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COUNTERCYCLICAL CURRENCY RISK PREMIA

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ABSTRACT

The average forward discount of the dollar against developed market currencies is the best predictor of average foreign currency excess returns earned by U.S. investors on a long position in a large basket of foreign currencies and a short position in the dollar. The predicted excess returns are strongly connected to the U.S. business cycle, and increase dramatically during U.S. recessions as the average forward discount increases. Adding the rate of U.S. industrial production growth as a predictor increases the predictability of foreign currency returns to 30% at the 12-month horizon. Using a no-arbitrage model of exchange rates we show that the counter-cyclical dollar risk premium reflects time-varying compensation to U.S. investors for taking on U.S. specific risk by shorting the dollar. The model implies that predictability of exchange rate changes, as opposed to excess returns, is much harder to detect in small samples, as is the case in the data.

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We find that the expected return on a short position in the dollar and a long position in a basket of foreign currencies is closely linked to the U.S. business cycle. The underlying mechanism is counter-cyclical risk compensation for going long in U.S.-specific risk by shorting the dollar. In recessions, U.S. investors demand a much higher return for taking on U.S. risk in currency markets than in expansions.

In any no-arbitrage model, the percentage change in the spot exchange rate reflects the difference between the domestic and the foreign log pricing kernel. As a simple thought experiment, we can decompose each pricing kernel into a country-specific and a global component. Consider the average return earned by a U.S. investor in currency markets. She borrows in U.S. dollars and invests in all the available risk-free securities denominated in foreign currencies. With many currencies in her well-diversified portfolio, the country-specific foreign risk averages out, and the U.S. investor is left bearing (i) the U.S.-specific risk and (ii) the difference between the U.S. exposure to the common risk and the average exposure of all the other countries to common risk. This paper starts off by assuming that the U.S. exposure to common risk is equal to the average exposure across all countries in the currency basket. In that case, the second source of risk exposure disappears for a U.S. investor who is short in the dollar and long in foreign currency. She is only compensated for the U.S. risks she is exposed to and the variation in this risk premium is driven by variation in the price of U.S. risk. Our empirical evidence supports this view.

To formalize our intuition, we use a simple no-arbitrage multi-country model of exchange rates that encompasses both country-specific and common innovations, which we developed in Lustig, Roussanov and Verdelhan (2009) in order to understand the carry trade in currency markets. Our model belongs to the essentially-affine class that is popular in the term structure literature. Models that belong to this class have been applied to currency markets by Frachot (1996), Backus, Foresi and Telmer (2001) and Brennan and Xia (2006). In this paper, we explore the implications of this model for the time-series predictability of currency excess returns. We make one key assumption: we assume that the loading of the U.S. log pricing kernel on the world risk factor is identical to that of the average developed country in the currency basket. In other words, we assume that the beta of the U.S. investor on the world risk factor is one. In that case, shocks that are specific to foreign pricing kernels and common shocks that equally affect the U.S. and foreign pricing kernel do not alter the U.S. dollar exchange rate against a large basket of currencies, but U.S.-specific shocks do. A short position in the dollar is risky because the dollar appreciates following negative U.S. shocks. U.S. investors expect to be compensated for that risk. We refer to this risk premium as the dollar risk premium.

The model then delivers a strong prediction: the average forward discount, the average difference between foreign and U.S. risk-free interest rates, on a broad basket of currencies is the best predictor of the average excess returns on currency markets, because, given our assumptions, the average forward discount measures the market price of U.S.-specific risk. In the model, as the average forward discount increases in U.S. recessions, the dollar risk price increases as well, and so do the expected excess returns on a basket of foreign currencies.

We take these predictions to the data, and we find that excess returns on a long position in a basket of foreign currencies and a short position in the dollar are highly predictable, more than stock returns, and about as much as bond returns. As the model suggests, the best predictor is the average dollar forward discount, measured as the interest rate difference between the average interest rates of a basket of *developed* currencies and the U.S. interest rate. The average forward discount on developed countries is the best predictor even when investing in a different basket of emerging market currencies, and it drives out individual currency interest rates when predicting returns on positions in individual currencies. The one-month ahead average forward discount explains 1 to 5 percent of the variation in the average foreign currency excess returns over the next month. When horizon increases, the R^2s increase too, because the average forward discount is persistent. At the 12-month horizon, the average forward discount explains up to 15 percent of the variation in returns over the next year.

These effects are economically meaningful. As the U.S. economy enters a recession, U.S. investors who short the dollar earn a larger interest rate spread, the average forward discount, and they earn an additional 150 basis points per annum in currency appreciation per 100 basis point increase in the interest rate spread. In other words, an increase in the average forward discount of 100 basis points increases the expected excess return by 250 basis points per annum and it leads to an annualized depreciation of the dollar by 150 basis points. This is not the case for the average forward discount computed on a basket of emerging market currencies, which does not have the same counter-cyclical properties. However, the average forward discount against a basket of developed currencies does forecast the returns on a basket of emerging market currencies, and the effect on returns is about 180 basis points per 100 basis point increase in the predictor.

Moreover, we find that the average forward discount has forecasting power at the individual currency level above and beyond that of the currency-specific interest rate differential. The corresponding slope coefficients are much larger than those typically found for bilateral exchange rates, because the average forward discount averages out the effect of heterogeneity in exposure to common shocks on interest rates. These slope coefficients are also more precisely estimated, because the average forward discount averages out idiosyncratic variation in currency-specific interest rate differences. The average slope coefficient in the predictability regression for bilateral exchange rates is only 44 basis points in our sample. There is a gap of more than 200 basis points between the average forward discount and the average of currency-specific forward discount slope coefficients. Even when forecasting individual currency returns, the average forward discount often outperforms the currency-specific forward discount. When we include both in the return predictability regressions at the 12-month horizon, we find an average slope coefficient of 1.95 for the average forward discount, compared to an average of -0.41 for the individual slope coefficients.

The predicted foreign currency excess returns on long position in foreign currency and a short position in the dollar are strongly counter-cyclical because they inherit the cyclical properties of U.S.-specific risk prices. We show that the U.S.-specific component of macroeconomic variables such as the rate of industrial production growth actually predict future excess returns even after controlling for the average forward discount. We investigate the one-month to one-year ahead predictability of the excess returns on baskets of foreign currency and we obtain R^2s of up to 23-30 percent when using the average forward discount and industrial production growth as predictors.[1] Industrial production, however, is correlated with foreign business cycles. We thus project industrial production growth on an average of foreign equivalents in order to remove the global component, and we use the residuals as predictors. Again, we obtain high R^2s, ranging from 17 up to almost 30 percent. These effects are large: a relatively small 100 basis point drop in year-over-year U.S. industrial output growth raises the expected excess return -and hence increases the expected rate of dollar depreciation over the following year–by 145 to 190 basis points per annum, after controlling for the average forward discount.

These findings point towards a risk-based view of exchange rates and short-term interest rates,

[1] We focus on the 12-month percentage change in U.S. industrial production index because it turns out to be the best forecaster. This variable is highly correlated with the output gap used by Cooper and Priestley (2009) to predict stock returns. Importantly, as documented in the term-structure literature (Duffee (2008), Ludvigson and Ng (2009), Joslin, Priebsch and Singleton (2010)), industrial production growth contains information about bond risk premia that is not captured by interest rates and, therefore, forward discounts.

as advocated by Atkeson and Kehoe (2008). Our model offers a potential account of our predictability results. A version of our model that is calibrated to match the key moments in the data quantitatively reproduces our predictability findings for currency returns, as well as the carry trade risk premium, provided that the maximum Sharpe ratio is high enough. As in the data, the statistical evidence for exchange rate predictability inside the model is weak in small samples, but the evidence for return predictability, which is what matters for Sharpe ratios, is strong. Furthermore, consistent with our model, the average dollar forward discount does not predict carry trade returns in the data.

Since the work by Meese and Rogoff (1983), the standard view in international economics is that individual exchange rates follow a random walk, with perhaps small departures from the random walk at very high frequencies (Evans and Lyons, 2005). This consensus emerged from the failure of a large class of models to outperform the random walk in forecasting changes in exchange rates for individual currency pairs. This standard view implies that currency investors simply expect to earn the forward discounts or interest rate differences between countries. In this paper, we show that the best predictor of currency returns against the dollar is not that individual currency's interest rate difference with the U.S., but rather the average interest rate difference on a basket of developed currencies. This evidence can obviously not be reconciled with the random walk view of the dollar against all other currencies.[2]

A large literature documents the predictability of excess returns in equity and bond markets (see Cochrane and Piazzesi (2005) and Cochrane (2005) for a survey). Macroeconomic and finan-

[2]There is no compelling asset pricing logic that would lead us to expect the currency risk premium to be exactly equal to the interest rate difference for that particular currency at all times. Indeed, the view in the finance literature has been somewhat more nuanced following the seminal results of Hansen and Hodrick (1980) and Fama (1984), who find that predicted excess returns move more than one-for-one with interest rate differentials, implying some predictability in exchange rates, even though the statistical evidence from currency pairs is typically weak.

cial variables predict stock market returns, particularly at long horizons. In recent work, Duffee (2008), Ludvigson and Ng (2009), Joslin et al. (2010) report similar findings for the bond market using industrial production growth, and Piazzesi and Swanson (2008) document that payroll growth predicts excess returns on interest rate futures. Hong and Yogo (2009) show that common predictors of bond and stock returns, such as the short rate and the yield spread, also predict returns on commodity futures.

Forecasting has been a longstanding challenge in international economics. Twenty years ago, Froot and Thaler (1990) counted at least 75 papers on the topic. There has been no shortage since. In general, the reported R^2s are small and the slope coefficients borderline significant. The existing literature, however, focuses mainly on forecasting bilateral exchange rates (see Bekaert and Hodrick (1992) and Bekaert and Hodrick (1993) for prominent examples), not portfolios of currency excess returns. Within such settings detecting the effect of macroeconomic variables, such as industrial production growth, on currency risk premia requires imposing tight parametric structure on the stochastic discount factor (e.g. as in Dong (2006)). More recently, using portfolios of currencies, Ang and Chen (2010) show that changes in interest rates and term spreads predict currency excess returns. Finally, in closely related work, Adrian, Etula and Shin (2010) show that the funding liquidity of financial intermediaries in the U.S. predicts currency excess returns on short positions in the dollar, where funding liquidity growth is interpreted as a measure of the risk appetite of these intermediaries.

Section 2 presents the no-arbitrage model developed by Lustig et al. (2009). We use this model to derive currency return predictability implications. Section 3 describes the data, how we build currency portfolios and their main characteristics. Section 4 reports the time variation in excess returns that U.S investors demand on these foreign currency portfolios. We first explore the predictive power of the average forward discount. We then show that macro variables such as the rate of industrial production growth have incremental explanatory power for future currency basket returns. Section 5 tests the out-of-sample predictability of the average forward discount. Section 6 returns to the model: we show that our standard, no-arbitrage model replicates quantitatively the predictability we report in the data. Section 7 concludes. The portfolio data can be downloaded from our web sites and are regularly updated.

2 Understanding Currency Predictability

The literature has mostly focused on the predictability of excess returns for individual foreign currency pairs. By shifting the focus to investments in baskets of foreign currencies, our paper shows that most of the predictability in currency markets actually reflects common variation in interest rates and exchange rates. We develop a standard affine model that reproduces this common variation in exchange rates and interest rates.

Our model has three main implications for return predictability in currency markets. First, the average forward discount (henceforth) AFD should be a good predictor of the average excess returns on foreign currency investments because it measures the price of dollar risk; it should only predict carry trade returns if the exposure of the U.S. to global innovations is different from of the average country in the basket. Second, uncovered interest rate parity (UIP) should be more strongly rejected for baskets of currencies than for bilateral exchange rates. The slope coefficients in regressions of average changes in exchange rates on the AFD should be larger than those for regressions of bilateral exchange rates on bilateral forward discounts. Third, the dollar risk premium should be counter-cyclical with respect to the U.S.-specific component of the business cycle.

As the price of this risk increases during U.S. recessions, the expected excess return on foreign currency increases. In the next sections, we will test these predictions: they are borne out by the data. We start now with a brief description of the model.

2.1 Setup

We assume that financial markets are complete, but that some frictions in the goods markets prevent perfect risk-sharing across countries. As a result, the change in the real exchange rate Δq^i between the home country and country i is $\Delta q^i_{t+1} = m_{t+1} - m^i_{t+1}$, where q^i is measured in country i goods per home country good and m denotes the log stochastic discount factor (SDF) or pricing kernel. An increase in q^i means a real appreciation of the home currency. For any variable that pertains to the home country (the U.S.), we drop the superscript. The real expected log currency excess return equals the interest rate difference plus the expected rate of appreciation. If pricing kernels are log-normal, the real expected log currency excess return is equal to:

$$E_t[rx^i_{t+1}] = -E_t[\Delta q^i_{t+1}] + r^i_t - r_t = \frac{1}{2}[Var_t(m_{t+1}) - Var_t(m^i_{t+1})].$$

We use the model developed by Lustig et al. (2009) to explain carry trade returns. In the model, there are two sources of priced risk: country-specific and world shocks.[3] Each type of risk has a different price. We assume that the risk prices of country-specific shocks depend only on the country-specific factors, and that the risk prices of world shocks can depend on world and country-

[3]Bakshi, Carr and Wu (2008), Brandt, Cochrane and Santa-Clara (2006), Colacito (2008) and Colacito and Croce (2008) emphasize the importance of a large common component in SDFs to make sense of the high volatility of SDFs and the relatively 'low' volatility of exchange rates. In addition, there is a lot evidence that much of the stock return predictability around the world is driven by variation in the global risk price, starting with the work of Harvey (1991) and Campbell and Hamao (1992). Lustig et al. (2009) show that, in order to reproduce cross-sectional evidence on currency excess returns, risk prices must load differently on this common component.

specific factors.

We consider a world with N countries and currencies. We do not specify a full economy complete with preferences and technologies; instead we posit a law of motion for the SDFs directly. Following Backus et al. (2001), we assume that in each country i, the logarithm of the real SDF m^i follows a two-factor Cox, Ingersoll and Ross (1985)-type process:

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

To be parsimonious, we limit the heterogeneity in the SDF parameters to the different loadings, denoted δ^i, on the world shock; all the other parameters are identical for all countries. Lustig et al. (2009) show that cross-sectional variation in δ is key to understanding the carry trade.

In this model, there is a common global factor z^w_t and a country-specific factor z^i_t. The currency-specific innovations u^i_{t+1} (uncorrelated across countries) and global innovations u^w_{t+1} are *i.i.d* gaussian, with zero mean and unit variance; u^w_{t+1} is a world shock, common across countries, while u^i_{t+1} is country-specific. The country-specific and world volatility components are governed by square root processes:

$$\begin{aligned} z^i_{t+1} &= (1-\phi)\theta + \phi z^i_t - \sigma \sqrt{z^i_t} u^i_{t+1}, \\ z^w_{t+1} &= (1-\phi)\theta + \phi z^w_t - \sigma \sqrt{z^w_t} u^w_{t+1}. \end{aligned}$$

These processes ensure that log SDFs have positive variances. As is common in the equity and bond asset pricing literature, we assume that the market price of U.S.-specific risk – and thus z^i – is counter-cyclical. This feature of asset markets is a key ingredient of leading dynamic asset pricing models (see Campbell and Cochrane (1999) and Bansal and Yaron (2004) for prominent examples).

In this model, the real interest rate investors earn on currency i is given by:

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

We assume that the precautionary effect dominates on real interest rates, lowering rates when volatility increases: $\chi - \frac{1}{2}(\gamma + \kappa) < 0$ and $\chi - \frac{1}{2}\delta^i < 0$. High interest rate currencies tend to have low loadings δ^i on common innovations, while low interest rate currencies tend to have high loadings δ^i. It follows that the forward discount between currency i and the U.S. is equal to:

$$r_t^i - r_t = \left(\chi - \frac{1}{2}(\gamma + \kappa)\right)(z_t^i - z_t) - \frac{1}{2}\left(\delta^i - \delta\right) z_t^w. \tag{2.1}$$

In our empirical work, we focus on the expected log currency excess return. In the model, the real log currency risk premium is given by:

$$E_t[rx_{t+1}^i] = \frac{1}{2}[(\gamma + \kappa)\left(z_t - z_t^i\right) + \left(\delta - \delta^i\right) z_t^w], \tag{2.2}$$

If $\chi = 0$, the Meese-Rogoff hypothesis holds: the log of real exchange rates follows a random walk, and the expected log excess return is simply proportional to the real interest rate difference.

