Common Risk Factors in Currency Markets*

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Abstract

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 4.8 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. This evidence suggests currency risk premia are large and time-varying. In a simple affine pricing model, we show that the high-minus-low currency return measures the component of the stochastic discount factor innovations that is common across countries. To match the carry trade returns in the data, low interest rate currencies need to load more on this common innovation when the market price of global 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 currency risk premia are determined by their exposure to a single, global risk factor, and that interest rates measure currency 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 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 the 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 than 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 the finding of Cochrane and Piazzesi (2005) that a linear combination of forward rates across maturities is a powerful predictor of 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 supports the risk premium view. 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 (2005) report a similar finding for the bond market, and Piazzesi and Swanson (2008) document that payroll growth predicts excess returns on interest rate futures. 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_{FX}, for high interest rate minus low interest rate currencies. The carry trade risk factor HML_{FX} explains about 70 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, consistent with a linear factor pricing model. Low interest rate currencies provide US investors with insurance against HML_{FX} risk, while high interest rate currencies expose investors to more HML_{FX} risk. By ranking currencies into portfolios based on their forward discounts, we find that forward discounts determine currencies' exposure to HML_{FX}, and hence their risk premia. As a check, we also rank currencies based on their HML_{FX}-betas, and we find that portfolios with high HML_{FX}-exposure do yield higher average returns and have higher forward discounts.

We use a standard no-arbitrage exponentially-affine asset pricing framework to explain why we build these currency portfolios. Our model features a large number of countries. The stochastic discount factor (SDF) that prices assets in the units of a given country's currency is composed of two risk factors: one is country-specific, the other is common for all countries. 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, i.e. in bad times. Using the model, we show analytically that by ranking currencies into portfolios and constructing HML_{FX}, 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. By building currency portfolios, we recover the two factors that drive the pricing kernel. The portfolio approach is critical. Bansal and Dahlquist (2000) take a time series approach by estimating UIP regressions for a large number of currencies and they find that country-specific attributes are critical to understanding the cross-sectional variation in currency risk premia. We document large differences in risk characteristics between different currency portfolios, regardless of the characteristics of the currencies in these portfolios.

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_{FX} 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 and hence offer insurance. In a version of the model that is calibrated to match 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).

[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), Burnside, Eichenbaum and Rebelo (2007b) and Burnside, Eichenbaum, Kleshchelski and Rebelo (2008).

These three models have two elements in common: a persistent variable drives the volatility of the log stochastic discount factor, and this variable comoves negatively with the country's risk-free interest rate. 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 for replicating our empirical findings; we show 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_{FX} is strongly related to macroeconomic risk; it has a US consumption growth beta between 1 and 1.5, consistent with the findings of Lustig and Verdelhan (2007). In recent related work, DeSantis and Fornari (2008) provide more evidence that currency returns compensate investors for systematic, business cycle risk.

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_{FX}, explains most of the cross-sectional variation in foreign currency excess returns. In section 3, we use a no-arbitrage model of exchange rates to interpret these findings. 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 in 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 methodology, and we conclude by giving a summary of the currency portfolio returns.

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

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

This excess return can also be stated as the log forward discount minus the change in the spot rate: $rx_{t+1} = f_t - s_t - \Delta s_{t+1}$. In normal conditions, forward rates satisfy the covered interest rate parity condition[3]; 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 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:

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

[3] **?** study high frequency deviations from covered interest rate parity (CIP). They conclude that CIP holds at daily and lower frequencies.

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.[4] These data are collected by Barclays and Reuters and available on Datastream.[5] Our main data set contains 37 currencies: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, Euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. Some of these currencies have pegged their exchange rate partly or completely to the US dollar over the course of the sample. We keep them in our sample because forward contracts were easily accessible to investors. We leave out Turkey and United Arab Emirates, even if we have data for these countries, because their forward rates appear disconnected from their spot rates. As a robustness check, we also a study a smaller data set that contains only 15 developed countries: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland and United Kingdom. We present all of our results on these two samples. 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_{t+1}^{j} for portfolio j by taking the average of the log currency excess returns in each portfolio j. For the purpose of computing returns net of bid-ask spreads we assume that investors *short* all the foreign currencies in the *first* portfolio and go *long* in all the other foreign currencies.

The total number of currencies in our portfolios varies over time. We have a total of 9 countries at the beginning of the sample in 1983 and 26 at the end in 2008. We only include currencies for which we have forward and spot rates in the current and subsequent period. The maximum number of currencies attained during the sample is 34; the launch of the euro accounts for the subsequent decrease in the number of currencies. The average number of portfolio switches per month is 6.01 for portfolios sorted on one-month forward rates. We define the average frequency as the time-average of the following ratio: the number of portfolio switches divided by the total number of

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

[5]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.

currencies at each date. The average frequency is 29.32 percent, implying that currencies switch portfolios roughly every three months. When we break it down by portfolio, we get the following frequency of portfolio switches (in percentage points): 19.9 for the 1st, 33.8 for the 2nd, 40.7 for the 3rd, 43.4 for the 4th, 42.0 for the 5th, and 13.4 for the 6th. Overall, there is quite some variation in the composition of these portfolios, but there is more persistence in the composition of the corner portfolios. As an example, we consider the Japanese yen (¥). The yen starts off in the fourth portfolio early on in the sample, then gradually ends up in the first portfolio as Japanese interest rates fall in the late eighties and it briefly climbs back up to the sixth portfolio in the early nineties. The yen stays in the first portfolio for the remainder of the sample.

1.2 Returns to Currency Speculation for a US investor

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

The first panel reports the average rate of depreciation for all currencies in portfolio j. According to the standard uncovered interest rate parity (UIP) condition, the average rate of depreciation $E_T\left(\Delta s^j\right)$ of currencies in portfolio j should equal the average forward discount on these currencies $E_T\left(f^j - s^j\right)$, 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 equally 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 sort 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

Linear factor models of asset pricing predict that average returns on a cross-section of assets can be attributed to risk premia associated with their exposure to a small number of risk factors. In the arbitrage pricing theory of Ross (1976) these factors capture common variation in individual asset returns. A principal component analysis on our currency portfolios reveals that two factors explain more than 80 percent of the variation in returns on these six portfolios. The top panel in table 2 reports the loadings of our currency portfolios on each of the principal components as well as the fraction of the total variance of portfolio returns attributed to each principal component. The first principal component explains 70 percent of common variation in portfolio returns, and can be interpreted as a *level* factor, since all portfolios load equally on it. The second principal component, which is responsible for over 12 percent of common variation, can be interpreted as a *slope* factor, since portfolio loadings increase monotonically across portfolios. The first principal component is indistinguishable from the average portfolio return. The second principal component is essentially the difference between the return on the sixth portfolio and the return on the first portfolio. As a consequence, we 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_{FX}. The correlation of the first principal component with RX is .99. The correlation of the second principal component with HML_{FX} is .94. Both factors are computed from net returns, after taking into account bid-ask spreads. The bottom panel confirms that we obtain similar results even when we exclude developing countries from the sample.

These currency risk factors have a natural interpretation. HML_{FX} is the return in dollars on a zero-cost strategy that goes long in the highest interest rate currencies and short in the lowest interest rate currencies. 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.

Before turning to our main asset pricing estimates, we report here a simple experiment to build intuition on our results. Following Cochrane and Piazzesi (2008), for each principal component, we compute its covariance with the currency portfolio returns, and we compare these covariances (indicated by triangles) to the average currency excess returns (indicated by squares). Figure 1 illustrates that the second principal component plays a key role. Its covariance with currency excess returns increases monotonically as we go from portfolio 1 to 6.[6] This is not the case for any of the

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

other principal components.

As a result, in the space of portfolio returns, the second principal component is crucial. A natural question is whether we discard lots of other interesting variations in currency returns by building these portfolios? This concern has been raised for equity portfolios. Daniel and Titman (2005) note that the 25 Fama and French (1993) equity portfolios lie in a subspace spanned by HML and SMB. Likewise, our currency portfolio excess returns lie in a two-dimensional subspace of all currency excess returns spanned by the first two principal components, which explain more than 80 percent of their time series variation. Since stock returns can be predicted by many other macro-economic variables, Daniel and Titman (2005) emphasize the importance of examining other sources of variation in stock returns to test asset pricing models. This criticism does not carry over to currencies, simply because very few macro-economic variables (other than interest rate differences) forecast changes in exchange rates and hence currency returns. This was first pointed out by Meese and Rogoff (1983) and confirmed in subsequent work. So it is not clear that there are other sources of variation in currency returns to explored. In fact, in the next section, we set up a standard no-arbitrage model of currencies and we show that the first two principal components explain 100 percent of the time series variation in portfolio returns. There are no other sources of cross-sectional variation in currency risk premia in this model than the ones we identify. By building these portfolios, we average out idiosyncratic shocks and we extract risk factors.

Cross-Sectional Asset Pricing We use Rx^j_{t+1} to denote the average excess return on portfolio j in period $t+1$.[7] In the absence of arbitrage opportunities, this excess return has a zero price and satisfies the following Euler equation:

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

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

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

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

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

where $\lambda = \Sigma_{ff}b$, $\Sigma_{ff} = E(f_t - \mu_f)(f_t - \mu_f)'$ is the variance-covariance matrix of the factor, and β^j denotes the regression coefficients of the return Rx^j on the factors. To estimate the factor prices

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

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 briefly describe these two techniques, starting with GMM, in Appendix A.

2.2 Results

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

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_{FX} risk is 546 basis points *per annum*. This means that an asset with a beta of one earns a risk premium of 5.46 percent per annum. Since the factors are returns, no arbitrage implies that the risk prices of these factors should equal their average excess returns. This condition stems from the fact that the Euler equation applies to the risk factor itself, which clearly has a regression coefficient β of one on itself. In our estimation, this no-arbitrage condition is satisfied. The average excess return on the high-minus-low strategy (last row in Table 3) is 537 basis points.[8] So the estimated risk price is only 9 basis points removed from the point estimate implied by linear factor pricing. The GMM standard error of the risk price is 234 basis points. The FMB standard error is 183 basis points. In both cases, the risk price is more than two standard errors from zero, and thus highly statistically significant.

The second risk factor RX, the average currency excess return, has an estimated risk price of 135 basis points, compared to a sample mean for the factor of 136 basis points. This is not surprising, because all the portfolios have a beta close to one with respect to this second factor. As a result, the second factor explains none of the cross-sectional variation in portfolio returns, and the standard errors on the risk price estimates are large: for example, the GMM standard error is 168 basis points. 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.

[8] 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.

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 imply an even better fit by construction.

These results are robust. They hold true in a smaller sample of developed countries, as shown in the right-hand side of Table 3.

Alphas in the Carry Trade? The bottom panel of Table 3 reports the constants (denoted α^j) and the slope coefficients (denoted β^j) obtained by running time-series regressions of each portfolio's currency excess returns Rx^j on a constant and risk factors. The returns and α's are in percentage points per annum. The first column reports α's estimates. The fourth portfolio has a large α of 162 basis points per annum, significant at the 10 percent level but not statistically significant at the 5 percent level. The other α estimates are much smaller and not significantly different from zero. The null that the α's are jointly zero cannot be rejected at the 5 or 10 % significance level.

