Common Risk Factors in Currency Markets*

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Abstract

We show that risk premia in currency markets are large and time-varying. Currency excess returns are highly predictable, more than stock returns, and about as much as bond returns. In addition, these predicted excess returns are strongly counter-cyclical. The average excess returns on low interest rate currencies are about 5 percent per annum smaller than those on high interest rate currencies after accounting for transaction costs. We show that a single return-based factor, the return on the highest minus the return on the lowest interest rate currency portfolios, explains the cross-sectional variation in average currency excess returns from low to high interest rate currencies. In a no-arbitrage model of exchange rates, we show that by building currency portfolio returns, we extract the common innovation to the stochastic discount factor in different countries. A reasonably calibrated version of our model can match the carry trade risk premium if low interest rates currencies are more exposed to this common innovation when the price of risk is high.

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In this paper, we demonstrate that currency risk premia are a robust feature of the data, even after accounting for transaction costs. We show that currencies' risk premia are determined by their exposure to a single, global risk factor, and that interest rates measure currencies' exposure to this factor. This global risk factor explains most of the cross-sectional variation in average excess returns between high and low interest rate currencies. We show that by investing in high interest rate currencies and borrowing in low interest rate currencies, US investors load up on global risk, especially during "bad times". After accounting for the covariance with this risk factor, there are no significant anomalous or unexplained excess returns in currency markets. In addition, we show that most of the time-series variation in currency risk premia is explained by the average interest rate difference between the US and foreign currencies, not the currency-specific interest rate difference. The average interest rate difference is highly counter-cyclical, and hence so are currency risk premia. We can replicate our main findings in a no-arbitrage model of exchange rates with two factors, a country-specific factor and a global factor, but only if low interest rate currencies are more exposed to global risk in bad times. Heterogeneity in exposure to country-specific risk cannot explain the carry trade returns.

We identify this common risk factor in the data by building portfolios of currencies. As in Lustig and Verdelhan (2007), we sort currencies on their forward discounts and allocate them to six portfolios. Forward discounts are the difference between forward rates and spot rates. Since covered interest rate parity typically holds, forward discounts equal the interest rate difference between the two currencies. As a result, the first portfolio contains the lowest interest rate currencies while the last portfolio contains the highest interest rate currencies. Unlike Lustig and Verdelhan (2007), we only use spot and forward exchange rates to compute returns. These contracts are easily tradable, and subject to minimal counterparty risk. As a consequence, our main sample comprises 37 currencies. We account for bid-ask spreads that investors incur when they trade these spot and forward contracts.

Risk premia in currency markets are large and time-varying. 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. Between the end of 1983 and the beginning of 2008, US investors earn an annualized log excess return of 4.8 percent by buying one-month forward contracts for currencies in the last portfolio and by selling forward contracts for currencies in the first portfolio. The annualized Sharpe ratio on such a strategy is .54. These findings are robust. We find similar results when we limit the sample to developed currencies, and when we take the perspective of investors in other countries. In this paper, we investigate the cross-sectional and time-series properties of these currency excess returns.

There is far more predictability in currency portfolio returns that in the returns on individual currencies. We show that the average forward discount rate is a better predictor than the forward discounts for individual currency portfolios. This result echoes Cochrane and Piazzesi (2005)'s finding that a linear combination of forward rates does better in predicting excess returns on bonds. Expected excess returns on portfolios with medium to high interest rates co-move negatively with the US business cycle as measured by industrial production or payroll help wanted indices, and they co-move positively with the term and default premia as well as the option-implied volatility index VIX. Since forecasted excess returns on high interest rate portfolios are strongly counter-cyclical and increase in times of crisis, this evidence is consistent with the view that trading strategies in currency markets earn average excess returns in compensation for exposure to macroeconomic risk. In fact, we find that US industrial production growth has predictive power for currency excess returns even when controlling for forward discounts. In recent work, Duffee (2008) and Ludvigson and Ng (2008) report a similar finding for the bond market. Currency risk premia are very similar to bond risk premia.

In the data, the first two principal components of the currency portfolio returns account for most of the time series variation in returns. The first principal component is 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 very close to the return on a zero-cost strategy that goes long in the last portfolio and short in the first portfolio. We label this excess return the carry trade risk factor HML, for high interest rate minus low interest rate currencies. The carry trade risk factor HML explains about 80 percent of the 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, as it should be. Low interest rate currencies provide US investors with insurance against HML risk, while high interest rate currencies expose investors to more HML risk. By ranking currencies into portfolios based on their forward discounts, we find that forward discounts determine currencies' exposure to HML, and hence their risk premia. As a check, we also rank currencies based on their HML-betas, and we find that portfolios with high HML-exposure do yield higher average returns and have higher forward discounts.

We use a standard no-arbitrage Cox, Ingersoll and Ross (1985)-model of the term structure to explain why we build these currency portfolios. Our version features a large number of countries. In each country, the stochastic discount factor (SDF) is composed of two risk factors: one is country-specific, the other is common. We show analytically that two conditions need to be satisfied in order to match the data. First, we need a common risk factor because it is the only source of cross-sectional variation in currency risk premia. Second, we need low interest rate currencies to be more exposed to the common risk factor in times when the price of common risk is high, e.g in bad times. Using the model, we show analytically that by ranking currencies into portfolios and constructing HML, we measure the common innovation to the SDF. Similarly, we show that the dollar risk factor RX measures the home-country-specific innovation to the SDF. Thus, we provide a theoretical foundation for building currency portfolios: these portfolios allow us to recover the two factors that drive pricing kernels.

In the model, currency risk premia are determined by a dollar risk premium and a carry trade risk premium. The size of the carry trade risk premium depends on the spread in the loadings on the common component between high and low interest rate currencies, and on the global risk price. As the global risk price increases, the spread increases endogenously and the carry trade risk premium goes up. If there is no spread, i.e. if low and high interest rate currencies share the same loadings on the common risk factor, then HML cannot be a risk factor, because the global component does not affect exchange rates. The larger the spread, the riskier high interest rate currencies become relative to low interest rate currencies, because the latter appreciate relative to the former in case of a negative global shock. In a version of the model that is reasonably calibrated to match the salient moments of exchange rates and interest rates in the data, we replicate the carry trade risk premium as well as the failure of the CAPM to explain average currency returns in the data.

The literature on currency excess returns that derive from the failure of the uncovered interest parity can broadly be divided into two different segments. The first strand of the literature aims to understand exchange rate predictability within a standard asset pricing framework based on systematic risk.[1] The second strand looks for non-risk-based explanations.[2] The risk-based literature offers three types of fully-specified, risk-based models of forward premium puzzle: Verdelhan (2005) uses habit preferences in the vein of Campbell and Cochrane (1999), Bansal and Shaliastovich (2007) build on the long run risk literature pioneered by Bansal and Yaron (2004), and Farhi and Gabaix (2007) augment the standard consumption-based model with disaster risk following Barro (2006). These three models have two elements in common: a persistent variable drives the log SDF, and the log SDF is heteroskedastic. Backus et al. (2001) show that the latter is a necessary condition for models with log-normals shocks to reproduce the forward premium puzzle. Our paper adds to this list of requirements. To explain our finding that a single global risk factor explains the cross-section of currency returns, the SDF in these models needs to have a global heteroskedastic component, and the SDF in low interest rate currencies needs to load more on the global component. This heterogeneity is critical to replicate our findings; we show

[1]This segment includes recent papers by Backus, Foresi and Telmer (2001), Harvey, Solnik and Zhou (2002), Alvarez, Atkeson and Kehoe (2005), Verdelhan (2005), Campbell, de Medeiros and Viceira (2006), Lustig and Verdelhan (2007), Graveline (2006), Bansal and Shaliastovich (2007), Brennan and Xia (2006), Farhi and Gabaix (2007) and Hau and Rey (2007), Colacito (2008) and Brunnermeier, Nagel and Pedersen (2008). Earlier work includes Hansen and Hodrick (1980), Fama (1984), Bekaert and Hodrick (1992), Bekaert (1995) and Bekaert (1996).

[2]This segment includes papers by Froot and Thaler (1990), Lyons (2001), Gourinchas and Tornell (2004), Bacchetta and van Wincoop (2006), Frankel and Poonawala (2007), Sarno, Leon and Valente (2006), Plantin and Shin (2007), Burnside, Eichenbaum, Kleshchelski and Rebelo (2006), Burnside, Eichenbaum and Rebelo (2007a) and Burnside, Eichenbaum and Rebelo (2007b).

that heterogeneity in the loadings on the country-specific factor cannot explain the cross-sectional variation in currency returns, even though it can generate negative UIP slope coefficients. Finally, we also show that HML is strongly pro-cyclical; it has a US consumption growth beta between 1 and 1.5, consistent with the findings of Lustig and Verdelhan (2007).

Our paper is organized as follows. We start by describing the data, how we build currency portfolios and the main characteristics of these portfolios in section 1. Section 2 shows that a single factor, HML, 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. Section 4 describes the time variation in excess returns that investors demand on these currency portfolios. Finally, section 5 considers a calibrated version of the model that replicates the key moments of the data. Section 6 concludes. All the tables and figures are in the appendix.

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 counterparty risks. 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 on equity markets, even after controlling for bid-ask spreads. In a separate appendix available on our web sites, we report several robustness checks considering only developed countries, non-US investors, and longer investment horizons.

1.1 Building Currency Portfolios

We start by setting up some notation. Then, we describe our portfolio building technology, 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. 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 he 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.[3] These data are collected by Barclays and Reuters and available on Datastream.[4] 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.

[3]When the last day of the month is Saturday or Sunday, we use the next business day.

[4]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.

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. These results are reported in a separate appendix. The currency portfolios excess returns are available on our websites. We present all of our results on these two samples. In a separate appendix, we present additional evidence on shorter and longer sub-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^j_{t+1} for portfolio j by taking the average of the log currency excess returns in each portfolio j. We assume that investors simply *short* 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. To illustrate this, figure 1 plots the forward discount and the portfolio to which the currency is allocated. We report the examples of the Japanese yen (¥) in the top panel and the UK pound (£) in the bottom panel. 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. The pound's experience (bottom panel) is quite different. Overall, it is subject to shorter spells in the medium to high interest rate portfolios.

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. These results are not surprising. A large body of empirical work starting with Hansen and Hodrick (1980) and Fama (1984) reports violations of UIP.

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* reflect any transaction cost.

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 these data or that currency excess returns are small in developed countries, as suggested by Burnside et al. (2006). We turn now to cross-sectional asset pricing tests on these currency portfolios.

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 equivalently on the first factor, which is 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. To show that a currency's interest rate relative to that of other currencies truly measures its exposure to carry risk, we also rank all the currencies into portfolios based on their carry-betas, and we recover a similar pattern in the forward discounts and in the excess returns. These results also hold for sub-samples of developed countries, foreign investors and longer investment horizons as reported in a separate appendix.

2.1 Methodology

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.[5] 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 consider two 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. The correlation of the first principal component with RX is .99. The correlation of the second principal component with HML is .94. Both factors are computed from net returns, after taking into account bid-ask spreads.

[5] Table 25 in the separate appendix reports the principal component coefficients.

These currency risk factors have a natural interpretation. HML 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. This is the portfolio return of a US investor engaged in the usual currency carry trade. Hence, this is a natural candidate currency risk factor, and, as we are about to show, it explains much of the cross-sectional variation in average excess returns. 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.

Cross-Sectional Asset Pricing We use Rx_{t+1}^j to denote the average excess return on portfolio j in period $t+1$.[6] In the absence of arbitrage opportunities, this excess return has a zero price and satisfies the following Euler equation:

$$E_t[M_{t+1} Rx_{t+1}^j] = 0.$$

We assume that the stochastic discount 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.[7] 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. We now briefly describe these two techniques, starting with GMM.