2.2 Predictability of Currency Basket Returns

We turn now to the implications of the model for return predictability on baskets of currencies. We use bar superscript ($\overline{x}$) to denote the average of any variable or parameter x across all the countries in the basket. All of the parameters are identical across countries except for the loadings on the global shock, δ. Hence, the average real expected log excess return of the basket is:

$$E_t[\overline{rx}_{t+1}] = \frac{1}{2}(\gamma + \kappa)\left(z_t - \overline{z_t}\right) + \frac{1}{2}\left(\delta - \overline{\delta}\right) z_t^w. \tag{2.3}$$

We assume that country-specific shocks average out within each portfolio. In this case, $\overline{z}$ is constant in the limit $N \rightarrow \infty$ by the law of large numbers. As a result, the real expected excess return on this basket consists of a dollar risk premium (the first term above, which depends only on z_t) and a global risk premium (the second term, which depends only on z_t^w).

The real expected excess return of this basket depends only on z and z^w. These are the same variables that drive the AFD:

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

Clearly, the AFD should have predictive power for average excess returns on a basket of currencies.

The Dollar Premium In the case of a basket consisting of a large number of developed currencies, we will assume that the average country's SDF has the same exposure to global innovations as the U.S.: $\overline{\delta} = \delta$. In this case, the log currency risk premium on the basket only depends on the U.S.-specific factor z_t, not the global factor:

$$E_t[\overline{rx}_{t+1}] = \frac{1}{2}(\gamma + \kappa)\left(z_t - \overline{z_t}\right). \tag{2.4}$$

Hence, the currency risk premium on this basket is the *dollar risk premium*, as it compensates U.S. investors proportionally to their exposures to the local risk governed by γ and exposure to global risk governed by κ . Given our assumption, the dollar risk premium is driven exclusively by U.S. variables (e.g. the state of the U.S. business cycle). Similarly, given the average exposure assumption, the AFD only depends on the U.S. factor z_t:

$$\overline{r_t} - r_t = \left(\chi - \frac{1}{2}(\gamma + \kappa)\right)(\overline{z_t} - z_t). \tag{2.5}$$

In section 4, we show that the average exposure assumption fits the data well for the U.S.

By creating a basket in which the average country shares the U.S. exposure to global shocks, we have eliminated the effect of foreign idiosyncratic factors on currency risk premia *and* on interest rates. For this specific basket, the slope coefficient in a predictability regression of the average log returns in the basket on the AFD is $-\frac{1}{2}(\gamma+\kappa)/\left(\chi - \frac{1}{2}(\gamma+\kappa)\right)$. Correspondingly, the UIP slope coefficient in regression of average real exchange rate changes for the basket on the real forward discount is $\chi/\left(\chi - \frac{1}{2}\gamma\right)$. On the one hand, if $\chi < \frac{1}{2}(\gamma+\kappa)$, a positive interest rate differential forecasts positive future returns. If $\chi = 0$, then interest rate differences and currency risk premia are perfectly correlated. On the other hand, when $\gamma = 0$ and $\chi > 0$, then UIP holds.

Carry Trade The model has also a strong prediction on currency carry trades. Those trades correspond to investments that are long high interest rate currencies and short low interest rate currencies. If we were to sort currencies by interest rates into portfolios, then, as shown by Lustig et al. (2009), investors who take a carry trade position would only be exposed to common innovations, not to U.S. innovations. The return innovations on this high-minus-low (denoted *hml*) investment are given by

$$hml_{t+1} - E_t[hml_{t+1}] \quad = \quad \left(\frac{1}{N_L} \sum_{i \in L} \sqrt{\delta^i z_t^w + \kappa z_t^i} - \frac{1}{N_H} \sum_{i \in H} \sqrt{\delta^i z_t^w + \kappa z_t^i} \right) u_{t+1}^w. \qquad (2.6)$$

The *hml* portfolio will have positive average returns if the pricing kernels of low interest rate currencies are more exposed to the global innovation. It is easy to show that the expected excess returns on the carry trade portfolio do not depend on z_t, the U.S. specific factor, given our assumptions, and hence we do not expect the AFD to predict carry trade returns.

2.3 Predictability of Individual Currency Returns

Next, we consider the case of investing in individual currencies. When the U.S.' exposure differs from that of the average foreign country ($\delta \neq \overline{\delta}$), then the currency risk premium loads on the global factor, and so does the forward discount for that currency. Given all of the symmetry we have imposed on the model, this type of heterogeneity will invariably lower the UIP slope coefficient in a regression of exchange rate changes on the forward discount in absolute value relative to the case of a basket of currencies. The UIP slope coefficient for individual currencies using the forward discount for that currency is given by the expression on the left hand side:

$$\left| \frac{\chi \left(\chi - \frac{1}{2}(\gamma + \kappa) \right) var(z_t^i - z_t)}{\left(\chi - \frac{1}{2}(\gamma + \kappa) \right)^2 var(z_t^i - z_t) + \frac{1}{4} \left(\delta^i - \delta \right)^2 var(z_t^w)} \right| < \left| \frac{\chi}{\chi - \frac{1}{2}(\gamma + \kappa)} \right|.$$

It is lower than the right hand side simply because $\frac{1}{4} \left(\delta^i - \delta \right)^2 var(z_t^w) > 0$. Intuitively, note that by considering only country-specific investments, the volatility of the forward discount has increased but the covariance between interest rate differences and exchanges rate changes has not, relative to the case of a basket of currencies. Hence, heterogeneity in exposure to the global innovations pushes the UIP slope coefficients towards zero, relative to the benchmark case with identical exposure. As a result, in the range of negative UIP slope coefficients, the slope coefficients in the predictability regressions will be smaller than $-\frac{1}{2}\gamma/\left(\chi - \frac{1}{2}(\gamma+\kappa)\right)$, the coefficient that we obtained in the benchmark case with average exposures to global innovations equal to U.S exposure. Hence, we expect to see larger slope coefficients in absolute value for UIP regressions on baskets of currencies, because these baskets eliminate the heterogeneity in exposure to global innovations.

2.4 Inflation and Currency Return Predictability

We end this section with a note on the role of inflation in the model. The nominal pricing kernel is the real pricing kernel minus the rate of inflation: $m_{t+1}^{i,\$} = m_{t+1}^{i} - \pi_{t+1}^{i}$. To keep the analysis simple, we assume that inflation innovations are not priced. Hence, the expected nominal excess returns in levels on the individual currencies and currency portfolios are identical to the expected real excess returns we have derived, but in logs they are slightly different, because of Jensen's inequality. However, these differences are of second order.

We simply assume that the same factors driving the real pricing kernel also drive expected inflation. Thus, country i's inflation process is given by

$$\pi_{t+1}^{i} = \pi_0 + \eta z_t^i + \eta^w z_t^w + \sigma_\pi \epsilon_{t+1}^i,$$

where the inflation innovations ϵ_{t+1}^i are i.i.d. gaussian. The nominal risk-free interest rate (in logarithms) is given by

$$r_t^{i,\$} = \pi_0 + \alpha + \left(\chi + \eta - \frac{1}{2}(\gamma + \kappa)\right) z_t^i + \left(\chi + \eta^w - \frac{1}{2}\delta^i\right) z_t^w - \frac{1}{2}\sigma_\pi^2.$$

Consider the simplest case in which the average country in the basket has the same exposure as the U.S. to global innovations (same δ and η^w). The nominal UIP slope coefficients in a regression of nominal exchange rate change for one currency on the nominal forward discount is given by $(\chi + \eta)/\left(\chi + \eta - \frac{1}{2}(\gamma + \kappa)\right)$. The slope coefficient in a predictability regression of the average log returns on the basket on the nominal dollar forward discount is

$$-\frac{1}{2}(\gamma + \kappa)/\left(\chi + \eta - \frac{1}{2}(\gamma + \kappa)\right). \tag{2.7}$$

Clearly, if $\eta = 0$ and expected inflation is driven by the global factors, then the forward discount and the risk premium are driven only by the common factor, and the UIP slope coefficients for currency baskets are unchanged from the 'real' slope coefficients that we have derived. The risk premium is still given by equation 2.4 and the AFD is still given by the expression in equation 2.5. However, if $\eta > 0$, the slope coefficients in predictability regressions for individual currency pairs tend to be smaller in absolute value as η increases. This is exactly what we find for baskets of emerging market currencies.

Summary This parsimonious model offers three sets of predictions. First, the return predictability on large baskets of developed currencies should largely reflect variation in the dollar risk premium. This variation is captured by the AFD. Second, average excess returns for baskets of currencies and average spot exchange rate changes should exhibit stronger predictability than can be obtained for individual currency pairs by eliminating the effect of foreign idiosyncratic and common shocks to interest rates and exchange rates. Third, we expect the dollar risk premium to be counter-cyclical with respect to the U.S.-specific component of the business cycle.

3 Forward and Spot Prices in Currency Markets

We now turn to the data to test the predictability of currency excess returns and exchange rates. In this section, we describe our data set and give a brief summary of currency returns at the level of currency baskets. We use the quoted prices of traded forward contracts of different maturities to study return predictability. Hence, there is no interest rate risk in the investment strategies that we consider. Moreover, these trades can be implemented at fairly low costs.

Currency Excess Returns using Forward Contracts We use s to denote the log of the nominal spot exchange rate in units of foreign currency per U.S. dollar, and f for the log of the forward exchange rate, also in units of foreign currency per U.S. dollar. An increase in s means an appreciation of the home currency. The log excess return rx on buying a foreign currency in the forward market and then selling it in the spot market after one month is simply $rx_{t+1} = f_t - s_{t+1}$. This excess return can also be stated as the log forward discount minus the change in the spot rate: $rx_{t+1} = f_t - s_t - \Delta s_{t+1}$. In normal conditions, forward rates satisfy the covered interest rate parity condition; the forward discount is equal to the interest rate differential: $f_t - s_t \approx i_t^\star - i_t$, where $i^\star$ and i denote the foreign and domestic nominal risk-free rates over the maturity of the contract. Akram, Rime and Sarno (2008) study high frequency deviations from covered interest rate parity (CIP). They conclude that CIP holds at daily and lower frequencies.[4] Hence, the log currency excess

[4] While this relation was violated during the extreme episodes of the financial crisis in the fall of 2008, including or excluding those observations does not have a major effect on our results.

return equals the interest rate differential less the rate of depreciation: $rx_{t+1} = i_t^\star - i_t - \Delta s_{t+1}$.

Horizons Forward contracts are available at different maturities. We use k-month maturity forward contracts to compute k-month horizon returns (where $k = 1,\ 2,\ 3,\ 6$, and 12). The log excess return on the k-month contract for currency i is $rx^i_{t+k} = -\Delta s^i_{t\to t+k} + f^i_{t\to t+k} - s^i_t$, where $f^i_{t\to t+k}$ is the k-month forward exchange rate, and the k-month change in the log exchange rate is $\Delta s^i_{t\to t+k} = s^i_{t+k} - s^i_t$. For horizons above one month our series consists of overlapping k-month returns computed at monthly frequency.

Data We start from daily spot and forward exchange rates in U.S. dollars. We build end-of-month series from November 1983 to June 2010. These data are collected by Barclays and Reuters and available on Datastream. Our main data set contains at most 37 different currencies of the following countries: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, 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, as well as the Euro. Some of these currencies have pegged their exchange rate partly or completely to the U.S. dollar over the course of the sample. We keep them in our sample because forward contracts were easily accessible to investors. The euro series start in January 1999. We exclude the euro area countries after this date and only keep the euro series. Based on large failures of covered interest rate parity, we chose to delete the following observations from our sample: South Africa from the end of July 1985 to the end of August 1985; Malaysia from the end of August 1998 to the end of June 2005; Indonesia from the end of December 2000 to the end of May 2007; Turkey from the end of October 2000 to the end of November 2001; United Arab Emirates from the end of June 2006 to the end of November 2006.

Baskets of Currencies We construct three currency baskets. The first basket is composed of the currencies of developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Finland, Germany, Greece, Italy, Ireland, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdom, as well as the Euro. The second basket groups all of the remaining currencies, corresponding to the emerging countries in our sample. The third basket consists of all of the currencies in our sample. All of the average log excess returns and average log exchange rate changes are equally weighted within each basket.

The average log excess return on currencies in basket j over horizon k is $\overline{rx}^j_{t\to t+k} = \frac{1}{N^j_t}\sum_{i=1}^{N^j_t} rx^i_{t+k}$, where N^j_t denotes the number of currencies in basket j at time t. Similarly, the average change in the log exchange rate is $\overline{\Delta s}^j_{t\to t+k} = \frac{1}{N^j_t}\sum_{i=1}^{N^j_t} \Delta s^i_{t\to t+k}$, and the AFD for maturity k is $\overline{f}^j_{t\to t+k} - \overline{s}^j_t = \frac{1}{N^j_t}\sum_{i=1}^{N^j_t} f^i_{t\to t+k} - s^i_t$.

Figure 1 displays the AFDs (Panel A) and cumulative average log excess returns (Panel B) on the three baskets. The shaded areas are NBER recessions determined by the U.S. The AFDs are negatively correlated with the U.S. short-term interest rates. However, the AFD is clearly stationary, while U.S. short-term interest rates trend downward from 10% (3-month Treasury bill rate) to 0% because of the secular decline in (global) inflation over this sample. The AFD differences out common variation in inflation expectations across countries and picks up real interest rate differences.

The behavior of the returns is generally similar over the sample period (with some differences in the magnitude of variation), mostly reflecting the swings in the U.S. dollar. The AFDs computed on developed and emerging countries are virtually identical in the first half of the sample, but diverge dramatically during the period around the Asian financial crisis of 1997-1998, with emerging countries interest rates shooting up relative to both the U.S. and the developed countries averages. This disparity suggest that one should expect different patterns of predictability for the two baskets.

Table I presents the summary statistics of the three currency baskets, in particular annualized means and standard deviations of AFDs, average spot rate changes, and average log excess returns, as well as autocorrelations of the AFDs for all horizons. The average AFD for the U.S. is between 68 and 100 basis points per annum. In the sample of developed countries, the unconditional average annualized dollar premium varies between 2.25 and 2.43% per annum depending on horizon. The AFDs are highly persistent, especially at longer horizons, with monthly autocorrelations between 0.83 and 0.98. Hence, the annualized autocorrelations vary between 0.11 and 0.78. Therefore, they are less persistent than the dividend yield on the U.S. stock market which has an annualized autocorrelation of 0.96.

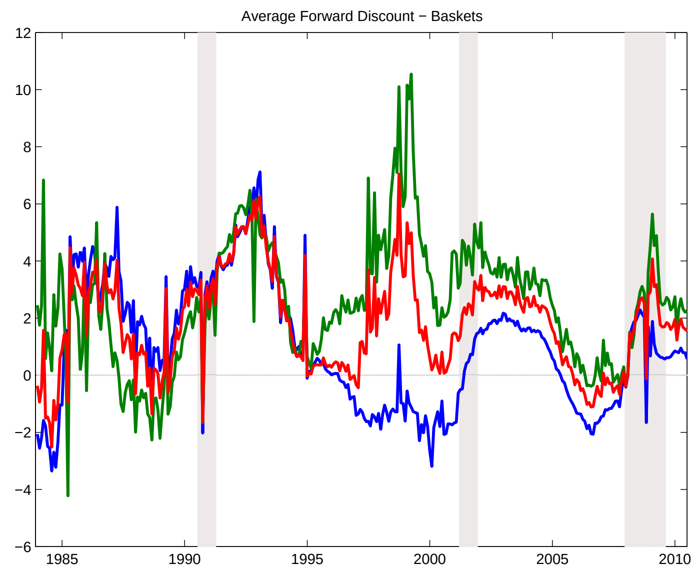
We now use this data set and our model's guidelines to uncover new sources of predictability in currency markets.

