Predictable Currency Risk Premia *

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Abstract

Currency excess returns are highly predictable, more than stock returns, and about as much as bond returns. We show that in a general, no-arbitrage setup, expected currency excess returns have two components: a dollar risk premium and a carry trade risk premium. The average forward discount across all countries is a good measure of the market price demanded by US investors for bearing US-specific risk, and thus a good predictor of currency excess returns. Predicted excess returns are strongly counter-cyclical because they inherit the cyclical properties of US-specific risk prices. Macroeconomic and financial variables, like the rate of industrial production growth, thus helps to predict the dollar risk premium. We investigate one-month to one-year ahead predictability and obtain R^2s up to 38 percent on portfolios of currency excess returns using the average forward discount and industrial production growth as predictors. US-specific variables that predict the dollar risk premium have no forecasting power on the carry trade risk premium. These findings point towards a risk-based view of exchange rates.

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Currency excess returns are highly predictable, more than stock returns, and about as much as bond returns. We show that in a general, no-arbitrage setup, expected currency excess returns have two components: a dollar risk premium and a carry trade risk premium. The dollar risk premium compensates US investors for bearing US-specific risk. The carry trade risk premium compensates investors for bearing world risk. In this framework, exchange rates are predictable because risk premia are. This decomposition of currency excess returns leads us to three novel empirical results. First, we show that the average interest rate difference (or forward discount) across all countries is a good measure of the market price demanded by US investors for bearing US-specific risk, and thus a good predictor of currency excess returns. As the average forward discount increases, the risk price increases as well, and so do the expected excess returns on foreign currency investments. Second, predicted excess returns are strongly counter-cyclical because they inherit the cyclical properties of US-specific risk prices. Macroeconomic and financial variables, like the rate of industrial production growth, thus helps to predict the dollar risk premium. We investigate one-month to one-year ahead predictability and obtain R^2s up to 38 percent on portfolios of currency excess returns using the average forward discount and industrial production growth as predictors. Third, US-specific variables that predict the dollar risk premium have no forecasting power on the carry trade risk premium. These findings point towards a risk-based view of exchange rates: as their equity and bond counterparts, expected currency excess returns are predictable. They are high in bad times and low in good times.

The standard view in international economics is that individual exchange rates follow a random walk. This view emerged from the failure to outperform the random walk in forecasting changes in exchange rates for individual currency pairs. This standard view implies that currency returns are predictable, because investors expect to earn the interest rate difference, and it is quite specific about the nature of predictability: expected excess returns should move one-for-one with the interest rate difference for that specific currency pair. In the standard view, this interest rate difference is the only variable with forecasting power for currency excess returns. We examine the returns on baskets of currencies and we reach a different conclusion.

Consider a US investor who invests in a large basket of foreign currencies. Investing in this basket exposes her to two different types of innovations that are priced: US-specific innovations to the US stand-in agent's marginal utility growth and common innovations to the marginal utility growth of all investors around the world. This decomposition is fairly general. Foreign currency investments always entail exposure to US-specific shocks. For example, high interest rates currencies tend to depreciate in case of an adverse shock to the marginal utility growth rate of US investors. Foreign currency investments also entail positive exposure to common innovations. In Lustig, Roussanov and Verdelhan (2008), we show that high interest rate currencies are less exposed to common innovations than low interest rate currencies.

We propose a simple, multi-country model of exchange rates that encompasses both country-specific and common innovations. We start off the law of motion of each SDF. We know from Backus, Foresi and Telmer (2001) that log-normal SDFs must be heteroscedastic in order to replicate deviations from uncovered interest rate parity. The standard deviation of the lognormal log SDF corresponds to market prices of risk. The necessary heteroscedasticity of these SDFs implies time-variation in the market price of risk. As is usual in the macro-finance literature, we assume that market prices of risk are counter-cyclical. This would be the case in the habit model of Campbell and Cochrane (1999), the long run risk model of Bansal and Yaron (2004) or the time-varying disaster risk model of Gabaix (2009).[1] As a result, our model decomposes expected currency excess returns into a dollar risk premium and a carry trade risk premium. This decomposition guides and illustrates our empirical results.

Our general framework has three sets of predictions. First, there should be no role for portfolio-specific variables in forecasting currency excess returns. There is no reason to include foreign real or nominal variables in predictability regressions on our portfolios. But the average forward discount should be a good predictor of currency excess returns because it measures the prices of dollar and carry risk. Second, the dollar risk premium should be counter-cyclical. The US-specific component of the risk price, and hence the dollar risk premium, should be counter-cyclical with respect to the US-specific component of the business cycle. As the price of this risk increases during US recessions, the expected excess return on foreign currency increases. This increase in the risk premium occurs directly through an increase in the average interest rate difference with foreign currencies, and indirectly, through an expected depreciation of the dollar. This explains why US-specific business cycle variables forecast foreign currency returns. Third, long-short returns –formed for example by going short the first portfolio and long any other portfolio– should depend only on global variables that proxy for common innovations, not on US-specific variables. These predictions are borne out by the data.

The one-month ahead forward discount explains 1 to 5 percent of the variation in the average foreign currency returns over the next month. When the horizon increases, R^2s increase too. At 12-month horizon, the forward discount explains 10 to 25 percent of the variation in returns over the next year. However, even when forecasting individual currency portfolio returns, the average forward discount outperforms the portfolio-specific forward discount. Again, this is inconsistent with the standard random walk view of exchange rates: if they were, then the portfolio-specific forward discount would always be the best predictor of foreign currency returns and exchange rates would move one for one with the portfolio-specific forward discount. We find that, on average, an increase of 100 basis points in the average interest rate difference implies a much larger increase in the expected excess return of 270 basis points over the next 12 months. Hence, the dollar is

[1] These models have been successfully applied to currency markets: see Verdelhan (2009), Bansal and Shaliastovich (2008) and Farhi and Gabaix (2008).

expected to depreciate against this basket of currencies by 170 basis points over the next year. At the 12-month horizon, the R^2 –obtained with the average forward discount across portfolios– varies between 30 percent for the lowest interest rate currencies and 15 percent for the highest interest rate currencies. This result echoes the finding of Cochrane and Piazzesi (2005) that a linear combination of forward rates across maturities is a powerful predictor of excess returns on bonds.

Using the portfolio-specific or the average forward discount as predictor, we form expected currency excess returns and study their business cycle properties. To assess their cyclicality, we use three standard business cycle indicators and three financial variables: (i) the 12-month percentage change in US industrial production index, (ii) the 12-month percentage change in total US non-farm payroll index, (iii) the 12-month percentage change in the Help Wanted index, (iv) the default spread the difference between the 20-Year Government Bond Yield and the S&P 15-year BBB Utility Bond Yield (v) the slope of the yield curve the difference between the 5-year and the 1-year zero coupon yield on Treasuries, and (vi) the S&P 500 VIX volatility index. On the one hand, the monthly contemporaneous correlation between predicted excess returns and macro indices are negative for all portfolios. On the other hand, monthly correlations between predicted excess returns and financial variables are positive for all portfolios. In both cases, the message is the same: expected excess returns are counter-cyclical. In bad times, our macro indices are low while our financial variables are high. In bad times, expected currency excess returns are high. This is in consistent with evidence on equity and bond markets, and with leading dynamic asset pricing models. In the habit model of Campbell and Cochrane (1999), bad times correspond to high risk-aversion. In the long run risk model of Bansal and Yaron (2004), bad times correspond to high uncertainty. In the time-varying disaster risk model of Gabaix (2009), bad times correspond to high probabilities of disasters. We obtain similar results at longer horizons. The average forward discount is counter-cyclical at one- to twelve-month horizons. Since currency excess returns load positively on it, they inherit its counter-cyclical behavior.

Such correlations suggest a new set of potential predictors for currency excess returns. Variables that predict risk premia on other markets should predict currency excess returns as well. To explore this idea, we focus on the 12-month percentage change in US industrial production index (IP for short), which turns out to present the highest forecasting power. This variable is highly correlated to the output gap used by Cooper and Priestley (2009) to predict stock returns. At the one-year horizon, IP delivers R^2s from 17 to 32 percent. Our model suggests that most of the predictability should come from US-specific variables. IP, however, is correlated with foreign business cycles. We thus project IP on an average of foreign equivalents in order to extract its world component. We use the residuals as predictors. Again, we obtain high R^2s, ranging from 13 to 29 percent. Even more striking, we obtain similar results on average exchange rates alone. IP does not simply predict the interest rate differentials, but also the average change in exchange rates in these portfolios. If we bunch together IP and average forward discounts, we obtain R^2s that range from 20 to 38 percent on our currency portfolios at the one-year horizon. US industrial production growth has predictive power for currency excess returns even when controlling for forward discounts. Our model also suggests that these US-specific IP residuals should have no predictive power on carry trade strategies that go short one portfolio and long the others. They do not.

Our predictability results might appear too-good-to-be-true when compared to the exchange rate literature. But there is far more predictability in currency portfolio returns than in the returns on individual currency pairs. This is not that surprising. By forming portfolios, we focus on the priced innovations to exchange rates, averaging out the foreign idiosyncratic components that are not priced from the US perspective. As in Lustig et al. (2008), we sort currencies on their forward discounts and allocate them to six portfolios. We rebalance portfolios monthly. As a result, the first portfolio contains the lowest interest rate currencies while the last portfolio contains the highest interest rate currencies. This is key. Our paper is about forecasting the compensation for risk, not forecasting a given bilateral exchange rate. And interest rates turn out to be a good signal for risk: as shown in the literature, high interest rate currencies offer large excess returns because they tend to depreciate in bad times, and are thus risky. Since diversifiable currency-specific risk is not priced, there is little reason to focus on forecasting returns on individual currency pairs. Similarly, in equity research, the focus has been on forecasting returns on the stock market, not individual stock returns. The same reasoning applies here. By creating baskets of currencies, we get rid of this diversifiable risk and we focus on US-specific and common innovations, both of which earn potentially time-varying risk premia. All our results point towards risk-based models of exchange rates.

A large literature already reports predictability on equity markets. We do not attempt to present it here, but refer the readers to Cochrane (2005) for a survey. It appears that macroeconomic and financial variables predict stock market returns, particularly at long horizons. Other returns turn out to be predictable as well. In recent work, Duffee (2008) and Ludvigson and Ng (2009) report similar findings for the bond market, 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. But forecasting has been a longstanding challenge in international economics. 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.

In a seminal paper, Meese and Rogoff (1983) show that the out-of-sample predictions of exchange rates based on a drift-less random walk dominate those of all macro-founded models available for up to 12-month ahead forecasts. This result has been difficult to overturn. Building on their paper, Engel and West (2005) show that exchange rates look like a random walk when fundamentals are I(1) and the discount factor is constant and near one. Note that in our approach the stochastic discount factor is not constant, and its time-variation is key to explain predictability in currency markets. Three challenges to the Meese and Rogoff (1983) result stand out. First, Mark (1995) shows that a model based on money demand beats the random walk if the horizon of the prediction increases from one to 16 quarter. Extending the sample period, however, Kilian (1999) does not confirm the result. Second, Evans and Lyons (2005) show that a model of exchange rate based on disaggregated order flow outperforms the random walk over horizons from one day to one month. Third, Gourinchas and Rey (2007), stressing the valuation effect of exchange rates foreign assets, show that deviations from trend of the ratio of net exports to net foreign assets predict net foreign asset portfolio returns one quarter to two years ahead. We complement these three approaches with a finance-based perspective. We focus on actual returns and uncover new sources of predictability in exchange rates. There is little reason to expect the risk premium to be exactly equal to the interest rate difference at all times. In fact, we find it is not. Risk premia in bond and stock markets are driven by a range of macro variables. We find that currency markets are no different.

Section 2 presents a simple model that guides our predictability tests. Section 3 describes the data, how we build currency portfolios and their main characteristics. Section 4 describes the time variation in excess returns that investors demand on these currency portfolios. Section 5 focuses on the predictability of long-short strategies. Section 6 considers several robustness checks: out-of-sample tests, foreign investors, and sub-samples of developed countries. Section 7 concludes. A separate appendix reports additional results. The portfolio data can be downloaded from our web sites and are regularly updated.

2 Where To Look For Currency Predictability?

We use a standard affine model to show that, by constructing currency portfolios, we extract currency risk premia from otherwise noisy data. In the model, currency risk premia are predictable even if exchange rates are close to random walks at short horizons. Expected currency excess returns depend on two risk factors: one is US-specific and one is common across countries. The model implies several predictability results that we test in the next sections.

2.1 A No-Arbitrage Model of Exchange Rates

We work out a simple model of currency excess returns to guide our predictability tests. We first state the basic assumptions that are necessary to make sense of currency excess returns. These assumptions define a fairly general class of models. We then present a simple example in this class to illustrate the model's predictions. In a separate appendix, we show that these predictions are also borne out in the general case.

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

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

where q^i is measured in country i goods per home country good. An increase in q^i means a real appreciation of the home currency. For any variable that pertains to the home country (the US), we drop the superscript. The expected log currency excess return equals the interest rate difference plus the expected rate of appreciation:

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

Note that up to a first order approximation, excess returns computed with nominal variables are similar to the ones above since the inflation differential cancels out. More importantly, for excess returns to be predictable, log-normal SDFs must be heteroscedastic.

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 SDF 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). We thus assume that each log SDF depends on country-specific and world shocks. This is our first assumption.

Lustig et al. (2008) show that, in order to reproduce cross-sectional evidence on currency excess returns, risk prices must load differently on this common component. If SDFs are lognormal, market prices of risk are equal to the standard deviation of the log SDFs.[2] Thus, world shocks must have different impacts on the standard deviation of the log SDFs.

Two sources of risk are priced in such an economy: country-specific shocks and world shocks.

[2]To see this point, start from the Euler equation $E_t[M_{t+1}R^e_{t+1}] = 0$ for any excess return R^e_{t+1}. Assuming that both returns and SDF are log-normal leads to:

$$E_t[r^e_{t+1}] = -\frac{Cov_t(m_{t+1}, r^e_{t+1})}{Var_t(m_{t+1})}\frac{Var_t(m_{t+1})}{E_t(m_{t+1})},$$

Each type of risk has a different price. To simplify our analysis, we further assume a dichotomy in these risk prices: we assume that risk prices of country-specific shocks depend only on country-specific variables. Likewise, risk prices of world shocks depend only on world variables. This last assumption is the most restrictive, since one could imagine a model in which risk prices of world shocks would depend on the country's economic conditions. We do not know, however, an example of a fully worked out model with this feature. As in common in the equity and bond literature, we assume that market prices of risk are counter-cyclical. As already noted, this feature of asset markets is a key ingredient of leading dynamic asset pricing models.

To summarize, we make the following sets of assumptions:

Assumption 1. *In each country, the log SDF is heteroscedastic and depends on country-specific and world shocks.*

Assumption 2. *World shocks have different impacts on the market prices of risk across countries.*

Assumption 3. *In each country, risk prices of country-specific (world) shocks depend only on country-specific (world) factors.*

Assumption 4. *Country-specific risk factors and risk-free rates are counter-cyclical.*

Exponentially Affine Model We now present a model that satisfies the four assumptions above. We focus on the essentially-affine class that is popular in the term structure literature. Special cases of this class of models applied to currency markets are proposed by Frachot (1996), Backus et al. (2001) and Brennan and Xia (2006), as well as Lustig et al. (2008). We review here this last case and derives its implications for exchange rate predictability.

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 SDF m^i follows a two-factor Cox, Ingersoll and Ross (1985)-type process:

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

To be parsimonious, we limit the heterogeneity in SDF parameters to the different loadings (denoted δ^i) on the world shock, and keep all the other parameters constant across countries.

where r^e_{t+1} represents the log excess return corrected for its Jensen term. The ratio $Var_t(m_{t+1})/E_t(m_{t+1})$ is the market price of risk. Lognormality implies that: to:

$$\frac{Var_t(m_{t+1})}{E_t(m_{t+1})} \simeq Std_t(m_{t+1}).$$

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

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

where the innovations v_{t+1}^i, v_{t+1}^w are uncorrelated across countries, *i.i.d* gaussian, with zero mean and unit variance. These processes ensure that log SDFs are heteroscedastic and that their variances remain positive. We assume that the market price of US-specific risk – and thus z^i– is counter-cyclical.