The second column of the same panel reports the estimated βs for the HML_{FX} factor. These βs increase monotonically from -.39 for the first portfolio to .61 for the last currency portfolio, and they are estimated very precisely. The first three portfolios have betas that are negative and significantly different from zero. The last two have betas that are positive and significantly different from zero. The third column shows that betas for the 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_{FX} 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_{FX}. For each date t, we first regress each currency i log excess return rx^i on a constant and HML_{FX} using a 36-month rolling window that ends in period $t-1$. This gives us currency i's exposure to HML_{FX}, and we denote it $\beta_t^{i,HML}$. Note that it only uses information available at date t. We then sort currencies into six groups at time t based on these slope coefficients $\beta_t^{i,HML}$. Portfolio 1 contains currencies with the lowest βs. Portfolio 6 contains currencies with the highest βs. Table 4 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. The last panel reports the post-formation betas. They vary monotonically from $-.31$ to .38. This finding is quite robust. When we estimate betas using a 12-month rolling window, we also obtain a 300 basis point spread between the first and the last portfolio.

2.4 Robustness

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_{FX} and RX) in local currencies, and we use the local currency returns as test assets. Note that HML_{FX} is essentially the same risk factor in all currencies, if we abstract from bid-ask spreads. Our initial spot and forward rates are quoted in US dollars. In order to convert these quotes into pounds, yen and Swiss francs, we use the corresponding midpoint quotes of these currencies against the US dollar.[9] The first panel in Table 5 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_{FX} risk is less than 70 basis points removed from the sample mean of the factor. The HML_{FX} risk price is estimated at 5.54 percent in the UK, 5.50 percent in Japan and 5.79 percent in Switzerland. These estimates are statistically different from zero in all three cases. The two currency factors explain between 47 and 71 percent of the variation (after adjusting for degrees of freedom). The mean squared pricing error is 95 basis points for the UK, 116 basis points for Japan and 81 basis points for Switzerland. The null that the underlying pricing errors are zero cannot be rejected except for Japan, for which the p-values are smaller than 10 percent.

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 et al. (2008). Following the methodology of Lustig and Verdelhan (2007), Burnside et al. (2008) build 5 currency portfolios and argue that these currency excess returns bear no relation to their riskiness. In their data, we show that the average excess returns on these portfolios are explained by the carry trade and aggregate currency market risk factors. The α's are smaller than 60 basis points per annum, but the high-minus-low return yields 6.3 percent per annum in their sample (without bid-ask spreads). Second, we report additional results on portfolio returns from the perspective of

[9] Table 18 in the appendix reports summary statistics on these portfolios.

foreign investors. Third, we divide our main sample into two sub-samples, starting in 1983 and in 1995. Fourth, we consider the longer sample of currency excess returns built using Treasury bills in Lustig and Verdelhan (2007). All these results confirm that currency excess returns are large and that they are well explained by the portfolios' covariances with these risk factors.

3 A No-Arbitrage Model of Exchange Rates

In order to interpret the empirical properties of the currency portfolios documented above, we consider a no-arbitrage model of exchange rates. Such models are characterized by a set of stochastic discount discount factors (intertemporal marginal rates of substitution) that price assets from the viewpoint of each country's investors. In this setting, we show that the HML_{FX} factor that we construct by building currency portfolios measures the common innovation to the SDFs. Similarly, RX measures the dollar-specific innovation to the SDF of U.S. investors. In addition, we show how ranking currencies based on interest rates 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_{FX}.

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

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

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

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

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

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

where the innovations v_{t+1}^w are also *i.i.d* gaussian, with zero mean and unit variance. In this model, the conditional market price of risk has a domestic component $\sqrt{\gamma^i z_t^i}$ and a global component $\sqrt{\delta^i z_t^w}$.[10] A major difference between our model and that proposed by Backus et al. (2001) is that we allow the loadings δ^i on the common component to differ across currencies. This will turn out to be critically important.

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

$$\Delta q_{t+1}^i = m_{t+1} - m_{t+1}^i,$$

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

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

The risk premium has a global and a dollar component. $\left(\sqrt{\delta}-\sqrt{\delta^i}\right)$ is the beta of the return on currency i w.r.t. the common shock, and z_t^w is the risk price. The beta w.r.t. the dollar shock is one for all currencies, and z_t is the risk price for dollar shocks. So, the expected return on currency i has a simple beta representation: $E_t[rx_{t+1}^i] + \frac{1}{2}Var_t[rx_{t+1}^i] = \beta^i\lambda_t$ with $\beta^i = \left[(\sqrt{\delta}-\sqrt{\delta^i}), 1\right]$ and $\lambda_t = [z_t^w, z_t]'$. The risk premium is *independent* of the foreign country-specific factor z_t^i and the foreign country-specific loading γ^i.[11] Hence, we need asymmetric loadings on the common

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

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

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

$$\begin{aligned} E_t[rx_{t+1}^i] &= -E_t[\Delta q_{t+1}^i] + r_t^i - r_t, \\ &= \frac{1}{2}[\gamma z_t - \gamma^i z_t^i + (\delta - \delta^i)\, z_t^w]. \end{aligned}$$

component as a source of variation across currencies. While asymmetric loadings on the country-specific component can explain the negative UIP slope coefficients in time series regression (as Backus et al. (2001) show), these asymmetries cannot account for any variation in risk premia across different currencies. As a consequence, and in order to simplify the analysis, we impose more symmetry on the model with the following assumption:

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

3.1 Building Currency Portfolios to Extract Factors

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

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

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

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

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

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

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

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

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

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

Condition.

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

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^i_t, and the heterogeneity in the SDF loadings δ^i on the world factor z^w. As a result, as z^w increases, on average, the currencies with the high loadings δ will tend to end up in the lowest interest rate portfolios, and the gap $\left(\overline{\sqrt{\delta^L_t}} - \overline{\sqrt{\delta^H_t}}\right)$ 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 in 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 carry trade risk premium and the dollar risk premium are:*

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

The carry trade risk premium is driven by the global risk factor. The size of the carry trade risk premium is governed by the spread in the loadings (δ) on the common factor between low and high interest rate currencies, and by the global price of risk. When this spread doubles, the carry trade risk premium doubles. However, the spread itself also increases when the global Sharpe ratio is high. As a result, the carry trade risk premium increases non-linearly when global risk increases. The dollar risk premium is driven only by the US risk factor, if the home country's exposure to global risk factor equals to the average δ[12]. When the home country's δ is lower than average, then the dollar risk premium also loads on the global factor:

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

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

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

The first component is the dollar risk premium part. The second component is the carry trade part. The highest interest rate portfolios load more on the carry trade component, because their loadings are smaller than the home country's δ, while the lowest interest rate currencies have a negative loading on the carry trade premium, because their loadings exceed the home country's δ.

If business cycle fluctuations drive SDF volatility in a way that bad times are associated with high prices of risk, then the US-specific component of the risk price, z_t, should be counter-cyclical with respect to the US-specific component of the business cycle, and the global component z_t^w should be counter-cyclical with respect to the global business cycle. Below, we show 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. We also 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 higher frequency variation in the global risk factor z_t^w.

[12]Note that $\overline{z}$ is constant in the limit $N \to \infty$ by the law of large numbers.

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 - portfolios long in high interest 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 regression of each portfolio's average log currency excess returns on each portfolio's average log forward discounts:

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

If UIP were an accurate description of the data, there would be no predictability in currency excess returns, and the slope coefficient κ_f would be zero. Table 6 reports regression results. 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.

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 κ^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. At the one-month horizon, the R^2 on these predictability regressions varies between 1.61 and 5.98 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. [13] 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:

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

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 6. This single factor explains between 2.68 and 7.85 percent of the variation in returns at the one-month horizon. The average forward discount outperforms the portfolio-specific forward discounts, except in portfolios 4 and 5. In this case, the slope coefficients vary much less across the different portfolios. Portfolio-specific time variation in expected exchange rate movements driven by the sorting variable (relative interest rates) does not appear to be the main driver of return predictability in currency markets. The average interest rate difference is the main driver.

The right panel of Table 6 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

[13] We also examined the optimal linear combination of forward discounts along the lines of Cochrane and Piazzesi (2005). However, it does not outperform the average forward discount as a predictor.

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:

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

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.

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:

$$rx^k_{t+k} = -\Delta s_{t\to t+k} + f^k_t - s_t.$$

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 7 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 7 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 7, 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 7, 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 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 7, 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 predictability of Treasury bill and bond returns. These studies show that linear combinations of forward rates across maturities outperform the forward rate of a particular maturity in forecasting 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 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:

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

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.[14] Macroeconomic variables are often revised. To check 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 8 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.[15] 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

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

[15]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 monthly time-series.

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 9 reports forecasting results for currency portfolios obtained using the 12-month change in industrial production and either the portfolio-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 (2005) report a similar finding for the bond market, while Piazzesi and Swanson (2008) find that the annual growth rate of the non-farm payroll predicts excess returns on interest rate futures.

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_{FX}, and we add $HML_{FX,t+1}z_t$. Our conditioning variable z is the CBOE volatility index VIX. Table 10 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 behavior of the second moments of currency returns over time.

4.3 Flight-to-Quality

In this section, we show that the average beta of HML_{FX} with the US stock market return is too small to explain carry trade risk premia, but this beta varies a lot through time, and is particularly high during episodes of global financial crises.

We 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_{FX}. 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. Panel A in table 11 reports the results. 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 11. 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. Panel B in table 11 reports the α's and the β's. The null that that the α's are zero is rejected at the 5 % significance level.

The failure of the CAPM could 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 10 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 Our carry risk factor HML_{FX} is much more correlated with the stock market when there is a lot of global risk. The recent subprime mortgage crisis offers a good example. A typical currency carry trade at the start of July 2007 was to borrow in yen - a low interest rate currency - and invest in Australian and New Zealand dollars - high interest rate currencies. Over the course of the summer, each large drop in the S&P 500 was accompanied by a large appreciation of the yen of up to 1.7 percent and a large depreciation of the New Zealand and Australian dollar of up to 2.3 percent .[16] Figure 4 plots the monthly returns on HML_FX at daily frequencies against the US stock market return. Clearly, a US investor who was long in these high interest rate currencies and short in low interest rate currencies, was heavily exposed to US aggregate stock market risk during the subprime mortgage crisis, and thus should have been compensated by a risk premium ex ante.

In the two-factor model, the conditional correlation of HML_{FX} and the SDF in the home country is:

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

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_{FX} 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 5 plots the difference

[16]The 2.3 percent depreciation of the New Zealand dollar on July 26 is 3 times the size of the daily standard deviation in 2007. The 2 percent drop in the Australian dollar is 3.5 times the size of the daily standard deviation in 2007 –the steepest one-day drop since it was allowed to trade freely in 1983.