4 Predictability in Currency Markets

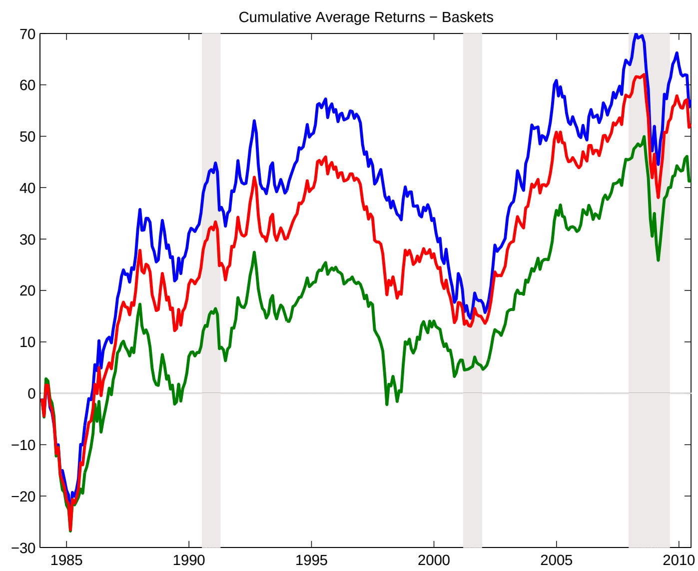
In this section, we investigate the predictability of currency excess returns and changes in exchange rates. We show that the AFD forecasts basket-level exchange rate changes and returns, and does a good job of describing the time variation in expected currency excess returns even compared with the individual currency pairs' forward discounts. Further, we document that expected excess returns on currency baskets are counter-cyclical, and that they are driven by the domestic-country specific component of the business cycle, consistent with the no-arbitrage model. Finally, we show

Figure 1: Average 12-month Forward Discounts and Returns on 3 Currency Baskets

Panel A.



Panel B.



This figure presents the average 12-month forward discounts (top panel) and currency excess returns (bottom panel) on 3 currency baskets. In each panel, the top line is for developing countries. The middle line is for all countries. The bottom line is for developed countries. The shaded areas are NBER recessions. The sample period is 11/1983–6/2010.

that industrial production predicts average currency excess returns even after controlling for the average forward discount.

4.1 The Average Dollar Forward Discount and the Dollar Risk Premium

We run the following regressions of basket-level average log excess returns on the AFD, and of average changes in spot exchange rates on the AFD:

$$\overline{rx}_{t\to t+k} = \psi_0 + \psi_{\mathbf{f}}(\overline{f}_{t\to t+k} - \overline{s}_t) + \eta_{t+k}, \tag{4.1}$$

$$-\overline{\Delta s}_{t\to t+k} = \zeta_0 + \zeta_{\mathbf{f}}(\overline{f}_{t\to t+k} - \overline{s}_t) + \epsilon_{t+k}. \tag{4.2}$$

We report several standard errors for the slope coefficients $\psi_{\mathbf{f}}$ and $\zeta_{\mathbf{f}}$. The AFD are strongly autocorrelated, albeit less so than individual countries' interest rates. This complicates statistical inference. To deal with this issue, we use two asymptotically-valid corrections. The Hansen-Hodrick standard errors (HH) are computed with one lag, plus the number of lags equal to horizon k for overlapping observation. The Newey-West standard errors (NW) are computed with the optimal number of lags following Andrews (1991). Both of these methods correct for 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. In particular, due to the persistence of the predictor variable, estimates of the slope coefficient can be biased (as pointed out by Stambaugh (1999)), as well as have wider dispersion than the asymptotic distribution. To address these problems, we computed bias-adjusted small sample t-statistics, generated by bootstrapping 10,000 samples of returns and forward discounts from a corresponding VAR under the null of no predictability.[5] We also report the Newey-West t-statistics for the coefficients estimated using only non-overlapping observations.

The regression equations 4.1 and 4.2 test different hypotheses. In the regression for excess returns in equation 4.1, the null states that the log expected excess currency returns are constant. In the regression for log exchange rates changes in equation 4.2, the null states that changes in the log spot rates are unpredictable, i.e., the expected excess returns are time varying and they are equal to the interest rate differentials (i.e, forward discounts).

Developed Countries Table II reports the estimated slope coefficients with the corresponding t-statistics reported in brackets below each estimate, and the R^2 of each regression. There is strong evidence against UIP in the returns on the developed countries basket, at all horizons. The estimated slope coefficients $\psi_{\mathbf{f}}$ in the predictability regressions are highly statistically significant, regardless of method used to compute the t-statistics, except for annual horizon non-overlapping returns; we have too few observations given the length of our sample. The R^2 increase from about 3% at the monthly horizon to up to 13% at one-year horizon. This increase in the R^2 as we increase the holding period is not surprising, given the persistence of the AFD.

Moreover, given that the coefficient is substantially greater than unity, the average exchange rate changes are also predictable, more so than is typically detected using individual currency returns: the coefficient $\zeta_{\mathbf{f}}$ is statistically significant according to most methods at all horizons above one month. Since the log excess returns are the difference between changes in spot rates at $t+1$ and the AFD at t, these two regressions are equivalent and $\psi_{\mathbf{f}} = \zeta_{\mathbf{f}} + 1$. The R^2s for the the exchange rate regressions are lower, ranging from just over 1 percent for monthly to almost 5

[5] Our bootstrapping procedure follows Mark (1995) and Kilian (1999) and is similar to the one recently used by Goyal and Welch (2005) on U.S. stock excess returns. It preserves the autocorrelation structure of the predictors and the cross-correlation of the predictors' and returns' shocks.

percent for annual horizon.

These effects are large. At the one-month horizon, each 100 basis point increase in the forward discount implies a 250 basis points increase in the expected return, and it increases the expected appreciation of the foreign currency basket by 150 basis points. The estimates are very similar for all maturities, except the 12-month estimate, which is 34 basis points lower.

Emerging Markets The second set of columns in Table II reports the results for the emerging markets basket. For the basket of emerging market currencies, the results are quite different if we use the corresponding emerging market AFD. The expected excess returns are less predictable. The estimated slope coefficients are small and negative, but statistically indistinguishable from zero for all maturities under one year, and exchange rate changes having negative coefficients, between -1.8 and -1.3, and significantly different from zero. The R^2 for the average exchange rate changes are as high as 8.5% at the twelve-month horizons, but do not rise much above 1% for excess returns. This is consistent with the UIP hypothesis: the excess returns are unforecastable, while the exchange rates are predicted to depreciate by a magnitude roughly equal to forward discount.

This result is not surprising in light of the sharp divergence between emerging and developed countries' AFDs without a corresponding divergence in returns exhibited in Figure 1. It is also consistent with the findings of Bansal and Dahlquist (2000), who argue that the UIP has more predictive power for exchange rates of high-inflation countries and in particular, emerging markets. Frankel and Poonawala (2007) report similar results. As we showed earlier in equation 2.5, this is consistent with the model: larger loadings of expected inflation on the domestic factor reduce the slope coefficients in predictability regressions. This is what we find for baskets of emerging market currencies.

Finally, with all currencies in our sample in the same basket, the results are, not surprisingly, mixed. While the excess returns are predictable (albeit with marginal statistical significance), the exchange rate changes are not, since all of the slope coefficients are attenuated due to the opposing effects of developed and emerging countries. This result suggests that environments characterized by high (expected) inflation may make it harder to extract risk premia from exchange rate data. This is consistent with our model for nominal exchange rates in Section 2.

The affine model in Section 2 suggests that the AFD should reflect the time-varying risk premia driven by the domestic state variables, as well as global state variable that affect the domestic investors asymmetrically. As such, they should have forecasting power for excess returns and spot exchange rate changes of currencies other than the ones used to construct the differential. To test this, we use the AFD of the developed countries' basket to forecast the emerging markets basket as well as the basket containing all countries (using matched-horizon forward discounts and exchange rate changes). Table III presents the results: there is equally strong predictability for average log excess returns and average spot rate changes for the emerging markets basket, as well as for the basket of all countries. The results are consistent across different maturities: there is a 170 basis point increase in the annualized expected excess return in response to a 100 basis point increase in the AFD for developed currencies. The signs of all slope coefficients are positive in all cases, with magnitudes between 1 and 2 and large t-statistics using most methods. The R^2s are between 1.7 percent for monthly data and 13.9 percent for annual data. This is despite the fact that predictability is quite weak for these baskets using their own AFDs. This is consistent with the view that, among emerging markets currencies, forward discounts mostly reflect inflation expectations rather than risk premia, but the latter are nevertheless important for understanding currency fluctuations.

4.2 The Average Forward Discounts and Bilateral Exchange Rates

By capturing the dollar risk premium, the average forward discount is able to forecast individual currency returns as well as their basket-level averages. In fact, it is often a better predictor than the individual forward discount specific to the given currency pair. One way to see this is via a pooled panel regression

$$rx^i_{t\to t+k} = \psi^i_0 + \tilde{\psi}_{\mathbf{f}}(\overline{f}^j_{t\to t+k} - \overline{s}^j_t) + \tilde{\psi}_f(f^i_t - s^i_t) + \eta^i_{t+k},$$

for excess returns on the average as well as the currency-specific forward discount, and a similar regression for spot exchange rate changes :

$$-\Delta s^i_{t\to t+k} = \zeta^i_0 + \tilde{\zeta}_{\mathbf{f}}(\overline{f}^j_{t\to t+k} - \overline{s}^j_t) + \tilde{\zeta}_f(f^i_t - s^i_t) + \tilde{\eta}^i_{t+k},$$

where ψ^i_0 and ζ^i_0 are currency fixed effects, so that only the slope coefficients are constrained to be equal across currencies.

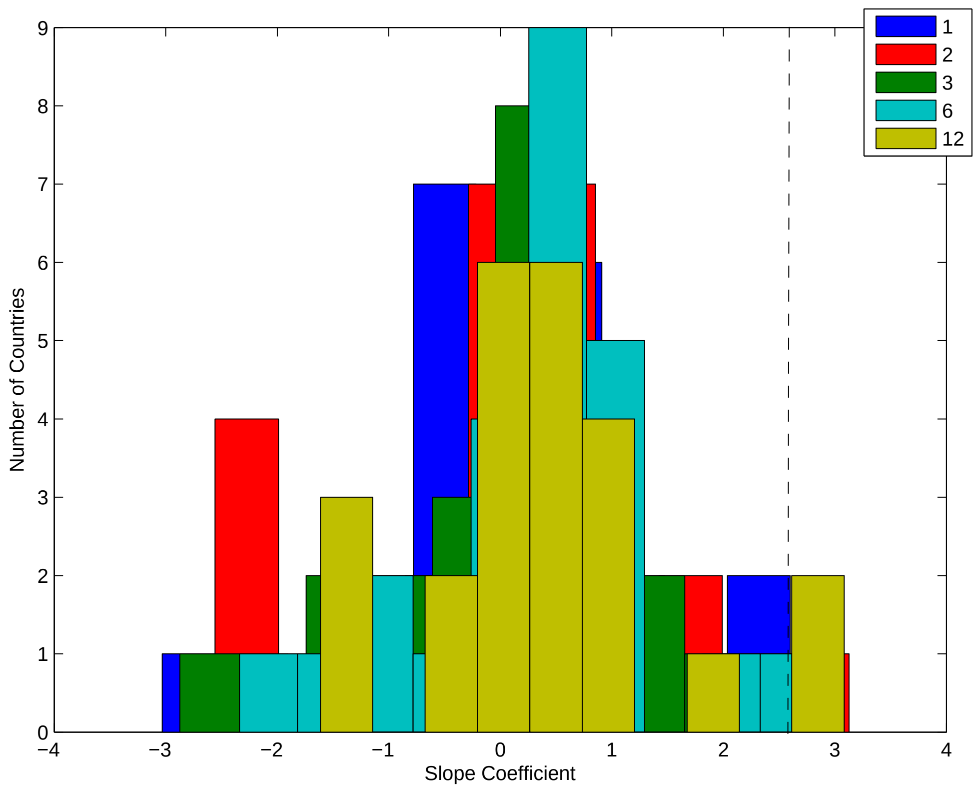
Table IV presents the results for the developed and emerging countries subsamples, as well as the full sample of all currencies that we use. The coefficients on the average forward discount are large, around 2 for developed countries for both excess returns and exchange rate changes (as we are controlling for individual forward discounts). They are robustly statistically significant. In contrast, the coefficients on the individual forward discount are small for the developed markets sample, not statistically different from zero (and in fact negative for spot rate changes). For emerging countries, individual forward discounts are equally important as the AFD for predicting excess returns, but not for exchange rate changes.

The restriction on the slope coefficients, while allowing for precise estimation, is likely to be misspecified. As we show in Section 2 using the framework of our model, heterogeneity in the exposures to the global shocks leads to differences in slope coefficients. However, a similar picture emerges from bivariate predictive regressions run separately for individual currencies. To save space, we summarize those briefly here, the full set of results are available upon request. Figure 2 shows the histogram of predictability regression slope coefficients estimated on bilateral exchange rates over the same sample. The means of the slope coefficients are 0.12, 0.16, 0.09, 0.35, 0.44, and 0.28 for $k = 1$, 2, 3, 6, and 12 respectively. On average, we find that a 100 basis points increase in the individual forward discount leads to an annualized appreciation of the dollar against this basket of than 44 basis points at the 12 month horizon. The red line is the estimate for the basket.

Finally, Figure 3 shows the histogram of predictability regression slope coefficients estimated on bilateral exchange rates over the same sample obtained when we include both the AFD (histogram shown in the panel on the left) and the individual forward discount (histogram shown in the panel on the right). As the maturity increases, the AFD slope distribution shifts to the right, while the individual forward discount distribution shifts to zero (or below zero). At the 12-month horizon, the average slope coefficient for the AFD is 1.95, while the average individual slope coefficient is $-.41$.[6] The implied UIP slope coefficient is now 1.41. After controlling for the AFD, the spot exchange rate depreciates more than 100 basis points in response to a 100 basis point increase in the individual forward discount. For example, in the case of France, the ADF slope coefficient is 2.03, while the individual forward discount coefficient is zero. In the case of Germany, the AFD

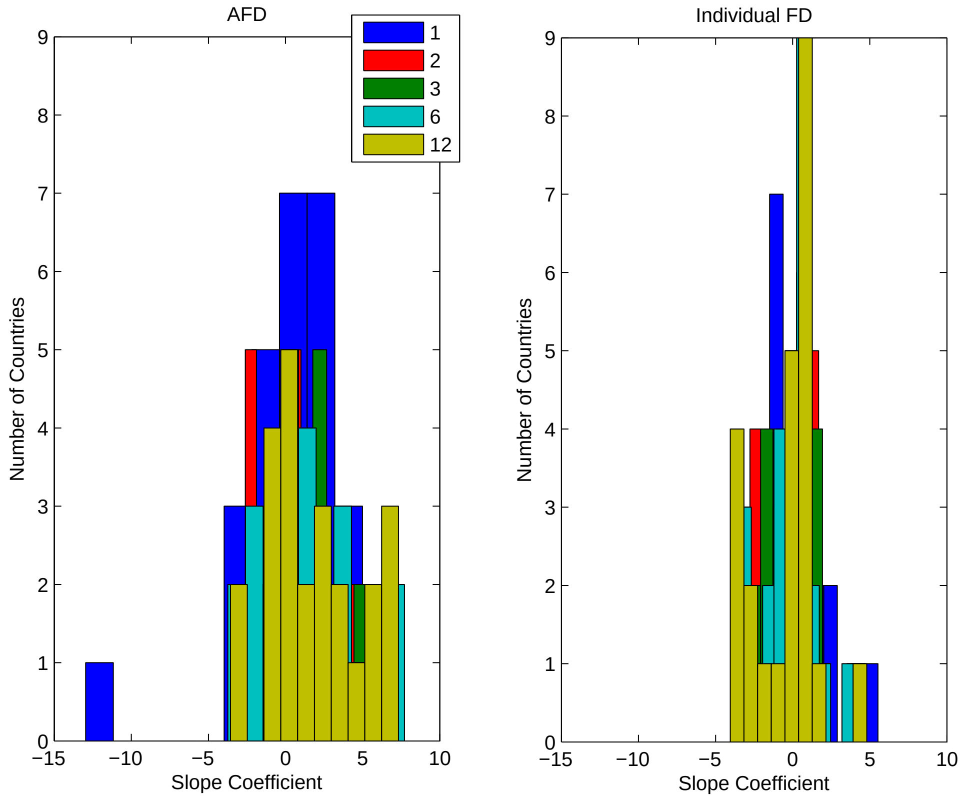
[6] The means of the AFD slope coefficients are 0.09, 0.53, 0.82, 1.27, and 1.95 for $k = 1, 2, 3, 6$, and 12 respectively. The means of the individual slope coefficients are 0.22, 0.02, -0.15, -0.19, and -0.41.

