one-month returns realized at the end of period $t-1$. We chose not to double-sort on interest rates and past returns, because of the limited number of currencies we have, so there is some overlap between the carry and momentum portfolios, but it does not appear to be the sole driver of momentum. The low momentum currencies tend to depreciate at an annualized rate of 4.48 %, while the high momentum tend to appreciate at an annualized rate 1.92 %. The rate of appreciation varies monotonically from low to high momentum portfolios. For the carry portfolios, there was no such pattern in portfolio-by-portfolio exchange rates. The high momentum portfolios do tend to have higher interest rates, but the spread between the lowest and the highest momentum portfolio is less than 300 basis points on average, much smaller than the spread between low and high interest rate portfolios of more than 11 percentage points that we reported in Table 1. Since high momentum currencies tend to have higher interest rates on average, there is a concern that these are too similar to the carry portfolios to provide an independent sort. However, momentum and carry strategies are very different. In fact, the return correlations between corresponding (i.e. high/high or low/low) carry and momentum strategies are small and sometimes even negative. These correlations are reported in the separate appendix.

The momentum strategy in currencies produces an impressive 9.32 % return before transaction costs. However, high momentum currencies tend to have larger bid/ask spreads. The annual excess return drops to 5.42 % per annum after accounting for transaction costs. The annualized Sharpe ratio for this momentum strategy is 0.5. Both the average excess returns and the Sharpe ratios increase monotonically from low to high momentum portfolios.

[Table 13 about here.]

The first principal component of these 12 portfolios is clearly the dollar risk factor. It accounts for 67 % of the time-series variation in returns on all of the 12 currency portfolios. The second principal component is clearly a momentum factor. This represents an investment strategy that shorts low momentum and goes long in high momentum portfolios. The portfolio weights are given by:

$$w^m = \left[\begin{array}{cccccccccccc} 1.54 & 2.17 & 0.78 & 2.34 & 1.49 & -4.31 & -11.33 & -1.37 & -0.11 & 2.12 & 3.32 & 4.34 \end{array} \right].$$

However, the most interesting one from our perspective is the third one. This component represents an investment strategy that goes long in high momentum and long in high interest rate currencies, while shorting low momentum and low interest rate currencies. The portfolio weights are given by:

$$w^c = \left[\begin{array}{cccccccccccc} 6.01 & 3.55 & 4.76 & 0.05 & -2.80 & -10.35 & 0.46 & 5.89 & 5.15 & 0.45 & -4.32 & -7.84 \end{array} \right].$$

The portfolio weights increase monotonically from low to high interest rates and from low to high momentum (except for portfolio 7). Not surprisingly, this third principal component is highly correlated with HML_{FX} (.75) and with the second principal component of the carry portfolios (.80). Hence, there is common variation in exchange rates along the interest rate and momentum dimension.

For each of 12 principal components, Figure 3 plots the covariance of excess returns with that principal component against the average excess returns. The first principal component is a flat line. The second principal component does not co-vary with the carry portfolios in the right way. However, the third principal component clearly does, and it is the only one, as is apparent from the other 11 subplots. This suggests that the carry risk factor that we identify has explanatory power for other currency portfolios not sorted on interest rates. We confirm this by estimating a linear factor model on the cross-section of currency returns.

[Figure 3 about here.]

In Table 14, we estimate a linear factor model. In the first subpanel, we use all 12 portfolios as test assets. In the second subpanel, we use only the 6 carry portfolios as test assets. In the third subpanel, we use the 6 momentum portfolios as test assets. In the baseline version, the three factors are the first three principal components: the dollar factor (denoted d, the first principal component), the momentum factor (denoted m, the second principal component) and the carry factor (denoted c, the third principal component). These results are reported in the left panel. We rescaled the principal component weights so they to sum to one, hence these three factors represent excess returns on zero cost investment strategies in these 12 currency portfolios. The panel on the right uses only two factors, dropping momentum.

With all 12 test assets and 3 risk factors, the risk prices of the factors equal their means. The risk price of the carry factor is precisely estimated and highly statistically significant. The adjusted R^2 of this three-factor model is .83 and the $RMSE$ is 70 basis points. The momentum portfolios load significantly on the carry factor, and the betas vary from -.18 on portfolio 8 to .24 on portfolio 12 (high momentum). Most of these betas (not reported) are highly statistically significant. The variation in these carry risk betas is enough to account for most of the variation in returns on the momentum portfolios. In the right panel of Table 14, we report estimates of a two-factor model, without the momentum factor, on the same 12 test assets (6 carry and 6 momentum currency portfolios). The carry factor can actually account for most of the cross-sectional variation in returns on the momentum portfolios, except for the lowest momentum portfolio (portfolio 7): in the two-factor model, the $RMSE$ increases to 1.02 basis points and the adjusted R^2 drops to .68. The null that the α's are jointly zero in the two-factor model cannot be rejected at standard significance levels.

[Table 14 about here.]

We also report estimates of the three-factor and the two-factor model that are obtained by using the carry portfolios and the momentum portfolios separately. The second subpanel in Table 14 uses only the carry portfolios as test assets. The bottom subpanel uses only the momentum portfolios as test assets. So, these estimates only use 6 test assets. On the carry portfolios, the carry factor that we construct from these 12 currency portfolios actually does slightly *better* than the carry factor constructed from the 6 carry portfolios. The results in the right panel can be compared to Table 15, which reports in the separate appendix asset pricing results obtained on our original set of 6 interest rate-based currency portfolios. The RMSE drops from 96 to 84 basis points and the adjusted R^2 increases from .7 to .76. So, bringing information from momentum portfolios to bear actually improves the fit. Also, the estimated price of carry risk is 9.96 % per annum, very close to its mean of 10 % per annum. However, the key finding is in the bottom panel, when we only use the momentum portfolios as test assets: the carry risk factor is statistically significant even when controlling for the momentum factor. In fact, when we drop the momentum factor, the model still explains half of the cross-sectional variation in momentum expected returns (in terms of adjusted R^2). The risk prices that we estimate in the two-factor model are almost invariant to the test assets: in both cases, the price of carry risk is estimated to be 10 % per annum. This evidence is a major challenge for the characteristics-based explanation because it shows that covariances with this carry trade risk factor line up with returns on portfolios that are sorted on an different characteristic.