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_{FX}. 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 Argentinean 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 12 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.[17] The NW standard error correction is computed with 20 lags. We estimate a market beta of HML_{FX} 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 12. 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 12, we document similar increases in the US market beta of HML_{FX} 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 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. For the Tequila crisis, the market betas of all the currency portfolios are negative. This is consistent with our model, as the dollar risk premium component is counter-cyclical with respect to the US business cycle, and hence the expected returns on all portfolios can be negative (see equation 3.2). In two of these crisis, the α on the high-minus-low strategy is negative: minus 271 basis over the 6 months preceding

[17] For example, we compute market betas $\beta^m_{\tau,HML}$ of HML_{FX} 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 $t \in [\tau, \tau - 128]$.

the Russian default and minus 382 basis points during the Tequila crisis.[18] 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.

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 some additional technical constraints.[19] The maximization attains all moments except the mean (0.65) and standard deviation of the Sharpe ratio (0.13). The top panel of Table 13 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 parameters δ^i to match the mean of the carry trade risk factor. The other parameters are unchanged. The bottom panel of Table 13 lists all the parameters of the calibration.

[18] These numbers need to be multiplied by 2 to be annualized

[19] We list those additional constraints in Appendix B.

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:

$$m^{i,\$}_{t+1} = m^i_{t+1} - \pi^i_{t+1}.$$

We assume that inflation is composed of a country-specific component and a global component. Both components follow AR(1) processes:

$$\begin{aligned}
\pi^w_{t+1} &= (1-\rho^w)\overline{\pi}^w + \rho^w \pi^w_t + \sigma^{w\$}\epsilon^w_{t+1}, \\
\pi^{ci}_{t+1} &= (1-\rho^i)\overline{\pi}^i + \rho^i \pi^i_t + \sigma^{i\$}\epsilon^i_{t+1},
\end{aligned}$$

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

$$\pi^i_{t+1} = \mu^i \pi^{ci}_{t+1} + (1-\mu^i)\pi^w_{t+1}.$$

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 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^i_t. We model each country's dividend process as a random walk with a drift for the logarithm $d^i_t = \log D^i_t$:

$$\Delta d^i_{t+1} = d^i_{t+1} - d^i_t = g^{Di} + \sigma^{Di} w^{Di}_{t+1}.$$

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 6 displays the distribution of average nominal interest rates, of the volatility of nominal 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 14 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_{FX} 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 7 illustrates these two effects.

Finally, the unconditional CAPM fails to explain currency return generated by our model, as in the data. In a sample of 1000 simulated periods, we run a time-series regression of HML_{FX} on the stock market return. We find that the CAPM α of HML_{FX} 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 0.26. This large α represents the bulk of the average HML_{FX} 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 consistent with the notion that carry trade profits are compensation for systematic risk.

Using a no-arbitrage model of exchange rates, we show that a 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	-1.24	1.52	4.11	3.24	5.06
Std	8.22	7.36	7.46	7.53	7.85	9.26	10.20	9.75	9.35	9.01	9.30
SR	-0.36	0.00	0.19	0.49	0.45	0.64	-0.12	0.16	0.44	0.36	0.54
	Net Excess Return: rx^j_{net} (with b-a)						rx^j_{net} (with b-a)				
Mean	-1.70	-0.95	0.12	2.31	2.04	3.14	-0.11	0.46	2.71	1.98	3.35
Std	8.21	7.35	7.43	7.48	7.85	9.25	10.20	9.75	9.32	9.02	9.30
SR	-0.21	-0.13	0.02	0.31	0.26	0.34	-0.01	0.05	0.29	0.22	0.36
	High-minus-Low: $rx^j - rx^1$ (without b-a)						$rx^j - rx^1$ (without b-a)				
Mean		2.95	4.33	6.59	6.46	8.83		2.75	5.35	4.47	6.29
Std		5.36	5.54	6.65	6.34	8.95		6.42	6.44	7.38	8.70
SR		0.55	0.78	0.99	1.02	0.99		0.43	0.83	0.61	0.72
	High-minus-Low: $rx^j_{net} - rx^1_{net}$ (with b-a)						$rx^j_{net} - rx^1_{net}$ (with b-a)				
Mean		0.75	1.82	4.00	3.73	4.83		0.57	2.82	2.09	3.46
Std		5.36	5.56	6.63	6.35	8.98		6.45	6.44	7.41	8.73
SR		0.14	0.33	0.60	0.59	0.54		0.09	0.44	0.28	0.40

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

Table 2: Principal Components

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

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

Table 3: Asset Pricing - US Investor

Panel I: 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	69.28	0.95		3.56	2.24	0.42	0.32	71.06	0.61	
	[1.82]	[1.34]	[0.19]	[0.25]			13.02	[1.80]	[1.71]	[0.20]	[0.20]			41.34
	(1.83)	(1.34)	(0.20)	(0.25)			14.32	(1.80)	(1.71)	(0.20)	(0.20)			42.35
$Mean$	**5.37**	**1.36**						**3.44**	**2.24**					

Panel II: Factor Betas

	All Countries						Developed Countries					
$Portfolio$	$\alpha_0^j(\%)$	$\beta^j_{HML_{FX}}$	β^j_{RX}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$	$\alpha_0^j(\%)$	$\beta^j_{HML_{FX}}$	β^j_{RX}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-0.56	-0.39	1.06	91.36			0.00	-0.50	1.00	94.95		
	[0.52]	[0.02]	[0.03]				[0.48]	[0.02]	[0.02]			
2	-1.21	-0.13	0.97	78.54			-0.90	-0.11	1.02	82.38		
	[0.76]	[0.03]	[0.05]				[0.81]	[0.04]	[0.04]			
3	-0.13	-0.12	0.95	73.73			1.01	-0.02	1.02	85.22		
	[0.82]	[0.03]	[0.04]				[0.83]	[0.03]	[0.03]			
4	1.62	-0.02	0.93	68.86			-0.12	0.13	0.97	81.43		
	[0.86]	[0.04]	[0.06]				[0.85]	[0.04]	[0.04]			
5	0.84	0.05	1.03	76.37			0.00	0.50	1.00	93.87		
	[0.80]	[0.04]	[0.05]				[0.48]	[0.02]	[0.02]			
6	-0.56	0.61	1.06	93.03								
	[0.52]	[0.02]	[0.03]									
All					10.11	0.12					2.61	0.76

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

Table 4: 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
	Pre-formation β's						Pre-formation β's				
Mean	−0.40	−0.24	−0.15	0.01	0.21	0.57	−0.39	−0.23	−0.04	0.15	0.46
Std	0.29	0.23	0.24	0.26	0.43	0.41	0.26	0.25	0.35	0.45	0.41
	Post-formation β's						Post-formation β's				
Estimate	−0.31	−0.20	−0.14	0.01	0.13	0.28	−0.26	−0.15	0.04	0.08	0.30
s.e	[0.04]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]

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

Table 5: Asset Pricing - Foreign Investors

	λ_{HML}	λ_{RX}	R^2	$RMSE$	χ^2	λ_{HML}	λ_{RX}	R^2	$RMSE$	χ^2	$\lambda_{HML_{FX}}$	λ_{RX}	R^2	$RMSE$	χ^2
			UK					**Japan**					**Switzerland**		
GMM_1	5.54	−2.13	70.12	0.95		5.50	1.18	60.16	1.16		5.79	0.41	78.57	0.81	
	[2.34]	[1.87]			24.83	[2.21]	[2.13]			9.35	[2.25]	[1.69]			27.81
GMM_2	5.47	−2.25	69.66	0.96		4.73	1.92	41.85	1.40		6.23	0.62	76.55	0.85	
	[2.17]	[1.70]			24.89	[2.12]	[2.10]			10.76	[2.11]	[1.61]			28.30
FMB	5.54	−2.13	70.12	0.95		5.50	1.18	60.16	1.16		5.79	0.41	78.57	0.81	
	[1.83]	[1.46]			20.57	[1.77]	[1.87]			6.00	[1.78]	[1.46]			28.04
	(1.83)	(1.46)			22.28	(1.77)	(1.87)			6.80	(1.78)	(1.46)			30.03
$Mean$	**5.44**	**-2.13**				**4.85**	**1.18**				**5.92**	**0.42**			

$Portfolio$	α_0^i	β_{HML}^i	β_{RX}^i	R^2	α_0^i	β_{HML}^i	β_{RX}^i	R^2	α_0^i	β_{HML}^i	β_{RX}^i	R^2
			UK				**Japan**				**Switzerland**	
1	−0.48	−0.39	0.98	91.40	−0.11	−0.37	0.96	93.83	−0.75	−0.38	0.99	89.05
	[0.56]	[0.02]	[0.03]		[0.47]	[0.02]	[0.02]		[0.53]	[0.02]	[0.02]	
2	−0.90	−0.15	1.00	81.97	−1.94	−0.17	1.05	86.61	−0.44	−0.13	1.00	77.39
	[0.84]	[0.03]	[0.04]		[0.79]	[0.03]	[0.03]		[0.95]	[0.04]	[0.05]	
3	−0.78	−0.08	1.02	79.06	−0.67	−0.11	1.02	86.47	−0.31	−0.12	1.09	79.23
	[0.85]	[0.03]	[0.04]		[0.71]	[0.03]	[0.03]		[0.82]	[0.03]	[0.04]	
4	1.57	−0.08	0.99	73.07	1.53	−0.07	1.05	84.58	1.10	−0.07	1.00	72.33
	[0.91]	[0.04]	[0.04]		[0.88]	[0.04]	[0.05]		[0.97]	[0.04]	[0.05]	
5	1.06	0.09	1.02	77.77	1.31	0.09	0.96	84.47	1.15	0.08	0.94	76.23
	[0.79]	[0.04]	[0.04]		[0.84]	[0.04]	[0.03]		[0.84]	[0.04]	[0.05]	
6	−0.48	0.61	0.98	92.14	−0.11	0.63	0.96	96.05	−0.75	0.62	0.99	93.76
	[0.56]	[0.02]	[0.03]		[0.47]	[0.02]	[0.02]		[0.53]	[0.02]	[0.02]	
			$\chi^2(\alpha)$				$\chi^2(\alpha)$				$\chi^2(\alpha)$	
			7.30	0.29			14.28	0.03			4.48	0.61

Notes: Panel I 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. Panel II 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). 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 $t-1$. Portfolio 1 contains currencies with the lowest previous excess return. Portfolio 5 contains currencies with the highest previous excess return. Data are monthly, from Barclays. 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.