Figure 2: Histogram of Predictability Slope Coefficients for Individual Currencies



Histogram of annualized predictability regression slope coefficients for individual currencies at 1-month, 2-month, 3-month, 6-month and 12-month horizons. The sample is 11/1983–6/20010. The line is the estimate for the basket of developed currencies using the AFD.

Figure 3: Histogram of Predictability Slope Coefficients for Individual Currencies



Histogram of annualized predictability regression slope coefficients for individual currencies at 1-month, 2-month, 3-month, 6-month and 12-month horizons. The sample is 11/1983–6/20010.

slope coefficient is 3.94, while the individual discount coefficient is -1.26.

Summary We find that a single return forecasting variable describes time variation in currency excess returns and changes in exchange rates even better than the forward discount rates on the individual currency portfolios. This variable is the average of all the forward discounts across currencies in the developed countries basket. The results are consistent across different baskets and maturities: a 100 basis points increase in the AFD leads to an annualized depreciation of the dollar against this basket of more than 150 basis points. These are much larger (in absolute value) than the estimates obtained for individual exchange rates. The calibrated model will reproduce this finding.

We now turn to the business cycle properties of *expected* currency excess returns.

4.3 Cyclical Properties of the 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 U.S. business cycle component: expected excess returns go up in U.S. recessions and go down in U.S. expansions, which is similar to the counter-cyclical behavior that 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 aggregate forward discount for a basket:

$$\widehat{E}_t rx^j_{t+1} = \psi^j_0 + \psi^j_{\mathbf{f}}(\overline{f}^j_{t\to t+k} - \overline{s}^j_t).$$

Therefore, expected excess returns on currency baskets inherit the cyclical properties of the AFDs. To assess the cyclicality of these forward discounts, we use three standard business cycle indicators and three financial variables: (i) the 12-month percentage change in U.S. industrial production index, (ii) the 12-month percentage change in total U.S. non-farm payroll index, (iii) the 12-month percentage change in the Help Wanted index, (iv) the term spread – the difference between the 20-year and the 1-year Treasury zero coupon yields, (v) the default spread – the difference between the BBB and AAA Bond Yield – and (vi) the CBOE VIX index of S&P 500 index-option implied volatility.[7]

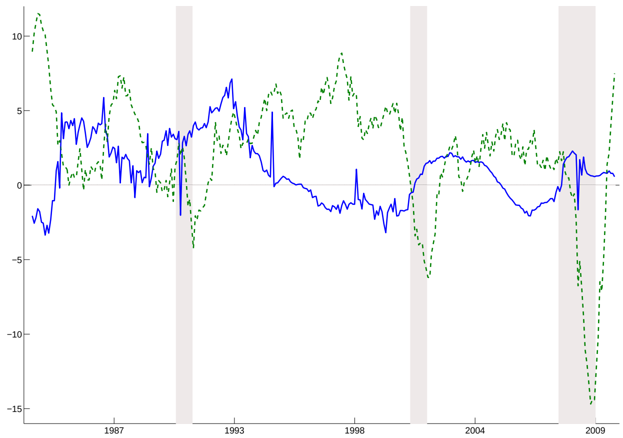
[7]Industrial production data are from the IMF International Financial Statistics. The payroll index is from the BEA. The Help Wanted Index is from the Conference Board. Zero coupon yields are computed from the Fama-Bliss series available from CRSP. These can be downloaded from `http://wrds.wharton.upenn.edu`.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

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. Note that macroeconomic variables are also published with a lag. For example, the industrial production index is published around the 15th of each month, with a one-month lag (e.g. the value for May 2009 was released on June 16, 2009). In our tables, we do not take into account this publication lag of 15 days or so and assume that the index is known at the end of the month. We check our results by lagging the index an extra month. The publication lag sometimes matters for short-horizon predictability but does not change our results over longer horizons.

Table V reports the contemporaneous correlations of the AFDs (across horizons) with these macroeconomic and financial variables. Developed countries are in the first panel and emerging countries in the second. As expected, average forward discounts (and, therefore, forecasted excess returns) are counter-cyclical. To illustrate this point, Figure 4 plots the dollar AFD for a basket of developed currencies against the growth rate of U.S. industrial production. There are some differences, however, between the two baskets.

On the one hand, both baskets they are positively correlated with the slope of the U.S. term structure. On the other hand, monthly correlations of the AFD with the default spread are positive for the developed markets basket, but negative for the emerging markets basket. The opposite is true of the macroeconomic variables: while the AFD of developed countries rises in recessions, it falls for the emerging countries. Figure 4 plots the AFD on the basket of developed currencies (blue line) against 12-month industrial production growth in the U.S (green line). The shaded areas are NBER recessions. We find roughly the same business cycle variation in AFD across horizons. At every maturity we consider, the AFD appears counter-cyclical. Since excess returns load positively

Figure 4: 12-month Average Forward Discount and U.S. Industrial Production Growth



The solid line plots the annualized one month average forward discount for the basket of developed currencies. The dotted line plots the 12-month seasonally adjusted rate of industrial production growth for the U.S. The shaded areas are NBER recessions.

on the AFD, they are also counter-cyclical.

In the model, the AFD captures the U.S.-specific variation in risk premia, if the average exposure to common shocks in the basket equals that of the U.S. To check that the U.S.-specific component of the AFD of developed countries matters most here, we run predictability tests using the residuals from the projection of the AFD on the average 12-month changes of foreign countries industrial production indices, which removes much of the covariation of the AFD with the global macroeconomic conditions:

$$
\begin{aligned}
(\overline{f}_{t\to t+k} - \overline{s}_t) &= \alpha + \beta\overline{\Delta \log IP_t} + AFD_{res,t}, \\
\overline{rx}_{t\to t+k} &= \psi_0 + \psi_{\mathbf{f}} AFD_{res,t} + \eta_{t+1},
\end{aligned}
$$

where $\overline{\Delta \log IP_t}$ denotes the average of the 12-month changes in IP indices across 28 developed countries (excluding the U.S.). The results are reported in Table VI. The t-stats reported do not reflect the statistical uncertainty from the estimation in the first stage. These results can be compared to the first column in Table II and Table III. For the basket of developed currencies, the slope coefficients are about 20 basis points lower across different maturities. For the other baskets, the results are similar.

Conversely, the equity option-implied volatility index (VIX) is positively correlated with the emerging markets AFD but negatively correlated with that of the developed markets in our sample. The VIX seems like a good proxy for the global risk factor z^w, because it is highly correlated with similar volatility indices abroad. This heterogeneity in exposures to the VIX is therefore consistent with the predictions of the no-arbitrage model in Lustig et al. (2009). The model predicts negative loadings on the common risk factor for the risk premia on low interest rate currencies and positive loadings for the risk premia on high interest rate currencies (which typically include more emerging than developed markets currencies). 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. The dollar AFD does not predict carry trade returns. Since the dollar AFD does not depend on the global factor, given our assumptions, that is in line with the model.

4.4 Macro Factors and Currency Return Predictability

So far we have focused on the predictive power of the AFD, but the counter-cyclical nature of excess returns suggests that macro variables themselves might help to forecast excess returns, potentially above and beyond what is captured by the AFDs. We check this conjecture by focusing on the predictive power of the industrial production (IP) index, controlling for the AFD.

In the model of Section 2, the AFD is the best and sole predictor of average currency excess returns. We can, however, easily extend the model to capture the predictive power of other macroeconomic variables. Suppose $\boldsymbol{z}_t$ is a vector of domestic factors. If one of these is not spanned by interest rates (i.e. $\chi = \frac{1}{2}\gamma$) but does affect conditional expected returns (i.e. the price of local risk is positive, $\gamma > 0$) then one needs to look beyond forward discounts for other variables that forecast excess currency returns. Evidence from the term structure of U.S. interest rates suggest that business cycle variables such as the growth of industrial production contain information about risk premia in the bond markets that is not captured by the interest rates themselves (Duffee (2008), Ludvigson and Ng (2009), Joslin et al. (2010)). In our context, if we are looking to identify those components of the domestic state variable $\boldsymbol{z}_t$ that are not captured by interest rate differentials, we expect a U.S.-specific macroeconomic variable to have forecasting power for currency excess returns, as well as spot exchange rate changes.

We use $\overline{rx}_{t\to t+k}$ to denote the k-month ahead excess return between time t and $t+k$, as well as the corresponding regression for exchange rate changes. Table VII reports two sets of regression results:

$$\overline{rx}_{t\to t+k} = \psi_0 + \psi_{IP}\Delta \log IP_t + \psi_{\mathbf{f}}(\overline{f}_{t\to t+k} - \overline{s}_t) + \eta_{t+k},$$

$$-\overline{\Delta s}_{t\to t+k} = \zeta_0 + \zeta_{IP}\Delta \log IP_t + \zeta_{\mathbf{f}}(\overline{f}_{t\to t+k} - \overline{s}_t) + \varepsilon_{t+k}.$$

We use the developed markets' AFD since it is the strongest predictor of returns on all baskets (developed, emerging, or all countries). The change in industrial production jointly with the AFD explain up to 25 percent of the variation in excess returns at the 12-month horizon. All the estimated slope coefficients are negative and, for horizons of 3 months and above, strongly statistically significant. The Wald tests reject the restriction that the two slope coefficients for excess returns are jointly equal to zero for all baskets at horizons of three months and above (using various methods) and, for exchange rate changes, at horizons of 6 and 12 months. The R^2 for average excess returns at twelve month horizon are between 24% and 32% across different baskets, and between 15% and 32% for average exchange rate changes.

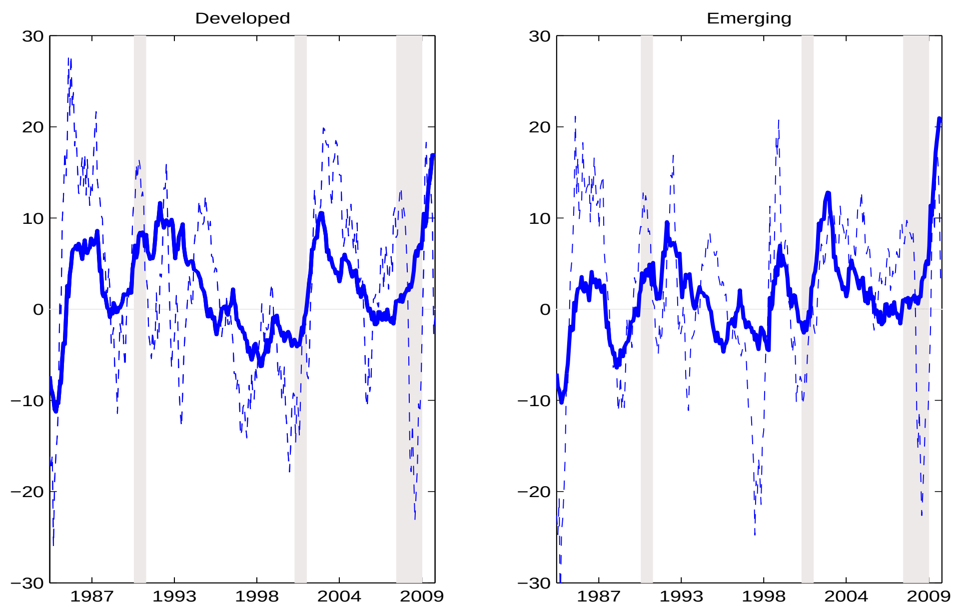
Since we are controlling for the average forward of the developed markets basket, the IP coefficient for this basket is the same for excess returns and exchange rate changes, capturing the pure effect of the counter-cyclical risk premium on expected depreciation of the dollar, rather than the return stemming from the interest rate differential. Thus, holding interest rates constant, a one percentage point drop in the annual change in industrial production raises the dollar risk premium by 50-100 basis points per annum at monthly horizon and by as much as 90-135 basis points at the annual horizon, all coming from the expected appreciation of the foreign currencies against the dollar. Since the AFD itself counter-cyclical, the total effect is even greater, implying an increase in expected returns of up to 120 basis points for annual data. Figure 5 plots the predicted vs. the realized excess returns at the 12-month horizon. The variation is in predicted returns is substantial: it varies from -10 % at the start of the sample to +20% at the end of the sample.

The U.S. industrial production appears highly correlated with similar indices in other developed countries. For example, its correlation with the average index for the G7 countries (excluding the U.S., and using 12-month changes in each index) is equal to 0.5. To check that the U.S.-specific component of the U.S. industrial production index matters most here, we run predictability tests using the residuals for the projection of these 12-month changes on the average foreign IP indices.

$$\Delta \log IP_t = \alpha + \beta \overline{\Delta \log IP_t} + IP_{res,t},$$

$$\overline{rx}_{t \to t+k} = \psi_0 + \psi_{IP_{res}} IP_{res,t} + \psi_{\mathbf{f}} (\overline{f}_{t \to t+k} - \overline{s}_t) + \eta_{t+k},$$

Figure 5: Dollar Return Predictability



The bold line is the 12-month-ahead forecast at t of the annual excess return at $t+12$. The dashed line is the realized excess return. The left panel shows the results for the basket of developed currencies. The right panel shows the results for the basket of emerging countries. The predictors are the basket-specific 12-month AFD and the 12-month rate of U.S. I.P. growth. The results are reported in Table VII.

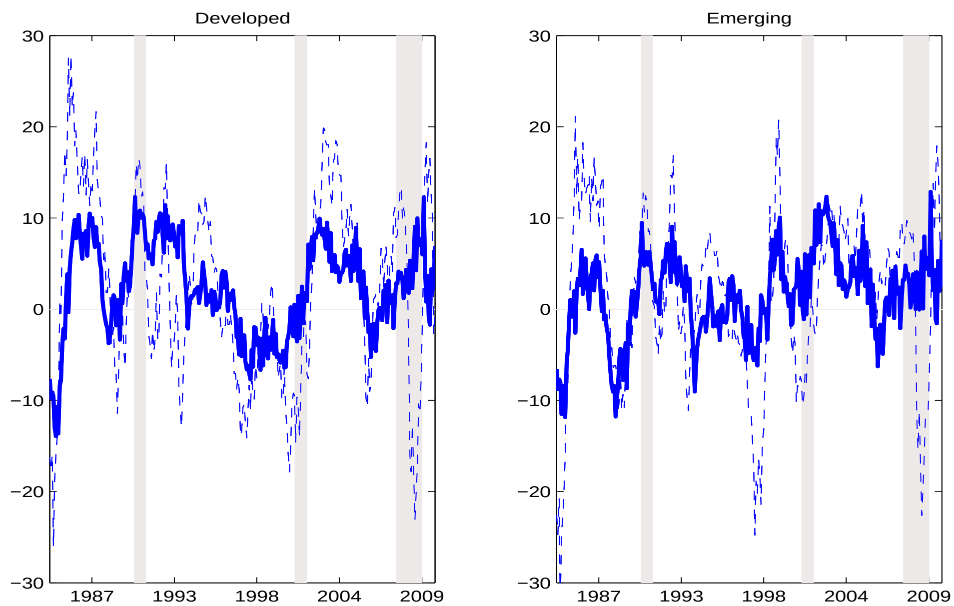
where $\overline{\Delta \log IP_t}$ denotes the average of the 12-month changes in IP indices across 28 developed countries (excluding the U.S.).

As demonstrated in Table VIII, the predictive power of IP lies mostly in the U.S.-specific component of IP, denoted $IP_{res,t}$, for long-horizon returns. We obtain R^2s between 16 and 25 percent with the IP residuals for both average excess returns and average spot exchange rate changes. The slope coefficients are lower for the short-horizon returns, but larger for long horizons. For annual holding periods, a one percentage point decline in the U.S. IP relative to the world average implies a 145 to 190 basis point increase in the risk premium, *even* if interest rate differentials do not change. Figure 6 clearly shows that U.S.-specific component of IP drives the predictability. In the most recent U.S. recession, which was global in nature, the actual IP-based forecast, shown in Figure 5, increased to 20 % and was arguably much too high, while the U.S.-specific-IP-based forecast is not subject to this problem.