GMM The moment conditions are the sample analog of the population pricing errors:

$$g_T(b) = E_T(M_t Rx_t) = E_T(Rx_t) - E_T(Rx_t f_t')b,$$

[6] All asset pricing tests are run on excess returns and not log excess returns.

[7] The Euler equation $E[MRx^j] = E[Rx^j - b(f - \mu)Rx^j] = 0$ implies that:

$$E[Rx^j] = \Sigma_{ff} b \frac{E[(f - \mu)Rx^j]}{\Sigma_{ff}}.$$

where $Rx_t = [Rx_t^1 \; Rx_t^2 \; .. \; Rx_t^N]'$ bunches all N currency portfolios. In the first stage of the GMM estimation, we use the identity matrix as the weighting matrix, while in the second stage we use the inverse of the spectral density S matrix of the pricing errors in the first stage: $S = \sum_{-\infty}^{\infty} E[(M_t Rx_t)(M_{t-j} Rx_{t-j})']$.[8] We use demeaned factors in both stages. Since we focus on linear factor models, the first stage is equivalent to an OLS-cross-sectional regression of average returns on the second moment of returns and factors. The second stage is a GLS cross-sectional regression of average excess returns on the second moment of returns and factors.

FMB In the first stage of the FMB procedure, for each portfolio j, we run a time-series regression of the currency returns Rx_{t+1}^j on a constant and the factors f_t, in order to estimate β^j. The only difference with the first stage of the GMM procedure stems from the presence of a constant in the regressions. In the second stage, we run a cross-sectional regression of the average excess returns $E_T[Rx_t^j]$ on the betas that were estimated in the first stage, to estimate the factor prices λ. The first stage GMM estimates and the FMB point estimates are identical, because we do *not* include a constant in the second step of the FMB procedure. Finally, we can back out the factor loadings b from the factor prices and covariance matrix of the factors.

2.2 Results

Table 2 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.

Market Prices of Risk 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 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 2) is 537 basis points.[9] So the estimated risk

[8]We use a Newey and West (1987) approximation of the spectral density matrix. The optimal number of lags is determined using Andrews (1991)'s criterion with a maximum of 6 lags.

[9]Note that 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.

price is only 9 basis points removed from the point estimate implied by the no-arbitrage theory of Ross (1976). 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 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. Overall, asset 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 are consistent with the average excess returns. Note that the predicted excess return is here simply the OLS estimate of the betas times the sample mean of the factors, not the estimated prices of risk. The latter would obviously imply an even better fit.

These results are robust. They hold true in a smaller sample of developed countries, as shown in the right-hand side of Table 2.

Alphas in the Carry Trade? The bottom panel of Table 2 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 all the α's are zero cannot be rejected.

The second column of the same panel reports the estimated βs for the HML 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 second factor are essentially all equal to one. Obviously, this second 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).

2.3 Sorting on HML exposure

To show that the ranking of forward discounts really does measure a currency's exposure to the risk factor, we build portfolios based on each currency's exposure to aggregate currency risk as measured by HML. For each date t, we first regress each currency i log excess return rx^i on a constant and HML using a 36-month rolling window that ends in period $t-1$. This gives us currency i's exposure to HML, 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 3 reports summary statistics on these portfolios. We do not take into account bid-ask spreads here, because it is not obvious a priori when the investor wants to go long or short. The first panel reports average changes in exchange rates. The second panel shows that average forward discounts increase monotonically in our portfolios. 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 excess returns. They are monotonically increasing from the first to the last portfolio. Clearly, currencies that covary more with our risk factor - and are thus riskier - provide higher excess returns. 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.

2.4 Other Currencies

Finally, as a robustness exercise, we now check the Euler equation of foreign investors in the UK, Japan and Switzerland. We construct the new asset pricing factors (HML and RX) in local currencies, and we use the local currency returns as test assets. Our initial spot and forward rates are quoted in US dollars. In order to convert these quotes in pounds, yen and Swiss francs, we use the corresponding midpoint quotes of these currencies against the US dollar.[10] The first panel in Table 4 reports results for the UK, the second panel for Japan and the third panel for Switzerland.

For all countries, the estimated market price of HML risk is less than 70 basis points removed from the sample mean of the factor. The HML 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 the Japan, for which the p-values are smaller than 10 percent.

[10] Table 17 in the appendix reports summary statistics on these portfolios.

We conduct several other robustness checks. To save space, we report these results in a separate appendix, available on our websites. First, we consider the sample proposed by Burnside, Eichenbaum, Kleshchelski and Rebelo (2008). Following the methodology of Lustig and Verdelhan (2007), Burnside et al. (2008) build 5 currency portfolios and claim that these currency excess returns are not related to any risk factor. We find that these currency excess returns are clearly explained by the carry trade and aggregate market risk factors. Second, we report additional results on foreign investors. Third, we divide our main sample into two sub-samples, starting either in 1983 or in 1995. Fourth, we consider the longer sample of currency excess returns built using Treasury bills in Lustig and Verdelhan (2007). All these results show that currency excess returns are large, time-varying, and that they reflect risk premia. We turn now to an interpretation of our currency portfolio and risk factors.

3 A No-Arbitrage Model of Exchange Rates

To explain why we build these currency portfolios and what our risk factors capture, we start off a no-arbitrage model of exchange rates. We essentially combine a large number of standard term structure models, one for each currency. In this setting, we show that the HML factor that we construct by building currency portfolios measures the common innovation to the SDF. Similarly, RX measures the dollar-specific innovation to the SDF. In addition, we show that ranking the currencies on interest rates in bad times is equivalent to ranking these currencies on their exposure to the global risk factor.

We derive conditions on stochastic discount factors at home and abroad that need to be satisfied in order to produce a carry trade risk premium that is explained by HML. We do so in a no-arbitrage model of exchange rates. Our model shares some features with the models proposed by Frachot (1996) and Brennan and Xia (2006), and it is closest to the model proposed by Backus et al. (2001).[11] We consider a world with N countries and currencies. Following Backus et al. (2001), we assume that in each country i, the log SDF m^i is given by a two-factor Cox et al. (1985) model:

$$-m^i_{t+1} = \lambda^i z^i_t + \sqrt{\gamma^i z^i_t} u^i_{t+1} + \tau^i z^w_t + \sqrt{\delta^i z^w_t} u^w_{t+1}.$$

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

$$z^i_{t+1} = (1-\phi^i)\theta^i + \phi^i z^i_t + \sigma^i \sqrt{z^i_t} v^i_{t+1},$$

[11]We start from the law of motion of the SDFs and do not specify preferences here.

where the innovations v^i_{t+1} 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:

$$z^w_{t+1} = (1-\phi^w)\theta^w + \phi^w z^w_t + \sigma^w \sqrt{z^w_t} v^w_{t+1},$$

where the innovations v^w_{t+1} are also *i.i.d* gaussian, with zero mean and unit variance. In this model, the conditional market price of risk has a domestic component $\sqrt{\gamma^i z^i_t}$ and a global component $\sqrt{\delta^i z^w_t}$.[12] The only difference with the model 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:

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

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 (corrected for the Jensen term) consists of two components:

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

The risk premium has a global and a dollar component, but it is *independent* of the foreign country-specific factor z^i_t and the foreign country-specific loading γ^i.[13] 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

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

$$r^i_t \quad = \quad \left(\lambda - \frac{1}{2}\gamma\right) z^i_t + \left(\tau - \frac{1}{2}\delta^i\right) z^w_t.$$

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

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

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: $\sqrt{\delta} = \overline{\sqrt{\delta}}$.

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 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. *The innovation to the* HML *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 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 measures the common innovation to the SDF. As a result, the return on the zero-cost strategy HML measures the stochastic discount factors' exposure to the common shock u^w_{t+1}.

Proposition. *The (conditional) HML betas of the returns in currency portfolio j with respect to HML are:*

$$\beta_t^j = \frac{\sqrt{\delta} - \sqrt{\overline{\delta_t^j}}}{\sqrt{\overline{\delta_t^L}} - \sqrt{\overline{\delta_t^H}}}.$$

If the ranking of currencies on interest rate produces a monotonic ranking of δ , then the 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 decreases. This case is summarized in the following condition:

Condition. *The precautionary effect on interest rates dominates the intertemporal substitution effect when:*

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

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_t^i, 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 $\left(\sqrt{\overline{\delta_t^L}} - \sqrt{\overline{\delta_t^H}}\right)$ increases. This implies that in bad times the spread in the loadings increases. In section 5, we provide 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 of the pricing kernel. Therefore, these two factors together do 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 component and a carry trade risk premium component. Our no-arbitrage model also delivers simple closed-form expression for these risk premia.

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

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

On the one hand, 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 a result, the carry trade risk premium increases non-linearly when global volatility increases. Below, we show that the predicted excess returns on a long position in the sixth portfolio and a short position in the first portfolio are highly correlated with the VIX volatility index, one proxy of the global risk factor. In addition, we report evidence that the VIX predicts excess returns.[14]

On the other hand, the size of the dollar risk premium is governed only by the conditional market price of risk at home, if the home country has the average δ.[15] This is consistent with our finding, discussed below, that the predicted excess returns on medium to high interest rate currencies are highly counter-cyclical, and that business cycle indices (like US industrial production growth) predict these excess returns, even after controlling for interest rate differences. The risk premia on individual 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. The next section discusses the currency return predictability in the data.

4 Return Predictability in Currency Markets

The vast literature on UIP considers country-by-country regressions of changes in exchange rates on forward discounts. Because UIP fails in the data, forward discounts predict currency excess returns. In this section, we investigate return predictability using our currency portfolios. We first consider each portfolio separately. We show that the average forward discount across portfolios does a better job of describing the time variation in expected currency excess returns than the individual portfolio forward discounts. We build expected excess returns using either portfolio-specific or average forward discounts. These expected excess returns are closely tied to the US business cycle: expected currency returns increase in downturns and decrease in expansions, as is the case in stock and bond markets. We then turn to portfolio spreads, going long in high interest

[14] In recent work, Brunnermeier et al. (2008) have also produced evidence that the VIX index predicts currency excess returns.

[15] Note that $\overline{z}$ is constant by the law of large numbers.

rate currencies and short in the lowest interest rate currencies. We show that these spreads are predictable, and the corresponding expected excess returns are linked to higher frequency variation in global credit spreads and global market volatility.

4.1 Predictability in Portfolio Excess Returns

We first investigate the predictive power of the portfolio-specific forward discount, and then turn to the predictive power of the average forward discount.

Individual Forward Discounts For each portfolio j, we run a time series regression of each portfolio's average log currency excess returns on each portfolio's average log forward discounts:

$$rx^j_{t+1} = \gamma^j_0 + \gamma^j_f (f^j_t - s^j_t) + \eta^j_t.$$

If UIP were an accurate description of the data, there would be no predictability in currency excess returns, and the slope coefficient γ_f would be zero. Table 5 reports regression results.[16]

Portfolio forward discounts account for between 1.8 percent and 6.4 percent of the monthly variation in excess returns on these currency portfolios. There is strong evidence against UIP in these portfolio returns, more so than in individual currency returns. Looking across portfolios, from low to high interest rates, the slope coefficient γ^j_f (column 3) varies a lot: it increases from 108 basis points for currencies in the first portfolio to 357 basis points for currencies in the fourth portfolio. The slope coefficient decreases to 72 basis points for the sixth portfolio. Deviations from UIP are highest for currencies with medium to high forward discounts. However, forward rates are strongly autocorrelated. This complicates statistical inference about these slope coefficients. To deal with this issue, we use two asymptotically-valid corrections. The Newey-West standard errors (NW) are computed with the optimal number of lags following Andrews (1991). The Hansen-Hodrick standard errors (HH) are computed with one lag. Both of these methods correct for arbitrary error correlation and conditional heteroscedasticity. Bekaert, Hodrick and Marshall (1997) note that the small sample performance of these test statistics is also a source of concern. To address this problem, we also report small sample standard errors. These were generated by bootstrapping 10,000 samples of returns and forward discounts from a bivariate VAR with one lag. The null of no predictability is rejected at the 1 percent significance level for all of these portfolios except for the third.