Table 6: One-Month Ahead Return Predictability

Portfolio	κ_{f}	W	R^2	κ_f	W	R^2	*Portfolio*	$\kappa_{\mathrm{sp,f}}$	W	R^2	$\kappa_{sp,f}$	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 (κ_{f}) in the left panel and the portfolio-specific log forward discount (κ_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 ($\kappa_{\mathrm{sp,f}}$). The right panel reports the statistics in the regression of one-month excess returns on that portfolio's one-month forward discount spread ($\kappa_{sp,f}$). W is the Wald-test χ^2 statistic for the slope coefficient. 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 7: 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: $rx^{j,k}_{net,t+k} = \kappa^j_0 + \kappa^j_1(f^{j,k}_t - s^j_t) + \eta^j_t$. 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: $rx^{j,k}_{net,t+k} = \kappa^j_0 + \kappa^j_1 \iota'(\mathbf{f}^k_t - \mathbf{s}^k_t) + \eta^j_t$ 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: $rx^{j,k}_{net,t+k} = \kappa^j_0 + \kappa^j_1 \iota'(\mathbf{f}^k_t - \mathbf{s}^k_t) + \eta^j_t$. 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: $rx^{j,k}_{net,t+k} = \kappa^j_0 + \kappa^j_1(f^k_t - s^k_t) + \epsilon^j_t$ 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 8: 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 9: Forecasting 12-month ahead Excess Returns with Industrial Production and Forward Discounts

	κ_{IP}	κ_f	W	R^2	κ_{IP}	κ_f	W	R^2	κ_{IP}	κ_f	W	R^2	κ_{IP}	κ_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: $rx^{j,12}_{net,t+12} = \kappa^j_0 + \kappa^j_1(f^{j,12}_t - s^j_t) + \kappa^j_1 \Delta IP_{t-12,t} + \eta^j_t$. 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. W is the Wald-test χ^2 statistic for the slope coefficients. 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 10: Conditional Asset Pricing

	Panel I: Conditional HML_{FX}								
	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	90.09	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_{FX} and $HML_{FX}VIX$, which is HML_{FX} 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 11: 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	63.95	1.03		2.23	20.87	0.31	0.80	26.83	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 12: 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			
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_{FX}	−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]		

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. We use the value-weighted return on the US stock market (CRSP).

Table 13: 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 14: 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.

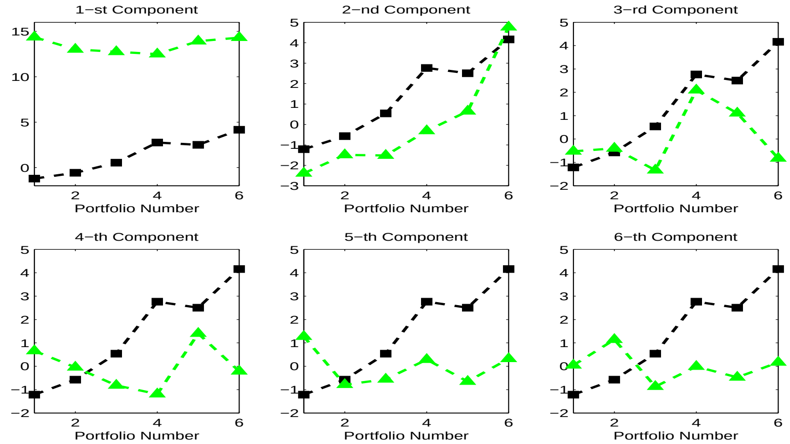


Figure 1: Mean Excess Returns and Covariances between Excess Returns and Principal Components - Developed and Emerging Countries

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

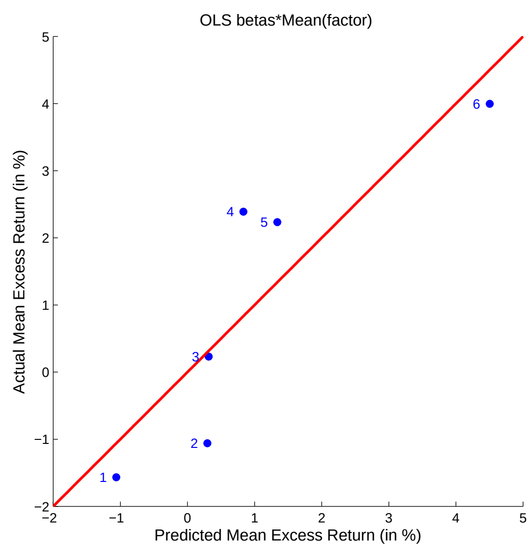


Figure 2: Predicted against Actual Excess Returns.

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

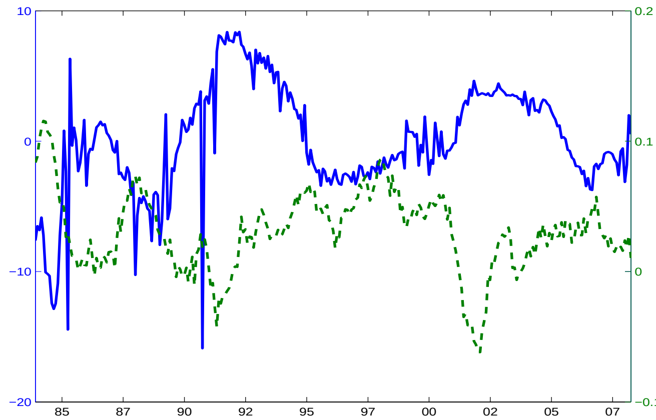


Figure 3: Forecasted Excess Return in Currency Markets and US Business Cycle.

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.

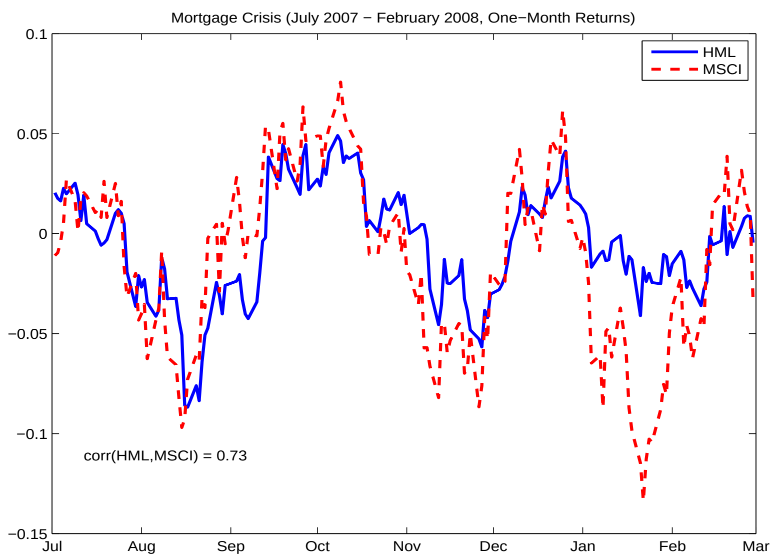


Figure 4: Carry Trade and US Stock Market Returns during the Mortgage Crisis - July 2007 to February 2008.

This figure plots the one-month HML_{FX} return at daily frequency against the one-month return on the US MSCI stock market index at daily frequency. The sample is 07/02/07-02/28/08.

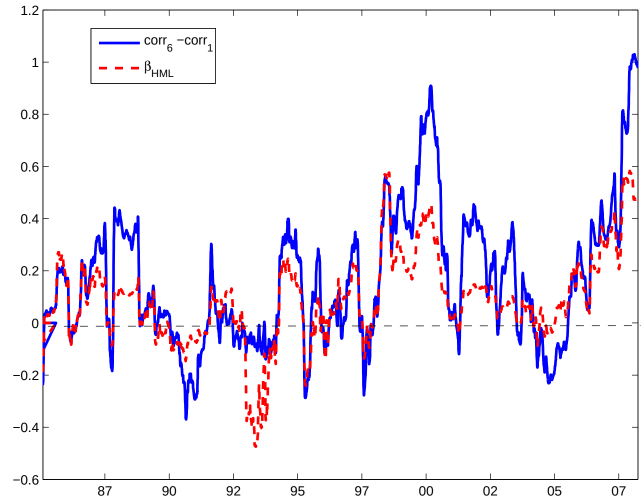


Figure 5: Market Correlation Spread of Currency Returns

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

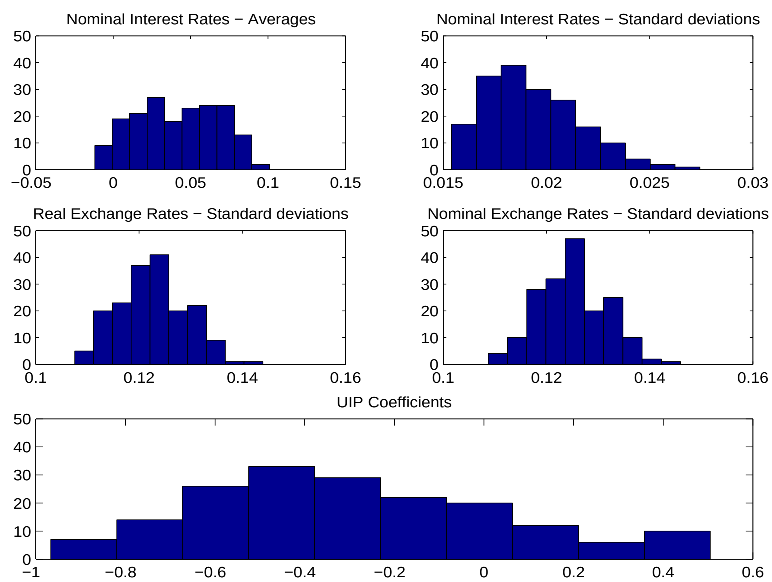


Figure 6: Exchange Rates, Interest Rates and UIP Slope Coefficients - Simulated Data.

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.

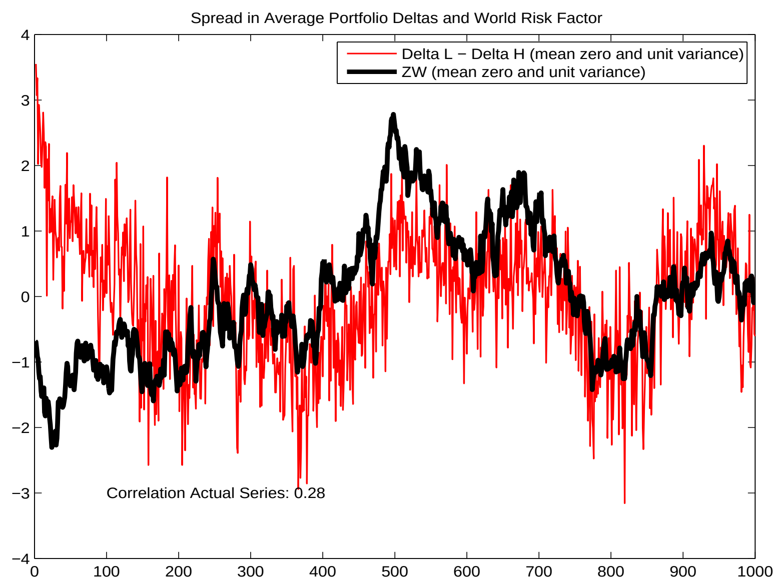


Figure 7: Spreads in Portfolio Deltas and World Risk Factor - Simulated Data.

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.