5 Out-of-Sample Evidence

We end our empirical work by looking at out-of-sample predictability. We check whether our predictors outperform the random walk in forecasting exchange rates as well as excess returns out-of-sample. For each horizon, we compute the one-step ahead root-mean-square errors (RMSE) for the two sets of competing models, both estimated recursively: the random walk with drift (i.e., i.i.d. changes in average exchange rates for the basket) and the forecast based on one of the three sets of predictors: industrial production growth, IP together with the average forward discount of developed countries, and the AFD alone. We report three standard test statistics: the ratio of the two square root mean squared errors, the MSE_t test statistic of Diebold and Mariano

Figure 6: Dollar Return Predictability–U.S.-specific IP



The bold line is the 12-month-ahead forecast at t of the annual excess return at $t + 12$. The dashed line is the realized excess return. The left panel shows the results for the basket of developed currencies. The right panel shows the results for the basket of emerging countries. The predictors are the basket-specific 12-month AFD and the 12-month rate of U.S. I.P. growth. The results are reported in Table VIII.

(1995), and the ENC test statistic of Clark and McCracken (2001) (details of these statistics as well as the full set of results are available upon request). Table IX reports our results, focusing on the developed-markets basket (the results are similar for other baskets). Panel A reports the results obtained using IP as the forecaster. Panel B reports results obtained using IP and AFD as forecasters. Finally, Panel C reports results obtained using the AFD. For excess returns, the hypothesis of equal prediction is rejected for all specifications at most horizons using both the Ratio test and the ENC test, bot not for the MSE_t tests. This suggests that the MSE_t test has low power in this setting.

On the other hand, for exchange rate changes, the evidence is more mixed, which is not surprising given the results in the literature and the weak evidence for exchange rate predictability inside our model. At the one-month horizon, Meese and Rogoff (1983)'s result stands. The ratio of the two mean squared errors is equal to one for all specifications. At longer horizons, however, changes in industrial production predict changes in exchange rates much better than a simple constant –the ratio of the two mean squared errors goes up to 1.10 at 12-month horizon. The p-values for this test statistic are below 5% at horizons 2, 3 and 12 months. The Diebold and Mariano (1995)'s and Clark and McCracken (2001)'s statistics are positive at almost all horizons, and the latter are marginally statistically significant. While the random walk is hard to beat as the best predictor of these changes in exchange rates, our results indicate that using business-cycle variables such as industrial production allows for some improvement in the forecasting power. In our calibrated model, the exchange rate is close to a random walk and the statistical evidence for exchange rate predictability is weak.

6 Calibrated Model

We now come back to the no-arbitrage model we outlined in Section 2 and check whether it is quantitatively consistent with the predictability evidence that we have documented. We first describe our calibration and then turn to simulation results. We learn three lessons from this experiment: (i) the amount of short- and long-term aggregate currency return predictability that we find in the data is consistent with a standard, no arbitrage model of interest rates and exchange rates, (ii) the average forward discount does not predict carry trade excess returns in the model as in the data, and (iii) exchange rates are close to random walks in the model as in the data. To the best of our knowledge, this is the first model that reproduces these empirical findings.

6.1 Calibration

We calibrate the model in two steps. We first consider a completely symmetric version of the model in which all countries share the same δ. Then we introduce heterogeneity in the model by considering a potential range of δs.

We first focus on real moments; we then calibrate the inflation process directly to match the data, and produce the nominal variables implied by the calibration. There are 8 parameters in the real part of the model: 5 parameters govern the dynamics of the real stochastic discount factors (α, χ, γ, κ, and δ) and 3 parameters (ϕ, θ, and σ) describe the evolution of the country-specific and global factors (z and z^w). We choose these parameters to match the following 10 moments in the data: the mean, standard deviation and autocorrelation of the U.S. real short-term interest rates, the standard deviation of changes in real exchanges rates, the real UIP slope coefficients, the average currency excess return, the R^2 in UIP regressions, the cross-country correlation of real interest rates, the conditional maximum Sharpe ratio (e.g the standard deviation of the log SDF) and a Feller parameter (equal to $2(1-\phi)\theta/\sigma^2$). These 10 moments as well as the targets in the data that we match are listed in Panel A of Table X. The first column reports the moments at the monthly frequency. The second column reports the annualized version. The third column reports the simulated moments (computed in closed form).[8]

We obtain the 3 inflation parameters (η^w, σ^π,π_0) by targeting the first two moments of inflation, as well as the fraction of inflation that is explained by the common component. We set $\eta = 0$, so expected inflation does not respond to the country-specific factor. As a result, there is no difference in UIP slope coefficients between the nominal and the real model. In Panel B of Table X, we list the expression for the variance of inflation and the fraction explained by the common component. We target an annualized standard deviation for inflation of 1.09% and an average inflation rate of 2.90%. 28% of inflation is accounted by the common component. Finally, for completeness, Panel C also shows the implied moments of nominal interest rates and exchange rates in this symmetric version of the model.

To obtain the 11 parameter values listed in Table XI, we minimized the sum of squared errors for the 13 moments listed in Table X. We target a UIP slope coefficient of -1.5 (which implies a coefficient of 2.5 for the regression of excess return on the forward discount), and an R^2 in the UIP regression of 3.40%, an average real interest rate of 1.72% per annum, an annualized standard deviation of the real interest rate of .57% per annum, and an autocorrelation (in monthly data) of 0.92. The annual standard deviation of real exchange rate changes is 10%. We target a maximum Sharpe ratio of 0.5. The average pairwise correlation of real interest rates is .3. The annual dollar

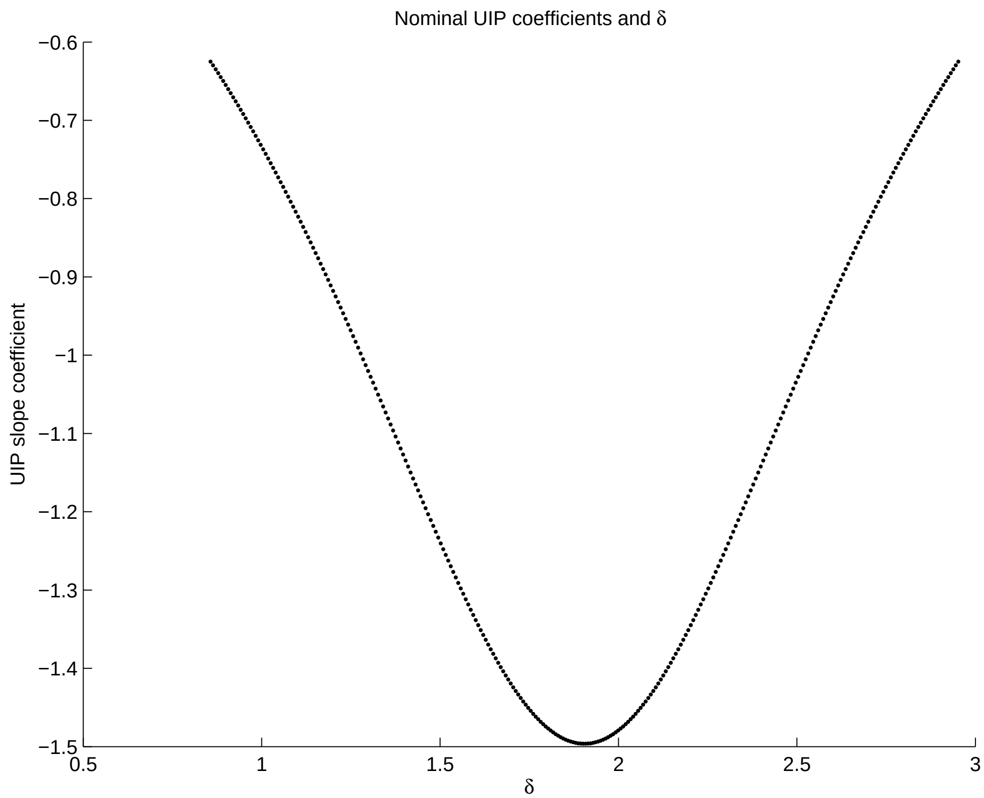
[8]The data for this calibration exercise come from Barclays and Reuters (Datastream). Because of data availability constraints, we focus on the subset of developed countries. The sample runs from 11/1983 to 12/2009. However, for the U.S. real interest rates data, we use the real zero-coupon yield curve data for the U.S. provided by J. Huston McCulloch on his web site; the sample covers 1/1997–10/2009.

risk premium is .5% per annum. A Feller coefficient of 20 guarantees that all of the state variables following square-root processes are positive (this is exact in the continuous-time approximation, and implies a negligible probability of crossing the zero bound in discrete time, a possibility never realized in our simulations given these parameter values, even with samples as long as 1,000,000 periods).

We cannot match all of the moments. In particular, the model overstates the volatility of the nominal risk-free rate and understates the average excess return on dollar positions. Moreover, the maximum Sharpe ratio is high: 0.68. All of the other moments are matched very closely. Given our assumptions, the model-implied nominal and real UIP slope coefficients are identical since there is no heterogeneity in expected inflation.

Finally, we introduce a single source of heterogeneity in the exposure to the global shocks. We chose the range of δs ($[0.85, 2.95]$) to match a carry trade premium of 8.5% (without bid-ask spreads) reported by Lustig et al. (2009). These parameters are assumed to be distributed uniformly and symmetrically around the home country δ of 1.90. Figure 7 plots the implied UIP slope coefficients for individual currencies against δ. UIP slope coefficients reach a minimum of -1.5 at the home country value of 1.9. As we increase/decrease δ, the slope coefficient shrinks to zero in absolute value. Table XII reports summary statistics for six portfolios obtained by sorting 30 currencies by their respective interest rates. The implied carry trade risk premium, the return on a long position in portfolio 6 and a short position in portfolio 1 is 8.48%. These results are similar to those reported in Lustig et al. (2009), except that here we abstract from bid-ask spreads.

Figure 7: Simulated UIP Slope Coefficients for Individual Currencies



This figure plots the implied UIP slope coefficients for individual currencies as a function of each country's exposure (δ) to common shocks. The range of δs is ($[0.85, 2.95]$). These parameters are assumed to be distributed uniformly and symmetrically around the home country δ of 1.90.

6.2 Predictability in the Simulated Data

We are interested in the extent to which average excess returns and exchange rate changes for baskets of currencies are forecastable by average forward discounts in the model, in particular at longer horizons. The term structure of interest rates - and therefore the long-horizon forward discounts - cannot be computed in closed form in the model. Instead we consider predictability of long-horizon returns obtained by rolling over one-month returns and long-horizon exchange rate changes using the one-month forward discount as the predictor:

$$\widetilde{rx}_{t\to t+k} = \psi_0 + \tilde{\psi}_{\mathbf{f}}(\overline{f}_{t\to t+1} - \overline{s}_t) + \eta_{t+k}, \tag{6.1}$$

$$-\overline{\Delta s}_{t\to t+k} = \zeta_0 + \tilde{\zeta}_{\mathbf{f}}(\overline{f}_{t\to t+1} - \overline{s}_t) + \epsilon_{t+k}. \tag{6.2}$$

where $\widetilde{rx}_{t\to t+k} = \overline{rx}_{t\to t+1} + \ldots + \overline{rx}_{t+k-1\to t+k}$.

Average Currency Returns Table XIII displays the results of these regressions. To facilitate comparison, we display the corresponding forecasting regression results obtained using the actual data, as well as the model-generated results using the small sample size $T = 336$ as in the actual data and a long sample of length $T = 33600$ that more closely approximates population values. The slope coefficients for average excess returns and average exchange rate changes are very similar in the actual and the simulated data, as are the R^2. In all three cases, the slope coefficient is about 2.5 for returns and 1.5 for exchange rate changes at the one-month horizon, declining to about 1.8 and 1, respectively, at the twelve-month horizon. The average forward discount can explain roughly 2% of the variation in one-month excess returns (slightly less than observed empirically), and 13% of variation in twelve-month returns, just as in the data; similarly, it explains up to 5% of variation in average exchange rate changes over twelve month periods, both in the data and in the model. The t-statistics for the small sample regressions in the simulated data are also essentially the same as in the actual data, and obviously much higher for the long simulated sample (we do not report the small-sample VAR t-statistics in this case). The return regression slope coefficient is statistically significant in the small simulated sample, but the exchange rate regression slope coefficient is not. Even though exchange rates are predictable in the model, since $\chi > 0$, the statistical evidence for exchange rate predictability in small samples is weak, as it is in the data. From the perspective of the no-arbitrage model it is no surprise that exchange rates are so close to the random walk that their changes are almost impossible to predict.

Finally, as it stands, the AFD in the model does not actually drive out individual forward discounts in regressions forecasting currency returns, but it does in the data. To match this feature of the data, we would need a country-specific expected inflation component in nominal interest rates. To keep the model tractable, we chose not go this route.

Carry Trade Another implication of the no arbitrage model described in Section 2 is that the excess returns on the long-short carry trade positions (return on a portfolio of currencies with high interest rates minus that with low interest rates) and associated exchange rate changes should not be predictable using the average forward discount, as long as it is formed from the perspective of a country whose δ is close the average. In this case the AFD captures only the domestic state variables, which do not determine the carry risk in equation (2.6).

Table XIV reports predictability results for carry trade returns, both in the actual and the simulated data. These are the returns on a long position in a highest interest rate portfolio and a short position in the lowest interest rate portfolio. In the data, we use two sets of portfolios sorted on forward discounts: 5 portfolios using the subsample of developed countries currencies, and 6 portfolios using the entire sample of all currencies; these portfolios are described in detail in Lustig et al. (2009). In the model, we use the 6 portfolios sorted on interest rate differentials described above. As before, we simulate both a short and a long sample from the model. There is no evidence that the AFD predicts carry trade returns, neither in the data nor in the model. In the data, the slope coefficients are mostly negative but statistically indistinguishable from zero. In the model, the coefficients for excess returns are positive but of similarly small magnitudes and not significantly different from zero in the short sample. The R^2 are essentially zero in all cases.

The absence of predictability for the carry trade strategies is not a surprise. By assuming that the U.S. has average exposure to global shocks in the model, we eliminated the effect of the global factor z^w, which drives the carry trade returns, on the dollar AFD. The fact that we obtain similar results in the data thus suggests that the no-arbitrage model we outlined provides a quantitatively reasonable description of currency risk premia.

7 Conclusion

We have documented in this paper that aggregate returns in currency markets are highly predictable. The average forward discount and the change in the U.S. industrial production index explain one quarter of the subsequent variation in average annual excess returns realized by shorting the dollar and going long in baskets of currencies. The time variation in expected returns has a clear business cycle pattern: U.S. macroeconomic variables are powerful predictors of these returns, especially at longer holding periods, and expected currency returns are strongly counter-cyclical. We view these findings as supportive of a risk-based explanation of exchange rate fluctuations and we provide a simple, no-arbitrage model that reproduces our findings.