Since log excess returns are the difference between changes in spot rates at $t + 1$ and forward

[16] We use net excess returns that take into account bid-ask spreads. Bid-ask spreads vary with time. For example, the average spread in the last portfolio increases with the volatility index VIX, but this time-variation is very small compared to the mean bid-ask spread and the mean excess return.

discounts at t, these are predictability regressions for spot changes in exchange rates.[17] At the one-month horizon, the R^2 on these predictability regressions varies between 1.8 and 6.36 percent. In other words, when considering currency portfolios, up to 6 percent of the variation in spot rates is predictable at a one-month horizon.

Average Forward Discount There is even more predictability in these excess returns than the standard UIP regressions reveal, because forward discounts on the other currency portfolios also help to forecast returns. We found that a single return forecasting variable describes time variation in the dollar risk premium even better than the forward discount rates on the individual currency portfolios. This variable is the average of all the forward discounts across portfolios. We use ι to denote the 6×1 vector with all elements equal to 1/6. For each portfolio j, we run the following regression of log excess returns after bid-ask spreads on the average forward rates:

$$rx^j_{net,t+1} = \gamma^j_0 + \gamma^j_{\mathbf{f}} \iota'(\mathbf{f}_t - \mathbf{s}_t) + \eta^j_t,$$

where $\mathbf{f}_t - \mathbf{s}_t$ bunches together all forward discounts. A summary of the results is reported in columns 3 and 4 of Table 5. This single factor explains between 3.0 and 8.3 percent of the variation in returns at the one-month horizon. The average forward discount outperforms the portfolio-specific forward discounts, except in portfolios 3 and 4. In this case, the slope coefficients vary much less across the different portfolios. Clearly, any time variation in the bid-ask spread does not eliminate the predictability of realized excess returns in currency markets.

The right panel of Table 5 focuses on the predictability of carry trade returns: the returns on a high-minus-low strategy that goes long in high interest rate currencies and short in low interest rate currencies. We run the following predictability regression of the one-month high-minus-low return $rx^j - rx^1$ on the spread in the one-month forward discount between the j-th and the first portfolio:

$$rx^j_{t+1} - rx^1_{t+1} = \gamma_{sp,0} + \gamma_{sp,f}\left[(f^j_t - s^j_t) - (f^1_t - s^1_t)\right] + \eta^j_t.$$

There is some evidence that the high-minus-low returns are forecastable by the forward spreads, but the evidence is less strong than on individual portfolio returns. Since the spread in forward discounts is much less persistent than the forward discount and there is no overlap in returns, there is less cause for concern about persistent regressor bias.

[17] From γ^j_f, the slope coefficient in the return predictability regression, we can back out the implied slope coefficients δ_f in the standard UIP regression:

$$-\Delta s^j_{t+1} = \delta^j_0 + \delta^j_f (f^j_t - s^j_t) + \eta^j_t,$$

where $\delta_f = 1 - \gamma_f$. For example, the implied UIP coefficient on the fourth portfolio is -2.6: each 100 basis point increase in the forward discount reduces the expected appreciation of the foreign currency by 260 basis points.

Longer Horizons At longer horizons, the fraction of changes in log spot rates explained by the forward discount is even greater than at short horizons. We use k-month maturity forward contracts to compute k-period horizon returns (where $k = 1,\ 2,\ 3,\ 6,\ 12$). The log excess return on the k-month contract is:

$$rx_{t+k}^{k} = -\Delta s_{t\to t+k} + f_t^k - s_t.$$

Then we sort the currencies into portfolios based on forward rates with the corresponding maturity, and we compute the average excess return for each portfolio. Table 6 provides a summary of the results: it lists the R^2s we obtained for each portfolio (rows) and for each forecasting horizon (columns). We only consider the corner portfolios.

At longer horizons, the returns on the first portfolio are most predictable; the returns on the last portfolio are least predictable. On the first portfolio, more than a quarter of the variation in excess returns is accounted for by the forward rate at the 12-month horizon. On the last portfolio, 10 percent is accounted for by the forward rate. One concern is that these measures of fit may be biased because we use overlapping returns and because the predictors are highly autocorrelated. In the bottom panel of Table 6 we also provide the same R^2 measures that we obtained for each forecasting horizon with non-overlapping data. To produce these measures, we simply used the first month of every period (quarter, year) to run the same regressions. Though there are some differences, these R^2s are not systematically lower. Even at longer horizons, the average forward discount seems to do a better job in describing the variation in expected excess returns. This single factor explains between 18 and 32 percent of the variation at the one-year horizon. This single factor mostly does as well and sometimes better than the forward discount of the specific portfolio in forecasting excess returns over the entire period.

Some developing countries like Saudi Arabia and Hong Kong have pegged their exchange rate to the dollar. This naturally inflates the predictability of currency returns. In the bottom panel of Table 6, we report the predictability results that we obtained on our smaller sample of developed countries. The R^2s are lower than those we reported in the top panel of Table 6, but that is mainly because there is more idiosyncratic variation in these returns, because the portfolios are composed of fewer currencies.

In a separate appendix, we take a closer look at these forecasting regressions and study the significance of each predictor at longer horizons. We use Newey-West, Hansen-Hodrick, non-overlapping data and bootstrapping techniques to compute standard errors. When we use the largest standard errors, the average forward discount remains a significant predictor, but the portfolio-specific forward discount does not. As a result, we conclude that the average forward discount contains additional information that is useful for forecasting excess returns on all currency portfolios, while little information is lost by aggregating all these forward discounts into a single predictor. The fact that the average forward discount is a *better predictor* of future excess returns on foreign currency than individual forward discount rates is consistent with the risk premium view: by using the average forward discount, we throw away all information related to country-specific inflation, and we do better in predicting future changes in exchange rates. In fact, if we take the residuals of the average forward discount forecasting regression and we project these on the individual portfolio forward discounts, there is no predictability left. In the right panel of Table 6, we also report the R^2s of these regressions. There is no information in the individual forward discounts left that helps to forecast currency returns. This finding is similar to results of Stambaugh (1988) and Cochrane and Piazzesi (2005) for the term structure of interest rates. These studies show that linear combinations of forward rates outperform the forward rate of a particular maturity in forcasting bond returns. In particular, Cochrane and Piazzesi (2005) report R^2s of up to 40 percent on one-year holding period returns for zero coupon bonds using a single forecasting factor. Currency returns are *more predictable* than stock returns, and almost as predictable as bond returns.

Counter-Cyclical Dollar Risk Premium Clearly, our predictability results imply that expected excess returns on currency portfolios vary over time. We now show that this time variation has a large US business cycle component: expected excess returns go up in US recessions and go down in US expansions. The same counter-cyclical behavior has been documented for bond and stock excess returns.

We use $\widehat{E}_t rx^j_{t+1}$ to denote the forecast of the one-month-ahead excess return based on the forward discount:

$$\widehat{E}_t rx^j_{t+1} = \gamma^j_0 + \gamma^j_f (f^j_t - s^j_t).$$

At high frequencies, forecasted returns on high interest rate currency portfolios – especially for the sixth portfolio – increase very strongly in response to events like the Asian crisis in 1997 and the LTCM crisis in 1998, but at lower frequencies, a big fraction of the variation in forecasted excess returns is driven by the US business cycle, especially for the third, fourth and fifth portfolios. To assess the cyclicality of these forecasted excess returns, we use three standard business cycle indicators and three financial variables: (i) the 12-month percentage change in US industrial production index, (ii) the 12-month percentage change in total US non-farm payroll index, (iii) the 12-month percentage change in the Help Wanted index, (iv) the default spread – the difference between the 20-Year Government Bond Yield and the $S\&P$ 15-year BBB Utility Bond Yield – (v) the slope of the yield curve – the difference between the 5-year and the 1-year zero coupon yield, and (vi) the $S\&P$ 500 VIX volatility index.[18] Macroeconomic variables are often revised. To check

[18] Industrial production data are from the IMF International Financial Statistics. The payroll index is from the BEA. The Help Wanted Index is from the Conference Board. Zero coupon yields are computed from the Fama-Bliss series available from CRSP. These can be downloaded from `http://wrds.wharton.upenn.edu`. Payroll data can be downloaded from `http://www.bea.gov`. The VIX index, the corporate bond yield and the 20-year government

that our results are robust to real-time data, we use vintage series of the payroll and industrial production indices from the Federal Reserve Bank of Saint Louis. The results are very similar to the ones reported in this paper.

Table 7 reports the contemporaneous correlation of the month-ahead forecasted excess returns with these macroeconomic and financial variables. As expected, forecasted excess returns for high interest rate portfolios are strongly counter-cyclical.

On the one hand, the monthly contemporaneous correlation between predicted excess returns and percentage changes in industrial production (first column), the non-farm payroll (second column) and the help wanted index (third column) are negative for all portfolios except the first one. For payroll changes, the correlations range from -.70 for the second portfolio to -.09. for the sixth. Figure 3 plots the forecasted excess return on portfolio 2 against the 12-month change in US industrial production. Forecasted excess returns on the other portfolios have similar low frequency dynamics, but in the case of portfolios 5 and 6, they also respond to other events, like the Russian default and LTCM crisis, the Asian currency crisis and the Argentine default.

On the other hand, monthly correlations of the high interest rate currency portfolio with the default spread (fourth column) and the term spread (fifth column) are, as expected, positive. Finally, the last column reports correlations with the implied volatility index (VIX). The VIX seems like a good proxy for the global risk factor. The VIX is highly correlated with similar volatility indices abroad.[19] The correlations in the last column reveal a clear difference between the low interest rate currencies with negative correlations, and the high interest rate currencies, with positive correlations. This is consistent with the predictions of our no-arbitrage model. Recall that the model predicts negative loadings on the common risk factor for the risk premia on low interest rate currencies and positive loadings for the risk premia on high interest rate currencies (see equation 3.2). In times of global market uncertainty, there is a flight to quality: investors demand a much higher risk premium for investing in high interest rate currencies, and they accept lower (or more negative) risk premia on low interest rate currencies.

Longer Horizons We find the same business cycle variation in expected returns over longer holding periods. The predictability is partly due to the countercyclical nature of the forward discount, but not entirely. Controlling for the forward discount reduces the IP slope coefficient by 50 basis points on portfolios 1-4, 20-30 basis points for portfolios 5-6, but the forward discount does not drive out the macroeconomic variable. Table 8 reports forecasting results for currency portfolios obtained using the 12-month change in industrial production and either the portfolio-

bond yield are from `http://www.globalfinancialdata.com`.

[19] The VIX starts in February 1990. The DAX equivalent starts in February 1992; the SMI in February 1999; the CAC, BEL and AEX indices start in January 2000. Using the longest sample available for each index, the correlation coefficients with the VIX are very high, respectively 0.85, 0.82, 0.88, 0.83 and 0.82 using daily time-series.

specific forward discount or the average forward discount. The currency risk premium increase in response to a one percentage point drop in the growth rate of industrial production varies between 90 (portfolio 1) and 170 basis points (portfolio 5). The IP slope coefficients are still significantly different from zero for the high interest rate portfolios, but the slope coefficients on the (average) forward discounts are not. In recent work, Duffee (2008) and Ludvigson and Ng (2008) report a similar finding for the bond market.