5 Conclusion

By sorting currencies on their interest rate, we identify a slope factor in currency returns, driven entirely by common exchange rate variation. The higher the currency's interest rate, the more the currency is exposed to this slope factor. This suggests a standard APT approach to explaining carry trade returns. The loadings on this slope factor line up with the average returns on the currency portfolios. We derive conditions under which a standard affine model can replicate these carry trade returns. Heterogeneity in the loadings on a common component in each country's SDF is critical. In times of heightened volatility of the common innovations to the SDF, lower interest rate currencies endogenously become more exposed to the common innovations and hence they offer insurance, because their exchange rate appreciates in case of an adverse global shock.

In addition, we can recover similar patterns in interest rates and currency returns by sorting currencies into portfolios based on their exposure to the carry trade risk factor and to a measure of global volatility in equity markets, not using any interest rate information whatsoever. This indicates that the common variation in exchange rates we have uncovered is not a statistical artifact produced by sorting the currencies on their interest rates.

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Table 1: Currency Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: All Countries						Panel II: Developed Countries				
	Spot change: Δs^j						Δs^j				
Mean	−0.97	−1.33	−1.55	−2.73	−0.99	1.88	−1.86	−2.54	−4.05	−2.11	−1.11
Std	8.04	7.29	7.41	7.42	7.74	9.16	10.12	9.71	9.24	8.92	9.20
	Forward Discount: $f^j - s^j$						$f^j - s^j$				
Mean	−3.90	−1.30	−0.15	0.94	2.55	7.78	−3.09	−1.02	0.07	1.13	3.94
Std	1.57	0.49	0.48	0.53	0.59	2.09	0.78	0.63	0.65	0.67	0.76
	Excess Return: rx^j (without b-a)						rx^j (without b-a)				
Mean	−2.92	0.02	1.40	3.66	3.54	5.90	−1.24	1.52	4.11	3.24	5.06
Std	8.22	7.36	7.46	7.53	7.85	9.26	10.20	9.75	9.35	9.01	9.30
SR	−0.36	0.00	0.19	0.49	0.45	0.64	−0.12	0.16	0.44	0.36	0.54
	Net Excess Return: rx^j_{net} (with b-a)						rx^j_{net} (with b-a)				
Mean	−1.70	−0.95	0.12	2.31	2.04	3.14	−0.11	0.46	2.71	1.98	3.35
Std	8.21	7.35	7.43	7.48	7.85	9.25	10.20	9.75	9.32	9.02	9.30
SR	−0.21	−0.13	0.02	0.31	0.26	0.34	−0.01	0.05	0.29	0.22	0.36
	High-minus-Low: $rx^j - rx^1$ (without b-a)						$rx^j - rx^1$ (without b-a)				
Mean		2.95	4.33	6.59	6.46	8.83		2.75	5.35	4.47	6.29
Std		5.36	5.54	6.65	6.34	8.95		6.42	6.44	7.38	8.70
SR		0.55	0.78	0.99	1.02	0.99		0.43	0.83	0.61	0.72
	High-minus-Low: $rx^j_{net} - rx^1_{net}$ (with b-a)						$rx^j_{net} - rx^1_{net}$ (with b-a)				
Mean		0.75	1.82	4.00	3.73	4.83		0.57	2.82	2.09	3.46
Std		5.36	5.56	6.63	6.35	8.98		6.45	6.44	7.41	8.73
SR		0.14	0.33	0.60	0.59	0.54		0.09	0.44	0.28	0.40

Notes: This table reports, for each portfolio j, the average change in log spot exchange rates Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads, the average log excess return rx^j_{net} with bid-ask spreads, and the average return on the long short strategy $rx^j_{net} - rx^1_{net}$ and $rx^j - rx^1$ (with and without bid-ask spreads). Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The portfolios are constructed by sorting currencies into six groups at time t based on the one-month forward discount (i.e nominal interest rate differential) at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rates. Portfolio 6 contains currencies with the highest interest rates. Panel I uses all countries, panel II focuses on developed countries. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 2: Principal Components

Panel I: All Countries						
Portfolio	1	2	3	4	5	6
1	0.43	0.41	−0.18	0.31	0.72	0.03
2	0.39	0.26	−0.14	−0.02	−0.44	0.75
3	0.39	0.26	−0.46	−0.38	−0.31	−0.57
4	0.38	0.05	0.72	−0.56	0.16	−0.01
5	0.42	−0.11	0.38	0.66	−0.37	−0.31
6	0.43	−0.82	−0.28	−0.10	0.18	0.11
% Var.	70.07	12.25	6.18	4.51	3.76	3.23
Panel II: Developed Countries						
Portfolio	1	2	3	4	5	
1	0.48	0.56	0.60	0.23	0.20	
2	0.47	0.29	−0.66	−0.32	0.40	
3	0.46	0.05	−0.30	0.36	−0.76	
4	0.42	−0.34	0.34	−0.72	−0.25	
5	0.41	−0.69	0.02	0.44	0.40	
% Var	79.06	9.33	4.73	3.58	3.30	

Notes: This table reports the principal component coefficients of the currency portfolios. In each panel, the last row reports (in %) the share of the total variance explained by each common factor. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 3: Asset Pricing - US Investor