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Table I: Summary Statistics

Horizon	1	2	3	6	12
Panel A: Developed Countries					
Average Forward Discount, $\overline{f}_{t\to t+1}-\overline{s}_t$					
Mean	0.91	0.90	0.87	0.78	0.60
Std.	2.11	2.02	1.97	1.88	1.75
Auto	0.89	0.96	0.97	0.98	0.98
Average Spot Change, $-\overline{\Delta s}_{t\to t+1}$					
Mean	1.33	1.32	1.45	1.56	1.80
Std.	8.65	9.06	9.30	9.92	9.87
Average Excess Returns, $\overline{rx}_{t+1}$					
Mean	2.25	2.23	2.33	2.35	2.43
Std.	8.73	9.20	9.50	10.27	10.37
Panel B: Emerging Countries					
Average Forward Discount, $\overline{f}_{t\to t+1}-\overline{s}_t$					
Mean	3.10	3.04	2.99	2.83	2.57
Std.	3.32	3.09	2.98	2.76	2.50
Auto	0.84	0.91	0.93	0.95	0.96
Average Spot Change, $-\overline{\Delta s}_{t\to t+1}$					
Mean	-3.55	-3.49	-3.36	-3.30	-3.14
Std.	8.30	8.76	9.19	10.42	11.26
Average Excess Returns, $\overline{rx}_{t+1}$					
Mean	-0.33	-0.49	-0.46	-0.72	-0.62
Std.	8.44	8.66	9.05	10.28	11.17
Panel C: All Countries					
Average Forward Discount, $\overline{f}_{t\to t+1}-\overline{s}_t$					
Mean	1.82	1.79	1.76	1.66	1.44
Std.	1.74	1.65	1.62	1.61	1.57
Auto	0.84	0.93	0.95	0.96	0.97
Average Spot Change, $-\overline{\Delta s}_{t\to t+1}$					
Mean	0.08	0.09	0.22	0.29	0.55
Std.	7.65	8.09	8.36	9.01	9.03
Average Excess Returns, $\overline{rx}_{t+1}$					
Mean	1.97	1.91	1.99	1.95	2.09
Std.	7.79	8.23	8.55	9.33	9.55

Notes: This table reports the summary statistics of the currency baskets for developed countries, emerging markets, and all countries in our sample. We consider different horizons: 1, 2, 3, 6, and 12 months. For each basket $j \in \{Developed, Emerging, All\}$ and each horizon, the table presents the annualized means, standard deviations and autocorrelations of average forward discounts $\overline{f}^j_{t\to t+1}-\overline{s}^j_t$, average spot rate changes $-\overline{\Delta s}^j_{t\to t+1}$, and average log excess returns $\overline{rx}^j_{t+1}$, in percentage points. The sample period is 11/1983–6/2010.

Table II: Forecasting Returns and Exchange Rates with the Average Forward Discount

Horizon	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2
	Developed Countries				Emerging Countries				All Countries			
1	2.45	2.91	1.45	1.04	-0.39	0.20	-1.33	2.38	2.11	1.84	1.04	0.46
HH	[2.55]		[1.51]		[-0.51]		[-1.92]		[1.97]		[0.98]	
NW	[2.25]		[1.33]		[-0.52]		[-2.11]		[1.76]		[0.88]	
VAR	[3.10]		[1.73]		[-0.82]		[-2.66]		[2.37]		[1.16]	
2	2.49	5.00	1.50	1.86	-0.87	1.60	-1.76	6.42	2.18	3.19	1.15	0.92
HH	[2.52]		[1.51]		[-1.01]		[-2.18]		[2.06]		[1.10]	
NW	[2.09]		[1.25]		[-0.73]		[-1.51]		[1.86]		[0.99]	
VAR	[2.32]		[1.49]		[-1.44]		[-3.12]		[1.93]		[1.14]	
Over/NW	[2.36]		[1.49]		[-0.74]		[-1.91]		[2.03]		[1.15]	
3	2.46	6.52	1.46	2.40	-0.79	1.71	-1.67	7.32	2.14	4.09	1.13	1.19
HH	[2.46]		[1.46]		[-0.92]		[-2.00]		[2.05]		[1.09]	
NW	[1.86]		[1.11]		[-0.68]		[-1.45]		[1.66]		[0.89]	
VAR	[2.31]		[1.43]		[-1.26]		[-2.82]		[1.82]		[1.05]	
Over/NW	[2.18]		[1.36]		[-0.84]		[-1.48]		[1.94]		[1.07]	
6	2.45	10.23	1.45	3.84	-0.58	1.23	-1.46	7.51	2.28	7.75	1.28	2.60
HH	[2.50]		[1.48]		[-0.69]		[-1.76]		[2.38]		[1.34]	
NW	[1.76]		[1.04]		[-0.59]		[-1.45]		[1.78]		[1.00]	
VAR	[2.41]		[1.45]		[-1.01]		[-2.34]		[2.21]		[1.24]	
Over/NW	[2.32]		[1.47]		[-0.82]		[-1.81]		[1.95]		[1.16]	
12	2.12	13.14	1.12	4.08	-0.43	0.94	-1.31	8.48	1.83	9.07	0.81	2.01
HH	[2.18]		[1.16]		[-0.45]		[-1.41]		[2.17]		[0.99]	
NW	[1.67]		[0.89]		[-0.44]		[-1.32]		[1.82]		[0.83]	
VAR	[2.07]		[1.07]		[-0.68]		[-2.15]		[1.80]		[0.86]	
Over/NW	[1.62]		[0.88]		[-0.96]		[-1.47]		[1.85]		[1.07]	

Notes: This table reports results of forecasting regressions for average excess returns and average exchange rate changes for baskets of currencies at horizons of one, two, three, six and twelve months. For each basket we report the R^2, and the slope coefficient $\psi_{\mathbf{f}}$ in the time-series regression of the log currency excess return on the average log forward discount, and similarly the slope coefficient $\zeta_{\mathbf{f}}$ and the R^2 for the regressions of average exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *HH* denotes Hansen and Hodrick (1980) standard errors computed with the number of lags equal to the length of overlap plus one lag. *NW* denotes Newey and West (1987) standard errors computed with the optimal number of lags following Andrews (1991). The *VAR*-based statistics are adjusted for the small sample bias using the bootstrap distributions of slope coefficients under the null hypothesis of no predictability, estimated by drawing from the residuals of a VAR with the number of lags equal to the length of overlap plus one lag. *Over/NW* denotes t-statistics for the regression coefficients estimated using non-overlapping observations only, computed using Newey-West. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

Table III: Forecasting Returns and Exchange Rates with the Average Forward Discount of Developed Countries

Horizon	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2
	Emerging Countries				All Countries			
1	2.06	2.21	2.04	2.24	2.19	2.93	1.50	1.43
HH	[2.09]		[2.01]		[2.54]		[1.74]	
NW	[2.12]		[1.78]		[2.19]		[1.50]	
VAR	[2.46]		[2.46]		[2.95]		[2.06]	
Over/NW	[2.12]		[1.78]		[2.19]		[1.50]	
2	2.09	3.96	2.14	4.05	2.25	5.08	1.57	2.57
HH	[2.14]		[2.05]		[2.50]		[1.74]	
NW	[1.58]		[1.40]		[2.04]		[1.40]	
VAR	[1.86]		[2.10]		[2.35]		[1.86]	
Over/NW	[1.77]		[1.68]		[2.30]		[1.66]	
3	2.04	4.94	2.08	4.99	2.21	6.49	1.53	3.28
HH	[1.97]		[1.87]		[2.40]		[1.67]	
NW	[1.52]		[1.35]		[1.82]		[1.25]	
VAR	[1.94]		[1.96]		[2.24]		[1.66]	
Over/NW	[1.58]		[1.34]		[2.09]		[1.49]	
6	2.02	6.96	2.10	7.28	2.19	9.95	1.53	5.20
HH	[1.80]		[1.72]		[2.38]		[1.66]	
NW	[1.53]		[1.37]		[1.72]		[1.19]	
VAR	[2.12]		[2.12]		[2.44]		[1.76]	
Over/NW	[1.55]		[1.43]		[2.26]		[1.61]	
12	2.27	12.94	2.34	13.52	1.90	12.37	1.24	5.91
HH	[1.91]		[1.80]		[2.10]		[1.37]	
NW	[1.67]		[1.48]		[1.67]		[1.06]	
VAR	[2.58]		[2.80]		[2.17]		[1.42]	
Over/NW	[1.83]		[1.66]		[1.81]		[1.17]	

Notes: This table reports results of forecasting regressions for average excess returns and average exchange rate changes for baskets of currencies at horizons of one, two, three, six and twelve months. For each basket we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return of a given basket on the average log forward discount for developed countries ($\psi_{\mathbf{f}}$), and similarly the slope coefficient $\zeta_{\mathbf{f}}$ and the R^2 for the regressions of average exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *HH* denotes Hansen and Hodrick (1980) standard errors computed with the number of lags equal to the length of overlap plus one lag. *NW* denotes Newey and West (1987) standard errors computed with the optimal number of lags following Andrews (1991). The *VAR*-based statistics are adjusted for the small sample bias using the bootstrap distributions of slope coefficients under the null hypothesis of no predictability, estimated by drawing from the residuals of a VAR with the number of lags equal to the length of overlap plus one lag. *Over/NW* denotes t-statistics for the regression coefficients estimated using non-overlapping observations only, computed using Newey-West methods. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

Table IV: Predictability Using Bilateral Forward Discount and U.S. Investor Average Forward Discount: Panel Regressions

	Developed Countries				Emerging Countries				All countries			
Horizon	$\tilde{\psi}_{\mathbf{f}}$	$\tilde{\psi}_f$	$\tilde{\zeta}_{\mathbf{f}}$	$\tilde{\zeta}_f$	$\tilde{\psi}_{\mathbf{f}}$	$\tilde{\psi}_f$	$\tilde{\zeta}_{\mathbf{f}}$	$\tilde{\zeta}_f$	$\tilde{\psi}_{\mathbf{f}}$	$\tilde{\psi}_f$	$\tilde{\zeta}_{\mathbf{f}}$	$\tilde{\zeta}_f$
1	1.87	0.60	1.87	-0.40	1.59	1.12	1.59	0.12	1.56	0.95	1.56	-0.05
Robust	[2.13]	[1.52]	[2.13]	[-0.99]	[1.91]	[2.30]	[1.91]	[0.25]	[2.02]	[2.47]	[2.02]	[-0.12]
NW	[1.87]	[0.60]	[1.87]	[-0.40]	[1.59]	[1.12]	[1.59]	[0.12]	[1.56]	[0.95]	[1.56]	[-0.05]
2	2.10	0.51	2.10	-0.49	1.35	1.19	1.35	0.19	1.52	1.01	1.52	0.01
Robust	[2.74]	[1.15]	[2.74]	[-1.12]	[1.81]	[2.15]	[1.81]	[0.34]	[2.22]	[2.26]	[2.22]	[0.01]
NW	[2.10]	[0.51]	[2.10]	[-0.49]	[1.35]	[1.19]	[1.35]	[0.19]	[1.52]	[1.01]	[1.52]	[0.01]
3	2.15	0.39	2.15	-0.61	1.15	1.30	1.15	0.30	1.38	1.07	1.38	0.07
Robust	[3.02]	[0.88]	[3.02]	[-1.36]	[1.66]	[2.47]	[1.66]	[0.57]	[2.18]	[2.44]	[2.18]	[0.16]
NW	[2.15]	[0.39]	[2.15]	[-0.61]	[1.15]	[1.30]	[1.15]	[0.30]	[1.38]	[1.07]	[1.38]	[0.07]
6	2.23	0.33	2.23	-0.67	1.02	1.31	1.02	0.31	1.34	1.09	1.34	0.09
Robust	[3.45]	[0.77]	[3.45]	[-1.53]	[1.53]	[2.77]	[1.53]	[0.66]	[2.54]	[2.75]	[2.54]	[0.23]
NW	[2.23]	[0.33]	[2.23]	[-0.67]	[1.02]	[1.31]	[1.02]	[0.31]	[1.34]	[1.09]	[1.34]	[0.09]
12	1.89	0.32	1.89	-0.68	1.00	1.56	1.00	0.56	1.10	1.22	1.10	0.22
Robust	[4.12]	[0.99]	[4.12]	[-2.13]	[1.52]	[3.00]	[1.52]	[1.08]	[2.38]	[2.83]	[2.38]	[0.52]
NW	[1.89]	[0.32]	[1.89]	[-0.68]	[1.00]	[1.56]	[1.00]	[0.56]	[1.10]	[1.22]	[1.10]	[0.22]

Notes: This table reports results of panel regressions for average excess returns and average exchange rate changes for individual currencies at horizons of one, two, three, six and twelve months, on both the average forward discount for developed countries and the currency specific forward discount, as well as currency fixed effects (to allow for different drifts). For each group of countries (developed, emerging, and all) we report the slope coefficients on the average log forward discount for developed countries ($\psi_{\mathbf{f}}$) and on the individual forward discount(ψ_f), and similarly the slope coefficient $\zeta_{\mathbf{f}}$ and ζ_f for the exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *Robust* denotes the robust standard errors clustered by month and country; NW denotes Newey and West (1987) standard errors computed with the number of lags equal to the horizon of forward discount plus one month. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

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

Panel A: Developed countries						
Horizon	IP	Pay	$Help$	$Term$	Def	VIX
1	-0.29	-0.20	-0.12	0.48	0.22	-0.09
2	-0.31	-0.21	-0.14	0.49	0.23	-0.09
3	-0.31	-0.21	-0.15	0.49	0.23	-0.08
6	-0.33	-0.23	-0.20	0.49	0.20	-0.06
12	-0.37	-0.28	-0.28	0.48	0.15	-0.05
Panel B: Emerging countries						
Horizon	IP	Pay	$Help$	$Term$	Def	VIX
1	0.13	0.23	0.11	0.06	-0.18	0.25
2	0.14	0.22	0.12	0.07	-0.20	0.25
3	0.15	0.22	0.11	0.08	-0.20	0.25
6	0.15	0.20	0.10	0.09	-0.24	0.24
12	0.15	0.14	0.09	0.10	-0.30	0.25

Notes: This table reports the contemporaneous correlation between average forward discounts and different macroeconomic and financial variables: the 12-month percentage change in industrial production (IP), the 12-month percentage change in the total U.S. non-farm payroll (Pay), and the 12-month percentage change of the Help-Wanted index ($Help$), the default spread (Def), the slope of the yield curve ($Term$) and the CBOE $S\&P$ 500 volatility index (VIX). Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–6/2010.

Table VI: Forecasting Returns and Exchange Rates with the U.S.-specific Component of the Average Forward Discount of Developed Countries

Horizon	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2
	Developed Countries				Emerging Countries				All Countries			
1	2.24	2.23	1.24	0.70	1.64	1.29	1.60	1.26	1.96	2.14	1.27	0.94
HH	[2.17]		[1.21]		[1.66]		[1.58]		[2.11]		[1.38]	
NW	[1.87]		[1.05]		[1.66]		[1.40]		[1.80]		[1.18]	
VAR	[2.43]		[1.41]		[1.99]		[1.88]		[2.38]		[1.63]	
2	2.23	3.66	1.23	1.16	1.61	2.17	1.65	2.23	1.95	3.51	1.29	1.58
HH	[2.07]		[1.15]		[1.61]		[1.56]		[2.01]		[1.34]	
NW	[1.76]		[0.99]		[1.20]		[1.10]		[1.69]		[1.12]	
VAR	[2.11]		[1.30]		[1.58]		[1.67]		[2.15]		[1.41]	
Over/NW	[1.98]		[1.20]		[1.34]		[1.33]		[1.89]		[1.34]	
3	2.16	4.63	1.16	1.40	1.51	2.48	1.55	2.55	1.86	4.25	1.21	1.87
HH	[1.98]		[1.08]		[1.41]		[1.38]		[1.88]		[1.23]	
NW	[1.53]		[0.83]		[1.09]		[1.01]		[1.45]		[0.95]	
VAR	[1.97]		[1.14]		[1.44]		[1.45]		[2.01]		[1.36]	
Over/NW	[1.59]		[0.92]		[1.05]		[0.94]		[1.48]		[0.98]	
6	2.20	7.60	1.20	2.43	1.51	3.57	1.60	3.89	1.89	6.78	1.25	3.16
HH	[2.05]		[1.13]		[1.32]		[1.31]		[1.90]		[1.27]	
NW	[1.45]		[0.80]		[1.09]		[1.04]		[1.37]		[0.91]	
VAR	[2.18]		[1.27]		[1.47]		[1.64]		[2.16]		[1.41]	
Over/NW	[1.83]		[1.11]		[1.09]		[1.06]		[1.72]		[1.20]	
12	1.95	9.96	0.95	2.63	1.80	7.32	1.89	7.93	1.66	8.53	1.03	3.64
HH	[1.88]		[0.93]		[1.46]		[1.42]		[1.71]		[1.07]	
NW	[1.45]		[0.71]		[1.27]		[1.18]		[1.36]		[0.83]	
VAR	[1.95]		[1.03]		[2.26]		[2.42]		[1.82]		[1.26]	
Over/NW	[1.42]		[0.70]		[1.51]		[1.42]		[1.53]		[0.96]	