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

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

High interest rate currencies tend to have low loadings δ^i, while low interest rate currencies tend to have high loadings δ^i. The interest rate differential between country i and the home country is thus equal to:

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

The expected excess return in levels (i.e. corrected for the Jensen term) consists of two components:

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

The risk premium is *independent* of the foreign country-specific factor z_t^i and is independent of the foreign country-specific parameters γ, λ and τ. This is why we do not introduce heterogeneity in these parameters and simply take them as constant across countries. The expected log currency excess return does depend on the foreign factor:

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

Currency Portfolios Assume that we sort currencies into portfolios based on their forward discounts. The excess return of portfolio j is:

$$rx_{t+1}^j = \frac{1}{N_j}\sum_{i=1}^{N_j} rx_{t+1}^i,$$

where N_j denotes the number of currencies in portfolio j. We let $\overline{\delta_t^j}$ denote the average of all the δ^i of the i currencies grouped in portfolio j. Note that the portfolio composition changes over time, and in particular, it depends on the global risk price z_t^w.

2.2 Predictability in No-Arbitrage Currency Model

Expected Excess Returns The expected excess return of portfolio j is:

$$E_t[rx_{t+1}^j] = \frac{1}{2}\gamma\left(z_t - \overline{z_t^j}\right) + \frac{1}{2}\left(\delta - \overline{\delta^j}\right)z_t^w. \tag{2.1}$$

We assume that the country-specific shocks average out within each portfolio. In this case, $\overline{z^j}$ is constant in the limit $N \to \infty$ by the law of large numbers. As a result, the expected excess return on portfolio j depends on a dollar-specific component (the first term above, which depends on z) and a common component (the second term, which moves with z^w).

This common component drives carry trade returns. Consider the return on a strategy that goes long in high-interest rate currencies and short in low-interest rate currencies. The expected excess return on this long-short strategy – denoted *hml* for high minus low interest rates – is equal to:

$$E_t[hml_{t+1}] = \frac{1}{2}\left(\overline{\delta_t^L} - \overline{\delta_t^H}\right)z_t^w,$$

where $\overline{\delta_t^H}$ and $\overline{\delta_t^L}$ denote the average loading on the high and low interest rate portfolios. Carry trade expected excess returns only depend on the common risk factor z^w. The carry trade risk premium is driven by the global risk factor. The size of the carry trade risk premium is governed by the spread in the loadings (δ) on the common factor between low and high interest rate currencies, and by the global price of risk. When this spread doubles, the carry trade risk premium doubles. However, the spread itself also increases when the global Sharpe ratio is high. As a result, the carry trade risk premium increases non-linearly when global risk increases.

Going back to our initial portfolios, we see why high interest rate portfolios are risky. These portfolios load more on the carry trade component, because their loadings are smaller than the home country's δ, while the lowest interest rate currencies have a negative loading on the carry trade premium, because their loadings exceed the home country's δ. Note that the expected excess return of portfolio j depends only on z and z^w, which are the same variables that drive the average interest rate differential across all portfolios:

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

Finally, let us consider the average risk premium across all portfolios. If the home country's exposure to global risk factor equals to the average δ, the average risk premium is driven only by the US risk factor z. When the home country's δ differs from the average, then the average risk premium also loads on the global factor:

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

Model's Predictions This simple model offers three predictions. First, there should be no role for portfolio-specific variables in forecasting currency excess returns. There is no reason to include foreign real or nominal variables in predictability regressions. Expected excess returns depend on dollar and world components. In our specific example, they depend on the dollar risk factor z and on the global risk factor z^w. This is exactly what we find. We show in the next section that the average interest rate difference is a better predictor than the portfolio-specific one.

Second, in any reasonably specified model, the US-specific component of the risk price and hence the dollar risk premium, should be counter-cyclical with respect to the US-specific component of the business cycle. As a result, expected currency excess returns should be counter-cyclical. Using the interest difference to form expectations, we find that expected currency excess returns are highly counter-cyclical with respect to a set of macro and financial variables.

Third, long-short returns should be harder to forecast since they depend only on global variables that proxy for z^w, not on US-specific variables. The latter should have no predictive power on carry trade risk premia. We also confirm this prediction in the data.

3 Extracting Currency Risk Premia

We now turn to the data to test the predictability of currency excess returns and exchange rates. We build the same currency portfolios as in Lustig et al. (2008). To save space, we only rapidly review their main characteristics in this section, and refer the reader to Lustig et al. (2008) for details.

3.1 Building Currency Portfolios

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

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

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

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

$$rx_{t+1} = i^{\star}_t - i_t - \Delta s_{t+1}.$$

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

$$rx^l_{t+1} = f^b_t - s^a_{t+1}.$$

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

$$rx^s_{t+1} = -f^a_t + s^b_{t+1}.$$

Data We start from daily spot and forward exchange rates in US dollars. We build end-of-month series from November 1983 to January 2009. These data are collected by Barclays and Reuters and available on Datastream. Our main data set contains 37 currencies: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, Euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. Some of these currencies have pegged their exchange rate partly or completely to the US dollar over the course of the sample. We keep them in our sample because forward contracts were easily accessible to investors. We leave out Turkey and United Arab Emirates, even if we have data for these countries, because their forward rates appear disconnected from their spot rates. As a robustness check, we also study a sub-sample of our main data set that contains only 15 developed countries: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland and United Kingdom. Finally, we also consider a sample of developed countries that does not have bid and ask spreads but start in 1976. To save space, we report predictability results on these additional samples in a separate appendix.

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

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 is:

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

We sort the currencies into portfolios based on forward rates with the corresponding maturity, and we compute the average excess return for each portfolio as we did for one-month returns.

3.2 Returns to Currency Speculation for a US investor

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

The first panel reports the average rate of depreciation for all currencies in portfolio j. According to the standard uncovered interest rate parity (UIP) condition, the average rate of depreciation

$E_T(\Delta s^j)$ of currencies in portfolio j should equal the average forward discount on these currencies $E_T(f^j - s^j)$, reported in the second panel. Instead, currencies in the first portfolio trade at an average forward discount of -385 basis points, but they appreciate on average only by around 60 basis points over this sample. This adds up to a log currency excess return of minus 325 basis points on average, which is reported in the third panel. Currencies in the last portfolio trade at an average discount of 775 basis points but they depreciate only by 290 basis points on average. This adds up to a log currency excess return of 485 basis points on average. A large body of empirical work starting with Hansen and Hodrick (1980) and Fama (1984) reports violations of UIP. However, our results are different because our investment strategy only considers whether the currency's interest rate is currently high, not whether it is higher than usual.

The fourth panel reports average log currency excess returns net of transaction costs. Since we rebalance portfolios monthly, and transaction costs are incurred each month, these estimates of net returns to currency speculation are conservative. After taking into account bid-ask spreads, the average return on the first portfolio drops to minus 200 basis points. Note that the first column reports *minus* the actual log excess return for the first portfolio, because the investor is short in these currencies. The corresponding Sharpe ratio on this first portfolio is minus 0.24. The return on the sixth portfolio drops to 210 basis points. The corresponding Sharpe ratio on the last portfolio is 0.21.

The fifth panel reports returns on zero-cost strategies that go long in the high interest rate portfolios and short in the low interest rate portfolio. The spread between the net returns on the first and the last portfolio is 410 basis points. This high-minus-low strategy delivers a Sharpe ratio of 0.44, after taking into account bid-ask spreads. Equity returns provide a natural benchmark. Over the same sample, the (annualized) Fama-French monthly excess return on the US stock market is 5.1 percent, and the equity Sharpe ratio is 0.33. Note that this equity return does *not* reflect any transaction cost. Table 1 also reports results obtained on a smaller sample of developed countries. The Sharpe ratio on a long-short strategy is 0.21.

In the rest of this paper, we focus on gross excess returns and gross changes in exchange rates. We observe that bid-ask spreads vary with time. For example, the average spread in the last portfolio increases with the volatility index VIX. But this time-variation is very small compared to the mean bid-ask spread and the mean excess return. We choose not to take into account these bid-ask spreads because we are not interested here in the implementation of a trading strategy. We are simply looking for predictability evidence of exchange rates.

[Table 1 about here.]

We have documented that a US investor with access to forward currency markets can realize large excess returns with annualized Sharpe ratios that are comparable to those in the US stock market. In a companion paper, we show that this cross-section of average excess returns correspond to covariances with risk factors. We do not pursue this route here and we turn instead to the predictability of these excess returns.

4 Predictability in Currency Markets

In this section, we investigate the predictability of currency returns and changes in exchange rates. We show that the average forward discount across portfolios does a better job of describing the time variation in expected currency excess returns than the individual portfolio forward discounts and that expected excess returns are counter-cyclical, as implied by our no-arbitrage model.

4.1 Portfolio-Specific versus Average Forward Discounts

We first investigate the predictive power of the portfolio-specific forward discount, and then turn to the predictive power of the average forward discount. We start by looking at one-month returns. Our first set of results is in Table 2. In the left panel, we consider excess returns. In the right panel, we focus on changes in exchange rates. In each panel, the first three columns correspond to results obtained with the average forward discount, and the next three columns pertain to the portfolio-specific forward discount.

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

$$rx_{t+1}^j = \kappa_0^j + \kappa_f^j (f_t^j - s_t^j) + \eta_t^j.$$

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

There is strong evidence against UIP in these portfolio returns, more so than in individual currency returns. Looking across portfolios, from low to high interest rates, the slope coefficient κ_f^j (column 3) varies a lot: it increases from 107 basis points for currencies in the first portfolio to 325 basis points for currencies in the fourth portfolio. The slope coefficient decreases to 73 basis points for the sixth portfolio. Deviations from UIP are highest for currencies with medium to high forward discounts. However, forward rates are strongly autocorrelated. This complicates statistical inference about these slope coefficients. To deal with this issue, we use two asymptotically-valid corrections. The Newey-West standard errors (NW) are computed with the optimal number of lags following Andrews (1991). The Hansen-Hodrick standard errors (HH) are computed with one lag. Both of these methods correct for arbitrary error correlation and conditional heteroscedasticity. Bekaert, Hodrick and Marshall (1997) note that the small sample performance of these test statistics is also a source of concern. To address this problem, we report small sample standard errors. These were generated by bootstrapping 1,000 samples of returns and forward discounts from a bivariate VAR with one lag. The null of no predictability is rejected at the 1 percent significance level for all of these portfolios except for the third. At the one-month horizon, the R^2 on these predictability regressions varies between 1.2 and 3.8 percent. In other words, when considering currency portfolios, up to almost 4 percent of the variation in spot rates is predictable at a one-month horizon.

Since log excess returns are the difference between changes in spot rates at $t+1$ and forward discounts at t, these are equivalent to predictability regressions for spot changes in exchange rates. From κ_f^j, the slope coefficient in the return predictability regression, we can back out the implied slope coefficients δ_f in the standard UIP regression:

$$-\Delta s_{t+1}^j = \zeta_0^j + \zeta_f^j (f_t^j - s_t^j) + \eta_t^j,$$

where $\kappa_f = 1 - \zeta_f$. For example, the implied UIP coefficient on the fourth portfolio is -2.25: each 100 basis point increase in the forward discount reduces the expected appreciation of the foreign currency by 247 basis points. Predictability tests on changes in exchange rates confirm these first results. R^2s on exchange rates appear lower, ranging from 0 to 2.4 percent.

Average Forward Discount Yet, there is even more predictability in these excess returns and exchange rates than the standard UIP regressions reveal, because forward discounts on the other currency portfolios also help to forecast returns. We found that a single return forecasting variable describes time variation in 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 portfolios. We also examined the optimal linear combination of forward discounts along the lines of Cochrane and Piazzesi (2005). However, it does not really outperform the average forward discount as a predictor.

We use ι to denote the 6×1 vector with all elements equal to $1/6$. For each portfolio j, we run the following regression of log excess returns after bid-ask spreads on the average forward rates:

$$rx_{net,t+1}^j = \kappa_0^j + \kappa_{\mathbf{f}}^j \iota' (\mathbf{f}_t - \mathbf{s}_t) + \eta_t^j,$$

where $\mathbf{f}_t - \mathbf{s}_t$ bunches together all forward discounts. This single factor explains between 2.3 and 7.3 percent of the variation in returns at the one-month horizon. The average forward discount outperforms the portfolio-specific forward discounts, except in portfolios 4 and 5. Slope coefficients are more stable across the different portfolios than before. Portfolio-specific time variation in expected exchange rate movements driven by the sorting variable (relative interest rates) does not appear to be the main driver of return predictability in currency markets. The average interest rate difference is the main driver.

The intercept varies from -6.89 percent on the first portfolio to 1.81 percent on the last portfolio. This is to be expected, because the intercept plus the slope times the average forward discount equals the average return on each portfolio. This monotonic variation in the intercept demonstrates the importance of sorting currencies into portfolios before running this regression. As currencies switch portfolios, the intercept on these regressions changes. If we run these regressions on currency pairs, we are fixing these intercepts for each currency pair.

[Table 2 about here.]

Longer Horizons We check the robustness of these findings by looking at longer horizons. There, the fraction of changes in log spot rates explained by the forward discount is even greater than at short horizons. Table 3 is similar to Table 2 but focuses on one-year instead of one-month returns and exchange rates. At this horizon, we obtain R^2s rarely seen in the exchange rate literature. The average forward discount surpasses the portfolio-specific discount for every portfolio. R^2s range from 10 to 31 percent. Even changes in exchange rates appear predictable, with R^2s ranging from 5 to 21 percent. At longer horizons, the returns on the first portfolio are most predictable; the returns on the last portfolio are least predictable. On the first portfolio, almost a third of the variation in excess returns is accounted for by the forward rate at the 12-month horizon. On the last portfolio, 15 percent is accounted for by the forward rate. Slope coefficients appear all significant. We report the same three sets of standard errors as in Table 2. The Hansen and Hodrick (1980) HH standard error are now computed with k lags for the k-month ahead returns. We add the Newey and West (1987) standard errors obtained with non-overlapping series. To produce these measures, we simply used the first month of every period (quarter, year) to run the same regressions.

[Table 3 about here.]

We obtain similar results at all horizons. Table 4 provides a summary: it lists the R^2s we obtained for each portfolio (rows) and for each forecasting horizon (columns). In only seven cases out of thirty, the portfolio-specific forward discount offers more predictability. In all the other cases, the average forward discount is a better predictor. In fact, if we take the residuals of the average forward discount forecasting regression and we project these on the individual portfolio forward discounts, there is no predictability left. In Table 4, we also report the R^2s of these regressions. There is no information in the individual forward discounts left that helps to forecast currency returns.

One concern is that these measures of fit may be biased because we use overlapping returns and because the predictors are highly autocorrelated. In the right panel of Table 4 we also provide the same R^2 measures that we obtained for each forecasting horizon with non-overlapping data. Though there are some differences, these R^2s are not systematically lower. Even at longer horizons, the average forward discount seems to do a better job in describing the variation in expected excess returns. This single factor explains between 18 and 32 percent of the variation at the one-year horizon. This single factor mostly does as well and sometimes better than the forward discount of the specific portfolio in forecasting excess returns over the entire period.

[Table 4 about here.]

As a result, we conclude that the average forward discount contains information that is useful for forecasting excess returns on all currency portfolios, while little information is lost by aggregating all these forward discounts into a single predictor. The fact that the average forward discount is a *better predictor* of future excess returns on foreign currency than individual forward discount rates is consistent with the risk premium view: by using the average forward discount, we downplay all information related to country-specific real and nominal variables (inflation for example), and we do better in predicting future changes in exchange rates. This finding is similar to results of Stambaugh (1988) and Cochrane and Piazzesi (2005) for the predictability of Treasury bill and bond returns. These studies show that linear combinations of forward rates across maturities outperform the forward rate of a particular maturity in forecasting returns. In particular, Cochrane and Piazzesi (2005) report R^2s of up to 40 percent on one-year holding period returns for zero coupon bonds using a single forecasting factor. Currency returns are *more predictable* than stock returns, and almost as predictable as bond returns. We now turn to the business cycle properties of *expected* currency excess returns.

4.2 Counter-Cyclical Expected Excess Returns

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

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

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

At high frequencies, forecasted returns on high interest rate currency portfolios – especially for the sixth portfolio – increase very strongly in response to events like the Asian crisis in 1997 and the LTCM crisis in 1998, but at lower frequencies, a big fraction of the variation in forecasted excess returns is driven by the US business cycle, especially for the third, fourth and fifth portfolios. To assess the cyclicality of these forecasted excess returns, we use three standard business cycle indicators and three financial variables: (i) the 12-month percentage change in US industrial production index, (ii) the 12-month percentage change in total US non-farm payroll index, (iii) the 12-month percentage change in the Help Wanted index, (iv) the default spread (v) the slope of the yield curve, and (vi) the $S\&P$ 500 VIX volatility index.[3] 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 5 about here.]