Appendix to 'Common Risk Factors in Currency Markets'

This Appendix reports additional robustness checks. We first consider different samples of currency returns. We then report principal component analysis of our currency portfolios. Finally, we report additional results on currency excess return predictability.

Appendix A Estimation

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

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

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 briefly describe these two techniques here.

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

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

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: $S = \sum_{-\infty}^{\infty} E[(M_t Rx_t)(M_{t-j} Rx_{t-j})']$.[20] 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.

[20]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.

FMB In the first stage of the FMB procedure, for each portfolio j, we run a time-series regression of the currency returns Rx^j_{t+1} 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 $E_T[Rx^j_t]$ 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.

Appendix B Model

Appendix B1 Calibration

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.

Appendix B2 Asset Prices

Stocks

The ex-dividend price of the stock market portfolio at time t in the units of domestic currency is given by

$$P^i_t = E_t \sum_{s=1}^{\infty} D^i_{t+s} \exp\left[\sum_{j}^{s} m^i_{t+j}\right].$$

Since all the relevant information at time t is summarized by the state vector $\left[z^i_t, z^w_t\right]$, we can write the price-dividend ratio as

$$\frac{P^i_t}{D^i_t} = E\left\{\sum_{s=1}^{\infty} \exp\left[\sum_{j=1}^{s}\left(\Delta d^i_{t+j} + m^i_{t+j}\right)\right] \middle| z^i_t, z^w_t\right\}$$

We compute the price-dividend ratios that correspond to the simulated values of the state vector using Monte Carlo simulation and interpolate them using a kernel regression. The price-dividend ratio process appears to have reasonable statistical properties. Figure 8 plots the simulated dividend yield process alongside the corresponding state variables.

Bonds

Nominal bond yields of maturity N can be computed similarly as

$$y^{\$,N}_t = -\frac{1}{N}\log E\left\{\exp\left[\sum_{j=1}^{N}\left(m^i_{t+j} - \pi^i_{t+j}\right)\right] \middle| z^i_t, z^w_t, \pi^{ci}_t, \pi^w_t\right\}$$

The real bond yields can be computed analytically using a standard affine formula:

$$y_t^N = -\frac{1}{N}\left(A_N + B_N z_t^i + C_N z_t^w\right),$$

where

$$\begin{aligned}
A_N &= A_{N-1} + B_{N-1}\left(1-\varphi^i\right)\theta^i + C_{N-1}\left(1-\varphi^w\right)\theta^w,\\
B_N &= -\left(\lambda^i - \frac{1}{2}\gamma^i\right) + B_{N-1}\varphi^i + \frac{1}{2}B_{N-1}^2\sigma^{i2},\\
C_N &= -\left(\tau^i - \frac{1}{2}\delta^i\right) + C_{N-1}\varphi^w + \frac{1}{2}C_{N-1}^2\sigma^{w2},\\
A_1 &= 0, B_1 = -\left(\lambda^i - \frac{1}{2}\gamma^i\right), C_1 = -\left(\tau^i - \frac{1}{2}\delta^i\right)
\end{aligned}$$

Given that the innovations to the state variables z^i and z^w as well as the innovations to the two volatility processes are all independent of the SDF shocks in our model, there are no term premia, so that both the nominal and the real term structures are essentially flat (the convexity effect is small). The level of nominal yields starts is 4.2 percent for the one year maturity, versus 1 percent for the real yields, reflecting the expected inflation. This is in contrast to Backus et al. (2001) who specify a completely affine model (i.e. the innovations to the state variables are the same as the innovations to the SDF), which generates extremely large term premia implied by the predictability of currency returns.

Appendix C Other Samples

We perform four robustness checks. First, we consider the sample proposed by Burnside et al. (2008). Following the methodology of Lustig and Verdelhan (2007), Burnside et al. (2008) build 5 currency portfolios. Burnside et al. (2008) claim that these currency excess returns are not related to any risk factor. Using the same methodology as in the main text, we find that these currency excess returns are clearly explained by two risk factors. Second, we consider different home countries. We take the perspective of the Swiss, UK and Japanese investors, and for each investor, we build currency portfolios, test their business cycle properties and we estimate the corresponding market prices of risk. 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).

Appendix C1 Burnside et alii (2006, 2008)

Countries Burnside et al. (2008) consider a sample of 21 developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, the UK, the U.S. and the Euro. They find large currency excess returns and note that, 'while transaction costs are quantitatively important, they do not explain the profitability of the carry trade' (page 9). As a result, they abstract from transaction costs and work with spot and forward rates that are the average of bid and ask rates. [21]

[21] Burnside et al. (2006) consider a smaller set of (at most) 10 developed countries: Belgium, Canada, Euro area, France, Germany, Italy, Japan, Netherlands, Switzerland, the United Kingdom and the United States. In comparison to the 10 countries in Burnside et al. (2006), we include Australia, Denmark, New Zealand, Norway, and Sweden in

Burnside et al. (2008) build 5 portfolios of currency excess returns following the methodology of Lustig and Verdelhan (2007). They conclude that risk factors do not explain the excess returns of these 5 portfolios. In this appendix, we build the same 5 portfolios and show that we obtain the same conclusion as with our two other samples: two simple risk factors reproduce the cross-section of excess returns, implying that these excess returns are compensations for risk.

Burnside et al. (2008) use spot and forward rates denominated in UK pounds, collected by Barclays and available on Datastream. We follow their assumption and convert these series into dollars using midquotes. The sample starts in 02/1976 and ends in 1/2008 as in Burnside et al. (2008). Table 15 below reports summary statistics on these 5 currency portfolios. The carry trade strategy that goes short the currencies in the first portfolio and long the currencies in the last portfolio offers an average log excess return of 6.47 percent per year and an average Sharpe ratio of 0.9.[22] These values are certainly upper bounds on carry trade excess returns since they do not take into account any transaction costs.

Cross-section of currency excess returns This cross-section of excess returns reflects different exposures to risk factors. In order to make this point, we build again two risk factors: the carry trade risk factor HML corresponds to the return on the fifth portfolio minus the return on the first portfolio, and the dollar risk factor RX is the average return across the test assets. Table 16 reports asset pricing results. The loadings on HML explain the cross-section of currency excess returns. The betas are highly significant. The first three portfolios have negative betas. The last two have positive betas. The loadings on the dollar factor RX do not vary across portfolios, as is to be expected. The alphas do not exceed 60 basis points per annum. They are not significantly different from zero on a case-by-case basis. We also cannot reject the null that the alphas are jointly zero. The market price of risk is highly significant; it is somehow higher than our own estimates because these excess returns do not take into account bid-ask spreads.

Figure 9 plots realized average excess returns on the vertical axis against predicted average excess returns on the horizontal axis. In order to draw this figure, we do not even estimate the market price of risk. 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 then obtained using the OLS estimate of β^j times the sample mean of the factors. It is obvious that these currency excess returns are risk premia.

As a final robustness check, 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 five groups at time t based on these slope coefficients β_t^{HML}. Portfolio 1 contains currencies with the lowest βs. Portfolio 5 contains currencies with the highest βs. Table 17 reports summary statistics on these portfolios. The first panel reports average changes in exchange rates. The second panel shows that average forward discounts increase monotonically in these portfolios. As in our main sample, sorts based on forward discounts and sorts based on betas are clearly related, which

our sample of 15 developed countries. Note that this sample is too restrictive because it does not even encompass forward (or equivalent futures) contracts traded on large institutionalized currency markets as the Chicago Mercantile Exchange. Burnside et al. (2006) conclude that there are no large exploitable excess returns that result from the failure of UIP because the difference between the forward discount and the rate of depreciation is absorbed largely by bid-ask spreads.

[22]Burnside et al. (2008) report monthly excess returns (see their table 3 page 29). For example, their last portfolio offers a monthly excess return of 0.0082 for a standard deviation of 0.028. Annualized, these values imply a Sharpe ratio of 1.01.

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.

Appendix C2 Foreign Investors

We now adopt the perspective of foreign investors and we consider currency excess returns denominated in foreign currency. We report summary statistics on these excess returns, test their business cycle properties and we estimate the market prices of risk.

Summary Statistics We consider the case of a UK investor, a Japanese investor and a Swiss investor. These are three countries with large and well-developed currency markets. We compute the excess returns that local investors would obtain if they had access to forward contracts in their own currency. We obtained these excess returns by converting dollars into local currency at the midpoint rate. This way, investors are not hit twice by the bid-ask spread. Summary statistics on these currency excess returns are reported in Table 18.

Business Cycle Properties Using employment data in each country, we show that foreign currency excess returns are predictable from the UK, Japan and Swiss perspectives. Table 19 reports these predictability results.

Cross-sectional Asset Pricing 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 currency and we use the local currency returns on our currency portfolios as test assets.

Table 5 in the main text reports market prices of risk and cross-sectional measures of fit. Table **??** in this appendix reports results of time series regressions of portfolio excess returns on the two factors, for each country.

Appendix C3 Time Sub-Samples

We also check the robustness of our results by dividing our main sample over the 1983-2008 period in two sub-samples, spanning the 1983-1994 and 1995-2008 periods. Table 20 report summary statistics on our portfolios of developed and emerging countries. Sharpe ratios appear higher in the second sub-sample; currency excess returns have clearly not disappeared in the last ten years. We run asset pricing tests for both samples of developed, and developed and emerging countries. For each time sub-sample, we redo all the cross-sectional asset pricing tests. To save space, we report only results obtained on our large sample of countries in table 21. We find that the HML betas are very similar in both time sub-samples. In both cases, they range from -0.4 to 0.6 on developed and emerging countries and from around -0.5 to 0.5 on developed countries. The market prices of risk differ across time periods; it is higher and more precisely estimated in the 1995-2008 period. The cross-sectional fit is also much higher in the second period. Because forward contracts were available only for a limited set of currencies, the first sub-sample uses, for example, at most 18 developed and emerging countries. The low number of countries and short sample clearly decreases the estimation power.

Appendix C4 Longer Sample of Treasury Bill-based Portfolios

Lustig and Verdelhan (2007) built eight portfolios of foreign T-bills sorted on interest rates, from a panel of 81 currencies. The data are annual, and the sample spans 1953-2002. We check whether the currency risk factors can explain the cross-sectional variation in excess returns on these foreign T-bills. HML is defined as the spread between the seventh and the first portfolio. Table 22 reports the results. The estimated risk price for HML varies between 4.10 percent on the whole sample and 6.20 percent on the post-Bretton-Woods subsample. This is very close to the estimate of 6.19 percent that we obtained on the basket of forward contracts. Also, these estimates are close to their respective sample means of 5.32 and 6.92 percentage points per annum. We also test whether the null that the αs are zero can be rejected. The results for both samples are reported in Table 23. The null cannot be rejected. Table 23 reports also all the portfolios βs on the two risk factors.

