Predicting currency returns: New evidence on the forward premium puzzle and dollar-trade strategy *

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January 2019

*We thank seminar participants at 2018 Paris Financial Management Conference, IDC Herzliya, Warwick, and Oxford for useful comments and suggestions.

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New evidence on the forward premium puzzle and dollar-trade strategy

This paper motivates a new predictive variable of currency returns and exchange rates, the lagged foreign interest rate. This predictor emerges from log-linearizing un-hedged foreign investment return, and is the dividend-to-price equivalent in currency markets. The evidence shows that the proposed variable reliably predicts future currency returns and moreover its predictive power goes well beyond carry. Then, forward premium regressions that exploit model-implied predictability consistently generate positive slope estimates, a step forward towards resolving uncovered interest rate parity. From a U.S. investor's perspective, currency strategies that condition on the lagged foreign interest rate deliver significant abnormal payoffs and outperform the dollar-trade strategy.

1 Introduction

The currency market is the largest financial market worldwide, with a trading volume orders of magnitude greater than that of other asset classes.[1] Starting with the seminal study of Meese and Rogoff (1983), exchange rate fluctuations seemed to be difficult to predict using economic models. In particular, a simple random walk specification often generated superior exchange rate forecasts. The evolving literature has already provided supportive evidence that cross-country differences of macroeconomic fundamentals, such as interest rates, inflations, outputs, and productivities, are predictive of exchange rate fluctuations.[2] From an investment perspective, a large body of work has studied the predictive ability of carry to generate outperforming currency trading strategies.[3]

This paper motivates a new predictor of currency returns and exchange rate fluctuations, the lagged foreign interest rate. This predictor emerges from log-linearizing un-hedged foreign investment return, and is the dividend-to-price equivalent in currency markets.[4] Our setup suggests that the lagged foreign interest rate should predict currency return or cash-flow (risk-free deposit income) growth. In particular, a higher lagged foreign interest rate is associated with lower cash-flow growth or higher future discount rates. The empirical analysis is applied to a universe of 25 economies over the sample period December 1979 through September 2017. The experiments reveal novel evidence on the predictability of currency returns and exchange rates, as well as on two prominent anomalies in currency markets, the forward premium puzzle and the dollar-trade.

[1] https://www.investopedia.com/financial-edge/0910/the-biggest-financial-market-youve-never-heard-of.aspx.

[2] Rossi (2013) provides a comprehensive review of the literature on predicting exchange rates. Chen and Rogoff (2003), Gourinchas and Rey (2007), and Gourinchas, Rey, and Govillot (2010) propose predictors that are not based on country differences: the first study employs commodity price, while the latter two studies motivate a measure of external imbalance.

[3] For example, see Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2011), Lustig, Roussanov, and Verdelhan (2014), Burnside, Han, Hirshleifer, and Wang (2011), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a).

[4] Un-hedged currency return obtains by converting one dollar to foreign currency unit at the current spot rate, depositing the converted amount in the foreign interest rate, and then converting back to dollar at the next period spot rate. Thus, currency return consists of both capital gain (spot rate appreciation) and cash-flow (risk free foreign interest rate) components.

In the first place, the foreign interest rate is statistically significant in return predictive regressions among 18 economies and the aggregate. As prescribed by the model, it is positively associated with future currency return among 24 economies. Moreover, the predictive power of the foreign interest rate goes beyond carry and the forward premium and is robust to various econometric considerations, including short-horizon and long-horizon predictive regressions, vector auto-regression (VAR) models, and the small-sample bias per Stambaugh (1999). Overall, the vast majority of the long-run variation in foreign interest rate is attributable to its covariation with expected currency return. Predictability of exchange rate fluctuations is directly derived from predictability in currency return. In contrast, the evidence on cash-flow growth predictability is rather weak.

We then employ the evidence on exchange rate predictability to re-examine uncovered interest rate parity (UIP) violations. UIP claims that the interest rate differential between two economies is equal to the expected rate of depreciation. However, past work shows that regressing ex post changes of spot exchange rates on the forward premium (the difference between spot and forward exchange rates) yields, for the most part, negative slope estimates, at odds with the predicted value of unity. There are various explanations for UIP violations, including currency risk premium, irrational expectations, or model mis-measurement and mis-specification (see, e.g., Hansen and Hodrick (1980), Fama (1984), Froot and Frankel (1989), and Engel (1996)). Still, the puzzle is challenging because there is substantial evidence that high interest-rate currencies do appreciate.