Table 5 reports in the first panel the contemporaneous correlation of the month-ahead forecasted excess returns with these macroeconomic and financial variables. As expected, forecasted excess returns are strongly counter-cyclical.

On the one hand, the monthly contemporaneous correlation between predicted excess returns and percentage changes in industrial production (first column), the non-farm payroll (second column) and the help wanted index (third column) are negative for all portfolios. For payroll changes, the correlations range from -.7 for the first portfolio to -.1. for the sixth. Figure 1 plots the forecasted excess return on portfolio 2 against the 12-month change in US industrial production. Forecasted excess returns on the other portfolios have similar low frequency dynamics.

[Figure 1 about here.]

On the other hand, monthly correlations of the high interest rate currency portfolio with the default spread (fourth column) and the term spread (fifth column) are, as expected, positive.

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

Finally, the last column reports correlations with the equity option-implied volatility index (VIX). The VIX seems like a good proxy for the global risk factor because it is highly correlated with similar volatility indices abroad.[4] The correlations in the last column reveal a clear difference between the low interest rate currencies with negative correlations, and the high interest rate currencies, with positive correlations. Returns on portfolios 5 and 6 respond to dramatic events, like the Russian default and LTCM crisis, the Asian currency crisis and the Argentine default. This is consistent with the predictions of the no-arbitrage model in Lustig et al. (2008). 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. 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.

We find the same business cycle variation in expected returns over longer holding periods. The predictability is partly due to the counter-cyclical nature of the forward discount, but not entirely. Table 5 reports the correlation of the currency risk factor (the average forward discount) with the business cycle variables. At every maturity we consider, the average forward discount appears counter-cyclical. Since excess returns load positively on the average forward discount, they are also counter-cyclical.

Industrial Production as Predictor We have focused so far on the predictive power of forward discounts. But the fact that expected excess returns are clearly counter-cyclical suggest that macro variables themselves might help to forecast excess returns. We check this conjecture by focusing on the predictive power of the industrial production (IP) index.

The left panel of Table 6 reports regression results for:

$$rx_{t+k}^{j,k} = \gamma_0 + \gamma_{IP} \Delta \log IP_t + \eta_t^j,$$

where $rx_{t+k}^{j,k}$ denotes the k-month ahead excess return on portfolio j between time t and $t+k$. The right panel focuses on similar regressions run with changes in exchange rates instead of returns. In both panels, the first three columns correspond to the actual IP changes, while the next three columns correspond to the IP residuals. The table focuses on $k = 12$, *e.g.* a one-year horizon.

The change in industrial production explains up to 32 percent of the variation in excess returns at the 12-month horizon. All the estimated slope coefficients are significantly negative. A one percentage point drop in the annual change in industrial production raises the dollar risk premium

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

by 130 to 200 basis points per annum. At shorter horizons, this number is in the 100 to 150 basis point range. To save space, we do not report these results. Except for the 1-month horizon forecasts, the Wald test for the slope coefficient has p-values that are smaller than 5 percent for all portfolios. We obtain similar results on changes in exchange rates. The R^2s range form 13 to 29 percent at the 12-month horizon, using IP as the sole predictor.

The US industrial production index characterizes the US economy. Yet, it appears highly correlated with similar indices in other developed countries. For example, its correlation with the average index for the G7 countries (excluding the US, and using 12-month changes in each index) is equal to 0.5. To check that the US-specific component of the US 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.

$$
\begin{aligned}
\Delta \log IP_t &= \alpha + \beta \overline{\Delta \log IP_t} + IP_{res,t}, \\
rx^{j,k}_{net,t+k} &= \gamma_0 + \gamma_{IP_{res}} IP_{res,t} + \eta^j_t,
\end{aligned}
$$

where $\overline{\Delta \log IP_t}$ denotes the average of the G7 (excluding the US) 12-month changes in IP indices.

The predictive power of IP lies mostly in the US-specific component of IP, denoted $IP_{res,t}$. We obtain R^2s between 14 and 26 percent with the IP residuals. And the slope coefficients appear close to the previous ones. We will contrast these results to the predictive power of IP residuals on long-short returns. There, US-specific variables should have no predictive power, and they do not.

Controlling for the forward discount reduces the IP slope coefficient by 50 to 70 basis points on portfolios 1-4, much less for portfolios 5-6, but the forward discount does not drive out the macroeconomic variable. Table 7 reports forecasting results for currency portfolios obtained using the 12-month change in industrial production and either the portfolio-specific forward discount or the average forward discount. The currency risk premium increase in response to a one percentage point drop in the growth rate of industrial production varies between 105 (portfolio 1) and 170 basis points (portfolio 5). The IP slope coefficients are still significantly different from zero for the high interest rate portfolios, but the slope coefficients on the (average) forward discounts are not. Table 13, in the separate appendix, reports forecasting results for currency portfolios obtained using the US-specific $IP_{res,t}$ residuals and either the portfolio-specific forward discount or the average forward discount. Here, both the IP residuals and the forward discounts appear significant. Note, however, that the standard errors do not take into account the uncertainty due the estimation of the IP residuals. Focusing on the US-specific component increases the R^2 up to 40%.

The strong response of currency excess returns to industrial production resembles results reported by Cooper and Priestley (2009) on stock market excess returns. Cooper and Priestley (2009) show that the output gap, defined using the deviation of industrial production from a trend, is a very robust predictor of excess returns on the stock market in all G-7 countries. This variable is highly correlated with the growth rate of industrial production in our sample.

[Table 6 about here.]

[Table 7 about here.]

5 Long-Short Carry Trades

We turn now to the predictability of carry trade excess returns that are dollar-neutral. We consider the five possible long-short strategies in which the investor shorts the first portfolio and is long one of the next five portfolios. These long-short strategies characterize an investor seeking to borrow at the best market conditions in order to invest in high-interest rate countries. Recall that we expect these long-short excess returns to be predicted by global, not US-specific variables. Only variables that contain some information about the world risk factor should predict these long-short portfolios. One the one hand, US industrial production, particularly its component that is US-specific, should have no predictive power here, even if it predicts each portfolio excess return. On the other hand, if the average loading on world risk $\overline{\delta^i}$ is not exactly equal to the home country loading δ, the average interest rate differential then loads on both US and global risk factors and might predict long-short returns.

We test these predictions by running in-sample predictability tests on our five long-short portfolios. We first consider the average forward discount as a predictor. There is some evidence that the high-minus-low returns are predictable by the average forward spreads, but the evidence is less strong than on individual portfolio returns. Since the average spread in forward discounts is much less persistent than the forward discount, there is, however, less cause for concern about persistent regressor bias.

We report results in Table 8. The left panel focuses on excess returns; the right panel focuses on changes in exchange rates. It appears that the mean interest rate differential do not predict much of these long-short excess returns. Slope coefficients are not statistically different from zero, except for the first long-short (e.g, second minus first) returns and exchange rates. R^2s are smaller than on the original portfolios and range between 1.5 and 21 percent on currency excess returns and between 3.5 and 19.4 percent on changes in exchange rates.

The only significant slope coefficient in the left panel is negative. We can make sense of this negative coefficients if the US loads less on the world risk factor than the average country in our sample. We have seen that expected excess returns should increase with world risk z^w. This happens because the difference $\overline{\delta_t^L} - \overline{\delta_t^H}$ is positive in general since low interest rate currencies tend to have high δs. If the home δ is lower than the average delta, then the interest rate differential loads negatively on world risk z^w. As a result, excess returns co-move negatively with average interest rate differentials in this case.

We then consider the addition of US-specific predictors. Adding the 12-month change in industrial production to the average forward discount does not increase forecasting power. Table 14 in the separate appendix reports predictability results with both variables. Changes in the industrial production index appear almost always not significant, and they do not increase the adjusted R^2s. To check this point, we test the predictive power of the US-specific 12-month changes IP_{res} residuals described in the previous section. Table 9 reports the results. The IP_{res} residuals are never significant and all the R^2s are below 1.5 percent. Recall that the same IP_{res} residuals predict each portfolio excess return. But, as the model suggests, they have no predictive power for long-short excess returns.

[Table 8 about here.]

[Table 9 about here.]

6 Robustness Checks

In this section, we consider several robustness checks. First, we investigate the out-of-sample predictability of industrial production growth on exchange rates. Second, we take the point of view of foreign investors and show that currency excess returns are also predictable from their perspectives. Third, we consider sub-samples of developed countries and check our main results.

6.1 Out-of-Sample

We compare the out-of-sample predictability properties of our best predictor to a simple random walk with drift. We focus in this section on changes in exchanges rates, not currency excess returns, in order to make contact with the literature. As mentioned earlier, Meese and Rogoff (1983) find that the out-of-sample predictions of exchange rates based on a random walk dominate those of all macro-founded models they consider for up to 12-month ahead forecasts. Beating the random walk has become the benchmark, and most subsequent papers fail to achieve it. We show in this section that changes in industrial production predict six-month changes in exchange rates better than a random walk with drift.

Experiment In out-of-sample tests, two trade-offs occur: the length of the in-sample versus out-of-sample periods, and the horizon. The in-sample period corresponds to the first set observations used to estimate the model. A longer in-sample period might provide better estimates for the model, but leaves less observations to test it. Likewise, changes in exchange rates over longer horizons are easier to forecast, but longer horizons entail less non-overlapping periods. Here, we divide the total sample of length T in two parts of equal length. We consider either one-, three-, six- and twelve-month changes in exchange rates. For horizons above one-month, we focus on samples of non-overlapping observations.

We use the first part (of length R) to obtain an initial estimation of the model. We use the second part (of length P) to generate out-of-sample tests. The model is estimated recursively. For $t = R, ..., T-1$, we use the first t observations to estimate two linear models:

$$\begin{aligned}\Delta s_{t+1} &= x_{1,t}'\beta_1 + u_{1,t+1}, \\ \Delta s_{t+1} &= x_{2,t}'\beta_2 + u_{2,t+1},\end{aligned}$$

where Δs_{t+1} denotes the one-period ahead change in exchange rates, and $x_{i,t}'$ the predictor. Since we focus on non-overlapping samples, the h-month ahead change in exchange rates correspond always to a one-period ahead change in s. In the first case, when the model is a random walk with drift, $x_{1,t}$ is simply a constant. In the second case, $x_{2,t}$ contains a constant and the twelve-month changes in industrial production index. Under the null hypothesis of equal forecast accuracy, model 2 nests model 1, e.g $\beta_2 = (\beta_1', 0')'$ and $u_{1,t+1} = u_{2,t+1}$. We compute the one-step ahead forecast error for both models: $\hat{u}_{1,t+1} = \Delta s_{t+1} - x_{1,t}'\widehat{\beta_{1,t}}$ and $\hat{u}_{2,t+1} = \Delta s_{t+1} - x_{2,t}'\widehat{\beta_{2,t}}$. Note that the one-step ahead forecast is computed using only information available at date t. The estimation is recursive, and thus $\beta_{1,t}$ and $\beta_{2,t}$ vary with time.

Test Statistics We report the square root of the two mean squared errors $RMSE_{RW}$ (for the random walk) and $RMSE$ (for the whole model), as well as their ratio ($Ratio = RMSE_{RW}/RMSE$). A ratio above 1 indicates that the model beats the random walk with drift. We also report two additional test statistics: the Diebold and Mariano (1995)'s and the Clark and McCracken (2001)'s statistics. We rapidly review them here.

Let $\overline{d}$ be the difference between the two mean-squared errors ($\overline{d} = MSE_2 - MSE_1$) based upon the sequence of loss differentials $\hat{d}_{t+1} = \hat{u}_{1,t+1}^2 - \hat{u}_{2,t+1}^2$. Denote the estimated spectral density matrix by $\hat{S}_{dd}$. Diebold and Mariano (1995) propose the following test statistic (denoted MSE_t):

$$MSE_t = \sqrt{P}\frac{\overline{d}}{\sqrt{\hat{S}_{dd}}}.$$

Following Clark and McCracken (2001), we use the covariance matrix instead of the spectral density matrix. Under the null that the mean squared error associated with model 1 is the same as that for model 2, the expected difference between $\hat{u}_{1,t+1}^2$ and $\hat{u}_{2,t+1}^2$ is zero. Under the alternative, the mean squared error associated with model 2 is smaller than that for model 1, and the test statistic is positive.

The second test statistic is based on the covariance between $\hat{u}_{1,t+1}$ and $\hat{u}_{1,t+1} - \hat{u}_{2,t+1}$. Under the null that model 1 encompasses model 2, the covariance between $\hat{u}_{1,t+1}$ and $\hat{u}_{1,t+1} - \hat{u}_{2,t+1}$ will be less than or equal to 0. Under the alternative that model 2 contains additional information, the covariance should be positive. Let us define $\hat{c}_{t+1} = \hat{u}_{1,t+1}(\hat{u}_{1,t+1} - \hat{u}_{2,t+1})$ and $\overline{c} = P^{-1}\sum_{t=R}^{T-1}\hat{c}_{1,t+1}$. Then, the second test statistics (denoted ENC) is:

$$ENC = P\frac{\overline{c}}{MSE_2}.$$

The limiting distributions of these different statistics are non-standard.[5] We bootstrap their computation to assess their significance. The bootstrap approach is the following: first, we compute a one-lag VAR including the changes in exchange rates and the predictor. Drawing randomly (with replacement) among the estimated residuals, we construct two new series. Then, for each set of series, we perform the same out-of-sample tests as described above and construct the above *Ratio*, $MSE - t$ and ENC statistics.

Results Table 10 reports our results, focusing on one- and six-month horizons. At the one-month horizon, Meese and Rogoff (1983)'s result stands. A simple random walk leads to more accurate forecasts than changes in industrial production. The ratio of the two mean squared errors is at best equal to one, and often below one. Accordingly, the Diebold and Mariano (1995)'s and Clark and McCracken (2001)'s statistics are often negative, and never significantly positive. At the six-month horizon, however, changes in industrial production predict changes in exchange rates much better than a simple constant. The ratio of the two mean squared errors is above one for all portfolios, except the second. For the last three portfolios, the three test statistics deliver a consistent message: the random walk is not the best predictor of these changes in exchange rates. Industrial production allows a decrease of up to 20 percent of the mean squared errors.

Table 15 in the separate appendix reports results on three- and twelve month changes in exchange rates. We do not find much predictability for three-month changes in exchange rates. But, again, for longer horizons, we obtain much better forecasts with industrial production than with a simple random walk.

[Table 10 about here.]

6.2 Foreign Investors

We now adopt the perspective of foreign investors and we consider currency excess returns denominated in foreign currency. We report summary statistics on these excess returns and test their business cycle properties using foreign employment.

[5] Diebold and Mariano (1995) highlight the asymptotic normal distribution of their statistic but their results apply only to non-nested models.

We consider the case of a UK investor, a Japanese investor and a Canadian investor. These are three countries with large and well-developed currency markets for which we find long time series of monthly macroeconomic variables. We compute the excess returns that local investors would obtain if they had access to forward contracts in their own currency. We obtained these excess returns by converting dollars into local currency at the midpoint rate. This way, investors are not hit twice by the bid-ask spread. Summary statistics on these currency excess returns are reported in Table 11.

[Table 11 about here.]

Using employment data in each country, we show that foreign currency excess returns are predictable from the US, UK, Japan and Canada perspectives. We consider one-year ahead predictability tests. Table 12 reports the results. In all the countries above, currency excess returns appear countercyclical. All the slope coefficients are negative on all portfolios. These slope coefficients are, however, not always statistically significant, and the R^2 remain low, in the 0 to 10% range. There is some predictability, but not much – at least compared to our previous results.

[Table 12 about here.]

6.3 Developed Countries

Finally, we check our results on our smaller sample of developed countries. The excess returns and changes in exchange rates correspond to the portfolios presented in the right panel of Table 1. The results are in the separate appendix. Table 16 reports predictability tests on one-month currency excess returns and one-month changes in exchange rates on a sample of developed countries. Table 17 reports similar tests at the one-year horizon. The R^2s are lower than those we reported in our large sample of developed and emerging countries, but that is mainly because there is more idiosyncratic variation in these returns, since the portfolios are composed of fewer currencies. At the one-year horizon, R^2s on currency excess returns still range form 7.9 to 20 percent. Some developing countries like Saudi Arabia and Hong Kong have pegged their exchange rate to the dollar. This could potentially inflate the predictability of currency returns but samples that exclude these countries offer similar results.