Panel I: Risk Prices

	All Countries							Developed Countries						
	$\lambda_{HML_{FX}}$	λ_{RX}	$b_{HML_{FX}}$	b_{RX}	R^2	$RMSE$	χ^2	$\lambda_{HML_{FX}}$	λ_{RX}	$b_{HML_{FX}}$	b_{RX}	R^2	$RMSE$	χ^2
GMM_1	5.46	1.35	0.59	0.26	69.28	0.95		3.56	2.24	0.43	0.32	71.06	0.61	
	[2.34]	[1.68]	[0.25]	[0.32]			13.83	[2.19]	[2.02]	[0.24]	[0.24]			41.06
GMM_2	4.88	0.58	0.52	0.12	47.89	1.24		3.78	3.03	0.46	0.42	20.41	1.00	
	[2.23]	[1.63]	[0.24]	[0.31]			15.42	[2.14]	[1.95]	[0.23]	[0.23]			44.36
FMB	5.46	1.35	0.58	0.26	69.28	0.95		3.56	2.24	0.42	0.32	71.06	0.61	
	[1.82]	[1.34]	[0.19]	[0.25]			13.02	[1.80]	[1.71]	[0.20]	[0.20]			41.34
	(1.83)	(1.34)	(0.20)	(0.25)			14.32	(1.80)	(1.71)	(0.20)	(0.20)			42.35
$Mean$	**5.37**	**1.36**						**3.44**	**2.24**					

Panel II: Factor Betas

	All Countries						Developed Countries					
$Portfolio$	α_0^j	$\beta_{HML_{FX}}^j$	β_{RX}^j	R^2	$\chi^2(\alpha)$	$p-value$	α_0^j	$\beta_{HML_{FX}}^j$	β_{RX}^j	R^2	$\chi^2(\alpha)$	$p-value$
1	-0.56	-0.39	1.06	91.36			0.00	-0.50	1.00	94.95		
	[0.52]	[0.02]	[0.03]				[0.48]	[0.02]	[0.02]			
2	-1.21	-0.13	0.97	78.54			-0.90	-0.11	1.02	82.38		
	[0.76]	[0.03]	[0.05]				[0.81]	[0.04]	[0.04]			
3	-0.13	-0.12	0.95	73.73			1.01	-0.02	1.02	85.22		
	[0.82]	[0.03]	[0.04]				[0.83]	[0.03]	[0.03]			
4	1.62	-0.02	0.93	68.86			-0.12	0.13	0.97	81.43		
	[0.86]	[0.04]	[0.06]				[0.85]	[0.04]	[0.04]			
5	0.84	0.05	1.03	76.37			0.00	0.50	1.00	93.87		
	[0.80]	[0.04]	[0.05]				[0.48]	[0.02]	[0.02]			
6	-0.56	0.61	1.06	93.03								
	[0.52]	[0.02]	[0.03]									
All					10.11	0.12					2.61	0.76

Notes: The panel on the left reports results for all countries. The panel on the right reports results for the developed countries. Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. Excess returns used as test assets and risk factors take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), p. 234). Data are monthly, from Barclays and Reuters in Datastream. The sample period is 11/1983 - 03/2008. The alphas are annualized and in percentage points.

Table 4: Conditional Betas - US Investor

	All Countries			Developed Countries		
Portfolio	$\beta^j_{HML_{FX}}$	β^j_{RX}	R^2	$\beta^j_{HML_{FX}}$	β^j_{RX}	R^2
1	0.37	−1.03	89.73	0.49	−0.98	94.59
	[0.02]	[0.03]		[0.02]	[0.02]	
2	0.13	−0.96	78.08	0.11	−1.01	81.54
	[0.03]	[0.05]		[0.05]	[0.04]	
3	0.12	−0.94	72.78	0.02	−1.00	84.89
	[0.03]	[0.04]		[0.03]	[0.03]	
4	0.02	−0.92	67.25	−0.12	−0.95	80.10
	[0.04]	[0.06]		[0.04]	[0.04]	
5	−0.05	−1.02	75.81	−0.50	−0.98	92.87
	[0.04]	[0.05]		[0.02]	[0.02]	
6	−0.62	−1.02	89.60			
	[0.02]	[0.04]				

Notes: The panel on the left reports results for all countries. The panel on the right reports results for the developed countries. The table reports OLS estimates of the factor betas obtained by regressing changes in log spot exchange rates Δs^j_{t+1} on the factors. R^2s are reported in percentage points. Data are monthly, from Barclays and Reuters in Datastream. The sample period is 11/1983 - 03/2008. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991).

Table 5: Asset Pricing - US Investor - Principal Components

	All Countries							Developed Countries						
Panel I: Factor Prices and Loadings	λ_c	λ_d	b_c	b_d	R^2	$RMSE$	χ^2	λ_2	λ_1	b_c	b_d	R^2	$RMSE$	χ^2
GMM_1	7.42	1.37	0.40	0.26	68.69	0.96		2.20	2.17	0.72	0.25	70.75	0.61	
	[3.12]	[1.65]	[0.17]	[0.31]			12.92	[1.22]	[2.02]	[0.40]	[0.23]			51.15
GMM_2	6.23	0.54	0.34	0.10	43.12	1.30		2.63	2.90	0.86	0.34	24.08	0.98	
	[2.86]	[1.60]	[0.15]	[0.30]			15.21	[1.17]	[1.94]	[0.38]	[0.23]			57.14
FMB	7.42	1.37	0.40	0.26	68.72	0.96		2.20	2.17	0.72	0.25	70.75	0.61	
	[2.52]	[1.35]	[0.14]	[0.25]			11.25	[1.02]	[1.72]	[0.33]	[0.20]			41.67
	[2.52]	[1.35]	[0.14]	[0.25]			12.37	[1.02]	[1.72]	[0.33]	[0.20]			42.64
$Mean$	**7.42**	**1.37**						**2.20**	**2.17**					

	All Countries						Developed Countries					
Panel II: Factor Betas — $Portfolio$	$\alpha_0^j(\%)$	β_c^j	β_d^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$	$\alpha_0^j(\%)$	β_d^j	β_c^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	−0.99	−0.23	1.06	85.69			−0.21	−0.72	1.07	91.14		
	[0.72]	[0.02]	[0.04]				[0.64]	[0.05]	[0.02]			
2	−0.85	−0.14	0.96	81.38			−0.43	−0.38	1.04	85.94		
	[0.69]	[0.02]	[0.04]				[0.72]	[0.07]	[0.03]			
3	0.31	−0.14	0.94	76.89			1.15	−0.07	1.02	85.59		
	[0.84]	[0.02]	[0.04]				[0.81]	[0.07]	[0.03]			
4	1.72	−0.03	0.92	68.16			−0.54	0.44	0.94	85.14		
	[0.86]	[0.03]	[0.06]				[0.77]	[0.06]	[0.03]			
5	0.64	0.06	1.03	77.41			0.01	0.89	0.92	93.64		
	[0.80]	[0.03]	[0.04]				[0.49]	[0.04]	[0.02]			
6	−0.64	0.45	1.06	96.83								
	[0.34]	[0.01]	[0.02]									
All					6.90	0.33					2.40	0.79