4.2 Connecting Predictability to the Cross-section of Returns

Our model implies that the price of carry trade risk increases when the global market price of risk rises. To test this implication of the model, we consider the conditional Euler equation of a US investor. As explained by Hansen and Richard (1987), a simple conditional factor model can be turned into an unconditional factor model using all the variables z_t in the information set of the investor. The conditional Euler equation for portfolio j, $E_t\left[M_{t+1}R^j_{t+1}\right] = 1$, is then equivalent to the following unconditional condition:

$$E\left[M_{t+1}z_tR^j_{t+1}\right] = 1.$$

We can interpret this condition as an Euler equation applied to a managed portfolio $z_tR^j_{t+1}$. This managed portfolio corresponds to an investment strategy that goes long portfolio j when z_t is positive and short otherwise. We can also interpret it as an Euler equation on portfolio j when the risk factor is $M_{t+1}z_t$. In our estimation, we assume that one scaling variable z_t summarizes all the information set of the investor. We scale both returns and risk factors as described in Cochrane (1996). As a result, we obtain twelve test assets: the original six portfolios and the same portfolios multiplied by the scaling variable. For the risk factors, we use the average currency return RX and HML, and we add $HML_{FX,t+1}z_t$. Our conditioning variable z is the CBOE volatility index VIX. Table 9 reports the results. We find that the implied market prices of risk associated with the carry trade factor vary significantly through time. They tend to increase in bad times, when the implied stock market volatility is high.

We have documented in this section that returns in currency markets are highly predictable. The average forward discount rate accurately predicts up to 33 percent of the variation in annual excess returns. The time variation in expected returns has a clear business cycle pattern: US macroeconomic variables are powerful predictors of these returns, especially at longer holding periods, and expected currency returns are strongly counter-cyclical. We now turn to the properties of HML in times of crisis.

4.3 Flight-to-Quality

We have shown that a currency's expected excess return depends on its exposure to HML: currency investments are HML bets. A natural question is then: Why are currency investors rewarded for taking on these HML bets? In this section, we show that the average market beta of HML is too small to explain risk premia, but this beta varies a lot through time, and is particularly high during episodes of global financial crises. Our carry risk factor HML is much more correlated with the stock market when there is a lot of global risk.

We now run the same asset pricing experiment on the cross-section of currency excess returns using the US stock market excess return as the pricing factor, instead of the slope risk factor HML. To measure the return on the market, we use the CRSP value-weighted return on the NYSE, AMEX and NASDAQ markets in excess of the one-month average Fama risk-free rate. Results are reported in table 10. The US stock market excess return and the level factor RX can explain 52 percent of the variation in returns. However, the estimated price of US market risk is 37 percent, while the actual annualized excess return on the market is only 7.1 percent over this sample. The risk price is 5 times too large. The CAPM betas are also reported in Table 10. They vary from -.05 for the first portfolio to .08 for the last one. Low interest rate currencies provide a hedge, while high interest rate currencies expose US investors to more stock market risk. These betas increase almost monotonically from low to high interest rates, but they are too small to explain these excess returns. Therefore, the cross-sectional regression of currency returns on market betas implies market price of risk that are far too high.

The failure of the CAPM may be due to time-variation in market betas and/or in the market price of risk. As shown by Lewellen and Nagel (2006), if the covariance between the market price of risk and the market betas is positive for the high interest rate portfolios, this can account for the large and positive CAPM pricing error α on the high-minus-low strategy. We show evidence of both time-variation effects.

Time Varying Risk Price First, we run the same asset pricing experiment using a conditioning variable as we did in the previous section. The bottom panel of table 9 reports results obtained on 12 test assets (the original 6 currency portfolios and the same ones multiplied by the lagged VIX index). Risk factors are the average return on the currency market RX, the value-weighted stock market excess return R^M and $R^M z$, which is R^M multiplied by the lagged value of the VIX index (scaled by its standard deviation). We find that the market price of risk increases significantly in bad times (when the stock market volatility index VIX is high). Taking into account such time-variation improves notably the fit of the CAPM, with an adjusted R^2 increasing from 95 percent on this set of 12 portfolios.

Time Varying Correlation In the two-factor model, the conditional correlation of HML and the SDF in the home country is:

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

As the global component of the conditional market price of risk increases, the conditional correlation between the stochastic discount factor at home and the carry trade returns HML increases. We find strong evidence for this type of time-varying correlation in the data.

In a first pass, we use the US stock market return as a proxy for the domestic SDF. We compute the correlation between one-month currency returns and the return on the value-weighted US stock market return using 12-month rolling windows on daily data. Figure 4 plots the difference between the correlation of the 6th and the 1st portfolio with the US stock market excess return. We denote it $[Corr_\tau[R_t^m, rx_t^6] - Corr_\tau[R_t^m, rx_t^1]$, where $Corr_\tau$ is the sample correlation over the previous 12 months $[\tau - 12, \tau]$ and R^m the stock market excess return. We also plot the stock market beta of HML. These market correlations exhibit enormous variation. In times of crisis and during US recessions, the difference in market correlation between high and low currencies increases significantly. During the Mexican, Asian, Russian and Argentinan crisis, the correlation difference jumps up by 50 to 90 basis points.

We now explore time-variation in market betas. There is some evidence that, in times of financial crisis, the CAPM market beta of the high-minus-low strategy in currency markets increases dramatically. We start by examining the recent sub-prime mortgage crisis, and we then consider other crisis episodes. The last 4 columns of Table 11 reports the market betas of all the currency portfolios that we obtain on a 6-month window before 08/31/2007. To estimate the market betas, we use daily observations on monthly currency and stock market returns.[20] The NW standard error correction is computed with 20 lags. We estimate a market beta of HML of up to 62 basis points. The estimated market betas increase monotonically as we move from low to high interest rate currency portfolios, as we would expect. We report the αs in the bottom panel of Table 11. Over this period, the estimated pricing errors α on the high-minus-low strategy dropped to 30 basis points over 6 months or 60 basis points per annum compared to an unconditional pricing error α_{HML} of more than 500 basis points per annum.

This is not an isolated event, as these results extend to other crises. In Table 11, we document similar increases in the US market beta of HML during the LTCM-crisis (column 1-4), the Tequila crisis (column 5-8) and the Brazilian/Argentine crisis (column 9-12). Again, the market betas

[20]For example, we compute market betas $\beta^m_{\tau,HML}$ of HML over rolling 6-month windows with the following regressions on daily data:

$$HML_t = \alpha_\tau + \beta^m_{\tau,HML} R_t^m + \eta_t,$$

where $t \in [\tau, \tau - 128]$.

increase monotonically in the forward discount rates. For example, $\beta^m_{\tau,HML}$ 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. Low interest rate currencies provide a hedge against market risk while high interest rate currencies expose US investors to more market risk in times of crisis. In two of these crisis, the α on the high-minus-low strategy is negative: minus 271 basis over the 6 months preceding the Russian default and minus 382 basis points during the Tequila crisis.[21] In the two other crisis, the αs are positive (96 and 29 basis points over 6 months respectively) but small, well below the average α of 4.46 percent per annum that we obtained over the entire sample. As we have shown, the market beta of the high-minus-low strategy increases dramatically in times when the price of global risk is high. This can account for the failure of the CAPM on the entire sample, as we show in a calibrated version of our model in the next section.

5 Calibrated Model

We conclude by showing that a reasonably calibrated version of the model can match the key moments of currency returns in the data. We calibrate our model at annual frequencies. We use annual end-of-year series from our set of developed countries over the 1983-2007 sample. To make contact with the data, we complete our model by adding a nominal component. The calibration proceeds in two stages. First, we present our calibration of the real SDFs and then we turn to the nominal SDFs.

5.1 Calibration

We start with a version of the model that is completely symmetrical. In this simple case, we need to pin down 7 parameters: 4 parameters govern the countries' SDFs (λ, γ, τ and δ), and 3 parameters describe the country and the world risk factor ($\theta = \theta^w$, $\phi = \phi^w$ and $\sigma = \sigma^w$). We target 7 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 (squared) conditional Sharpe ratio and the UIP slope coefficient. We target a real risk-free rate with a mean of 1.5 percent, a standard deviation of 2 percent and an autocorrelation of 0.8. We target a real exchange rate with a standard deviation of 12 percent and a Sharpe ratio with a mean of 0.5 and a standard deviation of 0.5. Finally, we target a UIP coefficient of -1. To find our initial set of parameters, we minimize the squared errors on the moments subject to

[21]These numbers need to be multiplied by 2 to be annualized.

some additional technical constraints.[22] The maximization attains all moments except the mean (0.65) and standard deviation of the Sharpe ratio (0.13). The top panel of Table 12 lists all of the moments that we target. Next, we introduce heterogeneity in the loadings on the common risk factor. We determine the range of the parameters δ^i to match the mean of the carry trade risk factor. The other parameters are unchanged.[23] The bottom panel of Table 12 lists all the parameters of the calibration.

We add a nominal component to the model, because we want 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. Both components follow AR(1) processes:

$$\begin{aligned}
\pi_{t+1}^w &= (1-\rho^w)\overline{\pi}^w + \rho^w \pi_t^w + \sigma^{w\$}\epsilon_{t+1}^w, \\
\pi_{t+1}^{ci} &= (1-\rho^i)\overline{\pi}^i + \rho^i \pi_t^i + \sigma^{i\$}\epsilon_{t+1}^i,
\end{aligned}$$

where the innovations ϵ_t^w and ϵ_t^i are also $i.i.d$ gaussian, with zero mean and unit variance. Inflation in country i is a weighted average of these two components:

$$\pi_{t+1}^i = \mu^i \pi_{t+1}^{ci} + (1-\mu^i)\pi_{t+1}^w.$$

We define world inflation as the cross-sectional, unweighted average of all annual inflation rates, denoted $\overline{\pi}^w$, and we measure the moments of the average world inflation rate for the countries in our sample. The autocorrelation ρ^w is equal to 0.88, the standard deviation θ^w is 3.2 percent. The relative weight μ on domestic versus world inflation set equal to 0.16; it is determined by the share of the total variance explained by the first principal component. We subtract the world component from each country inflation rate to obtain the autocorrelation and the shocks' standard deviation in each country. We use the average of these moments. This yields an average for the

[22]The parameter γ, δ and σ have to be positive, ϕ has to be between 0 and 1. The processes z and z^w follow Gamma distributions. The Feller parameters $F = 2(1-\phi)\theta/\sigma^2$ and $F^w = 2(1-\phi^w)\theta^w/(\sigma^w)^2$ govern the moments of these distributions. To ensure that these processes remain positive, the Feller parameters need to be above unity. The skewness of each process is is also pinned down by the Feller coefficients ($2/\sqrt{F}$ and $2/\sqrt{F^w}$). In our data, the average skewness of nominal interest rates is 0.6. As a result, we impose both Feller parameters to be above 15. This is only an approximation of the real interest rates' skewness because real interest rates depend on the two risk processes z and z^w.

[23]In our dataset, all countries have very persistent dividend yields. This argues in favor of the same risk factor's autocorrelation ϕ across countries. We chose to pin down ϕ using the autocorrelation of interest rates instead of dividend yields because these data are less noisy and available for all countries in our sample.

country-specific component $\overline{\pi}$ equal to 3 percent, an autocorrelation ρ to 0.58 and a volatility $\sigma^{\$}$ equal to 8.15 percent.