Our samples so far start in 1983. We can start earlier, in 1976, if we focus on one-month and three-month horizons for which forward contracts are available. Here again, the results are in the separate appendix. Table 18 reports predictability tests on one-month currency excess returns and one-month changes in exchange rates over a long sample (1976-2009) of developed countries. Table 19 reports similar tests at the three-month horizon. In both tables, the countries in sample are: Australia,Austria, Belgium, Canada, Denmark, Euro Area, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland and United Kingdom. The results obtained on this sample are similar to the ones obtained on previous samples at the same horizons.

7 Conclusion

We have documented in this paper that returns in currency markets are highly predictable. The average forward discount rate and the change in the US industrial production index accurately predict up to 38 percent of the variation in average annual excess returns across our portfolios. The time variation in expected returns has a clear business cycle pattern: US macroeconomic variables are powerful predictors of these returns, especially at longer holding periods, and expected currency returns are strongly counter-cyclical. We view these findings as supportive of a risk-based explanation of exchange rates.

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Table 1: Currency Portfolios - US Investor

Portfolio	1	2	3	4	5	6	1	2	3	4	5
	Panel I: All Countries						Panel II: Developed Countries				
	Spot change: Δs^j						Δs^j				
Mean	-0.63	-0.52	-0.94	-1.83	0.33	2.92	-1.69	-1.41	-2.87	-1.05	0.54
Std	8.23	7.41	7.60	7.68	8.24	9.70	10.21	9.89	9.68	9.56	9.96
	Forward Discount: $f^j - s^j$						$f^j - s^j$				
Mean	-3.85	-1.28	-0.12	0.97	2.58	7.76	-3.05	-0.98	0.10	1.18	3.97
Std	1.55	0.49	0.48	0.52	0.58	2.05	0.77	0.63	0.65	0.67	0.75
	Excess Return: rx^j (without b-a)						rx^j (without b-a)				
Mean	-3.23	-0.76	0.82	2.79	2.25	4.84	-1.35	0.44	2.98	2.23	3.43
Std	8.40	7.47	7.64	7.78	8.33	9.80	10.28	9.93	9.78	9.64	10.05
SR	-0.38	-0.10	0.11	0.36	0.27	0.49	-0.13	0.04	0.30	0.23	0.34
	Net Excess Return: rx^j_{net} (with b-a)						rx^j_{net} (with b-a)				
Mean	-1.99	-1.73	-0.46	1.45	0.75	2.08	-0.23	-0.61	1.58	0.97	1.74
Std	8.38	7.47	7.62	7.73	8.33	9.80	10.28	9.93	9.75	9.65	10.04
SR	-0.24	-0.23	-0.06	0.19	0.09	0.21	-0.02	-0.06	0.16	0.10	0.17
	High-minus-Low: $rx^j - rx^1$ (without b-a)						$rx^j - rx^1$ (without b-a)				
Mean		2.47	4.05	6.02	5.48	8.07		1.79	4.33	3.58	4.78
Std		5.62	5.60	6.72	6.68	9.17		7.19	7.06	8.09	9.51
SR		0.44	0.72	0.90	0.82	0.88		0.25	0.61	0.44	0.50
	High-minus-Low: $rx^j_{net} - rx^1_{net}$ (with b-a)						$rx^j_{net} - rx^1_{net}$ (with b-a)				
Mean		0.26	1.53	3.44	2.74	4.07		-0.38	1.82	1.20	1.98
Std		5.62	5.62	6.70	6.69	9.22		7.21	7.06	8.11	9.52
SR		0.05	0.27	0.51	0.41	0.44		-0.05	0.26	0.15	0.21

Notes: This table reports, for each portfolio j, the average change in log spot exchange rates Δs^j, the average log forward discount $f^j - s^j$, the average log excess return rx^j without bid-ask spreads, the average log excess return rx^j_{net} with bid-ask spreads, and the average return on the long short strategy $rx^j_{net} - rx^1_{net}$ and $rx^j - rx^1$ (with and without bid-ask spreads). Log currency excess returns are computed as $rx^j_{t+1} = -\Delta s^j_{t+1} + f^j_t - s^j_t$. All moments are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The portfolios are constructed by sorting currencies into five (right panel) or six (left panel) groups at time t based on the one-month forward discount (i.e nominal interest rate differential) at the end of period $t-1$. The first portfolio (1) contains currencies with the lowest interest rates. The last portfolio (5 or 6) contains currencies with the highest interest rates. Panel I uses all countries, panel II focuses on developed countries. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983–1/2009.

Table 2: One-Month Ahead Predictability

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
Forward Discount	Average			Individual			Average			Individual		
1	−6.89	3.63	7.27	0.88	1.07	3.87	−1.72	2.32	3.10	0.88	0.07	0.02
NW	[1.82]	[0.64]		[1.83]	[0.32]		[1.88]	[0.76]		[1.83]	[0.32]	
HH	[1.79]	[0.56]		[1.61]	[0.23]		[1.83]	[0.68]		[1.61]	[0.23]	
VAR	[1.70]	[0.71]		[1.93]	[0.34]		[1.82]	[0.78]		[1.90]	[0.34]	
2	−3.05	2.27	3.58	2.30	2.40	2.44	−1.30	1.80	2.30	2.30	1.40	0.84
NW	[1.82]	[0.70]		[1.55]	[0.97]		[1.80]	[0.72]		[1.55]	[0.97]	
HH	[1.84]	[0.69]		[1.61]	[0.91]		[1.81]	[0.70]		[1.61]	[0.91]	
VAR	[1.82]	[0.76]		[1.86]	[1.07]		[1.85]	[0.81]		[1.87]	[1.13]	
3	−1.08	1.88	2.35	1.03	1.78	1.25	−0.40	1.33	1.19	1.03	0.78	0.24
NW	[1.77]	[0.65]		[1.50]	[1.03]		[1.75]	[0.66]		[1.50]	[1.03]	
HH	[1.80]	[0.62]		[1.50]	[1.00]		[1.77]	[0.63]		[1.50]	[1.00]	
VAR	[1.75]	[0.72]		[1.50]	[0.99]		[1.69]	[0.71]		[1.56]	[1.01]	
4	0.66	2.11	2.87	−0.36	3.25	4.83	0.33	1.49	1.46	−0.36	2.25	2.38
NW	[1.73]	[0.66]		[1.52]	[0.87]		[1.64]	[0.63]		[1.52]	[0.87]	
HH	[1.72]	[0.63]		[1.54]	[0.81]		[1.68]	[0.60]		[1.54]	[0.81]	
VAR	[1.84]	[0.76]		[2.03]	[1.01]		[1.84]	[0.76]		[2.02]	[0.99]	
5	−0.30	2.52	3.57	−5.00	2.81	3.84	−2.18	1.83	1.93	−5.00	1.81	1.63
NW	[1.76]	[0.78]		[2.63]	[0.95]		[1.74]	[0.77]		[2.63]	[0.95]	
HH	[1.77]	[0.75]		[2.63]	[0.93]		[1.74]	[0.74]		[2.63]	[0.93]	
VAR	[1.88]	[0.84]		[2.94]	[0.93]		[1.91]	[0.83]		[2.99]	[0.95]	
6	1.81	3.01	3.67	−0.79	0.73	2.31	−3.56	0.64	0.17	−0.79	−0.27	0.34
NW	[2.18]	[0.87]		[2.56]	[0.22]		[2.26]	[1.02]		[2.56]	[0.22]	
HH	[2.13]	[0.85]		[2.55]	[0.21]		[2.20]	[1.02]		[2.55]	[0.21]	
VAR	[2.46]	[1.01]		[3.04]	[0.34]		[2.52]	[1.18]		[3.16]	[0.33]	
Average	−1.47	2.57	5.29	−1.47	2.57	5.29	−1.47	1.57	2.04	−1.47	1.57	2.04
NW	[1.53]	[0.57]		[1.53]	[0.57]		[1.53]	[0.57]		1.53	[0.57]	
HH	[1.56]	[0.54]		[1.56]	[0.54]		[1.56]	[0.54]		1.56	[0.54]	
VAR	[1.59]	[0.70]		[1.70]	[0.70]		[1.60]	[0.67]		1.65	[0.71]	

Notes: Panel I reports summary statistics for return predictability regressions at a one-month horizon. For each portfolio j and their average, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a one-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 3: One-Year Ahead Predictability

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
Forward Discount	Average			Individual			Average			Individual		
1	−2.73	3.87	30.84	8.74	3.26	25.48	0.58	3.00	21.35	8.74	2.26	14.11
NW	[1.87]	[0.75]		[1.73]	[0.74]		[1.85]	[0.75]		[1.73]	[0.74]	
HH	[2.07]	[0.71]		[1.79]	[0.77]		[2.05]	[0.71]		[1.79]	[0.77]	
VAR	[1.85]	[1.02]		[3.63]	[1.10]		[1.82]	[0.97]		[3.74]	[1.13]	
Over	[1.78]	[0.87]		[3.52]	[1.00]		[2.24]	[0.98]		[2.11]	[0.96]	
2	−1.72	1.82	10.45	1.86	1.91	10.21	0.04	1.04	3.67	1.86	0.91	2.52
NW	[1.69]	[0.70]		[1.11]	[0.67]		[1.67]	[0.71]		[1.11]	[0.67]	
HH	[1.86]	[0.65]		[1.18]	[0.64]		[1.84]	[0.66]		[1.18]	[0.64]	
VAR	[1.46]	[0.90]		[1.88]	[0.96]		[1.47]	[0.89]		[1.90]	[0.95]	
Over	[1.97]	[0.98]		[1.92]	[1.12]		[2.37]	[1.24]		[1.61]	[1.21]	
3	−0.42	2.59	18.87	1.85	2.52	17.61	0.41	1.67	8.82	1.85	1.52	7.23
NW	[1.60]	[0.80]		[1.45]	[0.84]		[1.60]	[0.82]		[1.45]	[0.84]	
HH	[1.77]	[0.84]		[1.65]	[0.87]		[1.77]	[0.86]		[1.65]	[0.87]	
VAR	[1.61]	[1.02]		[1.65]	[1.03]		[1.65]	[1.01]		[1.65]	[1.05]	
Over	[1.23]	[0.94]		[1.17]	[0.84]		[1.74]	[1.09]		[1.20]	[1.11]	
4	0.94	2.31	16.62	1.05	2.13	16.61	0.95	1.29	5.88	1.05	1.13	5.30
NW	[1.38]	[0.79]		[1.37]	[0.69]		[1.37]	[0.78]		[1.37]	[0.69]	
HH	[1.50]	[0.82]		[1.48]	[0.68]		[1.50]	[0.81]		[1.48]	[0.68]	
VAR	[1.65]	[0.91]		[1.59]	[0.84]		[1.65]	[0.93]		[1.55]	[0.84]	
Over	[2.35]	[1.11]		[2.16]	[0.96]		[2.45]	[1.24]		[2.31]	[1.10]	
5	1.71	2.66	15.65	−1.02	2.32	15.20	0.46	1.61	6.41	−1.02	1.32	5.47
NW	[1.58]	[0.82]		[1.88]	[0.77]		[1.54]	[0.81]		[1.88]	[0.77]	
HH	[1.68]	[0.74]		[1.89]	[0.78]		[1.64]	[0.74]		[1.89]	[0.78]	
VAR	[2.20]	[1.27]		[2.94]	[1.09]		[2.20]	[1.26]		[2.97]	[1.09]	
Over	[1.66]	[1.29]		[2.15]	[1.19]		[2.31]	[1.34]		[2.90]	[0.94]	
6	1.77	2.98	15.72	−3.02	1.21	9.56	−2.90	1.63	5.18	−3.02	0.21	0.33
NW	[1.61]	[1.12]		[2.51]	[0.47]		[1.79]	[1.01]		[2.51]	[0.47]	
HH	[1.78]	[1.23]		[2.69]	[0.50]		[1.98]	[1.11]		[2.69]	[0.50]	
VAR	[2.90]	[1.79]		[5.21]	[0.91]		[2.89]	[1.77]		[5.32]	[0.91]	
Over	[1.59]	[1.10]		[3.92]	[0.72]		[1.92]	[1.19]		[3.83]	[0.65]	
Average	−0.08	2.71	23.33	−0.08	2.71	23.33	−0.08	1.71	10.79	−0.08	1.71	10.79
NW	[1.48]	[0.73]		[1.48]	[0.73]		[1.48]	[0.73]		[1.48]	[0.73]	
HH	[1.62]	[0.72]		[1.62]	[0.72]		[1.62]	[0.72]		[1.62]	[0.72]	
VAR	[1.95]	[1.05]		[1.93]	[1.05]		[1.95]	[1.06]		[1.97]	[1.04]	
Over	[2.01]	[1.15]		[2.01]	[1.15]		[2.01]	[1.15]		[2.01]	[1.15]	

Notes: Panel I reports summary statistics for return predictability regressions at a twelve-month horizon. For each portfolio j and their average, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a twelve-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) *HH* standard error are computed with twelve lags. The bootstrapped standard errors *VAR* are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 4: Return Predictability: Portfolio-Specific versus Average Forward Discount

Horizon		1	2	3	6	12	1	2	3	6	12
Portfolio		Overlapping Data					No Overlapping Data				
1	*Portfolio*	3.87	4.52	7.76	24.79	25.48	3.87	2.44	8.66	24.07	27.12
	Average	7.27	12.64	16.54	27.25	30.84	7.27	13.28	17.50	29.34	27.32
	Residual	0.03	0.04	0.00	0.73	0.31	0.03	0.31	0.00	0.20	0.23
2	*Portfolio*	2.44	2.44	5.34	10.44	10.21	2.44	2.10	3.62	11.24	3.67
	Average	3.58	4.90	9.45	14.10	10.45	3.58	6.97	7.93	17.00	6.18
	Residual	0.08	0.04	0.02	0.10	0.03	0.08	0.00	0.00	0.00	0.21
3	*Portfolio*	1.25	4.16	5.81	8.99	17.61	1.25	4.42	6.87	17.55	13.03
	Average	2.35	4.92	6.38	9.19	18.87	2.35	5.37	7.37	20.27	18.64
	Residual	0.11	0.17	0.19	0.35	0.06	0.11	0.09	0.23	0.21	0.19
4	*Portfolio*	4.83	7.02	7.74	15.36	16.61	4.83	5.55	6.96	24.97	9.49
	Average	2.87	4.93	6.23	13.57	16.62	2.87	5.01	5.16	21.94	11.39
	Residual	0.24	0.31	0.26	0.14	0.08	0.24	0.22	0.30	0.20	0.00
5	*Portfolio*	3.84	7.13	6.31	12.44	15.20	3.84	7.71	5.82	33.30	19.94
	Average	3.57	6.47	6.56	14.67	15.65	3.57	6.32	5.92	29.32	14.20
	Residual	0.14	0.15	0.02	0.03	0.17	0.14	0.32	0.02	0.11	1.81
6	*Portfolio*	2.31	2.85	3.41	4.91	9.56	2.31	3.21	3.48	4.70	10.06
	Average	3.67	4.87	6.19	9.36	15.72	3.67	4.67	5.14	12.62	20.35
	Residual	0.06	0.21	0.29	0.83	0.87	0.06	0.02	0.30	0.90	0.39

Notes: This table reports R^2 of three sets of time-series regressions. The first set (denoted *Portfolio*) corresponds to regressions of the log k-period currency excess return on the log forward discount for each portfolio j:

$$rx_{t+k}^{j,k} = \kappa_0^j + \kappa_1^j (f_t^{j,k} - s_t^j) + \eta_t^{j,k}.$$

The second set (denoted *Average*) corresponds to regressions the log k-period currency excess return for each portfolio j on the average of log forward discounts across portfolios:

$$rx_{t+k}^{j,k} = \kappa_0^j + \kappa_1^j \iota' (\mathbf{f}_t^k - \mathbf{s}_t^k) + \eta_t^{j,k},$$

for each portfolio j. The third set (denoted *Residual*) corresponds to the residual predictability. We obtain it in two steps. First, we regress the log k-period currency excess return on the average log forward discount for each portfolio j:

$$rx_{t+k}^{j,k} = \kappa_0^j + \kappa_1^j \iota' (\mathbf{f}_t^k - \mathbf{s}_t^k) + \eta_t^{j,k}.$$

We then report the R^2 in the time-series regression of the residuals $\eta_t^{j,k}$ from the first step on the log forward discounts for each portfolio j:

$$\eta_{t+k}^{j,k} = \kappa_0^j + \kappa_1^j (f_t^k - s_t^k) + \epsilon_t^{j,k},$$

for each portfolio j. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983–1/2009. The left panel panel uses overlapping data and the right panel does not. We consider horizons of $k = 1,\ 2,\ 3,\ 6$ and 12 months.