Notes: The factors are the first and the second principal components (denoted d, for the "dollar" factor, and c, for the "carry" factor, respectively). The panel on the left reports results for all countries. The panel on the right reports results for the developed countries. Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. Excess returns used as test assets and risk factors take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), p. 234). Data are monthly, from Barclays and Reuters in Datastream. The sample period is 11/1983 - 03/2008. The alphas are annualized and in percentage points.

Table 6: Calibration

Panel I: Moments		
Moment		*Value*
Mean real interest rate	$E[r]$	1.2%
Std real interest rate	$Std[r]$	.2%
Autocorr. real interest rate	$\rho[r]$	.66
Mean volatility log SDF	$E[\sigma_t(m_{t+1})]$	.35
Std volatility log SDF	$Std\left[\sigma_t(m_{t+1})\right]$	.04
Std changes in real exchange rates	$Std[\Delta q_{t+1}]$	10%
UIP slope coefficient	β_{UIP}	-1

Panel II: Real SDF Parameters						
λ	γ	τ	δ	ϕ	θ	$\sigma(\%)$
1.01	0.68	8.17	14.75	0.96	0.00	0.19

Panel III: Inflation Moments	
Moment	*Value*
Mean World inflation rate	3%
Std World inflation rate	2.1%
Autocor. World Inflation	0.87
Mean Country Inflation Rate	3%
Std Country Inflation Rate	2.4%
Autocor. Country Inflation	0.7
Std Country-Specific component	10%
Autocor. Country-Specific component	0.5

Panel IV: Inflation Parameters						
$\sigma^{w\$}(\%)$	ρ^{w}	$\overline{\pi^{w}}(\%)$	$\sigma^{\$}(\%)$	$\rho^{\$}$	$\overline{\pi}(\%)$	μ
0.03	0.98	0.25	0.43	0.90	0.25	0.16

This table reports the annualized moments of the real variables (Panel I), as well as the corresponding parameters used in calibration (Panel II). The moments in Panel I are: mean, standard deviation and autocorrelation of the (nominal) risk-free rate, mean and variance of the conditional variance of the real SDF, average real exchange rate volatility and the coefficient from the regression of the exchange rate change on the forward discount, both real (the latter two moments are averages across all foreign countries). All countries share the same parameters except for δ. The parameters δ^i are linearly spaced on the interval $[0.5\delta, 1.5\delta]$. Panel III reports the moments of the common and country-specific inflation processes, and panel IV - the corresponding inflation process parameters (see appendix for details).

Table 7: Currency Portfolios - Simulated data

Portfolio	1	2	3	4	5	6
			Spot change: Δs^j			
Mean	0.87	0.69	0.37	0.31	0.20	−0.09
Std	9.62	8.74	7.89	7.01	7.70	8.81
			Forward Discount: $f^j - s^j$			
Mean	−2.23	−1.38	−0.65	0.08	0.82	1.86
Std	0.54	0.39	0.23	0.17	0.29	0.51
			Excess Return: rx^j			
Mean	−3.10	−2.08	−1.02	−0.23	0.62	1.95
Std	9.65	8.79	7.92	7.03	7.72	8.84
SR	−0.32	−0.24	−0.13	−0.03	0.08	0.22
			High-minus-Low: $rx^j - rx^1$			
Mean		1.02	2.08	2.87	3.72	5.05
Std		4.63	5.72	7.20	9.09	11.42
SR		0.22	0.36	0.40	0.41	0.44

Risk Prices

	λ_{RX}	$\lambda_{HML_{FX}}$	b_{RX}	$b_{HML_{FX}}$	R^2	$RMSE$	χ^2
GMM_1	−0.64	5.05	−0.08	0.32	99.73	0.08	
	[0.34]	[0.56]	[0.06]	[0.04]			79.06
GMM_2	−0.64	5.03	−0.08	0.32	99.73	0.08	
	[0.34]	[0.55]	[0.06]	[0.04]			79.07
FMB	−0.64	5.05	−0.08	0.32	99.65	0.08	
	[0.35]	[0.57]	[0.06]	[0.04]			77.45
	(0.35)	(0.57)	(0.06)	(0.04)			77.99
Mean	**-0.6**	**5.05**					

Notes: This table reports, for each portfolio j, the average change in log spot exchange rates Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j and the average return on the long short strategy $rx^j - rx^1$. Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized monthly values and reported in percentage points. For excess returns, the table also reports annualized Sharpe ratios. The portfolios are constructed by sorting currencies into six groups at time t based on the one-year forward discount (i.e nominal interest rate differential) at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rates. Portfolio 6 contains currencies with the highest interest rates. All data are simulated from the model.