Finally, we define 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 $d_t^i = \log D_t^i$:

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

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 compute the price-dividend ratios that correspond to the simulated values of the state vector using Monte Carlo simulations and interpolate them using a kernel regression. Details of the solution procedure are described in the appendix. This enables us to compute the stock market returns. We calibrate the dividend growth process as follows: we set the standard deviation of log dividend growth σ^{Di} to be 10 percent per annum, and the correlations with the two SDF shocks $\rho^{Dw} = \rho^{Di} = 0.7$. The equity premium is 5 percent per annum and the standard deviation of excess returns on stocks is 14 percent per annum.

5.2 Currency Portfolios

We simulate a version of the model with $N = 180$ countries over 10,000 periods. Figure 5 displays the distribution of average real interest rates, of the volatility of real interest rates, of the volatility of real and nominal exchange rates and UIP slope coefficients in our calibrated model. These variables are well-behaved. The average real one-period yields are mostly between 0 and 10 percent, with a few negative values. The standard deviations of the real risk-free rates are between 1.5 and 2.7 percent. The standard deviations of changes in the real and nominal exchanges rates lie between 11 and 15 percent. The average UIP slope coefficient is -0.3 on nominal data (-0.98 on real data). As a consequence, the calibrated version of our multi-country model delivers reasonable interest rates and exchange rates.

Portfolios We build currency portfolios on simulated data in the same way as with the actual data. Table 13 reports summary statistics on these portfolios and estimates of the market prices of risk. The model delivers a sizable cross-section of currency excess returns. The spread between the first and last portfolio is 6.9 percent per annum, implying a Sharpe ratio of 0.7. In the asset pricing experiment, the market price of the carry trade factor HML is 6.8 percent per annum, very close to the sample mean. The price of the aggregate market return RX is not significant. This is not surprising; with a large number of periods, the mean of RX should be zero according to equation (3.1). Thanks to its heterogeneity in the loadings on the world risk factor, our model reproduces our previous cross-sectional asset pricing results.

We note that the simulated market price of carry risk varies for two reasons: it is high when the world risk factor z^w is high, and this effect is amplified by a portfolio composition effect. As previously noted, in bad times, when z^w is high, the spread between the average δs in the first and last portfolio increases. Figure 6 illustrates these two effects.

Finally, the unconditional CAPM fails to explain currency return generated by our model, as in the data. Ina sample of 1,00 simulated periods, we run a time-series regression of HML on the stock market return. We find that the CAPM α of HML is large and statistically significantly different from zero: the CAPM understates the average return by over 5.15 percent per annum and the corresponding standard error is .26. This is a very large $alpha$ compared to the average HML return of 6.9 percent. As a result, the unconditional CAPM cannot explain currency returns in this no-arbitrage model of exchange rates.

6 Conclusion

In this paper, we show that currency markets offer large and time-varying risk premia. Currency excess returns are highly predictable. In addition, these predicted returns are strongly counter-cyclical. The average excess returns on low interest rate currencies are about 5 percent per annum smaller than those on high interest rate currencies after accounting for transaction costs. We show that a single return-based factor explains the cross-section of average currency excess returns. These findings are all consistent with the notion that carry trade profits are compensation for systematic risk.

Using a standard no-arbitrage term structure model, we show this single risk factor, obtained as the return on the highest minus the return on the lowest currency portfolio, measures exposure to common or global SDF shocks. We can replicate our main empirical findings in a reasonably calibrated version of this model, provided that low interest rate currencies are more exposed to global risk in bad times, when the price of global risk is high. This heterogeneity in the loadings on the global risk factor is critical.

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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	−0.60	2.06	4.62	3.74	5.67
Std	8.22	7.36	7.46	7.53	7.85	9.26	10.23	9.77	9.38	8.99	9.33
SR	−0.36	0.00	0.19	0.49	0.45	0.64	−0.06	0.21	0.49	0.42	0.61
	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	0.53	1.00	3.21	2.48	3.96
Std	8.21	7.35	7.43	7.48	7.85	9.25	10.25	9.76	9.35	8.99	9.31
SR	−0.21	−0.13	0.02	0.31	0.26	0.34	0.05	0.10	0.34	0.28	0.43
	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		2.66	5.22	4.34	6.27
Std		5.36	5.54	6.65	6.34	8.95		6.51	6.52	7.39	8.75
SR		0.55	0.78	0.99	1.02	0.99		0.41	0.80	0.59	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		0.47	2.68	1.95	3.44
Std		5.36	5.56	6.63	6.35	8.98		6.54	6.52	7.42	8.78
SR		0.14	0.33	0.60	0.59	0.54		0.07	0.41	0.26	0.39

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: Asset Pricing - US Investor

Panel I: Factor Prices and Loadings

	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	59.06	0.95		3.56	2.24	0.42	0.32	56.59	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					
$Portfolio$	$\alpha_0^j(\%)$	$\beta_{HML_{FX}}^j$	β_{RX}^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$	$\alpha_0^j(\%)$	$\beta_{HML_{FX}}^j$	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					−11.17	1.00					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). 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.

Table 3: Beta-Sorted Currency Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: Developed and Emerging 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)						Excess Return: rx^j (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

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 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. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 4: Asset Pricing - Foreign Investors

	$\lambda_{HML_{FX}}$	λ_{RX}	$b_{HML_{FX}}$	b_{RX}	R^2	$RMSE$	χ^2
				Panel I: UK			
GMM_1	5.54	−2.13	0.58	−0.28	70.12	0.95	
	[2.34]	[1.87]	[0.25]	[0.30]			24.83
GMM_2	5.47	−2.25	0.57	−0.30	69.66	0.96	
	[2.17]	[1.70]	[0.23]	[0.27]			24.89
FMB	5.54	−2.13	0.57	−0.28	60.16	0.95	
	[1.83]	[1.46]	[0.20]	[0.23]			20.57
	(1.83)	(1.46)	(0.20)	(0.23)			22.28
$Mean$	**5.44**	**-2.13**					
				Panel II: Japan			
GMM_1	5.50	1.18	0.63	0.00	60.16	1.16	
	[2.21]	[2.13]	[0.26]	[0.21]			9.35
GMM_2	4.73	1.92	0.53	0.10	41.85	1.40	
	[2.12]	[2.10]	[0.25]	[0.21]			10.76
FMB	5.50	1.18	0.63	0.00	46.88	1.16	
	[1.77]	[1.87]	[0.21]	[0.19]			6.00
	(1.77)	(1.87)	(0.21)	(0.19)			6.80
$Mean$	**4.85**	**1.18**					
				Panel III: Switzerland			
GMM_1	5.79	0.41	0.69	−0.11	78.57	0.81	
	[2.25]	[1.69]	[0.27]	[0.27]			27.81
GMM_2	6.23	0.62	0.74	−0.09	76.55	0.85	
	[2.11]	[1.61]	[0.25]	[0.26]			28.30
FMB	5.79	0.41	0.69	−0.11	71.43	0.81	
	[1.78]	[1.46]	[0.21]	[0.24]			28.04
	(1.78)	(1.46)	(0.21)	(0.24)			30.03
$Mean$	**5.92**	**0.42**					

Notes: This table reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, R^2, square-root of mean-squared errors $RMSE$ and p-values of χ^2 tests are reported in percentage points. b_1 represents the factor loading. The portfolios are constructed by sorting currencies into six groups at time t based on the interest rate differential at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rate. Portfolio 6 contains currencies with the highest interest rate. Data are monthly, from Barclays and Reuters in Datastream. The sample period is 11/1983 - 03/2008. Excess returns used as test assets take into account bid-ask spreads. All excess returns are multiplied by 12. Standard errors are reported in brackets. Shanken-corrected standard errors are reported in parenthesis.

Table 5: One-Month Ahead Return Predictability

Portfolio	$\gamma_{\mathbf{f}}$	W	R^2	γ_f	W	R^2	*Portfolio*	$\gamma_{\mathbf{sp,f}}$	W	R^2	$\gamma_{sp,f}$	W	R^2
	Panel A: Returns							Panel B: Spreads					
1	3.65		7.85	1.08		4.30							
NW	[0.64]	32.10		[0.33]	11.03								
HH	[0.57]	40.36		[0.23]	21.92								
VAR	[0.73]	37.57		[0.36]	17.28								
2	2.29		3.86	2.44		2.65	*2 minus 1*	8.31		3.05	9.08		4.81
NW	[0.70]	10.76		[0.97]	6.28		*NW*	[3.02]	7.57		[2.66]	11.64	
HH	[0.69]	11.13		[0.92]	6.98		*HH*	[0.43]	368.58		[2.44]	13.86	
VAR	[0.72]	16.49		[1.02]	8.79		*VAR*	[3.58]	8.51		[3.43]	12.66	
3	1.93		2.68	1.96		1.61	*3 minus 1*	7.10		2.09	7.28		2.89
NW	[0.65]	8.92		[1.04]	3.56		*NW*	[3.01]	5.58		[2.27]	10.26	
HH	[0.63]	9.48		[1.02]	3.67		*HH*	[3.03]	5.49		[2.40]	9.23	
VAR	[0.66]	12.88		[0.97]	5.94		*VAR*	[4.01]	5.74		[3.72]	7.75	
4	2.22		3.47	3.47		5.98	*4 minus 1*	8.33		1.99	9.27		3.28
NW	[0.65]	11.61		[0.87]	16.03		*NW*	[2.99]	7.75		[2.38]	15.22	
HH	[0.64]	12.16		[0.82]	18.02		*HH*	[2.85]	8.53		[2.38]	15.22	
VAR	[0.72]	14.28		[0.92]	18.32		*VAR*	[4.34]	6.69		[4.03]	10.97	
5	2.68		4.63	3.02		5.10	*5 minus 1*	7.13		1.61	6.83		2.15
NW	[0.74]	13.01		[0.91]	11.11		*NW*	[3.49]	4.17		[2.82]	5.86	
HH	[0.76]	12.44		[0.93]	10.61		*HH*	[1.68]	17.94		[0.96]	50.74	
VAR	[0.77]	19.80		[0.83]	16.33		*VAR*	[4.00]	6.18		[3.32]	8.31	
6	3.09		4.44	0.71		2.56	*6 minus 1*	9.93		1.57	3.73		0.80
NW	[0.84]	13.61		[0.21]	11.40		*NW*	[4.20]	5.59		[3.10]	1.45	
HH	[0.85]	13.27		[0.21]	11.48		*HH*	[3.73]	7.09		[3.08]	1.47	
VAR	[0.94]	16.80		[0.32]	12.78		*VAR*	[5.30]	7.36		[2.99]	3.60	

Notes: Panel A reports summary statistics for return predictability regressions at a one-month horizon. For each portfolio j, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\gamma_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (γ_f) in the right panel. Panel B reports summary statistics for return predictability regressions of the spread at a one-month horizon. The left panel reports the statistics in the regression of one-month excess returns on the average one-month forward discount spread ($\gamma_{\mathbf{sp,f}}$). The right panel reports the statistics in the regression of one-month excess returns on that portfolio's one-month forward discount spread ($\gamma_{sp,f}$). The Newey and West (1987) NW standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns take into account bid-ask spreads. The sample period is 11/1983 - 03/2008.