Table 5: Contemporaneous Correlations Between Expected Excess Returns or Average Forward Discounts and Macroeconomic and Financial Variables

	IP	Pay	$Help$	$Spread$	$Slope$	VIX	Vol
Portfolio	Panel I: Expected Excess Returns						
1	−0.56	−0.74	−0.48]	0.28	0.46	−0.09	0.05
	[0.12]	[0.11]	[0.16	[0.06]	[0.14]	[0.07]	[0.07]
2	−0.58	−0.78	−0.53]	0.38	0.41	−0.03	0.13
	[0.12]	[0.11]	[0.15	[0.06]	[0.15]	[0.07]	[0.07]
3	−0.55	−0.66	−0.45]	0.35	0.44	0.07	0.13
	[0.17]	[0.14]	[0.17	[0.05]	[0.12]	[0.06]	[0.06]
4	−0.49	−0.56	−0.39]	0.27	0.38	0.13	0.14
	[0.21]	[0.17]	[0.19	[0.05]	[0.12]	[0.06]	[0.06]
5	−0.33	−0.42	−0.22]	0.19	0.44	0.23	0.19
	[0.18]	[0.15]	[0.14	[0.05]	[0.09]	[0.06]	[0.06]
6	−0.05	−0.13	−0.06	0.13	0.14	0.52	0.40
	[0.19]	[0.16]	[0.12]	[0.05]	[0.10]	[0.06]	[0.07]
Maturity	Panel II: Average Forward Discount						
1	−0.28	−0.34	−0.16	0.18	0.33	0.18	0.12
	[0.16]	[0.14]	[0.15]	[0.05]	[0.09]	[0.05]	[0.06]
2	−0.40	−0.46	−0.27	0.25	0.40	0.23	0.17
	[0.18]	[0.16]	[0.15]	[0.05]	[0.09]	[0.06]	[0.06]
3	−0.45	−0.51	−0.32	0.29	0.41	0.25	0.18
	[0.18]	[0.16]	[0.15]	[0.05]	[0.10]	[0.06]	[0.06]
6	−0.50	−0.56	−0.38	0.35	0.40	0.33	0.25
	[0.19]	[0.16]	[0.15]	[0.05]	[0.10]	[0.06]	[0.06]
12	−0.45	−0.59	−0.37	0.29	0.41	0.25	0.24
	[0.20]	[0.16]	[0.16]	[0.05]	[0.10]	[0.06]	[0.06]

Notes: Panel I reports the contemporaneous correlation $Corr\left[\widehat{E}_t rx^j_{t+1}, x_t\right]$ between forecasted excess returns (obtained with the portfolio-specific forward discount) and different macroeconomicand financial variables x_t: the 12-month percentage change in industrial production (IP), the 12-month percentage change in the total US non-farm payroll (Pay), and the 12-month percentage change of the Help-Wanted index ($Help$), the default spread ($Spread$), the slope of the yield curve ($Slope$) and the CBOE $S\&P$ 500 volatility index (Vol). Panel II reports the contemporaneous correlation of the average forward discount with these variables. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–1/2009.

Table 6: Forecasting One-Year Ahead Excess Returns and Changes in Exchange Rates with Industrial Production

Portfolios	γ_0	γ_{IP}	R^2	γ_0	$\gamma_{IP_{res}}$	R^2	γ_0	γ_{IP}	R^2	γ_0	$\gamma_{IP_{res}}$	R^2
	Panel I: Excess Returns						Panel II: Exchange Rates					
1	4.92	−1.74	23.19	−0.17	−1.75	17.11	6.74	−1.42	17.94	2.56	−1.58	16.01
NW	[2.55]	[0.48]		[1.91]	[0.75]		[2.46]	[0.42]		[1.77]	[0.68]	
HH	[2.90]	[0.51]		[2.18]	[0.84]		[2.80]	[0.45]		[2.02]	[0.75]	
VAR	[3.24]	[0.67]		[2.59]	[0.78]		[3.17]	[0.67]		[2.26]	[0.71]	
Over	[2.78]	[0.55]		[1.94]	[0.79]		[2.75]	[0.46]		[1.83]	[0.72]	
2	3.28	−1.29	19.72	−0.52	−1.61	22.13	3.70	−1.01	13.07	0.73	−1.45	19.52
NW	[1.83]	[0.41]		[1.28]	[0.50]		[1.85]	[0.37]		[1.25]	[0.46]	
HH	[2.03]	[0.44]		[1.45]	[0.54]		[2.07]	[0.40]		[1.40]	[0.49]	
VAR	[2.19]	[0.48]		[1.37]	[0.48]		[2.21]	[0.49]		[1.31]	[0.47]	
Over	[2.06]	[0.50]		[1.62]	[0.55]		[2.10]	[0.47]		[1.64]	[0.51]	
3	6.02	−1.61	27.28	1.30	−1.82	25.15	5.42	−1.33	20.95	1.51	−1.65	23.29
NW	[1.83]	[0.36]		[1.34]	[0.46]		[1.76]	[0.33]		[1.24]	[0.39]	
HH	[2.06]	[0.40]		[1.51]	[0.51]		[1.98]	[0.36]		[1.39]	[0.43]	
VAR	[2.33]	[0.50]		[1.57]	[0.56]		[2.25]	[0.49]		[1.47]	[0.51]	
Over	[1.75]	[0.45]		[1.10]	[0.52]		[1.70]	[0.41]		[0.80]	[0.45]	
4	6.88	−1.50	26.24	2.47	−1.66	23.16	5.41	−1.23	19.92	1.80	−1.47	20.80
NW	[1.76]	[0.34]		[1.24]	[0.43]		[1.64]	[0.29]		[1.14]	[0.34]	
HH	[1.97]	[0.36]		[1.40]	[0.46]		[1.84]	[0.30]		[1.28]	[0.35]	
VAR	[2.00]	[0.46]		[1.61]	[0.54]		[2.12]	[0.48]		[1.46]	[0.48]	
Over	[2.18]	[0.40]		[1.82]	[0.49]		[2.10]	[0.29]		[1.79]	[0.44]	
5	9.28	−1.98	32.34	3.47	−2.09	26.11	6.77	−1.78	29.31	1.53	−1.97	25.90
NW	[1.89]	[0.37]		[1.39]	[0.49]		[1.66]	[0.33]		[1.24]	[0.40]	
HH	[2.05]	[0.38]		[1.55]	[0.51]		[1.78]	[0.33]		[1.36]	[0.41]	
VAR	[2.71]	[0.62]		[2.15]	[0.71]		[2.61]	[0.59]		[1.91]	[0.66]	
Over	[2.39]	[0.59]		[1.58]	[0.67]		[2.06]	[0.49]		[1.45]	[0.59]	
6	8.47	−1.61	17.23	3.74	−1.70	13.97	2.77	−1.57	17.91	−1.82	−1.77	16.69
NW	[1.81]	[0.47]		[1.69]	[0.57]		[1.57]	[0.46]		[1.52]	[0.51]	
HH	[2.00]	[0.49]		[1.89]	[0.62]		[1.72]	[0.50]		[1.69]	[0.54]	
VAR	[3.96]	[0.84]		[2.86]	[0.93]		[3.73]	[0.80]		[2.59]	[0.84]	
Over	[1.77]	[0.55]		[1.67]	[0.62]		[1.67]	[0.51]		[1.55]	[0.60]	
Average	6.48	−1.62	31.36	1.71	−1.77	27.11	5.13	−1.39	26.79	1.05	−1.65	27.34
NW	[1.76]	[0.37]		[1.30]	[0.48]		[1.63]	[0.32]		[1.17]	[0.40]	
HH	[1.97]	[0.40]		[1.47]	[0.53]		[1.82]	[0.34]		[1.31]	[0.43]	
VAR	[3.03]	[0.61]		[2.17]	[0.67]		[2.98]	[0.60]		[1.94]	[0.63]	
Over	[1.99]	[0.46]		[1.45]	[0.52]		[1.86]	[0.41]		[1.34]	[0.45]	

Notes: This table reports constant, slope coefficient and R^2 in predictability tests using either 12-month changes in the US industrial production index or 12-month residual changes in the US industrial production index. These residuals correspond to the US-specific component in IP. They are obtained by projecting the US 12-month change in IP on the average change in IP across G7 countries excluding the US. The left panel focuses on currency excess returns. The right panel focuses on changes in exchange rates. The Newey and West (1987) NW standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–1/2009.

Table 7: Forecasting One-Year Ahead Excess Returns and Changes in Exchange Rates with Industrial Production and Forward Discounts

Portfolios	κ_{IP}	κ_f	W	R^2	κ_{IP}	$\kappa_{\mathbf{f}}$	W	R^2	κ_{IP}	κ_f	W	R^2	κ_{IP}	$\kappa_{\mathbf{f}}$	W	R^2
	Panel I: Excess Returns								Panel II: Exchange Rates							
1	−1.05	2.96	0.00	37.60	−1.04	2.21		31.20	−0.91	2.21		27.20	−1.04	1.21		20.71
NW	[0.36]	[0.81]	40.84		[0.61]	[1.14]	36.35		[0.34]	[0.80]	24.25		[0.61]	[1.14]	21.10	
HH	[0.39]	[0.84]	42.22		[0.68]	[1.29]	35.09		[0.37]	[0.83]	24.69		[0.68]	[1.29]	20.42	
VAR	[0.64]	[1.09]	60.81		[0.72]	[1.29]	48.78		[0.64]	[1.12]	40.23		[0.72]	[1.30]	28.45	
Over	[0.48]	[1.41]	15.04		[0.70]	[1.49]	20.82		[0.48]	[1.25]	13.48		[0.70]	[1.49]	11.49	
2	−1.09	0.88		21.64	−1.14	0.56		20.29	−0.97	0.20		13.17	−1.14	−0.44		13.46
NW	[0.42]	[0.68]	15.73		[0.57]	[0.97]	16.04		[0.42]	[0.73]	7.97		[0.57]	[0.97]	7.29	
HH	[0.47]	[0.70]	16.86		[0.64]	[1.08]	16.42		[0.47]	[0.75]	7.97		[0.64]	[1.08]	7.05	
VAR	[0.50]	[0.93]	29.13		[0.54]	[1.10]	31.95		[0.52]	[0.95]	17.98		[0.54]	[1.11]	25.17	
Over	[0.55]	[1.32]	4.80		[0.67]	[1.48]	4.14		[0.55]	[1.38]	2.79		[0.67]	[1.48]	2.73	
3	−1.26	1.49		32.29	−1.29	1.15		29.84	−1.18	0.64		22.00	−1.29	0.15		21.00
NW	[0.34]	[0.77]	26.46		[0.39]	[0.85]	25.57		[0.33]	[0.83]	17.63		[0.39]	[0.85]	16.65	
HH	[0.37]	[0.85]	22.28		[0.44]	[0.93]	21.83		[0.37]	[0.91]	14.77		[0.44]	[0.93]	13.94	
VAR	[0.53]	[1.00]	44.77		[0.58]	[1.12]	38.45		[0.55]	[1.03]	27.02		[0.57]	[1.13]	27.43	
Over	[0.53]	[1.31]	18.53		[0.63]	[1.31]	14.14		[0.52]	[1.39]	9.72		[0.63]	[1.31]	8.45	
4	−1.21	1.26		30.20	−1.21	1.08		29.51	−1.16	0.28		20.14	−1.21	0.08		19.94
NW	[0.31]	[0.70]	27.39		[0.31]	[0.66]	29.02		[0.29]	[0.73]	19.94		[0.31]	[0.66]	19.22	
HH	[0.33]	[0.76]	24.40		[0.34]	[0.70]	26.41		[0.31]	[0.79]	17.61		[0.34]	[0.70]	16.98	
VAR	[0.50]	[0.91]	42.38		[0.50]	[0.83]	40.90		[0.50]	[0.93]	28.08		[0.51]	[0.84]	27.52	
Over	[0.35]	[1.38]	11.58		[0.40]	[1.32]	12.88		[0.33]	[1.46]	7.74		[0.40]	[1.32]	7.69	
5	−1.70	1.18		34.80	−1.72	1.34		36.88	−1.77	0.08		29.32	−1.72	0.34		29.64
NW	[0.39]	[0.77]	35.59		[0.34]	[0.62]	39.81		[0.37]	[0.72]	28.81		[0.34]	[0.62]	29.99	
HH	[0.42]	[0.77]	42.06		[0.36]	[0.65]	44.33		[0.40]	[0.72]	31.46		[0.36]	[0.65]	31.57	
VAR	[0.65]	[1.20]	45.81		[0.61]	[0.96]	47.30		[0.65]	[1.20]	32.93		[0.61]	[0.96]	34.32	
Over	[0.69]	[1.55]	13.06		[0.55]	[0.94]	27.89		[0.66]	[1.34]	13.36		[0.55]	[0.94]	18.13	
6	−1.15	1.98		22.76	−1.56	1.14		25.63	−1.49	0.34		18.08	−1.56	0.14		18.05
NW	[0.53]	[1.31]	17.46		[0.47]	[0.44]	23.94		[0.55]	[1.08]	12.16		[0.47]	[0.44]	12.40	
HH	[0.57]	[1.44]	15.35		[0.51]	[0.46]	19.89		[0.59]	[1.18]	10.54		[0.51]	[0.46]	10.48	
VAR	[0.91]	[1.82]	27.49		[0.78]	[0.80]	30.69		[0.88]	[1.74]	21.92		[0.79]	[0.80]	21.02	
Over	[0.61]	[1.47]	11.25		[0.53]	[0.53]	13.68		[0.66]	[1.36]	7.97		[0.53]	[0.53]	7.06	
Average	−1.25	1.63		38.08	−1.25	1.63		38.08	−1.25	0.63		27.95	−1.25	0.63		27.95
NW	[0.33]	[0.70]	32.44		[0.33]	[0.70]	32.44		[0.33]	[0.70]	21.40		[0.33]	[0.70]	21.40	
HH	[0.37]	[0.74]	30.63		[0.37]	[0.74]	30.63		[0.37]	[0.74]	19.57		[0.37]	[0.74]	19.57	
VAR	[0.61]	[1.11]	54.08		[0.61]	[1.11]	54.01		[0.61]	[1.11]	36.25		[0.62]	[1.12]	36.74	
Over	[0.47]	[1.29]	12.83		[0.47]	[1.29]	12.83		[0.47]	[1.29]	8.68		[0.47]	[1.29]	8.68	

Notes: This table reports forecasting results obtained on currency portfolios using the 12-month change in the industrial production index and either the portfolio-specific 12-month forward discount or the average 12-month forward discount. We report the slope coefficients, the Wald-test χ^2 statistic for the slope coefficients (denoted W) and the R^2 of each regression. The left panel focuses on currency excess returns. The right panel focuses on changes in exchange rates. The Newey and West (1987) (NW) standard errors are computed with the optimal number of lags. The Hansen and Hodrick (1980) (HH) standard errors are computed with 12 lags. For the bootstrapped standard errors, the VAR uses 12 lags. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–1/2009.