Notes: This table reports results of forecasting regressions for average excess returns and average exchange rate changes for baskets of currencies at horizons of one, two, three, six and twelve months. For each basket we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return of a given basket on the average log forward discount for developed countries ($\psi_{\mathbf{f}}$), and similarly the slope coefficient $\zeta_{\mathbf{f}}$ and the R^2 for the regressions of average exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *HH* denotes the Hansen and Hodrick (1980) standard errors computed with the number of lags equal to the length of overlap plus one lag. *NW* denotes Newey and West (1987) standard errors computed with the optimal number of lags following Andrews (1991). The *VAR*-based statistics are adjusted for the small sample bias using the bootstrap distributions of slope coefficients under the null hypothesis of no predictability, estimated by drawing from the residuals of a VAR with the number of lags equal to the length of overlap plus one lag. *Over/NW* denotes *t*-statistics for the regression coefficients estimated using non-overlapping observations only, computed using Newey-West and bootstrap methods. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

Table VII: Forecasting Returns and Exchange Rates with Industrial Production and the Average Forward Discount

Horizon	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2
	Developed Countries								Emerging Countries								All Countries							
1	-0.54	2.14	7.00	3.40	-0.55	1.14	3.18	1.54	-0.95	1.52	5.93	3.79	-1.03	1.46	4.95	4.18	-0.57	1.87	6.67	3.60	-0.55	1.19	3.69	2.08
HH	[-0.96]	[2.06]	[1.24]		[-0.96]	[1.10]	[29.51]		[-1.65]	[1.74]	[11.34]		[-1.78]	[1.63]	[11.38]		[-1.05]	[2.04]	[1.49]		[-1.02]	[1.30]	[20.22]	
NW	[-0.92]	[1.87]	[4.00]		[-0.93]	[1.00]	[39.48]		[-1.60]	[1.76]	[8.41]		[-1.83]	[1.53]	[15.57]		[-1.06]	[1.83]	[5.08]		[-1.02]	[1.16]	[30.96]	
VAR	[-0.96]	[2.44]	[0.00]		[-0.96]	[1.30]	[0.20]		[-1.86]	[1.63]	[0.00]		[-2.08]	[1.74]	[0.00]		[-1.14]	[2.32]	[0.10]		[-1.09]	[1.50]	[0.00]	
2	-0.65	2.09	10.35	6.25	-0.65	1.09	6.72	3.16	-1.02	1.46	6.02	7.43	-1.10	1.46	4.91	7.98	-0.66	1.84	8.88	6.68	-0.64	1.18	5.94	4.14
HH	[-1.34]	[2.02]	[0.63]		[-1.34]	[1.06]	[17.71]		[-2.09]	[1.78]	[5.27]		[-2.19]	[1.68]	[5.49]		[-1.44]	[2.00]	[0.79]		[-1.39]	[1.27]	[11.66]	
NW	[-2.14]	[1.93]	[0.27]		[-2.14]	[1.01]	[4.89]		[-2.44]	[1.52]	[7.94]		[-2.20]	[1.29]	[15.91]		[-2.17]	[1.94]	[0.94]		[-2.01]	[1.20]	[8.34]	
VAR	[-1.23]	[1.92]	[0.00]		[-1.21]	[1.06]	[0.20]		[-1.90]	[1.26]	[0.00]		[-2.25]	[1.30]	[0.00]		[-1.36]	[1.99]	[0.00]		[-1.45]	[1.26]	[0.00]	
Over/NW	[-0.92]	[2.03]	[1.88]		[-0.92]	[1.17]	[28.71]		[-1.60]	[1.61]	[10.76]		[-1.74]	[1.46]	[13.87]		[-1.05]	[1.97]	[1.69]		[-1.01]	[1.33]	[16.89]	
3	-0.72	1.99	23.67	8.68	-0.72	0.99	19.74	4.67	-1.14	1.30	8.46	10.86	-1.20	1.30	6.23	11.42	-0.74	1.73	13.96	9.28	-0.71	1.07	10.44	6.01
HH	[-1.66]	[1.97]	[0.43]		[-1.66]	[0.98]	[12.06]		[-2.54]	[1.60]	[3.58]		[-2.59]	[1.50]	[3.58]		[-1.83]	[1.93]	[0.56]		[-1.77]	[1.19]	[7.64]	
NW	[-4.05]	[1.66]	[0.00]		[-4.05]	[0.83]	[0.00]		[-2.86]	[1.42]	[1.32]		[-2.49]	[1.20]	[6.87]		[-3.38]	[1.66]	[0.01]		[-3.03]	[1.01]	[0.25]	
VAR	[-1.41]	[1.77]	[0.00]		[-1.58]	[0.96]	[0.00]		[-2.40]	[1.17]	[0.00]		[-2.56]	[1.16]	[0.00]		[-1.69]	[1.82]	[0.00]		[-1.64]	[1.19]	[0.00]	
Over/NW	[-1.49]	[1.89]	[3.30]		[-1.49]	[1.02]	[25.62]		[-2.88]	[1.40]	[1.03]		[-2.78]	[1.17]	[1.99]		[-1.79]	[1.85]	[3.78]		[-1.74]	[1.18]	[16.98]	
6	-0.87	1.84	38.02	15.58	-0.87	0.84	32.05	9.57	-1.34	1.08	7.12	19.75	-1.39	1.11	5.87	20.67	-0.90	1.56	16.35	16.96	-0.88	0.92	13.78	12.28
HH	[-2.60]	[2.03]	[0.00]		[-2.60]	[0.93]	[0.53]		[-3.16]	[1.41]	[0.35]		[-3.03]	[1.35]	[0.73]		[-2.99]	[1.96]	[0.01]		[-2.92]	[1.14]	[0.15]	
NW	[-4.83]	[1.47]	[0.00]		[-4.83]	[0.67]	[0.00]		[-2.66]	[1.31]	[3.68]		[-2.41]	[1.13]	[8.78]		[-3.61]	[1.46]	[0.00]		[-3.42]	[0.84]	[0.01]	
VAR	[-1.79]	[1.72]	[0.00]		[-1.87]	[0.82]	[0.00]		[-2.97]	[0.96]	[0.00]		[-3.12]	[1.03]	[0.00]		[-2.18]	[1.66]	[0.00]		[-2.16]	[1.00]	[0.00]	
Over/NW	[-1.91]	[1.90]	[0.00]		[-1.91]	[1.03]	[0.56]		[-2.80]	[1.23]	[2.02]		[-2.56]	[1.12]	[5.28]		[-2.59]	[1.92]	[0.00]		[-2.45]	[1.20]	[0.15]	
12	-0.91	1.37	16.75	23.20	-0.92	0.37	13.01	15.23	-1.33	1.18	8.65	31.37	-1.36	1.22	7.49	32.53	-0.94	1.13	15.46	24.86	-0.90	0.50	12.99	18.87
HH	[-3.39]	[1.50]	[0.00]		[-3.38]	[0.41]	[0.00]		[-3.22]	[1.49]	[0.19]		[-3.07]	[1.38]	[0.38]		[-3.57]	[1.44]	[0.00]		[-3.57]	[0.62]	[0.00]	
NW	[-3.27]	[1.19]	[0.00]		[-3.27]	[0.33]	[0.02]		[-2.88]	[1.34]	[1.13]		[-2.67]	[1.13]	[2.81]		[-3.35]	[1.17]	[0.00]		[-3.26]	[0.50]	[0.02]	
VAR	[-2.27]	[1.41]	[0.00]		[-2.32]	[0.34]	[0.00]		[-4.22]	[1.48]	[0.00]		[-4.36]	[1.51]	[0.00]		[-2.69]	[1.28]	[0.00]		[-2.68]	[0.57]	[0.00]	
Over/NW	[-4.49]	[0.90]	[0.00]		[-4.48]	[0.17]	[0.00]		[-3.87]	[1.50]	[0.00]		[-3.32]	[1.36]	[0.14]		[-5.05]	[0.98]	[0.00]		[-4.36]	[0.41]	[0.00]	

Notes: This table reports results of forecasting regressions for average excess returns and average exchange rate changes for baskets of currencies at horizons of one, two, three, six and twelve months. For each basket we report the R^2, and the slope coefficients in the time-series regression of the log currency excess return on the 12-month change in the U.S. Industrial Production Index (ψ_{IP}) and on the average log forward discount ($\psi_{\mathbf{f}}$), and similarly the slope coefficients ζ_{IP}, $\zeta_{\mathbf{f}}$ and the R^2 for the regressions of average exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *HH* denotes Hansen and Hodrick (1980) standard errors computed with the number of lags equal to the length of overlap plus one lag. *NW* denotes Newey and West (1987) standard errors computed with the optimal number of lags following Andrews (1991). The *VAR*-based statistics are adjusted for the small sample bias using the bootstrap distributions of slope coefficients under the null hypothesis of no predictability, estimated by drawing from the residuals of a VAR with the number of lags equal to the length of overlap plus one lag. *Over/NW* denotes t-statistics for the regression coefficients estimated using non-overlapping observations only, computed using Newey-West methods. We also report the Wald tests (W) of the hypothesis that both slope coefficients are jointly equal to zero; the percentage p-values in brackets are for the χ^2-distribution under the parametric cases (HH and NW) and for the bootstrap distribution of the F statistic under VAR. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

Table VIII: Forecasting Returns and Exchange Rates with Industrial Production Residual and the Average Forward Discount

Horizon	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2	ψ_{IP}	$\psi_{\mathbf{f}}$	W	R^2	ζ_{IP}	$\zeta_{\mathbf{f}}$	W	R^2
	Developed Countries								Emerging Countries								All Countries							
1	-0.22	2.42	5.44	2.94	-0.22	1.42	1.98	1.07	-0.79	-0.26	0.89	0.60	-0.83	-1.19	5.23	2.84	-0.44	2.09	3.39	1.99	-0.46	1.02	1.04	0.64
HH	[-0.25]	[2.48]	[3.88]		[-0.26]	[1.46]	[51.17]		[-0.73]	[-0.32]	[88.01]		[-0.77]	[-1.65]	[23.28]		[-0.55]	[1.97]	[23.54]		[-0.58]	[0.98]	[78.31]	
NW	[-0.24]	[2.21]	[11.54]		[-0.25]	[1.30]	[63.59]		[-0.71]	[-0.31]	[86.41]		[-0.74]	[-1.69]	[13.14]		[-0.52]	[1.79]	[35.79]		[-0.55]	[0.89]	[83.57]	
VAR	[-0.33]	[2.74]	[0.00]		[-0.31]	[1.68]	[0.20]		[-1.10]	[-0.57]	[0.30]		[-1.25]	[-2.38]	[0.00]		[-0.69]	[2.29]	[0.00]		[-0.77]	[1.18]	[0.10]	
2	-0.68	2.39	6.75	5.53	-0.68	1.40	3.10	2.41	-0.89	-0.69	1.31	2.56	-0.88	-1.58	2.44	7.34	-0.82	2.14	5.72	4.15	-0.81	1.11	2.40	1.90
HH	[-0.94]	[2.44]	[1.53]		[-0.95]	[1.42]	[30.55]		[-1.14]	[-0.84]	[67.81]		[-1.12]	[-2.08]	[15.63]		[-1.21]	[2.09]	[9.19]		[-1.20]	[1.10]	[50.62]	
NW	[-0.95]	[2.22]	[4.79]		[-0.96]	[1.29]	[40.85]		[-1.13]	[-0.62]	[77.93]		[-1.10]	[-1.49]	[53.79]		[-1.13]	[2.17]	[9.62]		[-1.12]	[1.14]	[54.76]	
VAR	[-0.93]	[2.29]	[0.00]		[-1.02]	[1.36]	[0.00]		[-1.27]	[-1.28]	[0.10]		[-1.29]	[-2.77]	[0.00]		[-1.36]	[2.06]	[0.00]		[-1.38]	[1.07]	[0.00]	
Over/NW	[-0.45]	[2.41]	[4.93]		[-0.45]	[1.50]	[45.78]		[-0.74]	[-0.64]	[87.50]		[-0.69]	[-1.91]	[30.15]		[-0.69]	[2.22]	[12.34]		[-0.68]	[1.25]	[63.50]	
3	-0.85	2.32	6.21	7.67	-0.85	1.32	3.29	3.61	-1.19	-0.55	2.02	4.09	-1.17	-1.43	2.60	9.56	-0.96	2.08	5.00	5.95	-0.94	1.07	2.55	3.04
HH	[-1.35]	[2.41]	[1.19]		[-1.35]	[1.37]	[23.09]		[-1.48]	[-0.68]	[55.32]		[-1.45]	[-1.86]	[19.09]		[-1.59]	[2.14]	[7.38]		[-1.56]	[1.11]	[40.06]	
NW	[-1.28]	[1.97]	[6.95]		[-1.29]	[1.12]	[37.44]		[-1.42]	[-0.52]	[62.70]		[-1.38]	[-1.39]	[50.55]		[-1.45]	[1.97]	[15.12]		[-1.42]	[1.02]	[51.55]	
VAR	[-1.18]	[2.32]	[0.00]		[-1.24]	[1.24]	[0.10]		[-1.78]	[-0.95]	[0.00]		[-1.65]	[-2.28]	[0.00]		[-1.61]	[1.92]	[0.00]		[-1.57]	[0.98]	[0.00]	
Over/NW	[-0.86]	[2.28]	[8.92]		[-0.86]	[1.40]	[49.21]		[-1.38]	[-0.62]	[57.79]		[-1.43]	[-1.32]	[36.62]		[-1.32]	[2.15]	[15.74]		[-1.31]	[1.24]	[55.92]	
6	-1.24	2.19	8.02	14.47	-1.24	1.19	5.27	8.38	-1.72	-0.21	3.30	9.00	-1.69	-1.09	3.10	14.80	-1.32	2.17	7.59	13.67	-1.29	1.17	4.47	8.64
HH	[-2.24]	[2.58]	[0.06]		[-2.24]	[1.40]	[3.52]		[-1.96]	[-0.29]	[26.40]		[-1.90]	[-1.58]	[20.33]		[-2.35]	[2.87]	[0.16]		[-2.30]	[1.55]	[7.08]	
NW	[-1.98]	[1.89]	[1.86]		[-1.98]	[1.03]	[12.82]		[-1.71]	[-0.26]	[37.38]		[-1.67]	[-1.32]	[40.92]		[-2.00]	[2.33]	[2.60]		[-1.96]	[1.25]	[20.53]	
VAR	[-1.92]	[2.18]	[0.00]		[-1.76]	[1.15]	[0.00]		[-2.78]	[-0.40]	[0.00]		[-2.73]	[-1.73]	[0.00]		[-2.25]	[2.08]	[0.00]		[-2.22]	[1.09]	[0.00]	
Over/NW	[-1.27]	[2.48]	[0.39]		[-1.28]	[1.53]	[12.96]		[-1.68]	[-0.18]	[46.27]		[-1.74]	[-1.45]	[19.65]		[-1.79]	[2.69]	[0.76]		[-1.83]	[1.62]	[14.20]	
12	-1.46	1.70	29.77	24.60	-1.47	0.71	24.75	16.79	-1.92	0.03	9.30	17.66	-1.86	-0.87	6.91	23.94	-1.51	1.67	17.74	23.96	-1.45	0.65	13.53	17.51
HH	[-4.13]	[2.07]	[0.00]		[-4.13]	[0.86]	[0.00]		[-2.84]	[0.03]	[0.43]		[-2.74]	[-1.08]	[2.70]		[-4.03]	[2.83]	[0.00]		[-3.90]	[1.13]	[0.00]	
NW	[-4.60]	[1.65]	[0.00]		[-4.59]	[0.68]	[0.00]		[-2.72]	[0.03]	[0.66]		[-2.61]	[-1.01]	[4.29]		[-3.88]	[2.44]	[0.00]		[-3.67]	[0.97]	[0.01]	
VAR	[-2.48]	[1.60]	[0.00]		[-2.44]	[0.77]	[0.00]		[-4.11]	[-0.05]	[0.00]		[-4.11]	[-1.53]	[0.00]		[-2.76]	[1.64]	[0.00]		[-2.78]	[0.64]	[0.00]	
Over/NW	[-2.16]	[1.63]	[0.00]		[-2.17]	[0.86]	[0.00]		[-2.79]	[-0.72]	[0.00]		[-2.84]	[-1.31]	[0.09]		[-2.42]	[2.26]	[0.00]		[-2.43]	[1.29]	[0.01]	

Notes: This table reports results of forecasting regressions for average excess returns and average exchange rate changes for baskets of currencies at horizons of one, two, three, six and twelve months. For each basket we report the R^2, and the slope coefficients in the time-series regression of the log currency excess return on the 12-month change in the U.S. Industrial Production Index orthogonalized with respect to the world average Industrial Production (ψ_{IP}) and on the average log forward discount ($\psi_{\mathbf{f}}$), and similarly the slope coefficients ζ_{IP}, $\zeta_{\mathbf{f}}$ and the R^2 for the regressions of average exchange rate changes. The t-statistics for the slope coefficients in brackets are computed using the following methods. *HH* denotes Hansen and Hodrick (1980) standard errors computed with the number of lags equal to the length of overlap plus one lag. *NW* denotes Newey and West (1987) standard errors computed with the optimal number of lags following Andrews (1991). The *VAR*-based statistics are adjusted for the small sample bias using the bootstrap distributions of slope coefficients under the null hypothesis of no predictability, estimated by drawing from the residuals of a VAR with the number of lags equal to the length of overlap plus one lag. *Over/NW* denotes t-statistics for the regression coefficients estimated using non-overlapping observations only, computed using Newey-West methods. Data are monthly, from Barclays and Reuters (available via Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–6/2010.