Table 6: Return Predictability: Longer Horizons

Horizon	1	2	3	6	12	1	2	3	6	12
Panel I: All Countries										
Overlapping Data										
Portfolio	Forward Discount					Residual Predictability				
1	4.30	4.64	8.03	25.30	25.93	0.23	0.00	0.01	1.18	0.20
6	2.56	3.07	3.82	5.72	10.03	0.01	0.03	0.06	0.03	0.05
	Average Forward Discount									
1	7.85	12.58	17.16	28.32	32.57					
6	4.44	6.13	8.46	12.70	17.54					
No Overlapping Data										
Portfolio	Forward Discount					Residual Predictability				
1	4.30	2.52	8.84	24.62	28.18	0.23	0.23	0.05	0.54	0.61
6	2.56	3.59	4.19	4.67	14.50	0.01	0.01	0.00	0.01	0.04
	Average Forward Discount									
1	7.85	13.41	17.87	31.74	30.22					
6	4.44	6.49	7.58	12.58	25.55					
Panel II: Developed Countries										
Overlapping Data										
Portfolio	Forward Discount					Residual Predictability				
1	1.95	3.51	6.86	14.41	17.23	0.01	0.25	0.17	0.12	0.06
5	3.29	5.74	7.67	12.26	13.55	0.24	0.24	0.21	0.42	1.22
	Average Forward Discount									
1	3.02	6.31	10.08	18.39	20.51					
5	2.85	5.34	7.80	12.27	10.43					
No Overlapping Data										
Portfolio	Forward Discount					Residual Predictability				
1	1.95	1.90	7.54	16.67	17.17	0.01	1.04	0.12	0.33	0.04
5	3.29	6.21	8.29	19.22	19.14	0.34	0.83	0.36	1.95	1.87
Portfolio	Average Forward Discount									
1	3.02	6.37	10.56	22.74	20.12					
5	2.85	4.19	7.79	15.81	14.19					

Notes: In the left panel, we report the R^2 in the time-series regressions of the log k-period currency excess return on the log forward discount for each portfolio j: $rx^{j,k}_{net,t+k} = \gamma^j_0 + \gamma^j_1(f^{j,k}_t - s^j_t) + \eta^j_t$. In the left panel, we also report the R^2 in the time-series regression the log k-period currency excess return on the linear combination of log forward discounts for each portfolio j: $rx^{j,k}_{net,t+k} = \gamma^j_0 + \gamma^j_1 \iota'(\mathbf{f}^k_t - \mathbf{s}^k_t) + \eta^j_t$ for each portfolio j. In the right panel, we report the residual predictability: In a first step, we regress the log k-period currency excess return on the average log forward discount for each portfolio j: $rx^{j,k}_{net,t+k} = \gamma^j_0 + \gamma^j_1 \iota'(\mathbf{f}^k_t - \mathbf{s}^k_t) + \eta^j_t$. We report the R^2 in the time-series regression of the residuals η^j_t from the first step on the log forward discounts for each portfolio j: $rx^{j,k}_{net,t+k} = \gamma^j_0 + \gamma^j_1(f^k_t - s^k_t) + \epsilon^j_t$ for each portfolio j. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008. Panel I uses developed and emerging countries. Panel II focuses on developed countries. In both cases, the top panel uses overlapping data and the bottom panel does not.

Table 7: Contemporaneous Correlations Between Expected Excess Returns or Forward Discounts and Macroeconomic and Financial Variables

	IP	Pay	$Help$	$spread$	$slope$	vol
Portfolio	Panel I: Expected Excess Returns					
1	0.18	0.02	0.19	−0.21	0.04	−0.17
	[0.04]	[0.02]	[0.11]	[0.03]	[0.04]	[0.02]
2	−0.57	−0.70	−0.41	0.34	0.42	−0.14
	[0.04]	[0.04]	[0.05]	[0.02]	[0.04]	[0.02]
3	−0.61	−0.64	−0.37	0.33	0.47	−0.04
	[0.05]	[0.05]	[0.06]	[0.02]	[0.04]	[0.02]
4	−0.57	−0.51	−0.30	0.26	0.42	0.09
	[0.06]	[0.05]	[0.06]	[0.02]	[0.04]	[0.02]
5	−0.51	−0.39	−0.24	0.28	0.38	0.28
	[0.05]	[0.05]	[0.05]	[0.02]	[0.03]	[0.02]
6	−0.14	−0.09	−0.05	0.17	0.15	0.52
	[0.05]	[0.05]	[0.05]	[0.02]	[0.05]	[0.02]
Maturity	Panel II: Average Forward Discount					
1	−0.31	−0.34	−0.13	0.17	0.33	0.18
	[0.12]	[0.04]	[0.14]	[0.04]	[0.08]	[0.05]
2	−0.46	−0.47	−0.24	0.26	0.40	0.24
	[0.15]	[0.05]	[0.15]	[0.04]	[0.09]	[0.05]
3	−0.51	−0.52	−0.30	0.30	0.41	0.27
	[0.16]	[0.05]	[0.15]	[0.04]	[0.09]	[0.05]
6	−0.54	−0.57	−0.38	0.35	0.40	0.32
	[0.18]	[0.05]	[0.15]	[0.05]	[0.10]	[0.07]
12	−0.50	−0.60	−0.37	0.29	0.41	0.24
	[0.18]	[0.05]	[0.17]	[0.06]	[0.12]	[0.08]

Notes: Panel I reports the contemporaneous correlation $Corr\left[\widehat{E}_t rx^j_{t+1}, x_t\right]$ of forecasted excess returns using the portfolio forward discount with different variables x_t: the 12-month percentage change in industrial production ($\Delta \log IP_t$), the 12-month percentage change in the total US non-farm payroll ($\Delta \log Pay_t$), and the 12-month percentage change of the Help-Wanted index ($\Delta \log Help_t$), the default spread ($spread_t$), the slope of the yield curve ($slope_t$) and the CBOE $S\&P$ 500 volatility index (vol_t). Panel II reports the contemporaneous correlation of the average forward discount with these variables. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 03/2008.

Table 8: Forecasting 12-month ahead Excess Returns with Industrial Production and Forward Discounts

	γ_{IP}	γ_f	W	R^2	γ_{IP}	$\gamma_{\mathbf{f}}$	W	R^2	γ_{IP}	γ_f	W	R^2	γ_{IP}	$\gamma_{\mathbf{f}}$	W	R^2
	All Countries								Developed Countries							
1	−0.92	2.23		30.20	−0.89	3.09		37.37	−1.30	1.27		23.45	−1.13	1.79		25.03
NW	[0.60]	[1.21]	37.13		[0.28]	[0.80]	41.77		[0.72]	[1.16]	19.66		[0.55]	[0.93]	21.24	
HH	[0.67]	[1.38]	38.95		[0.29]	[0.83]	47.75		[0.78]	[1.31]	17.37		[0.59]	[1.02]	19.39	
VAR	[0.71]	[1.31]	38.13		[0.61]	[1.10]	41.20		[0.91]	[1.55]	33.55		[0.89]	[1.49]	33.92	
No overlap	[0.78]	[1.60]	22.31		[0.51]	[1.37]	24.37		[0.91]	[1.48]	12.23		[0.78]	[1.38]	13.71	
2	−0.98	0.69		18.68	−0.94	0.98		20.13	−1.91	−0.21		21.25	−1.42	1.03		22.58
NW	[0.52]	[1.00]	15.30		[0.36]	[0.70]	15.11		[0.83]	[1.41]	16.63		[0.60]	[1.25]	17.89	
HH	[0.58]	[1.11]	16.11		[0.40]	[0.71]	16.36		[0.92]	[1.59]	14.45		[0.66]	[1.40]	15.64	
VAR	[0.54]	[1.08]	21.93		[0.51]	[0.92]	41.20		[0.88]	[1.56]	44.24		[0.89]	[1.49]	33.92	
No overlap	[0.68]	[1.61]	8.12		[0.48]	[1.25]	9.65		[0.96]	[1.94]	11.50		[0.79]	[1.98]	12.55	
3	−1.18	1.18		29.42	−1.15	1.51		31.75	−1.71	0.61		29.92	−1.68	0.71		30.02
NW	[0.36]	[0.92]	26.76		[0.30]	[0.82]	28.02		[0.43]	[0.86]	39.90		[0.46]	[0.99]	40.18	
HH	[0.40]	[0.99]	23.17		[0.33]	[0.90]	24.16		[0.46]	[0.93]	35.58		[0.48]	[1.09]	36.04	
VAR	[0.54]	[0.93]	62.73		[0.49]	[0.89]	56.88		[0.66]	[0.92]	52.70		[0.69]	[1.09]	48.97	
No overlap	[0.71]	[1.50]	14.59		[0.56]	[1.42]	16.13		[0.61]	[1.48]	92.52		[0.58]	[1.43]	92.46	
4	−1.19	1.02		31.66	−1.19	1.20		32.38	−1.48	0.84		32.46	−1.42	1.08		33.01
NW	[0.28]	[0.69]	32.51		[0.27]	[0.74]	31.14		[0.46]	[0.97]	51.55		[0.49]	[1.18]	49.47	
HH	[0.30]	[0.72]	29.88		[0.29]	[0.79]	28.37		[0.50]	[1.05]	49.98		[0.54]	[1.30]	47.69	
VAR	[0.46]	[0.64]	61.11		[0.44]	[0.77]	63.26		[0.57]	[0.85]	50.78		[0.58]	[1.02]	61.71	
No overlap	[0.39]	[1.44]	24.95		[0.31]	[1.48]	21.21		[0.62]	[1.54]	45.16		[0.57]	[1.82]	69.50	
5	−1.71	1.20		39.97	−1.72	0.97		37.90	−1.76	0.64		32.75	−2.14	−0.45		32.03
NW	[0.31]	[0.66]	43.03		[0.35]	[0.79]	38.81		[0.39]	[1.22]	41.94		[0.52]	[1.43]	48.03	
HH	[0.32]	[0.69]	47.98		[0.38]	[0.79]	43.60		[0.41]	[1.37]	38.25		[0.56]	[1.60]	44.46	
VAR	[0.41]	[0.71]	68.34		[0.46]	[0.81]	53.27		[0.68]	[1.10]	48.86		[0.73]	[1.25]	51.50	
No overlap	[0.54]	[0.98]	33.12		[0.70]	[1.51]	22.11		[0.45]	[1.46]	37.95		[0.67]	[1.86]	40.11	
6	−1.50	1.08		26.64	−1.08	1.95		24.09								
NW	[0.42]	[0.45]	23.97		[0.50]	[1.38]	17.97									
HH	[0.45]	[0.46]	20.20		[0.53]	[1.51]	15.68									
VAR	[0.52]	[0.57]	53.36		[0.65]	[1.13]	33.36									
No overlap	[0.45]	[0.50]	20.01		[0.50]	[1.40]	14.78									

Notes: This table reports forecasting results obtained on currency portfolios using the 12-month change in Industrial Production and either the portfolio 12-month forward discount or the average 12-month forward discount. We report the R^2 in the time-series regressions of the log 12-month currency excess return on the log forward discount for each portfolio j: $rx^{j,12}_{net,t+12} = \gamma^j_0 + \gamma^j_1(f^{j,12}_t - s^j_t) + \gamma^j_1 \Delta IP_{t-12,t} + \eta^j_t$. The left panel uses our sample of developed and emerging countries. The right panel uses our sample of developed countries. The Newey and West (1987) (NW) standard errors are computed with the optimal number of lags. The Hansen and Hodrick (1980) (HH) standard errors are computed with 12 lags for the 12-month returns. For the bootstrapped standard errors, the VAR uses 12 lags for the 12-month returns. All the returns are annualized and reported in percentage points. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 03/2008.