Table 8: Asset Pricing - Equity Volatility Risk Factor (Innovations)

Panel I: Factor Betas									
	All Countries			Developed Countries			Model		
Portfolio	$\beta^j_{Vol_{Equity}}$	β^j_{RX}	R^2	$\beta^j_{Vol_{Equity}}$	β^j_{RX}	R^2	$\beta^j_{Vol_{Equity}}$	β^j_{RX}	R^2
1	0.41	1.07	74.54	0.40	1.06	77.77	2.22	1.10	38.15
	[0.12]	[0.05]		[0.14]	[0.04]		[0.96]	[0.05]	
2	0.26	0.97	76.61	0.14	1.04	81.42	1.96	1.09	54.25
	[0.08]	[0.05]		[0.12]	[0.04]		[0.68]	[0.03]	
3	0.10	0.95	71.87	0.28	1.02	85.50	0.71	1.05	77.97
	[0.11]	[0.05]		[0.11]	[0.03]		[0.42]	[0.02]	
4	0.15	0.93	68.91	−0.21	0.95	80.14	−0.21	0.87	84.21
	[0.09]	[0.06]		[0.14]	[0.04]		[0.32]	[0.01]	
5	−0.18	1.03	76.25	−0.62	0.93	73.18	−1.45	0.98	56.42
	[0.10]	[0.05]		[0.14]	[0.05]		[0.60]	[0.03]	
6	−0.74	1.05	60.41				−3.22	0.90	19.91
	[0.16]	[0.07]					[1.28]	[0.06]	
Panel II: Risk Price									
	All Countries			Developed Countries			Model		
	$\lambda_{Vol_{Equity}}$	λ_{RX}	R^2	$\lambda_{Vol_{Equity}}$	λ_{RX}	R^2	$\lambda_{Vol_{Equity}}$	λ_{RX}	R^2
FMB	−4.32	1.33	63.64	−2.78	2.23	30.63	−1.69	−0.97	96.94
	[1.48]	[1.34]		[1.54]	[1.71]		[0.78]	[1.33]	
	(1.78)	(1.34)		(1.67)	(1.71)		(1.13)	(1.33)	

Notes: The panel on the left reports empirical results using actual data for all countries. The panel on the right reports results for the simulated data from the calibrated model. Panel I reports results the Fama-MacBeth cross-sectional regression. Market prices of risk λ, the adjusted R^2 are reported in percentage points. Excess returns used as test assets and risk factors take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991).

Table 9: HML_{FX}-Beta-Sorted Currency Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: All Countries						Panel II: Developed Countries				
	Spot change: Δs^j						Spot change: Δs^j				
Mean	−2.11	−1.80	−1.25	−1.97	−1.80	−0.14	−1.95	−2.33	−1.88	−2.20	0.28
Std	8.74	7.86	7.28	6.75	8.06	7.45	8.79	8.20	8.15	7.83	7.58
	Discount: $f^j - s^j$						Discount: $f^j - s^j$				
Mean	−1.45	−0.38	0.75	0.93	1.48	3.18	−1.46	−0.51	0.98	1.28	4.15
Std	0.77	0.56	1.23	0.64	0.80	1.26	0.69	0.60	0.71	0.82	1.65
	Excess Return: rx^j (without b-a)						Excess Return: rx^j (without b-a)				
Mean	0.66	1.42	2.00	2.90	3.29	3.32	0.48	1.82	2.86	3.48	3.87
Std	8.88	7.87	7.33	6.71	8.07	7.48	8.87	8.24	8.20	7.79	7.97
SR	0.07	0.18	0.27	0.43	0.41	0.44	0.05	0.22	0.35	0.45	0.49
	High-minus-Low: $rx^j - rx^1$ (without b-a)						High-minus-Low: $rx^j - rx^1$ (without b-a)				
Mean		0.76	1.34	2.24	2.63	2.66		1.34	2.38	2.99	3.38
Std		5.24	6.34	7.43	8.88	9.23		5.34	5.96	7.96	9.02
SR		0.15	0.21	0.30	0.30	0.29		0.25	0.40	0.38	0.38
	Pre-formation β's						Pre-formation β's				
Mean	−0.40	−0.24	−0.15	0.01	0.21	0.57	−0.39	−0.23	−0.04	0.15	0.46
Std	0.29	0.23	0.24	0.26	0.43	0.41	0.26	0.25	0.35	0.45	0.41
	Post-formation β's						Post-formation β's				
Estimate	−0.31	−0.20	−0.14	0.01	0.13	0.28	−0.26	−0.15	0.04	0.08	0.30
s.e	[0.04]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]

Notes: This table reports, for each portfolio j, the average change in the log spot exchange rate Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads and the average returns on the long short strategy $rx^j - rx^1$. The left panel uses our sample of developed and emerging countries. The right panel uses our sample of developed countries. Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. Portfolios are constructed by sorting currencies into six groups at time t based on slope coefficients β^i_t. Each β^i_t is obtained by regressing currency i log excess return rx^i on HML_{FX} on a 36-period moving window that ends in period $t-1$. The first portfolio contains currencies with the lowest βs. The last portfolio contains currencies with the highest βs. We report the average pre-formation beta for each portfolio. The last panel reports the post-formation betas obtained by regressing realized log excess returns on portfolio j on HML_{FX} and RX_{FX}. We only report the HML_{FX} betas. The standard errors are reported in brackets. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 10: Volatility Beta-Sorted Currency Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: All Countries						Panel II: Developed Countries				
	Spot change: Δs^j						Spot change: Δs^j				
Mean	−1.04	−0.93	−0.74	−2.23	−2.43	−0.89	−0.33	−1.44	−0.70	−2.41	−1.34
Std	8.42	8.19	7.67	7.65	7.80	6.45	8.77	8.63	7.92	6.74	7.32
	Discount: $f^j - s^j$						Discount: $f^j - s^j$				
Mean	0.01	0.23	0.84	1.15	1.80	2.32	−0.11	0.21	0.86	0.64	3.42
Std	0.71	0.78	0.86	0.81	1.00	1.32	0.69	0.83	0.86	0.67	1.78
	Excess Return: rx^j (without b-a)						Excess Return: rx^j (without b-a)				
Mean	1.05	1.16	1.58	3.37	4.23	3.21	0.22	1.65	1.57	3.05	4.75
Std	8.45	8.20	7.63	7.57	7.87	6.53	8.64	7.92	6.75	7.88	
SR	0.12	0.14	0.21	0.45	0.54	0.49	0.02	0.19	0.20	0.45	0.60
	High-minus-Low: $rx^j - rx^1$ (without b-a)						High-minus-Low: $rx^j - rx^1$ (without b-a)				
Mean		0.11	0.53	2.32	3.18	2.16		1.43	1.35	2.83	4.53
Std		5.67	6.19	6.47	6.62	7.50		5.02	5.39	6.29	8.23
SR		0.02	0.09	0.36	0.48	0.29		0.29	0.25	0.45	0.55
	Pre-formation β's						Pre-formation β's				
Mean	−1.78	−1.05	−0.70	−0.33	0.10	1.50	−2.17	−1.37	−0.89	−0.16	1.19
Std	1.65	1.26	1.10	1.07	1.07	1.14	1.90	1.61	1.31	0.70	0.80
	Post-formation β's						Post-formation β's				
Estimate	0.22	−0.06	−0.05	0.13	0.00	−0.24	0.25	0.06	−0.05	−0.05	−0.20
s.e	[0.18]	[0.10]	[0.22]	[0.12]	[0.11]	[0.19]	[0.15]	[0.18]	[0.10]	[0.18]	[0.19]
	Post-formation HML_{FX} β's						Post-formation HML_{FX} β's				
Estimate	−0.38	−0.06	−0.05	0.01	0.10	0.37	−0.30	−0.12	−0.06	0.01	0.46
s.e	[0.02]	[0.03]	[0.03]	[0.02]	[0.02]	[0.06]	[0.02]	[0.03]	[0.02]	[0.03]	[0.02]