Table 8: One-Year Ahead Predictability – Long-Short Portfolios

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2
	Panel I: Excess Returns			Panel II: Exchange Rates		
2 *Minus* 1	1.01	−2.05	21.00	−0.54	−1.96	19.38
NW	[1.00]	[0.47]		[1.01]	[0.46]	
HH	[1.26]	[0.50]		[1.29]	[0.49]	
VAR	[0.81]	[0.53]		[0.85]	[0.56]	
Over	[2.23]	[0.88]		[2.18]	[0.85]	
3 *Minus* 1	2.32	−1.28	8.75	−0.17	−1.33	9.19
NW	[0.89]	[0.48]		[0.90]	[0.48]	
HH	[1.02]	[0.50]		[1.03]	[0.50]	
VAR	[1.01]	[0.55]		[1.01]	[0.60]	
Over	[2.79]	[1.59]		[2.81]	[1.63]	
4 *Minus* 1	3.67	−1.56	10.45	0.37	−1.71	12.14
NW	[1.23]	[0.65]		[1.19]	[0.63]	
HH	[1.40]	[0.70]		[1.36]	[0.69]	
VAR	[1.24]	[0.73]		[1.24]	[0.76]	
Over	[2.30]	[0.98]		[2.36]	[1.04]	
5 *Minus* 1	4.44	−1.21	5.40	−0.11	−1.39	6.79
NW	[1.22]	[0.62]		[1.26]	[0.66]	
HH	[1.38]	[0.65]		[1.43]	[0.70]	
VAR	[1.87]	[1.07]		[1.93]	[1.04]	
Over	[1.97]	[0.96]		[2.24]	[1.08]	
6 *Minus* 1	4.50	−0.89	1.47	−3.48	−1.37	3.48
NW	[1.80]	[1.13]		[1.97]	[0.99]	
HH	[2.01]	[1.22]		[2.22]	[1.05]	
VAR	[2.56]	[1.45]		[2.45]	[1.41]	
Over	[3.06]	[1.62]		[3.47]	[1.43]	

Notes: Panel I reports summary statistics for return predictability regressions at a twelve-month horizon. We focus here on long-short strategies: for each portfolio j, we assume that the investor is short the first portfolio and long portfolio j. For each excess return, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$). Panel II reports similar statistics for exchange rate predictability regressions at a twelve-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard errors at horizon h are computed with h lags. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 9: One-Year Ahead Predictability – Long-Short Portfolios, Industrial Production Residuals

Portfolio	κ_0	$\kappa_{IP_{res}}$	R^2	κ_0	$\kappa_{IP_{res}}$	R^2
	Panel I: Excess Returns			Panel II: Exchange Rates		
2 $Minus$ 1	−0.34	0.14	0.27	−1.83	0.13	0.22
NW	[1.09]	[0.40]		[1.09]	[0.40]	
HH	[1.31]	[0.47]		[1.31]	[0.47]	
VAR	[0.97]	[0.37]		[1.02]	[0.38]	
Over	[1.28]	[0.47]		[1.27]	[0.47]	
3 $Minus$ 1	1.47	−0.07	0.06	−1.05	−0.07	0.07
NW	[0.98]	[0.41]		[1.00]	[0.43]	
HH	[1.13]	[0.46]		[1.15]	[0.49]	
VAR	[0.99]	[0.39]		[1.03]	[0.39]	
Over	[1.38]	[0.63]		[1.37]	[0.65]	
4 $Minus$ 1	2.64	0.09	0.10	−0.76	0.10	0.12
NW	[1.29]	[0.46]		[1.32]	[0.50]	
HH	[1.48]	[0.52]		[1.51]	[0.56]	
VAR	[1.41]	[0.47]		[1.34]	[0.48]	
Over	[1.38]	[0.53]		[1.37]	[0.56]	
5 $Minus$ 1	3.64	−0.34	1.13	−1.03	−0.39	1.46
NW	[1.29]	[0.49]		[1.34]	[0.53]	
HH	[1.45]	[0.56]		[1.51]	[0.60]	
VAR	[1.81]	[0.60]		[1.95]	[0.60]	
Over	[1.25]	[0.58]		[1.32]	[0.61]	
6 $Minus$ 1	3.91	0.05	0.01	−4.39	−0.20	0.20
NW	[1.93]	[0.68]		[1.94]	[0.72]	
HH	[2.18]	[0.75]		[2.19]	[0.79]	
VAR	[3.04]	[0.93]		[3.00]	[0.96]	
Over	[2.03]	[0.79]		[2.07]	[0.85]	

Notes: Panel I reports summary statistics for return predictability regressions at a twelve-month horizon. We focus here on long-short strategies: for each portfolio j, we assume that the investor is short the first portfolio and long portfolio j. For each excess return, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the 12-month residual change in the industrial production index ($\kappa_{IP_{res}}$). These residuals correspond to the US-specific component in IP. They are obtained by projecting the US 12-month change in IP on the average change in IP across G7 countries excluding the US. Panel II reports similar statistics for exchange rate predictability regressions at a twelve-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard errors at horizon h are computed with h lags. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 10: Out-of-Sample Exchange Rate Predictability: Comparison with a Random Walk

	Panel I: One-Month Changes					Panel II: Six-Month Changes				
Portfolios	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC
1	2.14	2.15	0.99	−0.37	0.34	5.73	5.59	1.03	0.47	1.48
	[0.17]	[0.17]	[0.01]	[1.01]	[1.15]	[0.92]	[0.97]	[0.07]	[1.10]	[0.96]
2	1.90	1.91	0.99	−0.60	−0.05	5.04	5.18	0.97	−0.49	0.58
	[0.17]	[0.17]	[0.01]	[0.89]	[1.00]	[0.84]	[0.88]	[0.06]	[1.11]	[1.04]
3	1.91	1.92	1.00	−0.55	−0.28	4.95	4.74	1.04	0.60	1.60
	[0.15]	[0.15]	[0.00]	[0.90]	[1.00]	[0.86]	[0.89]	[0.07]	[1.15]	[1.01]
4	1.90	1.91	1.00	−0.12	0.48	4.41	3.62	1.22	2.53	2.91
	[0.20]	[0.20]	[0.01]	[1.01]	[1.15]	[0.74]	[0.79]	[0.08]	[1.02]	[0.84]
5	2.05	2.08	0.99	−0.87	−0.35	5.39	4.61	1.17	2.97	3.65
	[0.21]	[0.21]	[0.01]	[0.90]	[1.00]	[1.01]	[1.05]	[0.08]	[1.08]	[0.91]
6	2.86	2.87	0.99	−0.46	−0.08	6.30	5.70	1.11	2.66	3.47
	[0.21]	[0.21]	[0.01]	[0.87]	[0.97]	[0.90]	[0.92]	[0.06]	[1.09]	[0.94]

Notes: This table reports one-step-ahead out-of-sample predictability test statistics. We first assume that changes in exchange rates 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 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 $t+1$. We use at least half of the sample to estimate the model. Standard errors are reported between brackets. They are obtained from bootstrapping the whole procedure assuming a one-lag VAR for changes in exchange rates and in industrial production. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983 - 04/2009. Panel I focuses on one-month changes in exchange rates. Panel II focuses on six-month changes in exchange rates. In Panel II, we consider non-overlapping 6-month periods.

Table 11: Summary Statistics - Foreign Investors - Portfolios of Developed and Emerging Countries - Midpoint Conversion

Portfolio	1	2	3	4	5	6
Panel I: UK						
			Excess Return: rx_{net}^j			
$Mean$	-4.16	-3.49	-3.07	-1.00	-1.11	0.03
SR	-0.46	-0.42	-0.35	-0.11	-0.13	0.00
			Long-Short: $rx_{net}^j - rx_{net}^1$			
$Mean$		0.68	1.09	3.16	3.05	4.20
SR		0.12	0.18	0.48	0.44	0.46
Panel II: Japan						
			Excess Return: rx_{net}^j			
$Mean$	-2.13	-3.17	-1.44	0.54	0.62	1.43
SR	-0.22	-0.29	-0.14	0.05	0.06	0.11
			Long-Short: $rx_{net}^j - rx_{net}^1$			
$Mean$		-1.04	0.69	2.68	2.75	3.56
SR		-0.18	0.12	0.44	0.41	0.40
Panel III: Canada						
			Excess Return: rx_{net}^j			
$Mean$	-2.21	-1.67	-0.55	1.18	0.20	1.99
SR	-0.23	-0.20	-0.07	0.14	0.02	0.21
			Long-Short: $rx_{net}^j - rx_{net}^1$			
$Mean$		0.54	1.66	3.39	2.41	4.20
SR		0.10	0.29	0.51	0.34	0.45

Notes: This table reports summary statistics for currencies sorted into portfolios. We report averages and Sharpe ratios of log excess returns rx_{net}^j with bid-ask spreads and log excess returns on the long short strategy $rx_{net}^j - rx_{net}^1$ in *UK pounds*, in *Japanese yen*, and in *Canadian dollars*. All moments are annualized and reported in percentage points. The portfolios are constructed by sorting currencies into six groups at time t based on the one-month forward discount (i.e nominal interest rate differential) at the end of period $t-1$. Portfolio 1 contains currencies with the lowest interest rates. Portfolio 6 contains currencies with the highest interest rates. Data are monthly, from Barclays and Reuters (Datastream). The sample period is 11/1983 - 01/2009.

Table 12: One-Year Ahead Predictability: Forecasting Foreign Excess Returns with Foreign Employment

Months	γ_0	γ_{EM}	R^2	γ_0	γ_{EM}	R^2	γ_0	γ_{EM}	R^2	γ_0	γ_{EM}	R^2
		US			**UK**			**Canada**			**Japan**	
1	3.41	−2.30	5.66	−1.20	−3.40	3.24	−1.49	−0.53	2.84	−0.33	−0.19	0.14
	[1.92]	[1.15]		[1.86]	[1.62]		[2.16]	[0.45]		[1.85]	[0.75]	
2	1.30	−1.17	2.23	−1.83	−2.45	2.09	−1.75	−0.43	2.71	−1.94	−0.57	0.94
	[1.40]	[0.91]		[2.18]	[1.11]		[1.64]	[0.37]		[2.54]	[1.01]	
3	3.78	−1.59	3.70	0.59	−3.05	3.29	−0.32	−0.30	1.60	0.44	−1.09	3.93
	[1.91]	[1.08]		[1.55]	[1.43]		[1.47]	[0.33]		[2.12]	[0.82]	
4	5.31	−1.82	5.38	0.48	−1.07	0.60	1.11	−0.32	1.75	1.41	−1.53	7.27
	[2.20]	[1.19]		[1.53]	[1.60]		[1.38]	[0.36]		[2.18]	[0.82]	
5	7.57	−2.63	7.94	4.85	−4.28	7.03	2.45	−0.30	1.44	2.81	−1.60	7.44
	[2.26]	[1.27]		[2.32]	[3.19]		[1.37]	[0.40]		[2.18]	[0.84]	
6	7.31	−2.29	4.83	6.11	−5.09	5.88	2.69	0.06	0.06	2.19	−2.12	10.04
	[2.66]	[1.56]		[4.38]	[5.36]		[1.22]	[0.34]		[2.59]	[0.92]	
Average	4.78	−1.97	6.41	1.50	−3.22	4.97	0.45	−0.30	1.94	0.76	−1.19	5.04
	[1.75]	[1.09]		[1.76]	[2.07]		[1.37]	[0.32]		[2.14]	[0.83]	

Notes: This table reports the constant, slope coefficient and R^2 in predictability tests of currency excess returns. We take the perspective of foreign investors in the US, UK, Canada and Japan. For each home country, we use the corresponding 12-month change in the log employement index. The standard errors in brackets are Newey-West standard errors computed with the optimal number of lags. All the returns annualized and reported in percentage points. Data are monthly, from Datastream and IFS (IMF). The sample period is 11/1983 - 1/2009 (4/1992 - 1/2009 for UK).

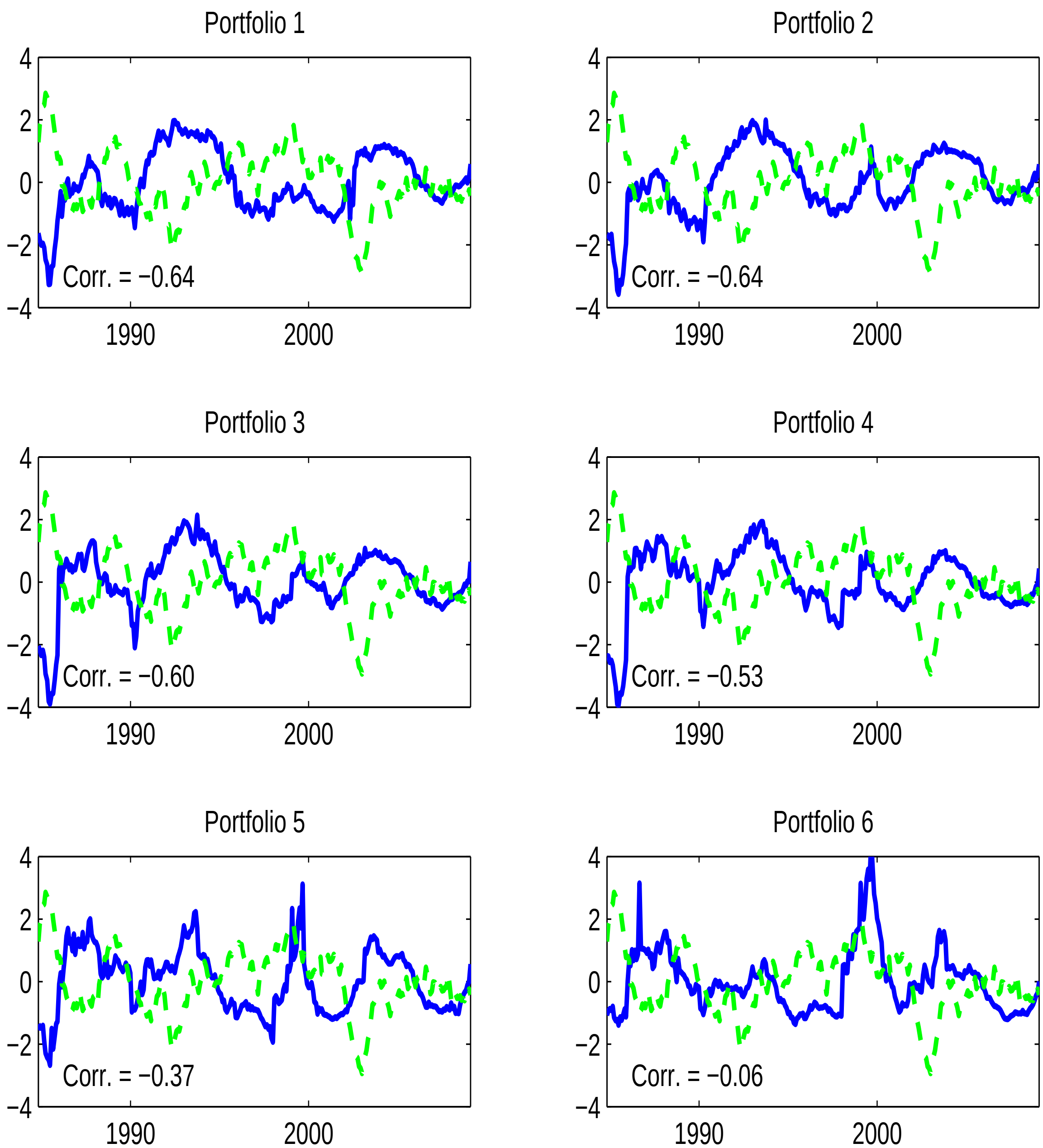

Figure 1: Forecasted Excess Return in Currency Markets and US Business Cycle.

This figure plots the one-month ahead forecasted excess returns on each portfolio j ($\widehat{E}_t rx^j_{t+1}$) using the portfolio-specific forward discount. All returns are annualized. The dashed line is the year-on-year log change in US Industrial Production Index. Both variables are de-meaned and scaled by their standard deviation.

A Model: A Generalization

Affine Models of SDFs We consider a world with N countries and currencies. We assume that in each country i, the logarithm of the SDF m^i follows an affine process:

$$-m^i_{t+1} = r^i_t + \frac{1}{2}\|\lambda^i_t\|^2 + \lambda^{i'}_t u^i_{t+1} + \frac{1}{2}\|\delta^i_t\|^2 + \delta^{i'}_t u^w_{t+1},$$

where $\|x\|^2$ denotes the variance of x, r^i_t is the risk-free rate in country i, u^i_{t+1} is a vector of country-specific shocks, u^w_{t+1} is a vector of world shocks, and λ^i_t and δ^i_t are the market prices of risk associated with these two sets of shocks. The currency-specific innovations u^i_{t+1} and global innovations u^w_{t+1} are *i.i.d* gaussian, with zero mean and unit variance. To simplify the algebra, we assume that u^i and u^w are orthogonal. We do not specify the law of motion of the risk-free rate r^i_t, but assume that it is countercyclical with respect to state variables. Our SDF is fairly general and simply ensures that the no-arbitrage Euler condition for the risk-free rate is satisfied.

Market prices of risk are time-varying. We assume that the market price of world risk depends only on world factors (denoted z^w). Countries might differ though in the way their SDFs respond to these world factors. As a result, loadings on world factors $\delta^{i'}_t$ differ across countries. We further assume that SDFs differ only in this dimension. Market prices of country risk depends on country factors (denoted z^i) in the same way across countries. To summarize, we assume that λ^i_t is a function of z^i, but all countries respond to their own risk factors in the same way. We assume that $\delta^{i'}_t$ is a function of z^w. But countries respond to the common risk factor in different ways.