Table 9: Conditional Asset Pricing

				Panel I: Conditional HML					
	λ_{RX}	$\lambda_{HML_{FX}}$	$\lambda_{HML_{FX}VIX}$	b_{RX}	$b_{HML_{FX}}$	$b_{HML_{FX}VIX}$	R^2	$RMSE$	χ^2
GMM_1	1.92	8.12	20.58	0.05	2.57	-0.52	90.09	1.47	
	[3.69]	[3.39]	[9.70]	[0.21]	[2.67]	[0.78]			30.83
GMM_2	1.62	7.80	23.99	0.02	1.07	-0.05	82.07	1.98	
	[3.24]	[2.43]	[8.10]	[0.18]	[0.97]	[0.29]			56.48
FMB	1.92	8.12	20.58	0.05	2.56	-0.52	88.87	1.47	
	[2.80]	[2.52]	[6.76]	[0.17]	[2.01]	[0.59]			27.71
	[2.80]	[2.57]	[6.78]	[0.17]	[2.10]	[0.61]			35.35
$Mean$	**1.99**	**5.86**	**21.04**						
				Panel II: Conditional CAPM					
	λ_{RX}	λ_{R^m}	$\lambda_{R^m z}$	b_{RX}	b_{R^m}	$b_{R^m z}$	R^2	$RMSE$	χ^2
GMM_1	2.05	48.45	150.33	0.16	5.64	-1.00	95.77	0.96	
	[4.95]	[23.18]	[70.12]	[0.34]	[4.48]	[1.06]			54.47
GMM_2	1.12	26.54	89.50	0.02	2.01	-0.24	70.04	2.56	
	[4.42]	[15.60]	[50.23]	[0.27]	[2.16]	[0.48]			85.02
FMB	2.05	48.45	150.33	0.16	5.62	-0.99	95.26	0.96	
	[2.80]	[13.55]	[42.87]	[0.20]	[2.32]	[0.55]			11.73
	(2.81)	(19.91)	(62.56)	(0.24)	(3.42)	(0.80)			70.55
$Mean$	**1.99**	**6.93**	**23.51**						

Notes: This table 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 are reported in percentage points. In the top panel, the risk factors are the average return on the currency market RX, HML and $HML_{FX}VIX$, which is HML multiplied by the lagged value of the VIX index (scaled by its standard deviation). b_{RX}, $b_{HML_{FX}}$ and $b_{HML_{FX}VIX}$ represent the corresponding factor loadings. In the bottom panel, the risk factors are the average return on the currency market RX, the value-weighted stock market excess return R^m and $R^m z$, which is R^m multiplied by the lagged value of the VIX index (scaled by its standard deviation). b_{RX}, $b_{R^m VIX}$ and b_{R^m} represent the corresponding factor loadings. The portfolios are constructed by sorting currencies into six groups at time t based on the 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. In both panels, we use 12 test assets: the original 6 portfolios and 6 additional portfolios obtained by multiplying the original set by the conditioning variable (VIX). Data are monthly, from Barclays and Reuters (Datastream). The sample is 02/1990-03/2008. Standard errors are reported in brackets. Shanken-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure.

Table 10: Asset Pricing - CAPM

	Panel I: Factor Prices and Loadings														
	All Countries								Developed Countries						
	λ_{RX}	λ_{R^m}	b_{RX}	b_{R^m}	R^2	$RMSE$	χ^2		λ_{RX}	λ_{R^m}	b_{RX}	b_{R^m}	R^2	$RMSE$	χ^2
GMM_1	1.34	37.36	0.31	1.43	63.95	1.03			2.23	20.87	0.31	0.80	26.83	0.96	
	[1.93]	[16.37]	[0.37]	[0.62]			18.33		[2.16]	[14.11]	[0.25]	[0.54]			35.23
GMM_2	0.53	26.34	0.14	1.01	33.60	1.40			2.94	19.65	0.39	0.76	−13.55	1.20	
	[1.88]	[15.28]	[0.35]	[0.58]			25.18		[2.11]	[13.55]	[0.25]	[0.52]			36.97
FMB	1.34	37.36	0.31	1.42	51.97	1.03			2.23	20.87	0.31	0.80	−9.75	0.96	
	[1.34]	[12.56]	[0.26]	[0.48]			9.91	[1.71]	[11.72]	[0.20]	[0.45]			11.90	
	(1.34)	(15.40)	(0.26)	(0.59)			27.90	(1.71)	(12.64)	(0.20)	(0.48)			17.27	
$Mean$	**1.36**	**7.11**							**2.23**	**6.82**					
	Panel II: Factor Betas														
$Portfolio$	$\alpha_0^i(\%)$	β_{RX}^i	β_m^i	$R^2(\%)$	$\chi^2(\alpha)$	p			$\alpha_0^i(\%)$	β_{RX}^i	β_m^i	$R^2(\%)$	$\chi^2(\alpha)$	p	
1	−2.29	1.06	−0.05	74.66					−1.45	1.06	−0.06	77.86			
	[1.05]	[0.05]	[0.01]						[0.96]	[0.04]	[0.02]				
2	−1.71	0.97	−0.03	76.50					−1.06	1.04	−0.04	81.65			
	[0.77]	[0.05]	[0.01]						[0.84]	[0.04]	[0.02]				
3	−0.66	0.95	−0.01	71.89					1.10	1.02	−0.02	85.31			
	[0.84]	[0.05]	[0.02]						[0.81]	[0.03]	[0.02]				
4	1.63	0.93	−0.02	68.93					−0.13	0.95	0.07	81.14			
	[0.83]	[0.06]	[0.02]						[0.88]	[0.04]	[0.02]				
5	0.85	1.03	0.04	76.52					1.54	0.93	0.05	72.21			
	[0.83]	[0.05]	[0.02]						[1.03]	[0.04]	[0.02]				
6	2.17	1.06	0.08	59.88											
	[1.20]	[0.06]	[0.02]												
					20.25	0.00							6.47	0.26	

Notes: The panel on the left reports results for all countries in the sample. The panel on the right reports results for developed countries. The top panel 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 are reported in percentage points. b_1 represents the factor loading. The bottom panel reports results OLS estimates of the factor betas. The intercept α_0 β, and the R^2 are reported in percentage points. The standard errors in brackets are Newey-West standard errors computed with the optimal number of lags. 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 (Cochrane (2001), p. 234). Data are monthly, from Barclays and Reuters in Datastream. Excess returns used as test assets take into account bid-ask spreads. All excess returns are multiplied by 12 (annualized). Standard errors are reported in brackets. Shanken-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. The sample period is 11/1983 - 03/2008.

Table 11: CAPM in Crisis

Portfolio	α_m^i	β_m^i	$p(\%)$	R^2	α_m^i	β_m^i	$p(\%)$	R^2	α_m^i	β_m^i	$p(\%)$	R^2	α_m^i	β_m^i	$p(\%)$	R^2
Sample	26-May-1998				02-Aug-1995				10-Oct-1999				31-Aug-2007			
	Panel I: US CAPM															
1	−1.13	0.02	86.16	0.10	4.24	−1.22	0.09	18.20	−0.16	−0.13	16.91	7.33	0.15	−0.13	1.38	11.85
	[0.62]	[0.14]			[1.57]	[0.37]			[0.57]	[0.09]			[0.38]	[0.05]		
2	−0.64	−0.05	75.70	0.59	3.48	−0.90	8.76	8.52	−0.45	−0.11	5.19	9.30	0.17	0.21	0.04	27.84
	[0.92]	[0.16]			[1.90]	[0.53]			[0.35]	[0.05]			[0.37]	[0.06]		
3	−1.45	0.21	11.09	10.97	3.51	−0.89	7.88	11.97	0.85	−0.05	34.63	1.93	0.74	0.18	0.02	28.38
	[0.71]	[0.13]			[1.80]	[0.50]			[0.34]	[0.05]			[0.27]	[0.05]		
4	−1.43	0.28	2.50	13.55	2.21	−0.48	5.52	11.88	−0.24	−0.23	3.95	29.24	0.31	0.21	0.00	40.08
	[0.59]	[0.12]			[0.83]	[0.25]			[0.22]	[0.11]			[0.25]	[0.03]		
5	−1.81	0.50	0.00	23.41	2.14	−0.55	5.20	10.14	−0.40	0.06	22.28	4.82	0.51	0.25	0.00	45.52
	[0.47]	[0.11]			[0.92]	[0.28]			[0.30]	[0.05]			[0.23]	[0.04]		
6	−3.84	1.14	0.00	23.41	0.42	−0.00	98.46	10.14	0.80	0.25	0.00	4.82	0.44	0.50	0.00	45.52
	[1.53]	[0.27]			[0.43]	[0.14]			[0.48]	[0.05]			[0.43]	[0.10]		
HML	−2.71	1.11	0.00	20.15	−3.82	1.22	0.02	11.24	0.96	0.37	0.03	20.87	0.29	0.62	0.00	56.12
	0.60	0.16			1.38	0.33			0.75	0.10			[0.38]	[0.08]		
	Panel II: World CAPM															
1	−0.94	−0.05	75.66	0.48	1.73	−0.71	0.51	24.89	−0.14	−0.15	14.24	8.54	0.08	−0.14	0.81	14.48
	[0.67]	[0.18]			[0.93]	[0.25]			[0.55]	[0.10]			[0.39]	[0.05]		
2	−0.39	−0.14	44.51	4.72	1.87	−0.81	0.21	28.38	−0.41	−0.13	1.09	12.58	0.27	0.21	0.06	27.57
	[0.98]	[0.19]			[0.76]	[0.26]			[0.33]	[0.05]			[0.37]	[0.06]		
3	−1.31	0.13	44.49	4.03	1.86	−0.71	0.44	31.54	0.82	−0.04	53.76	0.86	0.82	0.18	0.02	28.90
	[0.80]	[0.17]			[0.65]	[0.25]			[0.33]	[0.06]			[0.27]	[0.05]		
4	−1.27	0.19	24.99	5.87	1.28	−0.34	0.08	24.07	−0.21	−0.25	2.33	30.82	0.41	0.22	0.00	42.22
	[0.68]	[0.16]			[0.29]	[0.10]			[0.21]	[0.11]			[0.26]	[0.03]		
5	−1.70	0.40	1.08	14.62	1.07	−0.38	0.68	19.92	−0.38	0.05	32.38	3.11	0.64	0.26	0.00	47.64
	[0.55]	[0.16]			[0.38]	[0.14]			[0.30]	[0.05]			[0.22]	[0.04]		
6	−3.55	0.90	1.08	14.62	0.26	0.19	0.14	19.92	0.75	0.29	0.00	3.11	0.68	0.53	0.00	47.64
	[1.85]	[0.35]			[0.18]	[0.06]			[0.48]	[0.06]			[0.39]	[0.11]		
HML	−2.62	0.96	0.00	17.95	−1.47	0.90	0.03	10.83	0.89	0.44	0.00	20.59	0.60	0.67	0.00	61.92
	[0.88]	[0.22]			[0.85]	[0.25]			[0.72]	[0.11]			[0.33]	[0.08]		

Notes: This table reports results OLS estimates of the factor betas. The sample period is 129 days (6 months) before and including the mentioned date. The intercept α_0 β, and the R^2 are reported in percentage points. The standard errors in brackets are Newey-West standard errors computed with the optimal number of lags. The p-value is for a t-test on the slope coefficient. The portfolios are constructed by sorting currencies into six groups at time t based on the the currency excess return at the end of period $t-1$. The returns are 1-month returns, and take into account bid-ask spreads. Portfolio 1 contains currencies with the lowest previous excess return. Portfolio 6 contains currencies with the highest previous excess return. Data are daily, from Barclays and Reuters in Datastream. In panel I, we use the value-weighted return on the US stock market (CRSP). In panel II, we use the return on the MSCI World Index.