Using the HML we constructed from the longer time series, we can explore the business cycle properties of HML. We run a time series regression of HML on US non-durable consumption growth and on durable consumption growth. Over the 1953-2002 sample, the consumption β of HML is one; in the post-Bretton-Woods sample, it increases to 1.50. These estimates are statistically significant at the 5 percent level. The currency risk factor HML_{FX} is strongly pro-cyclical.

Appendix D Principal Component Analysis

Principal component analysis provides a simple framework for extracting factors that are important for capturing common variation in asset returns. Let Σ be the sample covariance matrix of excess returns on the original set of portfolios $\mathbf{R}^e$. The eigenvalue decomposition of this covariance matrix

$$\Sigma = Q\Lambda Q',$$

yields a new covariance matrix Λ which is diagonal, and the orthogonal transformation matrix Q with $QQ' = I$. This matrix contains the loadings of the original portfolios on the orthogonal *common factor* (or principal component) portfolios. These new portfolio excess returns are formed by

$$\tilde{\mathbf{R}}^e = Q'\mathbf{R}^e.$$

Since the original test assets are excess returns, this procedure also creates zero-investment portfolios, i.e. the resulting factors are excess returns. The variance-covariance matrix of these portfolios is the diagonal matrix Λ above.

Table 2 reports the loadings of our currency portfolios on each of the principal components (i.e. the Q matrix) as well as the fraction of the total variance of portfolio returns attributed to each principal component ($\frac{\operatorname{diag}\Lambda}{\operatorname{tr}\Lambda}$). The first principal component explains 70 percent of common variation in portfolio returns, and can be interpreted as a *level* factor, since all portfolios load equally on it. The (negative of) the second principal component, which is responsible for over 12 percent of common variation, can be interpreted as a *slope* factor, since portfolio loadings increase monotonically across portfolios. The remaining 4 components together are responsible for less than 20 percent of total return variance across portfolios and are likely to represent portfolio-level idiosyncratic shocks.

Appendix E Additional Predictability Tests

Table 9 also checks whether IP growth predicts future currency returns in our smaller sample of developed countries. The slope coefficients in the projection of 12-month future returns on industrial production growth are larger than those we found on the entire sample of currencies; the coefficient varies between 127 and 174 basis points, when we control for the individual portfolio discount, and between 109 and 212 basis points when we control for the average forward discount. There is evidence that industrial production growth drives out the forward discount as a predictor.

The strong response of currency excess returns to industrial production resembles results reported by Cooper and Priestley (2007) on stock market excess returns. Cooper and Priestley (2007) show that the output gap, defined using the deviation of industrial production from a trend, is a very robust predictor of excess returns on the stock market in all G-7 countries. This variable is highly correlated with the growth rate of industrial production in our sample.

Table 25 reports the slope coefficient estimates for the 1-month, 3-month, 6-month and 12-month returns. In this case, inference about the slope coefficients is complicated by overlapping observations and autocorrelated returns. Hansen and Hodrick (1980) (HH) is the standard procedure to deal with overlapping observations. We use n lags to compute the HH variance-covariance matrix when dealing with n-month returns. We also report the Newey and West (1987) (NW) standard errors computed with the optimal number of lags; we allow for a maximum of $n+6$ lags. The NW and HH standard errors are very close at all the horizons we consider. The null that the slope coefficients are zero can be rejected at the 1% significance level in all cases.

To deal with the overlap problem, we simply dropped the overlapping observations by selecting only the first month in each period; we report the NW standard errors for this shorter sample. These standard errors are only slightly larger than those obtained on the whole sample; deleting these observations from the sample does not alter the inference. In addition, to guard against the poor performance of these tests statistics in small samples, we report bootstrapped standard errors. We bootstrap 10.000 samples from the residuals of an n-lag VAR that includes the returns and the forward discount. These small sample standard errors are 40 to 50 % larger at 3 to 12 month horizons. As a result, the null that the slope coefficients of the individual portfolio forward discounts are zero can no longer be rejected at the 5 % significance level for 3, 6 and 12 month returns. However, the null that the average forward discount does not predict excess returns can still be rejected at the 5% significance level. The p-values on the slope coefficients are invariably lower for the average discount than those for the individual portfolio forward discount regressions.

Appendix E1 Counter-cyclicality

Table 8 reports the correlation of the currency risk factor (the average forward discount) with the business cycle variables. Macro variables themselves help to forecast excess returns. In fact, the change in industrial production (IP) explains up to 37 percent of the variation in excess returns at the 12-month horizon. Table 26 reports regression results for :

$$rx^{j,k}_{net,t+k} = \gamma_0 + \gamma_{IP} \Delta \log IP_t + \eta^j_t.$$

At the 12-month horizon, all the estimated slope coefficients are significantly negative. A one percentage point drop in the annual change in industrial production raises the dollar risk premium by 150 to 200 basis points per annum. At shorter horizons, this number is in the 100 to 150 basis point range. Except for the 1-month horizon forecasts, the Wald test for the slope coefficient has p-values that are smaller than 5 percent for all portfolios.

Appendix E2 Spreads

Table 27 lists the correlations with our macro and financial variables.

We report the predictability results in Table 28. We consider the volatility index and the credit default spread. In the top panel we consider the returns on the sixth minus the first portfolio. In the bottom panel, we consider the returns on the second minus the first portfolio. To construct these, we sort all the currencies into two portfolios. The left panel reports the results for one-month ahead forecasts. The right panel reports the results for 12-month ahead forecasts. These variables have some forecasting power for the HML_{FX} returns.

Table 15: US Investor - Portfolios of Countries in Burnside et alii (2008)

Portfolio	1	2	3	4	5
			Spot change: Δs^j		
Mean	-1.47	-1.19	-0.16	-0.34	2.23
Std	10.07	10.02	9.00	8.88	9.90
			Discount: $f^j - s^j$		
Mean	-3.23	-0.78	0.79	2.44	6.94
Std	0.78	0.72	0.72	0.85	1.56
			Excess Return: rx^j (without bid-ask)		
Mean	-1.77	0.41	0.96	2.77	4.71
SR	-0.17	0.04	0.11	0.31	0.48
			Long-Short: $rx^j - rx^1$ (without bid-ask)		
Mean		2.17	2.72	4.54	6.47
SR		0.44	0.47	0.71	0.90

Notes: This table reports summary statistics for currencies sorted into portfolios. We report the moments in dollars for average changes in log of the spot exchange rate Δs^j in portfolio 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 $rx^j - rx^1$. 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. Averages and standard deviations are reported in percentage points. The portfolios are constructed by sorting currencies into five groups at time t based on the one-month forward discount at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rates. Portfolio 5 contains currencies with the highest interest rates. Data are monthly, from Barclays (Datastream). The sample period is 02/1976 - 01/2008.

Table 16: Asset Pricing - Portfolios of Countries in Burnside et alii (2008)

Panel I: Factor Prices and Loadings							
	$\lambda_{HML_{FX}}$	λ_{RX}	$b_{HML_{FX}}$	b_{RX}	R^2	$RMSE$	χ^2
GMM_1	6.60	3.39	1.04	0.33	95.70	0.38	
	[2.06]	[2.15]	[0.33]	[0.22]			74.53
GMM_2	6.29	3.42	0.99	0.33	95.36	0.39	
	[2.04]	[2.13]	[0.33]	[0.22]			75.08
FMB	6.60	3.39	1.04	0.33	95.70	0.38	
	[1.49]	[1.83]	[0.24]	[0.19]			64.74
	(1.49)	(1.83)	(0.24)	(0.19)			67.51
$Mean$	**6.38**	**3.41**					

Panel II: Factor Betas						
$Portfolio$	$\alpha_0^j(\%)$	$\beta^j_{HML_{FX}}$	β^j_{RX}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-0.22	-0.50	1.01	95.41		
	[0.48]	[0.02]	[0.02]			
2	-0.45	-0.11	1.10	92.83		
	[0.68]	[0.03]	[0.02]			
3	0.31	-0.01	0.97	91.22		
	[0.59]	[0.03]	[0.02]			
4	0.59	0.12	0.91	86.15		
	[0.75]	[0.03]	[0.02]			
5	-0.22	0.50	1.01	95.54		
	[0.48]	[0.02]	[0.02]			
All					1.24	0.94

Notes: 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 Datastream. The sample of currencies corresponds to the one used in Burnside et alii (2008). The sample period is 2/1976 - 01/2008. The alphas are annualized.

Table 17: Beta-Sorted Currency Portfolios - Portfolios of Countries in Burnside et alii (2008)

Portfolio	1	2	3	4	5
			Spot change: Δs^j		
Mean	−1.54	0.14	0.75	1.11	0.41
Std	10.03	10.71	9.93	9.75	8.74
			Discount: $f^j - s^j$		
Mean	−2.80	−0.53	1.46	2.46	4.25
Std	0.75	0.84	0.80	0.89	1.07
			Excess Return: rx^j (without b-a)		
Mean	−1.26	−0.67	0.71	1.35	3.85
Std	10.16	10.78	10.00	9.73	8.80
SR	−0.12	−0.06	0.07	0.14	0.44
			High-minus-Low: $rx^j - rx^1$ (without b-a)		
Mean		0.59	1.97	2.61	5.10
Std		5.53	5.71	6.40	7.81
SR		0.11	0.34	0.41	0.65

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 is 2/1976 - 01/2008.

Table 18: Summary Statistics - Foreign Investors - Portfolios of Developed and Emerging Countries - Midpoint Conversion

Portfolio	1	2	3	4	5	6
		Panel I: UK				
		Excess Return: rx_{net}^j				
Mean	−5.21	−4.26	−3.88	−1.50	−1.16	−0.24
SR	−0.61	−0.52	−0.46	−0.18	−0.14	−0.03
		Long-Short: $rx_{net}^j - rx_{net}^1$				
Mean		0.94	1.33	3.70	4.04	4.96
SR		0.18	0.23	0.56	0.61	0.55
		Panel II: Japan				
		Excess Return: rx_{net}^j				
Mean	−1.31	−2.12	−0.63	1.71	2.24	2.80
SR	−0.14	−0.21	−0.06	0.16	0.23	0.24
		Long-Short: $rx_{net}^j - rx_{net}^1$				
Mean		−0.81	0.68	3.03	3.55	4.11
SR		−0.15	0.12	0.50	0.55	0.47
		Panel III: Switzerland				
		Excess Return: rx_{net}^j				
Mean	−3.02	−1.17	−1.09	0.58	1.56	2.23
SR	−0.40	−0.15	−0.12	0.07	0.20	0.22
		Long-Short: $rx_{net}^j - rx_{net}^1$				
Mean		1.85	1.93	3.59	4.57	5.25
SR		0.33	0.32	0.55	0.72	0.60

Notes: This table reports summary statistics for currencies sorted into portfolios. We report averages and Sharpe ratios of log excess returns rx_{net}^j with bid-ask spreads and log excess returns on the long short strategy $rx_{net}^j - rx_{net}^1$ in *UK pounds*, in *Japanese yen*, and in *Swiss francs*. All moments are annualized and reported in percentage points. 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. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 03/2008.