Notes: This table reports, for each portfolio j, the average change in the log spot exchange rate Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads and the average returns on the long short strategy $rx^j - rx^1$. The left panel uses our sample of developed and emerging countries. The right panel uses our sample of developed countries. Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. Portfolios are constructed by sorting currencies into five or six groups at time t based on slope coefficients β^i_t. Each β^i_t is obtained by regressing currency i log change in exchange rate Δs^i on Vol_{Equity} on a 36-period moving window that ends in period $t-1$. The first portfolio contains currencies with the lowest βs. The last portfolio contains currencies with the highest βs. We report the average pre-formation beta for each portfolio. The last two panels report the post-formation betas obtained by regressing realized log excess returns on portfolio j on either HML_{FX} and RX_{FX}, or Vol_{Equity} and RX_{FX}. We only report the Vol_{Equity} and HML_{FX} betas. The standard errors are reported in brackets. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 11: Currency Portfolios - Splitting Samples

Portfolio	1	2	3	4	1	2	3	4
	Panel I: First Sub-sample				Panel II: Second Sub-sample			
	Spot change: Δs^j				Δs^j			
Mean	−1.17	−0.91	−1.37	−0.03	−1.33	−3.83	−1.23	1.76
Std	6.74	5.61	7.74	9.33	9.02	8.90	8.42	8.69
	Forward Discount: $f^j - s^j$				$f^j - s^j$			
Mean	−3.69	−0.33	1.37	5.17	−2.15	−0.15	2.00	7.25
Std	2.07	0.41	0.49	1.35	0.62	0.62	0.67	1.46
	Excess Return: rx^j (without b-a)				rx^j (without b-a)			
Mean	−2.53	0.58	2.75	5.20	−0.83	3.68	3.24	5.49
Std	6.97	5.63	7.78	9.36	9.10	8.97	8.49	8.76
SR	−0.36	0.10	0.35	0.56	−0.09	0.41	0.38	0.63
	Net Excess Return: rx^j_{net} (with b-a)				rx^j_{net} (with b-a)			
Mean	−1.21	−0.48	1.55	3.30	0.10	2.40	1.53	2.83
Std	6.94	5.64	7.75	9.39	9.11	8.93	8.51	8.72
SR	−0.17	−0.09	0.20	0.35	0.01	0.27	0.18	0.32

Notes: This table reports, for each portfolio j, the average change in log spot exchange rates Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads, the average log excess return rx^j_{net} with bid-ask spreads, and the average return on the long short strategy $rx^j_{net} - rx^1_{net}$ and $rx^j - rx^1$ (with and without bid-ask spreads). Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The portfolios are constructed by sorting currencies into four groups at time t based on the one-month forward discount (i.e nominal interest rate differential) at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rates. Portfolio 4 contains currencies with the highest interest rates. Panel I uses the first sub-sample of countries, panel II uses the second sub-sample. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 5/1984 - 03/2008.

Table 12: Asset Pricing - Splitting Samples

			Panel I: Risk Prices				
	$\lambda_{HML_{FX}}$	λ_{RX}	$b_{HML_{FX}}$	b_{RX}	R^2	$RMSE$	χ^2
FMB	9.88	1.72	1.24	0.38	94.20	0.40	
	[3.58]	[1.70]	[0.44]	[0.25]			67.76
	(3.75)	(1.72)	(0.46)	(0.25)			70.84
$Mean$	2.95	2.30					
			Panel II: Factor Betas				
$Portfolio$	α_0^j	$\beta_{HML_{FX}}^j$	β_{RX}^j	R^2	$\chi^2(\alpha)$	$p-value$	
1	-1.79	-0.21	0.68	68.83			
	[0.91]	[0.03]	[0.0]4				
2	-1.27	-0.05	0.52	52.40			
	[0.92]	[0.03]	[0.05]				
3	0.19	0.03	0.76	58.43			
	[1.08]	[0.05]	[0.06]				
4	1.44	0.29	0.85	53.98			
	[1.48]	[0.06]	[0.08]				
All					6.67	0.15	

Notes: The panel on the left reports results for all countries. The panel on the right reports results for the developed countries. Panel I reports results the Fama-MacBeth cross-sectional regression. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. Excess returns used as test assets and risk factors take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). The χ^2 test statistic $\alpha' V_{\alpha}^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), p. 234). Data are monthly, from Barclays and Reuters in Datastream. The sample period is 5/1984 - 03/2008. The alphas are annualized and in percentage points.