Table 12: Calibration

Panel I: Moments		
Moment	*Closed Form Expression*	*Target*
$E[r]$	$\left(\lambda - \frac{1}{2}\gamma\right)\theta + \left(\tau - \frac{1}{2}\delta\right)\theta$	.015
$Var[r]$	$\left(\lambda - \frac{1}{2}\gamma\right)^2 \sigma_z^2 + \left(\tau - \frac{1}{2}\delta\right)^2 \sigma_{z^w}^2$	$.02^2$
$\rho[r]$	$\frac{\phi\left(\lambda - \frac{1}{2}\gamma\right)^2 \sigma_z^2 + \phi\left(\tau - \frac{1}{2}\delta\right)^2 \sigma_{z^w}^2}{Var[r]}$	.8
$E\left[Var_t[\Delta q_{t+1}]\right]$	$2\gamma\theta$	$.12^2$
$E[SR^2]$	$\gamma\theta + \delta\theta$	.5
$Var\left[SR^2\right]$	$(\gamma\sigma_z)^2 + (\delta\sigma_{z^w})^2$	$.5^2$
β_{UIP}	$\frac{-\lambda}{\lambda - \frac{1}{2}\gamma}$	-1

Panel II: Parameters							
Real SDFs	λ	γ	τ	δ	ϕ	θ	$\sigma(\%)$
	1.24	0.14	2.79	7.35	0.997	0.05	0.47
Inflation	$\sigma^{w\$}(\%)$	ρ^w	$\overline{\pi^w}(\%)$	$\sigma^{\$}(\%)$	ϕ	$\overline{\pi}(\%)$	μ
	0.66	0.88	3.20	8.15	0.58	3.00	0.16

This table reports moments used in the calibration and the chosen parameters. All countries share the same parameters except for δ. The parameters δ^i are linearly distributed around the value reported in the table: $\delta^i \in [0.8\delta, 1.2\delta]$. The unconditional standard deviations of z and z^w are respectively equal to $\sigma\sqrt{\theta/[2(1-\phi)]}$ and $\sigma^w\sqrt{\theta^w/[2(1-\phi^w)]}$.

Table 13: Currency Portfolios - Simulated data

Portfolio	1	2	3	4	5	6	
			Spot change: Δs^j				
Mean	−0.04	0.59	0.64	0.91	1.04	1.71	
Std	9.55	8.83	8.28	8.35	8.81	9.45	
			Forward Discount: $f^j - s^j$				
Mean	−3.41	−1.33	0.22	1.79	3.28	5.23	
Std	1.45	1.31	1.24	1.11	1.07	1.07	
			Excess Return: rx^j				
Mean	−3.36	−1.92	−0.42	0.88	2.24	3.52	
Std	9.55	8.82	8.29	8.39	8.87	9.54	
SR	−0.35	−0.22	−0.05	0.10	0.25	0.37	
			High-minus-Low: $rx^j - rx^1$				
Mean		1.44	2.94	4.24	5.61	6.89	
Std		2.80	4.22	6.23	8.13	9.57	
SR		0.52	0.70	0.68	0.69	0.72	

	λ_{RX}	$\lambda_{HML_{FX}}$	b_{RX}	$b_{HML_{FX}}$	R^2	$RMSE$	χ^2
GMM_1	0.16	6.81	0.19	7.45	99.82	0.09	
	[0.32]	[0.37]	[0.47]	[0.41]			1.12
GMM_2	0.04	7.08	0.01	7.74	99.31	0.17	
	[0.31]	[0.36]	[0.47]	[0.39]			1.50
FMB	0.16	6.81	0.19	7.44	99.76	0.09	
	[0.26]	[0.31]	[0.39]	[0.33]			0.07
	(0.26)	(0.31)	(0.39)	(0.34)			1.19
Mean	**0.15**	**6.89**					

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 annual and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annual means to annual standard deviations. 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 our model.

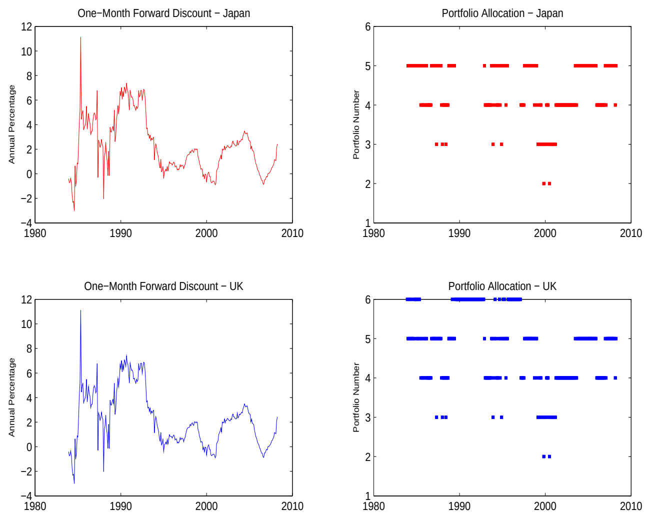

Figure 1: Portfolio Allocation for the UK pound and the Japanese yen.

This figure plots, for the UK pound and the Japanese yen, the one-month forward discount and the portfolio to which the currency was allocated. Data are monthly. The sample is 11/1983 - 03/2008.

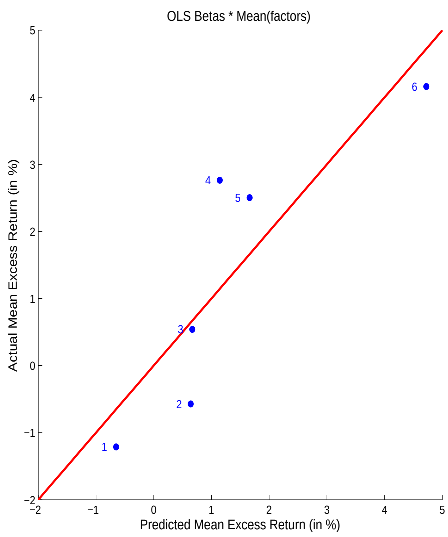

Figure 2: Predicted against Actual Excess Returns.

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 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.

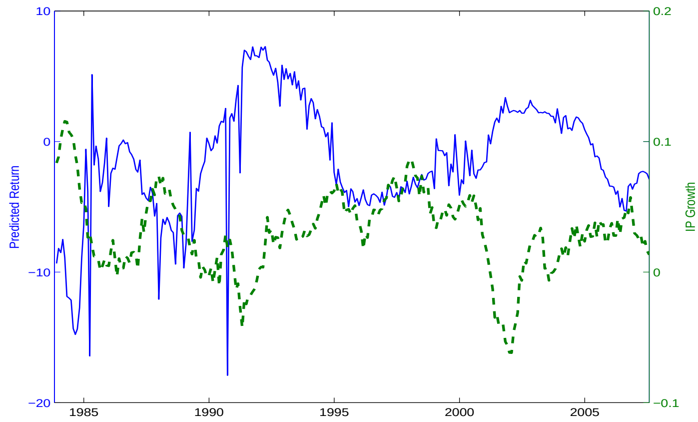

Figure 3: Forecasted Excess Return in Currency Markets and US Business Cycle.

This figure plots the one-month ahead forecasted excess returns on portfolio 2 ($\widehat{E}_t rx^2_{t+1}$). All returns are annualized. The dashed line is the year-on-year log change in US Industrial Production Index.

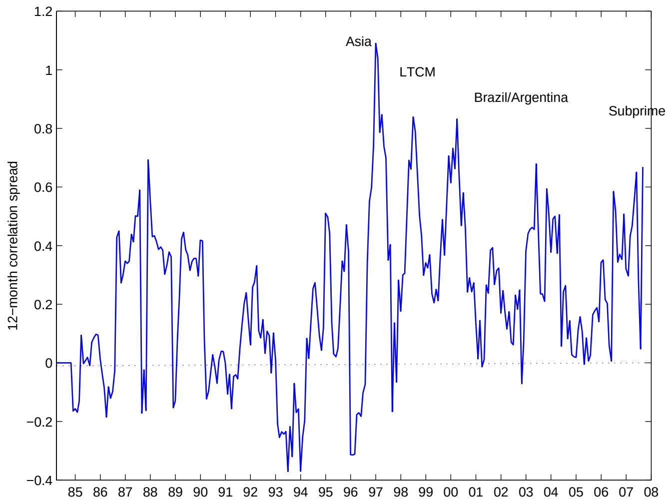

Figure 4: Market Correlation Spread of Currency Returns

This figure plots $Corr_\tau[R^m_t, rx^6_t] - Corr_\tau[R^m_t, rx^1_t]$, where $Corr_\tau$ is the sample correlation over the previous 12 months $[\tau - 253, \tau]$. We use monthly returns at daily frequency. We also plot β_{HML} . The stock market return is the return on the value-weighted US index (CRSP).

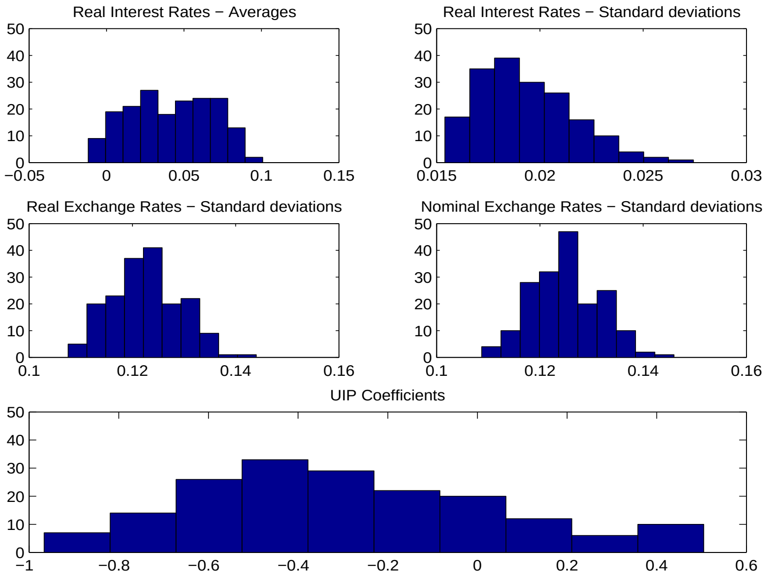

Figure 5: Exchange Rates, Interest Rates and UIP Slope Coefficients - Simulated Data.

This figure plots several histograms summarizing our simulated data. We report the distributions of the interest rates' first two moments, the volatility of real and nominal exchange rates and the UIP slope coefficients.

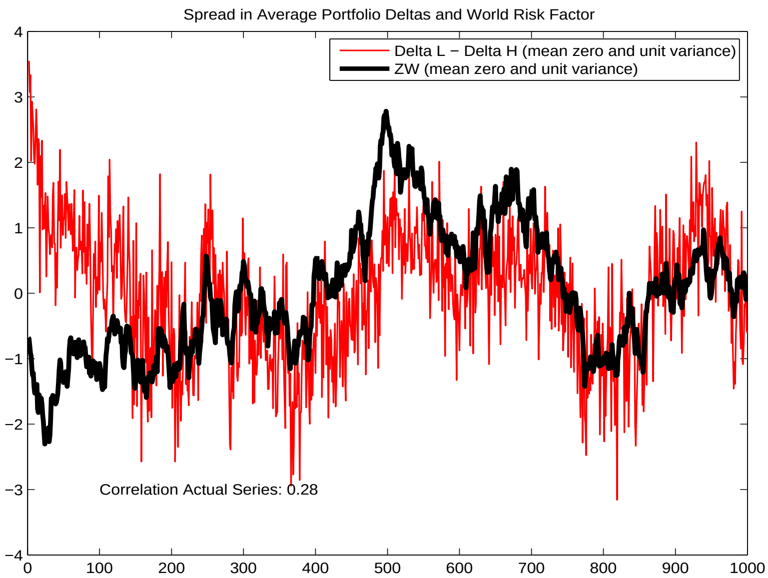

Figure 6: Spreads in Portfolio Deltas and World Risk Factor - Simulated Data.

This figure plots the difference between the average delta in the first portfolio and the average delta in the last portfolio, along with the world risk factor ZW. Both series are centered and scaled by their standard deviations.