Expected Excess Returns The expected excess return of portfolio j is:

$$E_t[rx^j_{t+1}] = \frac{1}{2}[\overline{\|\lambda^j_t\|^2} - \|\lambda_t\|^2 + \overline{\|\delta^j_t\|^2} - \|\delta_t\|^2],$$

where $\overline{\|\delta^j_t\|^2}$ denote the average of all the $\|\delta^i_t\|^2$ of the i currencies grouped in portfolio j.

We assume that the country-specific shocks average out within each portfolio. In this case, $\overline{\|\lambda^j_t\|^2}$ is constant in the limit $N \to \infty$ by the law of large numbers. The same reasoning does not apply to $\overline{\|\delta^j_t\|^2}$ because it contains common components that do not cancel out but reinforce each other. As a result, the expected excess return on portfolio j depends on a dollar-specific component λ_t and a common component embedded in the price of world risk δ_t. This common component drives carry trade returns. Consider the return on a strategy that goes long in high-interest rate currencies and short in low-interest rate currencies. The expected excess return on this long-short strategy – denoted *hml* for high minus low interest rates) – is equal to:

$$E_t[hml_{t+1}] = \frac{1}{2}\left(\overline{\|\delta^H_t\|^2} - \overline{\|\delta^L_t\|^2}\right),$$

where $\overline{\|\delta_t^L\|^2}$ and $\overline{\|\delta_t^H\|^2}$ denote the average loading on the high and low interest rate portfolios. The carry trade risk premium is solely driven by the global risk factor.

This fairly general model bears the same predictions as the example developed in the main text: there should be no role for portfolio-specific variables in forecasting currency excess returns; the dollar risk premium should be counter-cyclical; long-short returns do not depend on US variables.

B Empirical Methodology

Small sample and look-ahead biases When the predictor is persistent and shocks to the predictor are correlated to the excess return, Stambaugh (1999) shows that the OLS estimator's finite-sample properties can lead to spurious predictability. Assume that X_t follows an $AR(1)$ and consider the following system, estimated over a sample of size N:

$$\begin{aligned} R^e_{t,t+1} &= C^1 + \alpha X_t + \varepsilon^1_{t+1}, \\ X_{t+1} &= C^2 + \beta_1 X_t + \varepsilon^2_{t+1}. \end{aligned}$$

Then, Stambaugh (1999) shows that the bias in estimating α is proportional to the bias in β:

$$\begin{aligned} E(\hat{\beta} - \beta) &\simeq -(1+3\beta)/N, \\ E(\hat{\alpha} - \alpha) &= [cov(\varepsilon^1, \varepsilon^2)/Var(\varepsilon^2)]E(\hat{\beta} - \beta). \end{aligned}$$

Thus, to derive correct standard errors even in small samples, we use a bootstrapping method described below.

Bootstrapping Our bootstrapping procedure follows Mark (1995) and Kilian (1999) and is similar to the one recently used by Goyal and Welch (2005) on US stock excess returns. It preserves the autocorrelation structure of the predictors and the cross-correlation of the predictors' and returns' shocks. Under the null, the currency excess return follows a random walk with drift. We impose that hypothesis in the data generating process.

The boostrapping procedure can be decomposed into 3 steps.

- For each horizon h, we first estimate:

$$R^e_{t,t+h} = C^1_h + \varepsilon^1_{t+h} \tag{B.1}$$

$$X_{t+1} = C^2 + \sum_{i=0}^{p} \beta_{i,h} X_{t-i} + \varepsilon^2_{t+1} \tag{B.2}$$

  X is a $[T \times P]$ matrix of P potential predictors. We assume that there is no predictability in excess return (H0) and that the predictors of the excess return can be characterized by an AR(p) process, where p is the higher optimal index determined using the AIC criterion on each predictor. We verify that the residuals are uncorrelated through time and we store $[\varepsilon^1, \varepsilon^2]$ in an $[T \times (1+P)]$ matrix. ε^1 and ε^2 are correlated, but this is a natural and interesting feature of the problem. Shocks to the price-dividend ratio may affect simultaneously the stock excess return. Likewise, shocks to some measure of macro risk may affect simultaneously the currency excess return.

- For each iteration of the boostrap, we draw with replacement $T + 500$ pairs of residuals $[\varepsilon^1, \varepsilon^2]$. We use the recursive structure embedded in (B.2) to construct new series $[\widehat{R^e_{t,t+h}}, \widehat{X_{t+1}}]$ of excess returns and predictors. We discard the first 500.

  With each new series $[\widehat{R^e_{t,t+h}}, \widehat{X^e_{t+1}}]$ of T excess returns and predictors, we run the univariate equation (**??**) using OLS and store the implied slope coefficients $\widehat{\alpha_h}$.

- We repeat the boostrapping $B = 1000$ times and report the standard errors of the estimated $\widehat{\alpha_h}$. As a comparison, we also report the standard errors computed using a GMM estimator following Hansen (1982). To compute the spectral density matrix, we use Bartlett weights and the optimal bandwidth criterium proposed by Andrews (1991).

C Additional Results

- **US-Specific Industrial Production:** Table 13 reports predictability tests on one-year currency excess returns and changes in exchange rates. The predictors are the residual 12-month changes in the industrial production index (IP_{res}) and either the portfolio-specific 12-month forward discount or the average 12-month forward discount. These residuals correspond to the US-specific component in IP. They are obtained by projecting the US 12-month change in IP on a constant and the average change in IP across G7 countries excluding the US.

- **Long-Short Excess Returns:** Table 14 reports predictability tests on one-year, long-short currency excess returns and changes in exchange rates. The predictors are the residual 12-month changes in the industrial production index (IP) and the average 12-month forward discount.

- **Out-of-Sample – Other Horizons:** Table 15 reports out-of-sample test statistics on three- and twelve-month changes in exchange rates.

- **In-Sample – Developed Countries:** Table 16 reports predictability tests on one-month currency excess returns and one-month changes in exchange rates on a sample of developed countries. These excess returns and changes in exchange rates correspond to the portfolios presented in the right panel of Table 1. Table 17 reports predictability tests on one-year currency excess returns and one-year changes in exchange rates on the same sample of developed countries.

- **In-Sample – 1976-2009:** Table 18 reports predictability tests on one-month currency excess returns and one-month changes in exchange rates over a long sample (1976-2009) of developed countries. Table 19 reports predictability tests on three-month currency excess returns and changes in exchange rates over the same long sample (1976-2009) of developed countries. In both tables, the countries in sample are: Australia,Austria, Belgium, Canada, Denmark, Euro Area, France, Germany, Ireland, Italy, Japan, Netherlands, New Zeland, Norway, Portugal, South Africa, Spain, Sweden, Switzerland and United Kingdom.

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Table 13: Forecasting One-Year Ahead Excess Returns with Industrial Production Residuals and Forward Discounts

Portfolios	$\kappa_{IP_{res}}$	$\kappa_{\mathbf{f}}$	W	R^2	$\kappa_{IP_{res}}$	κ_f	W	R^2	$\kappa_{IP_{res}}$	$\kappa_{\mathbf{f}}$	W	R^2	$\kappa_{IP_{res}}$	κ_f	W	R^2
	Panel I: Excess Returns								Panel II: Exchange Rates							
1	−1.33	3.43		40.34	−1.27	2.74		33.92	−1.26	2.58		31.18	−1.27	1.74		23.84
NW	[0.50]	[0.76]	41.70		[0.69]	[0.92]	33.29		[0.50]	[0.75]	23.93		[0.69]	[0.92]	19.74	
HH	[0.55]	[0.79]	46.76		[0.77]	[1.03]	32.33		[0.55]	[0.78]	25.52		[0.77]	[1.03]	19.25	
VAR	[0.62]	[1.00]	64.77		[0.68]	[1.09]	45.63		[0.61]	[1.00]	46.33		[0.67]	[1.11]	29.38	
Over	[0.61]	[1.32]	17.21		[0.81]	[1.22]	22.27		[0.64]	[1.15]	14.72		[0.81]	[1.22]	12.99	
2	−1.45	1.34		27.58	−1.41	1.22		26.00	−1.38	0.58		20.63	−1.41	0.22		19.67
NW	[0.43]	[0.57]	25.35		[0.50]	[0.74]	21.94		[0.44]	[0.60]	13.88		[0.50]	[0.74]	12.50	
HH	[0.47]	[0.56]	31.88		[0.56]	[0.79]	24.22		[0.49]	[0.59]	15.65		[0.56]	[0.79]	12.92	
VAR	[0.46]	[0.80]	44.97		[0.48]	[0.92]	43.68		[0.45]	[0.81]	32.70		[0.49]	[0.87]	35.49	
Over	[0.52]	[1.16]	8.78		[0.57]	[1.28]	7.87		[0.53]	[1.21]	6.87		[0.57]	[1.28]	6.48	
3	−1.56	2.07		36.74	−1.51	1.82		33.59	−1.50	1.17		27.46	−1.51	0.82		25.22
NW	[0.33]	[0.67]	33.62		[0.36]	[0.72]	29.46		[0.34]	[0.72]	23.86		[0.36]	[0.72]	21.52	
HH	[0.36]	[0.72]	28.80		[0.40]	[0.76]	25.60		[0.37]	[0.78]	20.24		[0.40]	[0.76]	18.22	
VAR	[0.50]	[0.85]	55.40		[0.52]	[0.93]	44.33		[0.51]	[0.88]	35.99		[0.53]	[0.95]	30.93	
Over	[0.47]	[1.12]	25.71		[0.52]	[0.99]	21.70		[0.49]	[1.23]	18.36		[0.52]	[0.99]	14.62	
4	−1.43	1.84		33.24	−1.37	1.55		31.28	−1.37	0.84		23.17	−1.37	0.55		21.95
NW	[0.32]	[0.61]	36.34		[0.32]	[0.59]	38.16		[0.30]	[0.64]	25.45		[0.32]	[0.59]	25.14	
HH	[0.34]	[0.64]	34.76		[0.35]	[0.62]	39.01		[0.33]	[0.69]	23.79		[0.35]	[0.62]	24.50	
VAR	[0.49]	[0.80]	52.87		[0.50]	[0.73]	41.96		[0.50]	[0.84]	32.75		[0.51]	[0.74]	27.71	
Over	[0.44]	[1.30]	9.89		[0.49]	[1.28]	10.21		[0.43]	[1.38]	7.69		[0.49]	[1.28]	7.40	
5	−1.83	2.05		35.04	−1.87	1.85		35.50	−1.85	1.00		28.26	−1.87	0.85		28.10
NW	[0.39]	[0.68]	40.55		[0.36]	[0.50]	45.27		[0.38]	[0.64]	32.53		[0.36]	[0.50]	32.27	
HH	[0.42]	[0.63]	58.58		[0.36]	[0.48]	54.19		[0.39]	[0.58]	44.76		[0.36]	[0.48]	36.15	
VAR	[0.65]	[1.03]	52.20		[0.64]	[0.93]	45.39		[0.65]	[1.04]	39.78		[0.64]	[0.98]	33.12	
Over	[0.65]	[1.18]	24.72		[0.59]	[0.81]	35.20		[0.62]	[1.12]	18.82		[0.59]	[0.81]	23.77	
6	−1.40	2.52		24.73	−1.80	1.31		25.02	−1.64	1.08		18.89	−1.80	0.31		17.37
NW	[0.55]	[1.11]	26.51		[0.51]	[0.45]	26.91		[0.53]	[0.88]	17.38		[0.51]	[0.45]	14.75	
HH	[0.59]	[1.22]	24.55		[0.54]	[0.48]	22.72		[0.57]	[0.95]	15.73		[0.54]	[0.48]	12.66	
VAR	[0.87]	[1.65]	27.84		[0.82]	[0.77]	31.00		[0.83]	[1.57]	22.41		[0.84]	[0.79]	20.61	
Over	[0.66]	[1.22]	16.17		[0.61]	[0.52]	14.01		[0.67]	[1.06]	10.82		[0.61]	[0.52]	9.01	
Average	−1.50	2.21		42.02	−1.50	2.21		42.02	−1.50	1.21		32.54	−1.50	1.21		32.54
NW	[0.34]	[0.60]	43.26		[0.34]	[0.60]	43.26		[0.34]	[0.60]	29.30		[0.34]	[0.60]	29.30	
HH	[0.37]	[0.61]	45.58		[0.37]	[0.61]	45.58		[0.37]	[0.61]	29.70		[0.37]	[0.61]	29.70	
VAR	[0.57]	[1.01]	79.47		[0.56]	[0.95]	74.02		[0.57]	[1.00]	48.01		[0.58]	[0.97]	48.01	
Over	[0.43]	[1.14]	19.45		[0.43]	[1.14]	19.45		[0.43]	[1.14]	15.28		[0.43]	[1.14]	15.28	

Notes: This table reports forecasting results obtained on currency portfolios using the residual 12-month changes in the industrial production index (IP) and either the portfolio-specific 12-month forward discount or the average 12-month forward discount. These residuals correspond to the US-specific component in IP. They are obtained by projecting the US 12-month change in IP on the average change in IP across G7 countries excluding the US. We report the slope coefficients, the Wald-test χ^2 statistic for the slope coefficients (denoted W) and the R^2 of each regression. The left panel focuses on currency excess returns. The right panel focuses on changes in exchange rates. The Newey and West (1987) (NW) standard errors are computed with the optimal number of lags. The Hansen and Hodrick (1980) (HH) standard errors are computed with 12 lags. For the bootstrapped standard errors, the VAR uses 12 lags. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–1/2009.

Table 14: One-Year Ahead Predictability – Long-Short Portfolios, Industrial Production and Average Forward Discount

Portfolio	κ_0	$\kappa_{IP_{res}}$	$\kappa_{\mathbf{f}}$	R^2	κ_0	$\kappa_{IP_{res}}$	$\kappa_{\mathbf{f}}$	R^2
	Panel I: Excess Returns				Panel II: Exchange Rates			
2 *Minus* 1	1.16	−0.04	−2.09	21.03	−0.34	−0.06	−2.01	19.43
NW	[1.52]	[0.22]	[0.54]		[1.54]	[0.23]	[0.52]	
HH	[1.83]	[0.24]	[0.60]		[1.89]	[0.25]	[0.57]	
VAR	[1.36]	[0.31]	[0.61]		[1.40]	[0.31]	[0.61]	
Over	[2.37]	[0.19]	[0.86]		[2.22]	[0.18]	[0.83]	
3 *Minus* 1	3.07	−0.22	−1.47	9.49	0.79	−0.27	−1.57	10.34
NW	[1.35]	[0.21]	[0.56]		[1.39]	[0.21]	[0.55]	
HH	[1.55]	[0.22]	[0.60]		[1.59]	[0.22]	[0.58]	
VAR	[1.54]	[0.34]	[0.60]		[1.64]	[0.36]	[0.67]	
Over	[3.33]	[0.32]	[1.69]		[3.33]	[0.31]	[1.74]	
4 *Minus* 1	4.24	−0.16	−1.70	10.78	1.26	−0.26	−1.93	12.95
NW	[1.77]	[0.24]	[0.72]		[1.75]	[0.23]	[0.68]	
HH	[2.03]	[0.26]	[0.78]		[2.00]	[0.24]	[0.74]	
VAR	[2.09]	[0.44]	[0.83]		[2.16]	[0.45]	[0.86]	
Over	[2.55]	[0.36]	[0.88]		[2.37]	[0.34]	[0.92]	
5 *Minus* 1	6.74	−0.65	−1.78	10.13	2.89	−0.86	−2.13	14.50
NW	[1.82]	[0.31]	[0.68]		[1.82]	[0.30]	[0.66]	
HH	[2.01]	[0.33]	[0.71]		[2.00]	[0.32]	[0.68]	
VAR	[2.66]	[0.55]	[1.05]		[2.73]	[0.56]	[1.02]	
Over	[3.05]	[0.43]	[1.10]		[2.90]	[0.41]	[1.14]	
6 *Minus* 1	4.87	−0.10	−0.98	1.53	−1.45	−0.58	−1.87	5.33
NW	[2.42]	[0.58]	[1.43]		[2.43]	[0.54]	[1.16]	
HH	[2.68]	[0.62]	[1.55]		[2.70]	[0.58]	[1.22]	
VAR	[4.28]	[0.95]	[1.65]		[4.20]	[0.94]	[1.53]	
Over	[4.03]	[0.51]	[1.75]		[4.03]	[0.53]	[1.49]	