Table 13: Currency Momentum Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: All Countries						Panel II: Developed Countries				
	Spot change: Δs^j						Δs^j				
Mean	4.48	0.17	−0.49	−2.12	−2.22	−1.92	−0.37	−1.02	−2.27	−3.83	−1.69
Std	10.28	8.34	8.24	7.67	8.20	8.35	9.47	9.85	9.92	9.66	8.79
	Forward Discount: $f^j - s^j$						$f^j - s^j$				
Mean	0.47	0.70	1.39	1.32	1.86	3.39	0.16	0.42	0.71	0.86	1.54
Std	1.92	0.80	1.69	0.79	0.83	1.26	1.04	0.98	0.94	0.78	0.78
	Excess Return: rx^j (without b-a)						rx^j (without b-a)				
Mean	−4.01	0.53	1.88	3.44	4.08	5.31	0.53	1.44	2.98	4.69	3.23
Std	10.30	8.38	8.25	7.77	8.31	8.42	9.55	9.92	10.03	9.74	8.93
SR	−0.39	0.06	0.23	0.44	0.49	0.63	0.06	0.15	0.30	0.48	0.36
	Net Excess Return: rx^j_{net} (with b-a)						rx^j_{net} (with b-a)				
Mean	−1.98	−0.83	0.43	2.05	2.73	3.44	1.88	0.11	1.64	3.37	1.77
Std	10.26	8.36	8.21	7.74	8.28	8.42	9.56	9.90	10.04	9.73	8.92
SR	−0.19	−0.10	0.05	0.26	0.33	0.41	0.20	0.01	0.16	0.35	0.20
	High-minus-Low: $rx^j - rx^1$ (without b-a)						$rx^j - rx^1$ (without b-a)				
Mean		4.54	5.90	7.45	8.09	9.32		0.91	2.45	4.16	2.70
Std		8.69	8.97	9.36	10.00	10.79		7.14	7.53	8.32	8.63
SR		0.52	0.66	0.80	0.81	0.86		0.13	0.33	0.50	0.31
	High-minus-Low: $rx^j_{net} - rx^1_{net}$ (with b-a)						$rx^j_{net} - rx^1_{net}$ (with b-a)				
Mean		1.15	2.41	4.03	4.71	5.42		−1.76	−0.24	1.49	−0.11
Std		8.66	8.91	9.34	9.98	10.75		7.13	7.53	8.31	8.61
SR		0.13	0.27	0.43	0.47	0.50		−0.25	−0.03	0.18	−0.01

Notes: This table reports, for each portfolio j, the average change in log spot exchange rates Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads, the average log excess return rx^j_{net} with bid-ask spreads, and the average return on the long short strategy $rx^j_{net} - rx^1_{net}$ and $rx^j - rx^1$ (with and without bid-ask spreads). Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The portfolios are constructed by sorting currencies into six groups at time t based on the return realized at the end of period $t-1$. Portfolio 1 contains currencies with the lowest returns. Portfolio 6 contains currencies with the highest returns. Panel I uses all countries, panel II uses developed countries only. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 14: Asset Pricing - US Investor - Carry and Momentum Currency Portfolios

	All Countries															
	3 Factors									2 Factors						
	λ_c	λ_m	λ_d	b_c	b_m	b_d	R^2	$RMSE$	χ^2	λ_c	λ_d	b_c	b_d	R^2	$RMSE$	χ^2
	All 12 Portfolios															
FMB	10.00	3.62	1.51	0.47	0.21	0.28	83.23	0.70		10.00	1.51	0.47	0.28	68.13	1.02	
	[2.70]	[2.44]	[1.37]	[0.13]	[0.14]	[0.25]			49.82	[2.70]	[1.37]	[0.13]	[0.25]			39.19
	(2.70)	(2.44)	(1.37)	(0.13)	(0.14)	(0.25)			54.45	(2.70)	(1.37)	(0.13)	(0.25)			43.55
$Mean$	**10.00**	**3.62**	**1.51**							**10.00**	**1.51**					
	6 Carry Portfolios															
FMB	13.02	5.63	1.34	0.61	0.32	0.25	75.39	0.74		9.96	1.51	0.47	0.28	76.13	0.84	
	[4.22]	[5.54]	[1.38]	[0.20]	[0.32]	[0.25]			14.00	[3.30]	[1.38]	[0.16]	[0.25]			17.89
	(4.34)	(5.76)	(1.38)	(0.20)	(0.33)	(0.25)			17.38	(3.33)	(1.38)	(0.16)	(0.25)			20.06
$Mean$	**10.00**	**3.62**	**1.51**							**10.00**	**1.51**					
	6 Momentum Portfolios															
FMB	6.65	4.76	1.63	0.31	0.27	0.30	96.01	0.29		10.05	1.50	0.47	0.27	50.98	1.18	
	[3.61]	[2.61]	[1.37]	[0.17]	[0.15]	[0.25]			85.93	[3.68]	[1.38]	[0.17]	[0.25]			38.76
	(3.64)	(2.61)	(1.38)	(0.17)	(0.15)	(0.25)			86.60	(3.72)	(1.38)	(0.18)	(0.25)			41.49
$Mean$	**10.00**	**3.62**	**1.51**							**10.00**	**1.51**					

Notes: The momentum portfolios are constructed by sorting currencies into six groups at time t based on the return realized at the end of period $t-1$. Portfolio 1 contains currencies with the lowest returns. Portfolio 6 contains currencies with the highest returns. The risk factors are the third (the carry factor denoted c), the second (the momentum factor denoted m) and the first principal component (the dollar factor denoted d) of the 12 currency portfolios. The test assets are the six carry and the six momentum currency portfolios. The first subpanel reports results Fama-McBeth asset pricing procedures using all 12 test assets. The second subpanel uses only the 6 carry trade portfolios as test assets. The third subpanel uses only the 6 momentum portfolios as test assets. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. Excess returns used as test assets and risk factors take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. R^2s and p-values are reported in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), p. 234). Data are monthly, from Barclays and Reuters in Datastream. The sample period is 11/1983 - 03/2008.