Table 19: Forecasting Excess Returns with *EM*

Months	γ_{EM}	$p(\%)$	R^2	γ_{EM}	$p(\%)$	R^2	γ_{EM}	$p(\%)$	R^2
		US			**UK**			**Japan**	
1	-1.88	5.15	6.09	-2.88	0.10	17.93	-0.30	90.58	0.37
	[1.08]			[0.92]			[0.75]		
2	-0.81	23.21	1.85	-1.91	4.46	9.21	-0.73	42.75	1.64
	[0.79]			[1.06]			[1.01]		
3	-1.67	2.96	6.87	-1.33	5.44	5.36	-1.15	11.12	4.68
	[0.85]			[0.78]			[0.83]		
4	-1.72	3.82	8.09	-0.87	24.73	2.16	-1.51	4.26	7.62
	[0.92]			[0.88]			[0.83]		
5	-2.49	0.94	12.29	-1.40	3.38	4.74	-1.52	4.44	7.83
	[1.04]			[0.73]			[0.85]		
6	-2.12	2.11	7.17	-0.83	22.19	1.39	-2.13	1.20	11.46
	[1.01]			[0.80]			[0.92]		

Notes: This table reports the forecasted excess returns using the 12-month change in the level of employment for the US, UK and Japan. The standard errors in brackets are Newey-West standard errors computed with the optimal number of lags. The p-values (reported in percentage points) are for a Wald-test: $\gamma_{EM} = 0$. All the returns annualized and reported in percentage points. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 04/2007.

Table 20: Currency Portfolios - US Investor - Time Sub-Samples

Portfolio	1	2	3	4	5	6	1	2	3	4	5	6
	Panel I: 1983-1995						Panel II: 1995-2008					
	Spot change: Δs^j						Δs^j					
Mean	−2.59	−2.64	−1.29	−4.25	−1.61	1.67	0.42	−0.28	−1.87	−1.49	−0.49	2.06
Std	8.81	8.11	8.38	8.85	9.56	10.00	7.31	6.51	6.49	5.91	5.76	8.37
	Forward Discount: $f^j - s^j$						$f^j - s^j$					
Mean	−2.95	−1.28	0.18	1.53	3.12	7.72	−4.70	−1.33	−0.43	0.43	2.04	7.79
Std	0.68	0.65	0.63	0.67	0.65	2.45	2.02	0.29	0.29	0.30	0.49	1.72
	Excess Return: rx^j (without b-a)						rx^j (without b-a)					
Mean	−0.36	1.36	1.47	5.77	4.73	6.05	−5.11	−1.05	1.43	1.91	2.53	5.73
Std	8.91	8.22	8.42	8.99	9.70	10.17	7.53	6.52	6.54	5.97	5.83	8.41
SR	−0.04	0.17	0.17	0.64	0.49	0.60	−0.68	−0.16	0.22	0.32	0.43	0.68
	Net Excess Return: rx^j_{net} (with b-a)						rx^j_{net} (with b-a)					
Mean	1.00	0.29	−0.20	3.99	3.06	3.27	−4.00	−1.94	0.49	0.91	1.18	2.99
Std	8.92	8.21	8.35	8.91	9.68	10.15	7.49	6.52	6.56	5.97	5.86	8.41
SR	0.11	0.04	−0.02	0.45	0.32	0.32	−0.53	−0.30	0.08	0.15	0.20	0.35
	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		4.06	6.55	7.03	7.65	10.84
Std		5.52	5.82	6.55	6.74	8.98		5.21	5.23	6.75	5.97	8.89
SR		0.31	0.32	0.94	0.76	0.71		0.78	1.25	1.04	1.28	1.22
	High-minus-Low: $rx^j_{net} - rx^1_{net}$ (with b-a)						$rx^j_{net} - rx^1_{net}$ (with b-a)					
Mean		−0.71	−1.20	2.99	2.06	2.27		2.06	4.49	4.91	5.18	6.98
Std		5.56	5.86	6.55	6.79	9.03		5.17	5.20	6.69	5.91	8.88
SR		−0.13	−0.20	0.46	0.30	0.25		0.40	0.86	0.73	0.88	0.79

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. Both panels use data from developed and emerging countries. Data are monthly, from Barclays and Reuters (Datastream). The sample periods are 11/1983 - 1/1995 and 1/1995 - 03/2008.

Table 21: Asset Pricing - US Investor - Time Sub-Samples

Panel I: Factor Prices and Loadings

	1983-1995							1995-2008						
	$\lambda_{HML_{FX}}$	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	3.41	2.52	0.34	0.33	36.09	1.21		7.21	0.36	0.81	0.18	77.93	1.03	
	[2.91]	[2.86]	[0.30]	[0.40]			44.23	[3.35]	[1.83]	[0.38]	[0.53]			22.93
GMM_2	3.22	1.78	0.33	0.23	11.75	1.42		7.37	0.26	0.83	0.16	77.67	1.03	
	[2.70]	[2.82]	[0.28]	[0.39]			45.29	[3.15]	[1.74]	[0.36]	[0.50]			22.98
FMB	3.41	2.52	0.34	0.33	36.09	1.21		7.21	0.36	0.81	0.18	77.93	1.03	
	[2.75]	[2.32]	[0.28]	[0.32]			43.14	[2.43]	[1.49]	[0.27]	[0.42]			31.32
	(2.75)	(2.32)	(0.28)	(0.32)			44.20	(2.44)	(1.49)	(0.27)	(0.42)			34.36
Mean	**2.65**	**2.48**						**7.66**	**0.44**					

Panel II: Factor Betas

	1983-1995						1995-2008					
Portfolio	$\alpha_0^j(\%)$	$\beta^j_{HML_{FX}}$	β^j_{RX}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$	$\alpha_0^j(\%)$	$\beta^j_{HML_{FX}}$	β^j_{RX}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	−0.01	−0.40	1.03	93.33			−1.12	−0.38	1.11	89.03		
	[0.76]	[0.02]	[0.04]				[0.68]	[0.03]	[0.04]			
2	−1.40	−0.08	0.96	83.00			−0.78	−0.17	0.98	73.17		
	[1.03]	[0.04]	[0.05]				[1.11]	[0.03]	[0.07]			
3	−1.50	−0.17	0.90	72.15			0.94	−0.07	1.06	78.62		
	[1.50]	[0.06]	[0.06]				[0.85]	[0.03]	[0.04]			
4	2.03	0.01	1.00	76.30			1.42	−0.06	0.81	56.83		
	[1.33]	[0.06]	[0.08]				[1.03]	[0.04]	[0.07]			
5	0.90	0.03	1.08	77.25			0.67	0.06	0.94	75.46		
	[1.45]	[0.07]	[0.07]				[0.85]	[0.03]	[0.05]			
6	−0.01	0.60	1.03	94.77			−1.12	0.62	1.11	90.97		
	[0.76]	[0.02]	[0.04]				[0.68]	[0.03]	[0.04]			
All					3.71	0.72					7.66	0.26

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. Both panels use data from developed and emerging countries. Data are monthly, from Barclays and Reuters (Datastream). The sample periods are 11/1983 - 1/1995 and 1/1995 - 03/2008.

Table 22: Asset Pricing - T-Bill portfolios

	λ_{HML}	λ_{RX}	b_{HML}	b_{RX}	R^2	$RMSE$	χ^2
				1953-2002			
GMM_1	4.10	0.25	8.39	-2.05	42.47	1.11	
	[1.25]	[1.10]	[2.76]	[3.60]			44.44
GMM_2	3.89	0.18	8.00	-2.13	42.09	1.11	
	[0.81]	[0.91]	[1.95]	[3.05]			45.47
FMB	4.10	0.25	8.22	-2.01	42.47	1.11	
	[1.17]	[0.84]	[2.34]	[2.54]			10.18
	(1.21)	(0.84)	(2.43)	(2.56)			24.16
$Mean$	**5.32**	0.128					
				1971-2002			
GMM_1	6.20	0.31	9.25	-2.48	72.50	0.92	
	[2.07]	[1.93]	[3.29]	[4.17]			78.19
GMM_2	5.80	0.30	8.65	-2.29	72.13	0.92	
	[1.09]	[1.18]	[1.96]	[2.73]			80.26
FMB	6.20	0.31	8.96	-2.41	72.50	0.92	
	[1.66]	[1.30]	[2.37]	[2.55]			68.36
	(1.73)	(1.30)	(2.49)	(2.57)			86.28
$Mean$	**6.92**	0.255					

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. 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 rates. Portfolio 8 contains currencies with the highest interest rates. Data are annual, from Global Financial Data. 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 23: Factor Betas - US Investor

$Portfolio$	α_0^j	β_{HML}^j	β_{RX}^j	R^2	α_0^j	β_{HML}^j	β_{RX}^j	R^2
	1971-2002				**1953-2002**			
1	-0.02	-0.46	0.97	80.91	0.02	-0.47	0.95	79.28
	[0.71]	[0.06]	[0.10]		[0.44]	[0.06]	[0.09]	
2	0.07	-0.03	0.62	41.16	-1.16	0.04	0.64	32.92
	[0.92]	[0.07]	[0.16]		[0.96]	[0.10]	[0.18]	
3	-0.77	-0.04	0.99	74.28	-0.58	-0.05	0.97	72.11
	[0.86]	[0.09]	[0.12]		[0.52]	[0.08]	[0.12]	
4	0.40	0.06	1.20	78.00	-0.33	0.09	1.19	73.25
	[1.02]	[0.10]	[0.13]		[0.75]	[0.09]	[0.13]	
5	-0.32	-0.09	0.98	56.83	0.38	-0.12	0.98	55.44
	[1.15]	[0.11]	[0.12]		[0.72]	[0.11]	[0.12]	
6	-1.38	0.16	1.05	67.44	-1.12	0.15	1.05	64.26
	[1.21]	[0.10]	[0.14]		[0.78]	[0.09]	[0.14]	
7	-0.02	0.54	0.97	88.39	0.02	0.53	0.95	87.25
	[0.71]	[0.06]	[0.10]		[0.44]	[0.06]	[0.09]	
8	2.07	-0.13	1.22	34.31	2.76	-0.17	1.28	34.00
	[3.40]	[0.19]	[0.44]		[2.10]	[0.15]	[0.40]	
$\chi^2(\alpha)$	1.09			4.55				
$p-value$	99.06			80.33				

Notes: This table 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). 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. Data are annual from Global Financial Data. Standard errors are reported in parenthesis. Shanken-corrected standard errors are reported in brackets.