Notes: Panel I reports summary statistics for return predictability regressions at a twelve-month horizon. We focus here on long-short strategies: for each portfolio j, we assume that the investor is short the first portfolio and long portfolio j. For each excess return, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the 12-month change in the industrial production index (κ_{IP}) and the average log forward discount ($\kappa_{\mathbf{f}}$). Panel II reports similar statistics for exchange rate predictability regressions at a twelve-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard errors at horizon h are computed with h lags. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 15: Out-of-Sample Exchange Rate Predictability: Comparison with a Random Walk – Three- and Twelve-Month Horizons

	Panel I: Three-Month Changes					Panel II: Twelve-Month Changes				
Portfolios	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC	$RMSE_{RW}$	$RMSE$	*Ratio*	MSE_t	ENC
1	3.75	3.67	1.02	0.60	1.33	7.37	6.83	1.08	0.66	1.69
	[0.44]	[0.43]	[0.03]	[0.94]	[0.95]	[1.64]	[1.80]	[0.10]	[1.35]	[1.08]
2	3.32	3.35	0.99	−0.38	0.35	9.01	8.86	1.02	0.94	1.62
	[0.42]	[0.42]	[0.02]	[1.07]	[1.16]	[1.92]	[2.05]	[0.07]	[1.34]	[1.05]
3	3.72	3.72	1.00	0.07	0.51	7.52	7.84	0.96	−0.25	0.55
	[0.64]	[0.65]	[0.02]	[1.17]	[1.27]	[1.35]	[1.69]	[0.10]	[1.30]	[1.06]
4	4.07	4.05	1.01	0.27	0.52	8.96	8.37	1.07	1.54	1.40
	[0.79]	[0.80]	[0.02]	[1.24]	[1.38]	[1.98]	[2.09]	[0.09]	[1.42]	[1.11]
5	5.02	5.05	0.99	−0.23	0.39	7.96	6.49	1.23	1.75	1.77
	[1.16]	[1.17]	[0.02]	[1.20]	[1.32]	[1.58]	[2.11]	[0.12]	[1.28]	[1.07]
6	5.75	5.75	1.00	−0.05	0.31	8.54	7.60	1.12	1.52	1.49
	[0.86]	[0.87]	[0.02]	[1.15]	[1.26]	[1.64]	[2.00]	[0.10]	[1.31]	[1.07]

Notes: This table reports one-step-ahead out-of-sample predictability test statistics. We first assume that changes in exchange rates 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 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 $t+1$. We run out-of-sample tests in the second half of the sample. Standard errors are reported between brackets. They are obtained from bootstrapping the whole procedure assuming a one-lag VAR for changes in exchange rates and in industrial production. Data are monthly, from Datastream and Global Financial Data. The sample period is 11/1983–1/2009. Panel I focuses on three-month changes in exchange rates. Panel II focuses on twelve-month changes in exchange rates. In both panels, we consider non-overlapping series.

Table 16: One-Month Ahead Predictability - Developed Countries

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
1	−1.99	2.60	2.46	3.74	1.67	1.59	1.32	1.53	0.86	3.74	0.67	0.26
NW	[2.02]	[0.89]		[3.01]	[0.98]		[2.04]	[0.91]		[3.01]	[0.98]	
HH	[1.98]	[0.89]		[3.03]	[1.04]		[2.01]	[0.91]		[3.03]	[1.04]	
VAR	[2.04]	[0.98]		[3.40]	[0.95]		[2.02]	[0.98]		[3.26]	[0.95]	
2	−0.15	2.37	2.18	1.82	1.42	0.82	1.06	1.44	0.81	1.82	0.42	0.07
NW	[2.13]	[0.97]		[2.23]	[0.99]		[2.14]	[0.97]		[2.23]	[0.99]	
HH	[2.11]	[0.95]		[2.25]	[0.98]		[2.12]	[0.95]		[2.25]	[0.98]	
VAR	[2.21]	[1.04]		[2.38]	[1.10]		[2.20]	[1.07]		[2.22]	[1.14]	
3	2.25	2.95	3.48	2.69	2.74	3.26	2.40	1.93	1.52	2.69	1.74	1.34
NW	[1.97]	[1.02]		[1.96]	[1.05]		[1.97]	[1.01]		[1.96]	[1.05]	
HH	[2.00]	[1.04]		[2.00]	[1.06]		[2.00]	[1.03]		[2.00]	[1.06]	
VAR	[2.04]	[1.06]		[2.02]	[1.06]		[2.05]	[1.02]		[1.99]	[1.06]	
4	1.58	2.62	2.83	−0.42	2.24	2.41	0.66	1.58	1.05	−0.42	1.24	0.75
NW	[1.98]	[1.13]		[1.97]	[1.05]		[1.98]	[1.12]		[1.97]	[1.05]	
HH	[2.03]	[1.18]		[1.99]	[1.10]		[2.03]	[1.17]		[1.99]	[1.10]	
VAR	[2.15]	[1.11]		[2.39]	[0.97]		[2.20]	[1.14]		[2.42]	[0.96]	
5	2.87	2.25	1.92	−4.69	2.04	2.35	−0.87	1.31	0.66	−4.69	1.04	0.62
NW	[2.18]	[1.20]		[4.24]	[1.14]		[2.17]	[1.22]		[4.24]	[1.14]	
HH	[2.12]	[1.23]		[4.08]	[1.12]		[2.11]	[1.24]		[4.08]	[1.12]	
VAR	[2.30]	[1.20]		[4.10]	[0.95]		[2.32]	[1.16]		[4.29]	[0.96]	

Notes: Panel I reports summary statistics for return predictability regressions at a one-month horizon. For each portfolio j, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a one-month horizon. The Newey and West (1987) NW standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 17: One-Year Ahead Predictability - Developed Countries

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
1	0.32	2.98	20.01	7.47	2.51	16.79	3.16	1.94	9.45	7.47	1.51	6.82
NW	[2.03]	[0.77]		[2.37]	[0.78]		[2.06]	[0.78]		[2.37]	[0.78]	
HH	[2.32]	[0.80]		[2.62]	[0.85]		[0.17]	[0.91]		[0.25]	[1.04]	
VAR	[2.31]	[1.14]		[4.66]	[1.27]		[0.18]	[0.98]		[0.28]	[0.97]	
Over	[2.15]	[1.10]		[3.46]	[1.07]		[2.18]	[1.11]		[3.46]	[1.07]	
2	1.36	2.46	13.61	3.10	1.54	6.07	2.49	1.49	5.29	3.10	0.54	0.78
NW	[2.14]	[1.04]		[2.13]	[0.94]		[2.21]	[1.06]		[2.13]	[0.94]	
HH	[2.44]	[1.15]		[2.42]	[1.04]		[0.18]	[0.95]		[0.19]	[0.98]	
VAR	[2.67]	[1.30]		[3.95]	[1.59]		[0.19]	[1.10]		[0.19]	[1.12]	
Over	[2.66]	[1.49]		[2.92]	[1.38]		[2.76]	[1.52]		[2.92]	[1.38]	
3	2.34	2.42	15.63	2.25	2.25	15.08	2.30	1.39	5.72	2.25	1.25	5.20
NW	[1.76]	[0.89]		[1.80]	[0.83]		[1.78]	[0.90]		[1.80]	[0.83]	
HH	[1.98]	[0.96]		[2.03]	[0.89]		[0.17]	[1.03]		[0.17]	[1.06]	
VAR	[1.95]	[1.03]		[1.87]	[0.90]		[0.17]	[1.02]		[0.18]	[1.03]	
Over	[1.84]	[1.11]		[1.92]	[1.14]		[1.86]	[1.13]		[1.92]	[1.14]	
4	2.55	2.48	18.50	0.59	2.19	17.41	1.66	1.41	6.87	0.59	1.19	5.88
NW	[1.60]	[0.94]		[1.64]	[0.80]		[1.60]	[0.94]		[1.64]	[0.80]	
HH	[1.78]	[1.01]		[1.80]	[0.83]		[0.17]	[1.17]		[0.17]	[1.10]	
VAR	[2.42]	[1.29]		[2.22]	[1.00]		[0.18]	[1.12]		[0.21]	[1.01]	
Over	[2.08]	[1.29]		[2.64]	[1.12]		[2.13]	[1.33]		[2.64]	[1.12]	
5	4.23	1.71	7.87	−1.33	1.83	10.20	1.19	0.82	1.98	−1.33	0.83	2.28
NW	[1.92]	[1.30]		[3.25]	[1.13]		[1.84]	[1.28]		[3.25]	[1.13]	
HH	[2.17]	[1.45]		[3.61]	[1.26]		[0.18]	[1.24]		[0.34]	[1.12]	
VAR	[3.50]	[1.55]		[5.03]	[1.51]		[0.20]	[1.17]		[0.34]	[0.95]	
Over	[2.19]	[1.51]		[4.04]	[1.26]		[2.07]	[1.46]		[4.04]	[1.26]	

Notes: Panel I reports summary statistics for return predictability regressions at a twelve-month horizon. For each portfolio j, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a twelve-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) *HH* standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. *Over* denotes the Newey and West (1987) standard errors obtained with non-overlapping series. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays and Reuters (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1983–1/2009.

Table 18: One-Month Ahead Predictability, 1976-2009

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
1	−4.07	1.89	2.03	5.66	2.31	3.03	−0.04	1.22	0.86	5.66	1.31	0.99
NW	[1.98]	[0.71]		[2.79]	[0.73]		[1.95]	[0.70]		[2.79]	[0.73]	
HH	[1.92]	[0.72]		[2.83]	[0.67]		[1.89]	[0.71]		[2.83]	[0.67]	
VAR	[2.05]	[0.70]		[2.70]	[0.70]		[1.95]	[0.71]		[2.67]	[0.69]	
2	−3.05	2.33	3.17	1.96	2.80	3.95	−1.33	1.55	1.43	1.96	1.80	1.67
NW	[2.02]	[0.78]		[1.91]	[0.86]		[2.00]	[0.77]		[1.91]	[0.86]	
HH	[2.06]	[0.82]		[2.02]	[0.91]		[2.03]	[0.81]		[2.02]	[0.91]	
VAR	[2.10]	[0.75]		[1.89]	[0.79]		[2.18]	[0.74]		[1.87]	[0.79]	
3	−1.36	1.39	1.29	−1.28	2.03	2.36	−1.07	0.50	0.17	−1.28	1.03	0.62
NW	[1.93]	[0.81]		[1.77]	[0.82]		[1.89]	[0.79]		[1.77]	[0.82]	
HH	[1.94]	[0.85]		[1.80]	[0.88]		[1.93]	[0.84]		[1.80]	[0.88]	
VAR	[1.95]	[0.68]		[1.83]	[0.76]		[1.96]	[0.74]		[1.85]	[0.78]	
4	0.09	1.67	1.89	−0.94	1.28	1.29	−1.06	0.64	0.28	−0.94	0.28	0.06
NW	[1.78]	[0.79]		[2.23]	[0.73]		[1.79]	[0.80]		[2.23]	[0.73]	
HH	[1.81]	[0.84]		[2.30]	[0.77]		[1.82]	[0.84]		[2.30]	[0.77]	
VAR	[2.02]	[0.72]		[2.52]	[0.69]		[1.98]	[0.74]		[2.45]	[0.70]	
5	1.26	1.78	1.74	0.48	0.43	0.41	−3.63	0.15	0.01	0.48	−0.57	0.69
NW	[1.92]	[0.78]		[2.91]	[0.36]		[1.96]	[0.81]		[2.91]	[0.36]	
HH	[1.93]	[0.83]		[2.97]	[0.37]		[1.97]	[0.85]		[2.97]	[0.37]	
VAR	[2.13]	[0.82]		[3.32]	[0.39]		[2.32]	[0.83]		[3.31]	[0.40]	

Notes: Panel I reports summary statistics for return predictability regressions at a one-month horizon. For each portfolio j, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a one-month horizon. The Newey and West (1987) NW standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) HH standard error are computed with one lag. The bootstrapped standard errors VAR are computed by drawing from the residuals of a VAR with one lag. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1976–1/2009.

Table 19: Three-Month Ahead Predictability, 1976-2009

Portfolio	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2	κ_0	$\kappa_{\mathbf{f}}$	R^2	κ_0	κ_f	R^2
	Panel I: Returns						Panel II: Exchange Rates					
1	−4.16	2.30	6.52	5.91	2.44	8.06	−0.24	1.54	3.12	5.91	1.44	2.96
NW	[1.81]	[0.67]		[2.48]	[0.59]		[1.74]	[0.65]		[2.48]	[0.59]	
HH	[2.03]	[0.77]		[2.93]	[0.73]		[1.98]	[0.75]		[2.93]	[0.73]	
VAR	[2.79]	[1.03]		[3.97]	[1.01]		[2.76]	[1.05]		[3.94]	[1.04]	
Over	[1.87]	[2.75]		[2.80]	[2.93]		[1.87]	[2.75]		[2.80]	[2.93]	
2	−1.99	1.94	4.66	1.78	2.17	5.57	−0.30	1.09	1.53	1.78	1.17	1.68
NW	[1.97]	[0.72]		[1.92]	[0.73]		[1.93]	[0.71]		[1.92]	[0.73]	
HH	[2.01]	[0.79]		[2.05]	[0.83]		[1.98]	[0.77]		[2.05]	[0.83]	
VAR	[2.82]	[0.98]		[2.69]	[1.09]		[2.77]	[1.02]		[2.47]	[1.07]	
Over	[2.03]	[3.14]		[1.98]	[3.30]		[2.03]	[3.14]		[1.98]	[3.30]	
3	−1.07	1.86	4.88	−0.61	1.99	5.15	−0.84	0.92	1.25	−0.61	0.99	1.32
NW	[1.88]	[0.73]		[1.82]	[0.75]		[1.88]	[0.73]		[1.82]	[0.75]	
HH	[1.91]	[0.78]		[1.86]	[0.81]		[1.90]	[0.78]		[1.86]	[0.81]	
VAR	[2.51]	[0.96]		[2.37]	[0.98]		[2.53]	[0.96]		[2.40]	[0.96]	
Over	[1.95]	[3.14]		[1.89]	[3.23]		[1.95]	[3.14]		[1.89]	[3.23]	
4	−0.00	1.56	3.46	−1.12	1.24	2.52	−1.17	0.54	0.42	−1.12	0.24	0.10
NW	[1.89]	[0.73]		[2.29]	[0.65]		[1.92]	[0.74]		[2.29]	[0.65]	
HH	[1.87]	[0.81]		[2.28]	[0.72]		[1.89]	[0.82]		[2.28]	[0.72]	
VAR	[2.77]	[1.03]		[3.33]	[0.95]		[2.62]	[1.03]		[3.21]	[0.93]	
Over	[1.86]	[3.33]		[2.17]	[2.72]		[1.86]	[3.33]		[2.17]	[2.72]	
5	0.90	1.49	2.51	0.02	0.41	0.57	−3.77	0.05	0.00	0.02	−0.59	1.21
NW	[1.97]	[0.84]		[3.09]	[0.42]		[2.06]	[0.86]		[3.09]	[0.42]	
HH	[1.98]	[0.90]		[3.13]	[0.42]		[2.05]	[0.91]		[3.13]	[0.42]	
VAR	[3.29]	[1.16]		[4.88]	[0.66]		[3.30]	[1.18]		[4.93]	[0.63]	
Over	[2.03]	[3.47]		[3.18]	[1.78]		[2.03]	[3.47]		[3.18]	[1.78]	

Notes: Panel I reports summary statistics for return predictability regressions at a three-month horizon. For each portfolio j, we report the R^2, and the slope coefficient in the time-series regression of the log currency excess return on the average log forward discount ($\kappa_{\mathbf{f}}$) in the left panel and the portfolio-specific log forward discount (κ_f) in the right panel. Panel II reports similar statistics for exchange rate predictability regressions at a three-month horizon. The Newey and West (1987) *NW* standard errors are computed with the optimal number of lags following Andrews (1991). The Hansen and Hodrick (1980) *HH* standard error are computed with one lag. The bootstrapped standard errors *VAR* are computed by drawing from the residuals of a VAR with one lag. All the returns are annualized and reported in percentage points. Data are monthly, from Barclays (Datastream). The returns do not take into account bid-ask spreads. The sample period is 11/1976–1/2009.