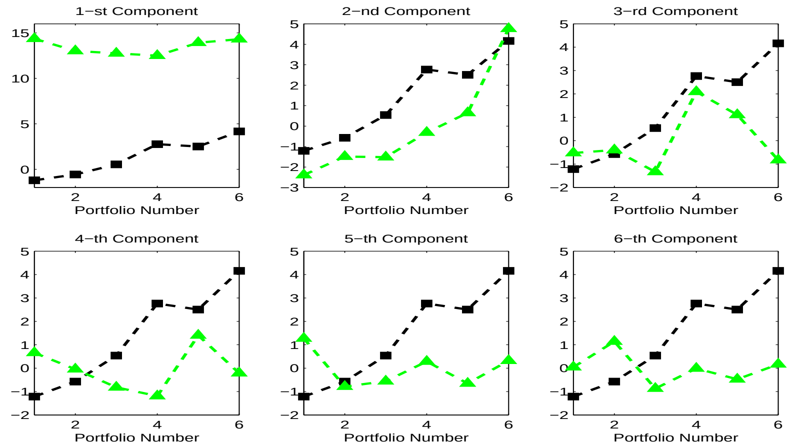

Figure 1: Mean Excess Returns and Covariances between Excess Returns and Principal Components - Developed and Emerging Countries

Each panel corresponds to a principal component. The upper left panel uses the first principal component. The black squares represent the average currency excess returns for the six portfolios. Each green triangle represents a covariance between a given principal component and a given currency portfolio. The covariances are rescaled (multiplied by 15,000). The average excess returns are annualized (multiplied by 12) and reported in percentage points. The sample is 11/1983 - 03/2008.

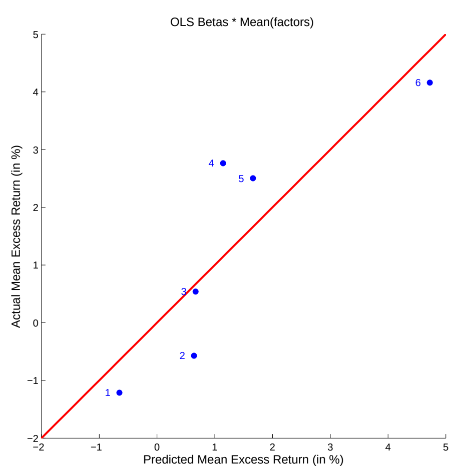

Figure 2: Predicted against Actual Excess Returns (RX and HML_{FX}).

This figure plots realized average excess returns on the vertical axis against predicted average excess returns on the horizontal axis. We regress each actual excess return on a constant and the risk factors RX and HML_{FX} to obtain the slope coefficient β^j. Each predicted excess returns is obtained using the OLS estimate of β^j times the sample mean of the factors. All returns are annualized. The date are monthly. The sample is 11/1983 - 03/2008.

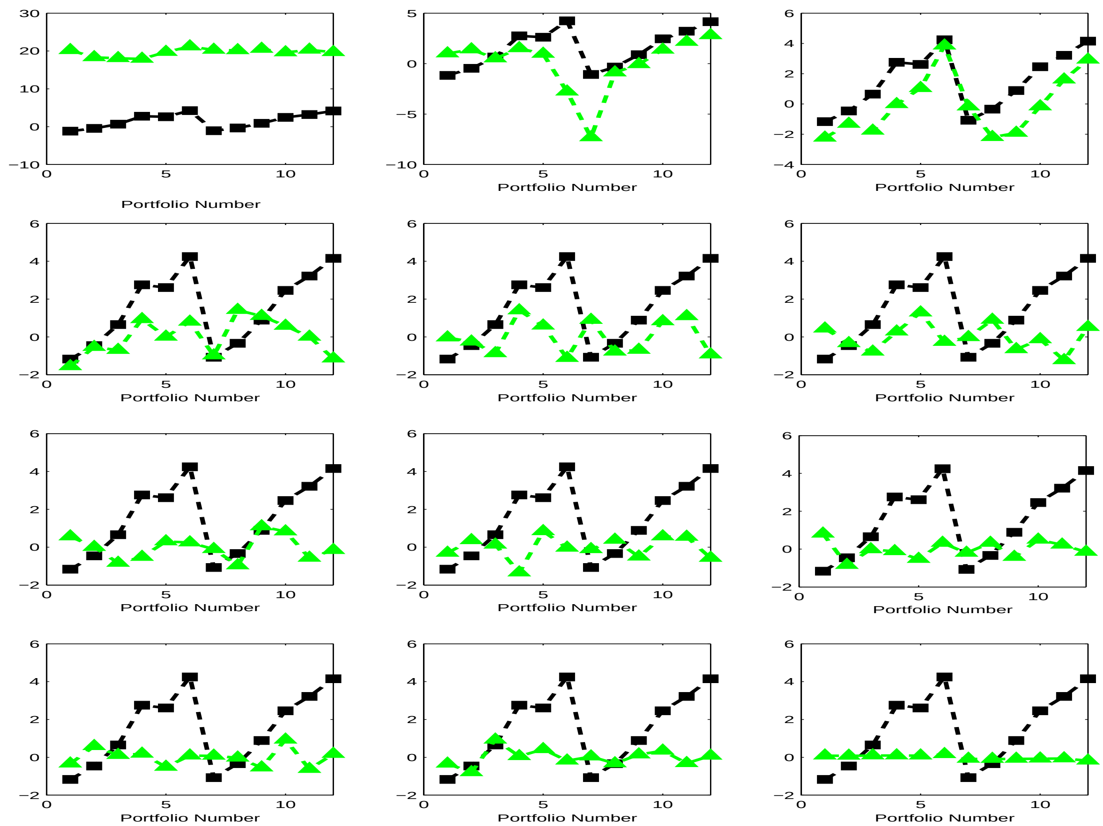

Figure 3: Mean Excess Returns and Covariances between Excess Returns and Principal Components - Carry and Momentum Currency Portfolios

Each panel corresponds to a principal component of the 6 carry trade portfolios (1-6) and the 6 momentum portfolios (7-12). The upper left panel uses the first principal component. The lower right panel uses the 12-th principal component. The black squares represent the average currency excess returns for the twelve portfolios. Each green triangle represents a covariance between a given principal component and a given currency portfolio. The covariances are rescaled (multiplied by 15,000). The average excess returns are annualized (multiplied by 12) and reported in percentage points. The sample is 11/1983 - 03/2008.