Table IX: Out-of-Sample Return and Exchange Rate Predictability: Comparison with a Random Walk

	Excess Returns					Exchange Rate Changes				
Horizon	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC
					Panel A: IP					
1	2.41	2.41	1.00	0.06	1.09	2.39	2.39	1.00	0.04	0.82
			(0.13)	(0.15)	(0.09)			(0.14)	(0.15)	(0.13)
2	3.69	3.63	1.01	0.51	2.20	3.64	3.59	1.01	0.61	1.98
			(0.04)	(0.16)	(0.05)			(0.04)	(0.13)	(0.07)
3	4.63	4.53	1.02	0.54	2.60	4.55	4.45	1.02	0.66	2.34
			(0.04)	(0.19)	(0.06)			(0.04)	(0.17)	(0.09)
6	7.17	7.05	1.02	0.25	3.45	6.98	6.82	1.02	0.40	3.07
			(0.16)	(0.35)	(0.09)			(0.10)	(0.30)	(0.11)
12	10.38	9.63	1.08	1.13	5.87	9.74	8.97	1.09	1.33	5.24
			(0.05)	(0.22)	(0.04)			(0.05)	(0.19)	(0.06)
					Panel B: IP and AFD					
1	2.41	2.40	1.01	0.41	1.56	2.39	2.39	1.00	-0.16	0.57
			(0.05)	(0.08)	(0.04)			(0.21)	(0.20)	(0.22)
2	3.69	3.62	1.02	0.79	2.65	3.64	3.61	1.01	0.48	1.75
			(0.04)	(0.09)	(0.03)			(0.11)	(0.14)	(0.12)
3	4.63	4.46	1.04	1.11	3.55	4.55	4.45	1.02	0.76	2.46
			(0.02)	(0.07)	(0.02)			(0.07)	(0.14)	(0.10)
6	7.17	6.79	1.06	0.92	4.04	6.98	6.78	1.03	0.54	2.94
			(0.05)	(0.19)	(0.07)			(0.14)	(0.28)	(0.19)
12	10.38	9.27	1.12	1.85	6.25	9.74	9.29	1.05	0.82	4.30
			(0.05)	(0.13)	(0.05)			(0.18)	(0.31)	(0.17)
					Panel C: AFD					
1	2.41	2.39	1.01	0.70	1.90	2.39	2.39	1.00	0.19	0.95
			(0.02)	(0.09)	(0.02)			(0.15)	(0.20)	(0.11)
2	3.69	3.65	1.01	0.53	2.43	3.64	3.64	1.00	0.04	1.25
			(0.06)	(0.15)	(0.04)			(0.27)	(0.28)	(0.16)
3	4.63	4.53	1.02	0.80	3.36	4.55	4.53	1.00	0.27	1.94
			(0.04)	(0.12)	(0.02)			(0.20)	(0.26)	(0.13)
6	7.17	6.95	1.03	0.81	4.12	6.98	6.94	1.01	0.21	2.45
			(0.08)	(0.20)	(0.05)			(0.29)	(0.36)	(0.18)
12	10.38	9.40	1.10	2.20	6.11	9.74	9.40	1.04	1.34	3.90
			(0.03)	(0.09)	(0.03)			(0.15)	(0.21)	(0.16)

Notes: This table reports one-step-ahead out-of-sample predictability test statistics. We first assume that the average changes in exchange rates against the U.S. dollar for the developed markets basket follow a random walk with drift. $RMSE_{RW}$ denotes the corresponding square root of the mean squared error (in percentages). We then use the twelve-month change in the industrial production index (IP) and/or average forward discount for the same basket (AFD) to predict changes in exchange rates $RMSE$ denotes the corresponding square root of the mean squared error (in percentages). We add three test statistics: the ratio of the two square root mean squared errors ($Ratio = RMSE_{RW}/RMSE$), the Diebold-Mariano (MSE_t) and the Clark-McCraken (ENC) statistics. Each model is estimated recursively. Using information up to date t, we use the model to predict the changes in exchange rates between t and $t+k$, for $k = 1$, 2, 3, 6, and 12 months. We use at least half of the sample to estimate the model. P-values for the test statistics reported in the parentheses are computed via bootstrap under the null hypothesis of no predictability. They are obtained from bootstrapping the whole procedure assuming a VAR with the number of lags equal to the horizon of forward discount for the predictor variable. Panel A uses the industrial production as predictor, Panel B uses both IP and the average forward discount across developed countries currencies, and Panel C uses only the AFD. Data are monthly, obtained from Datastream. The sample period is 11/1983 - 06/2010.

Table X: Calibrating The Symmetric Model

Panel A: 10 Targets – Moments of Real Variables				
	Model	Target	Target	Actual
		Monthly	Annual	Annual
β_{UIP}	$\frac{\chi}{\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)}$	-1.50	-1.50	-1.50
R^2_{UIP}	$\frac{2*\beta^2_{UIP}\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)^2*var(z)}{var(\Delta q)}$	3.40%	3.40%	3.40%
$E(r)$	$\theta\left[\alpha+\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)+\left(\tau-\frac{1}{2}\delta^i\right)\right]$	0.14%	1.72%	1.52%
$Std(r)$	$\sqrt{\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)^2 var(z^i)+\left(\tau-\frac{1}{2}\delta^i\right)^2 var(z^w)}$	0.17%	0.57%	0.34%
$Corr(r_t, r_{t-1})$	ϕ	0.92	0.37	0.28
$Std(\Delta q)$	$\sqrt{2\gamma\theta+2\chi^2 var(z^i)+o}$	2.89%	10.00%	7.76%
$Std(m)$	$\sqrt{(\gamma+\delta+\kappa)\theta+\chi^2 var(z^i)+\tau^2 var(z^w)}$	0.14	0.50	0.68
$Corr(r_t, r^i_t)$	$\left(\tau-\frac{1}{2}\delta^i\right)^2 \frac{Var(z^w)}{Var(r)}$	0.30	0.30	0.28
$E(rx^{dollar}_t)$	$\gamma\theta$	0.04%	0.50%	0.07%
$Feller$	$2(1-\phi)\frac{\theta}{Var(z^w)}$	20.00	20.00	20.00
Panel B: 3 Targets – Moments of Inflation				
$Std(inflation)$	$\sqrt{(\eta^w)^2 var(z^w)+\sigma^2_\pi}$	0.32%	1.10%	1.09%
R^2	$\frac{(\eta^w)^2 var(z^w)}{var(inflation)}$	0.28	0.28	0.28
$E(inflation)$	$\pi_0+\eta^w\theta$	0.24%	2.91%	2.59%
Panel C: Moments of Nominal Variables				
	Model	Implied	Implied	Actual
		Monthly	Annual	Annual
$E(r^\$)$	$\theta\left[\alpha+\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)+\left(\tau+\eta^w-\frac{1}{2}\delta^i\right)\right]-\frac{1}{2}\sigma^2_\pi$	0.39%	4.69%	4.12%
$Std(r^\$)$	$\sqrt{\left(\chi-\frac{1}{2}(\gamma+\kappa)\right)^2 var(z^i)+\left(\tau+\eta^w-\frac{1}{2}\delta^i\right)^2 var(z^w)}$	0.14%	0.50%	0.82%
$Std(\Delta s)$	$\sqrt{2\gamma\theta+2\chi^2 var(z^i)+2\sigma^2_\pi+o}$	3.91%	11.07%	7.88%
$Corr(r^\$_t, r^{\$,i}_t)$	$\left(\tau+\eta^w-\frac{1}{2}\delta^i\right)^2 \frac{Var(z^w)}{Var(r)}$	0.78	0.78	0.85

Note that $var(z^w)=\frac{\sigma^2_w\theta}{1-\phi^2}$ and $var(z^i)=\frac{\sigma^2_i\theta}{1-\phi^2}$. $o=2(\delta+\kappa)\theta-2E\left(\sqrt{\delta^i z^w_t+\kappa^i z_t}\right)\left(\sqrt{\delta^i z^w_t+\kappa^i z^i_t}\right)$ is an order of magnitude smaller than the other terms.

Table XI: Parameter Values

Pricing Kernel Parameters					
α (%)	χ	γ	κ	$\delta*$	
0.75	0.66	0.01	2.21	1.90	
Factor and Inflation Dynamics					
ϕ	θ (%)	σ (%)	η^w	σ^π (%)	π_0 (%)
0.92	0.85	0.82	-0.86	0.27	0.98

This table reports the parameter values for the calibrated version of the model. These 11 parameters were chosen to match the 13 moments in Table X under the assumption that all countries share the same parameter values. α, σ, θ and π_0 are reported in percentage points.

Table XII: Currency Portfolios – Simulated data

Portfolio	1	2	3	4	5	6
Sorting on Current Forward Discounts						
Spot change: Δs^j						
Mean	0.03	−0.65	−0.28	−0.08	0.19	1.00
Std	11.96	8.56	6.57	5.47	6.79	10.27
Forward Discount: $f^j - s^j$						
Mean	−5.33	−3.53	−2.02	−0.39	1.29	4.11
Std	1.27	1.23	0.96	0.99	1.06	1.31
Excess Return: rx^j						
Mean	−5.37	−2.88	−1.74	−0.31	1.10	3.11
Std	10.69	8.10	6.34	5.53	7.06	10.05
SR	−0.50	−0.36	−0.27	−0.06	0.16	0.31
High-minus-Low: $rx^j - rx^1$						
Mean		2.49	3.63	5.06	6.47	8.48
Std		5.24	7.81	9.34	12.67	17.69
SR		0.47	0.46	0.54	0.51	0.48

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 $rx^j - rx^1$. All these moments are defined as in Table I. 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 $t-1$. The first portfolio contains currencies with the lowest interest rates. The last portfolio contains currencies with the highest interest rates. All data are simulated from the model. The range of δ's is ($[0.85, 2.95]$). These parameters are assumed to be distributed unformly and symmetrically around the home country δ of 1.90.

Table XIII: Forecasting Returns and Exchange rates with the Average Forward Discount – Simulated Data

Horizon	$\tilde{\psi}_{\mathbf{f}}$	R^2	$\tilde{\zeta}_{\mathbf{f}}$	R^2	$\tilde{\psi}_{\mathbf{f}}$	R^2	$\tilde{\zeta}_{\mathbf{f}}$	R^2	$\tilde{\psi}_{\mathbf{f}}$	R^2	$\tilde{\zeta}_{\mathbf{f}}$	R^2
	Data: Developed Countries				Model: Short Sample				Model: Long Sample			
1	2.45	2.91	1.45	1.04	2.47	1.85	1.47	0.66	2.48	2.19	1.48	0.79
HH	[2.55]		[1.51]		[2.23]		[1.33]		[17.05]		[10.17]	
NW	[2.25]		[1.33]		[2.31]		[1.37]		[17.06]		[10.17]	
VAR	[2.92]		[1.71]		[2.27]		[1.18]		–		–	
2	2.36	4.88	1.42	1.84	2.21	3.11	1.26	1.03	2.36	4.05	1.40	1.45
HH	[2.58]		[1.55]		[2.24]		[1.28]		[18.56]		[10.97]	
NW	[2.17]		[1.30]		[2.07]		[1.18]		[17.25]		[10.20]	
VAR	[2.70]		[1.66]		[1.85]		[1.04]		–		–	
Over/NW	[2.51]		[1.64]		[2.28]		[1.35]		[16.91]		[9.91]	
3	2.15	5.70	1.23	1.96	2.38	5.35	1.49	2.10	2.27	5.71	1.34	2.04
HH	[2.42]		[1.38]		[2.53]		[1.57]		[19.24]		[11.34]	
NW	[1.87]		[1.06]		[2.37]		[1.48]		[17.39]		[10.25]	
VAR	[2.44]		[1.40]		[2.23]		[1.37]		–		–	
Over/NW	[2.13]		[1.11]		[2.19]		[1.40]		[16.78]		[9.83]	
6	2.22	10.32	1.35	4.12	2.34	10.22	1.59	4.72	2.01	9.41	1.19	3.34
HH	[2.62]		[1.58]		[2.76]		[1.86]		[19.89]		[11.62]	
NW	[1.84]		[1.10]		[2.13]		[1.44]		[17.07]		[9.97]	
VAR	[2.52]		[1.66]		[2.33]		[1.64]		–		–	
Over/NW	[2.27]		[1.50]		[2.30]		[1.45]		[16.16]		[9.28]	
12	1.83	13.70	1.06	5.30	1.83	12.93	1.30	6.34	1.68	13.55	1.01	5.02
HH	[2.27]		[1.30]		[2.28]		[1.56]		[19.74]		[11.66]	
NW	[1.78]		[1.00]		[1.67]		[1.14]		[16.36]		[9.67]	
VAR	[2.22]		[1.35]		[2.22]		[1.55]		–		–	
Over/NW	[1.68]		[1.06]		[0.24]		[-0.26]		[15.83]		[9.48]	

Notes: This table reports slope coefficients and R^2 for the regressions of cumulative long-horizon excess returns and exchange rate changes on the one-month average forward discount, obtained both in the data and in the model. The left set of columns reports the empirical results for the basket of developed countries. The middle set of columns reports the simulated predictability results for a basket of 30 currencies. The set of columns shows results for a a simulated large sample of $T = 33,600$ monthly observations. The average country has the same δ as the home country (U.S.).

Table XIV: Forecasting Carry Trade Returns and Exchange rates with the Average Forward Discount – Simulated Data

Horizon	$\psi_{\mathbf{f}}$	R^2	$\zeta_{\mathbf{f}}$	R^2
		Panel A: Data		
		Developed Countries		
High - Low	-0.54	0.11	-0.66	0.17
HH	[-0.59]		[-0.70]	
NW	[-0.58]		[-0.66]	
		All Countries		
High-Low	-0.59	0.16	0.22	0.02
HH	[-0.64]		[0.22]	
NW	[-0.61]		[0.20]	
		Panel B: Model		
		Short Sample		
High - Low	0.14	0.34	-0.06	0.06
HH	[1.10]		[-0.46]	
NW	[1.10]		[-0.46]	
		Long Sample		
High - Low	0.06	0.07	0.02	0.01
HH	[4.75]		[1.38]	
NW	[4.78]		[1.39]	

Notes: This table reports predictability results for carry trade returns. Panel A reports predictability results obtained by sorting currencies based on their forward discounts into 5 portfolios for the sample of developed countries and 6 portfolios using the full sample. Carry trade excess returns correspond to returns on the last portfolio minus returns on the first portfolio. Panel B reports predictability results using artificial data simulated from the model. These portfolios are constructed by sorting 30 currencies by interest rates into 6 portfolios in the model. The top row shows results fora simulated small sample of $T = 336$ monthly observations. The bottom row shows results for a large simulated sample of $T = 33,600$ monthly observations. This table reports results of forecasting regressions for one-month returns (left hand side) and one-month changes in exchange rates (right hand side) using the one-month average forward discount rate (in the data, we use the developed countries basket).