Table 24: Consumption Betas for HML_{FX}

	$\beta_c^{HML_{FX}}$	$p(\%)$	R^2	$\beta_d^{HML_{FX}}$	$p(\%)$	R^2
	Panel I: Nondurables			*Panel II: Durables*		
$1953-2002$	1.00		4.04	1.06		9.07
	[0.44]	2.23		[0.40]	0.89	
$1971-2002$	1.54		8.72	1.65		14.02
	[0.52]	0.28		[0.60]	0.63	

Notes: Each entry of this table reports OLS estimates of β_1 in the following time-series regression of the spread on the factor: $HML_{FX,t+1} = \beta_0 + \beta_1 f_t + \epsilon_{t+1}$. $HML_{FX,t+1}$ is the return on the seventh minus the return on the first portfolio. The estimates are based on annual data. The standard errors are reported in brackets. We use Newey-West heteroskedasticity-consistent standard errors with an optimal number of lags to estimate the spectral density matrix following Andrews (1991). The p-values (reported in %) are for a t-test on the slope coefficient. The factor f_t is non-durable consumption growth (Δc) in the left panel and durable consumption growth (Δd) in the right panel. The sample is $1953-2002$ in the upper panel and $1971-2002$ in the lower panel.

Table 25: Forecasting Excess Returns with Forward Discounts

Portfolio	γ_F	R^2	γ_F	R^2	γ_F	R^2	γ_F	R^2
		one-month				3-months		
1	1.08	4.29	3.76	8.35	2.41	8.35	4.55	19.23
NW	[0.33]		[0.64]		[1.34]		[0.89]	
HH	[0.23]		[0.57]		[1.40]		[0.92]	
No overlap	[0.33]		[0.64]		[1.24]		[0.96]	
12 lag VAR	[0.36]		[0.73]		[1.35]		[1.17]	
6	0.72	2.65	3.12	4.59	0.96	4.03	3.52	8.82
NW	[0.21]		[0.84]		[0.44]		[1.17]	
HH	[0.21]		[0.85]		[0.44]		[1.23]	
No overlap	[0.21]		[0.84]		[0.48]		[1.15]	
12 lag VAR	[0.32]		[0.94]		[0.61]		[1.53]	
		six-months				one-year		
1	4.12	26.62	4.82	32.38	3.30	26.85	4.15	35.40
NW	[0.73]		[0.78]		[0.73]		[0.74]	
HH	[0.78]		[0.81]		[0.76]		[0.67]	
No overlap	[1.01]		[0.80]		[0.99]		[1.37]	
12 lag VAR	[1.21]		[1.14]		[1.17]		[0.98]	
6	1.07	6.40	3.41	13.68	1.30	11.50	3.18	19.10
NW	[0.47]		[1.14]		[0.46]		[1.11]	
HH	[0.50]		[1.21]		[0.49]		[1.22]	
No overlap	[0.55]		[1.05]		[0.69]		[1.26]	
12 lag VAR	[0.73]		[1.62]		[0.85]		[1.65]	

Notes: This table reports the n-month ahead forecasted excess returns using the n-month portfolio-specific forward discount and the average n-month forward discount. 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 n lags for the n-month returns. The VAR uses n lags for the n-month returns. All the returns are annualized and reported in percentage points. Data are monthly from Datastream . The sample period is 11/1983 - 08/2007.

Table 26: Forecasting Excess Returns with IP

Portfolios	γ_{IP}	R^2	*Portfolios*	γ_{IP}	R^2	*Portfolios*	γ_{IP}	R^2
				Panel I: All Countries				
1	−1.68	23.06	2	−1.20	18.57	3	−1.55	27.80
NW	[0.42]			[0.37]			[0.33]	
HH	[0.44]			[0.38]			[0.36]	
12 lag VAR	[0.69]			[0.45]			[0.45]	
No overlap	[0.58]			[0.46]			[0.46]	
4	−1.50	29.20	5	−1.98	36.79	6	−1.66	19.22
NW	[0.31]			[0.33]			[0.44]	
HH	[0.33]			[0.33]			[0.47]	
12 lag VAR	[0.43]			[0.49]			[0.72]	
No overlap	[0.37]			[0.60]			[0.53]	
				Panel II: Developed Countries				
1	−1.84	20.96	2	−1.84	21.70	3	−1.98	30.34
NW	[0.47]			[0.46]			[0.32]	
HH	[0.50]			[0.49]			[0.34]	
12 lag VAR	[0.83]			[0.80]			[0.60]	
No overlap	[0.58]			[0.52]			[0.30]	
4	−1.86	31.45	5	−1.98	33.06			
NW	[0.31]			[0.32]				
HH	[0.32]			[0.34]				
12 lag VAR	[0.52]			[0.68]				
No overlap	[0.28]			[0.32]				

Notes: This table reports the forecasted excess returns using the 12-month change in US Industrial Production. All the returns annualized and reported in percentage points. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 04/2007. Panel I uses the entire sample of countries. Panel II focuses on developed countries.

Table 27: Forecasted HML_{FX} Return Correlations

Portfolio	IP	Pay	$Help$	$Spread$	$Slope$	Vol
2	−0.37	−0.24	−0.34	0.33	0.09	0.12
	[0.07]	[0.01]	[0.20]	[0.05]	[0.08]	[0.07]
3	−0.38	−0.22	−0.33	0.32	0.10	0.14
	[0.09]	[0.02]	[0.19]	[0.05]	[0.09]	[0.07]
4	−0.38	−0.20	−0.32	0.31	0.10	0.17
	[0.11]	[0.03]	[0.19]	[0.05]	[0.10]	[0.08]
5	−0.36	−0.16	−0.30	0.31	0.09	0.19
	[0.14]	[0.03]	[0.19]	[0.05]	[0.12]	[0.09]
6	−0.23	−0.09	−0.19	0.28	0.08	0.25
	[0.28]	[0.08]	[0.20]	[0.06]	[0.22]	[0.19]

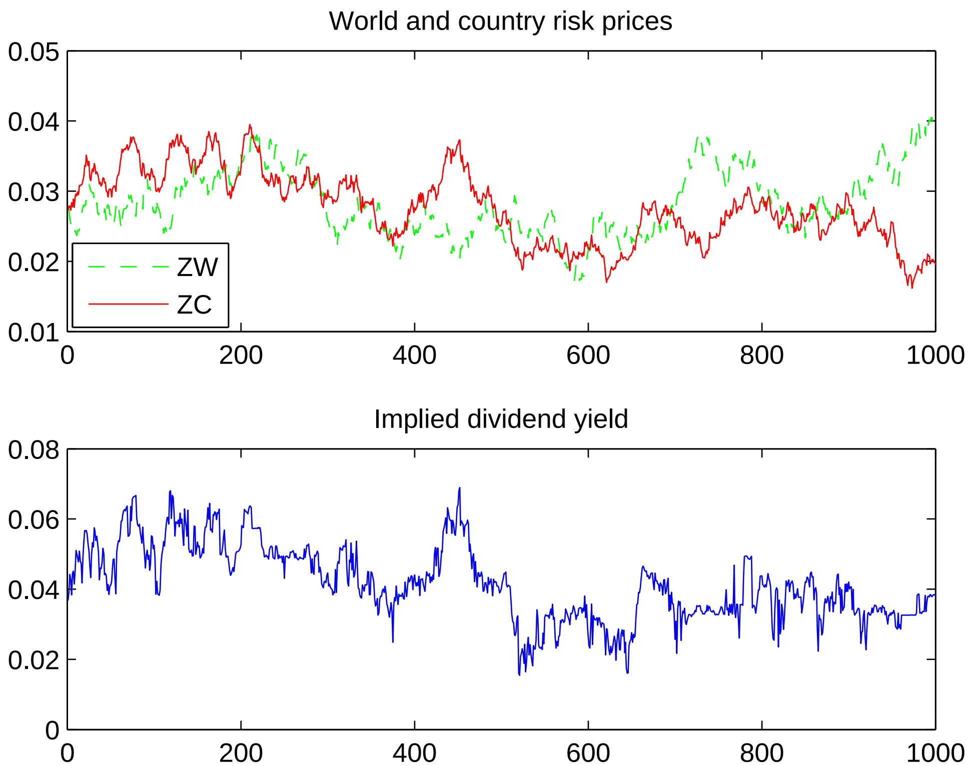
Notes: This table reports the contemporaneous correlation $Corr\left[\widehat{E}_t[rx^j_{t+1} - rx^1_{t+1}], x_t\right]$ of forecasted excess returns with different variables x_t: the 12-month percentage change in industrial production ($\Delta \log IP_t$), in the total US non-farm payroll ($\Delta \log Pay_t$), and 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). Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 08/2007.

Table 28: Predictability of Spread Returns

	Panel I: $rx^6 - rx^1$				Panel II: $rx^2 - rx^1$			
	1-month		12-month		1-month		12-month	
Portfolios	γ_x	R^2	γ_x	R^2	γ_x	R^2	γ_x	R^2
VIX	37.12	1.96	18.57	4.44	23.16	2.24	12.08	5.61
NW	[18.10]		[8.61]		[8.35]		[5.17]	
HH	[18.85]		[9.44]		[8.93]		[8.93]	
VAR	[24.00]		[13.99]		[11.79]		[9.48]	
No overlap	[18.10]		[3.04]		[8.35]		[3.24]	
Spread	6.64	1.97	3.48	4.23	3.56	1.65	2.66	8.08
NW	[2.65]		[1.70]		[1.43]		[0.84]	
HH	[2.68]		[1.73]		[1.46]		[1.46]	
VAR	[3.39]		[3.09]		[1.98]		[1.67]	
No overlap	[2.65]		[0.95]		[1.43]		[0.98]	

Notes: This table reports slope coefficients and R^2 of predictability regressions. In the left panel, we use the returns on the sixth minus the returns on the first portfolios. In the right panel, we rank all currencies in two portfolios and use the difference in returns between these two portfolios. In both panels, we consider returns at one-month and twelve-month horizons. All returns annualized and reported in percentage points. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 04/2007.

Figure 8: Simulated state variables and stock market price-dividend ratios



This figure plots the simulated paths of the two state variables, z_t^i and z_t^w, and the corresponding values of the stock market dividend yield, $\frac{D_t^i}{P_t^i}$

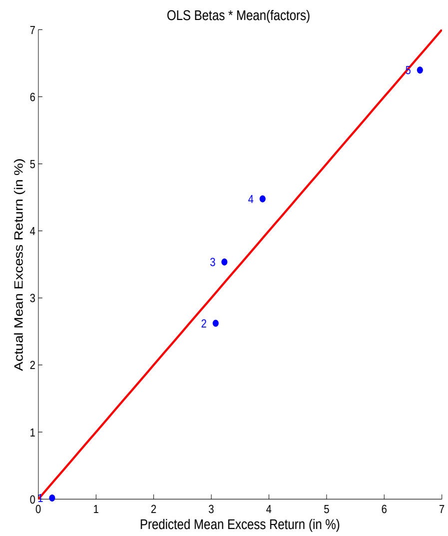


Figure 9: Predicted against Actual Excess Returns - Portfolios of Countries in Burnside et alii (2008).

This figure plots realized average excess returns on the vertical axis against predicted average excess returns on the horizontal axis. We regress each actual excess return on a constant and the risk factors RX and HML_{FX} to obtain the slope coefficient β^j. Each predicted excess returns is obtained using the OLS estimate of β^j times the sample mean of the factors. All returns are annualized. The data are monthly. The sample is 2/1976 - 01/2008.