We argue that averaging through ex post currency realizations could establish an inadequate proxy for *expected* rate of depreciation. Recall, UIP essentially maintains that the expected spot rate is equal to the forward rate. Indeed, the difficulty in estimating expected payoffs is comprehensively discussed in Merton (1980) and Pastor, Sinha, and Swaminathan (2008), among others. Thus, in forward premium regressions, it could be useful to consider the model-implied expected rate of depreciation, recovered from currency return predictive regressions, rather than the realized one.

Remarkably, regressing the expected depreciation rate on the forward premium delivers slope coefficients that are consistently positive and significant for both individual countries and the aggregate. For perspective, the average slope estimate of the 25 currencies using conventional Fama regressions (pooled with country fixed effects) amounts to -0.247 with a t-value of -2.950.

Employing instead the model-implied expected rate of depreciation, the average slope turns to 0.145 with a t-value of 2.800. Focusing on G6 countries only (Canada, France, Germany, Italy, Japan, and U.K.), the average slope is -0.646 using the ex-post realized rate of depreciation, while it is 0.358 using the model-prescribed measure. Considering longer-horizon regressions with expected depreciation rates, average slope estimates are 0.368 (three month), 0.668 (six month), and 1.182 (twelve month).Notably, forward premium regressions that utilize predictability by carry, rather than the lagged foreign interest rate, still generate negative slopes. This evidence reinforces the notion that the information content of the lagged foreign interest rate is incremental and moreover using the model-prescribed depreciation rate helps resolve UIP violations.

UIP violations can thus be traced to measurement errors attributable to using an inadequate proxy for expected depreciation rate. Hassan and Mano (2015) also advocate in favor of measurement errors, although in a different setup. Thus, both Hassan and Mano (2015) and our study suggest implications for asset pricing theory. In particular, consistent with the wide evidence on negative slopes, Fama (1984) derives two conditions: (i) currency risk premium must be negatively correlated with expected rate of depreciation and (ii) currency risk premium must be highly volatile. These conditions have challenged the ability of traditional consumption based asset pricing models to explain currency returns (see, e.g., Frankel and Engel (1984) and Mark (1988)). New generation of consumption models applied to currency markets have been more successful (see, e.g., Bacchetta and Wincoop (2010), Bansal and Shaliastovich (2010), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009), and Verdelhan (2010)). Relaxing Fama conditions could make traditional consumption models more meaningful in explaining the drivers of currency returns.

The findings described thus far rely on the United States as the home currency. Our setup, however, applies more broadly to any global investor. We thus reexamine the evidence on predictability and UIP from every single country's perspective and repeat the battery of empirical experiments. The evidence from the United States as the home country is largely representative.

Beyond statistical significance, we examine whether currency return predictability by the lagged foreign interest rate is economically meaningful. In particular, we propose a conditional trading strategy that draws on the dollar strategy of Lustig, Roussanov, and Verdelhan (2014). The strategy buys a basket of foreign currencies and sells short the dollar, or the opposite, depending on signals emerging from currency return predictive regressions. Our dollar strategy generates annualized mean return and Sharpe ratio of 4.212% and 0.481, respectively, outperforming the "dollar carry trade" strategy. Further, adjusting portfolio payoffs using the Lustig, Roussanov, and Verdelhan (2011) two currency factors (level and slope), the proposed strategy yields significant alpha (about 2% per year). Currency risk could evolve from sudden crashes, which accounts for a significant portion of carry trade returns (Jurek (2014), Farhi et al. (2009), Brunnermeier, Nagel, and Pedersen (2008)). The dollar-trade strategy that conditions on the lagged foreign interest rate performs reasonably well during financial crises. For example, during 2007 and 2008, it earns 65 basis points per month in excess of the "dollar carry trade."

Related to our study is the exact decomposition of Campbell and Clarida (1987), Froot and Ramadorai (2005), and Engel (2016). However, there are important differences. While both decomposition methods are special cases of the general present-value model, as in Engel and West (2005), we log-linearize the total un-hedged return rather than the excess currency return. Our decomposition thus exclusively identifies the foreign interest rate as the currency market equivalent to the dividend-to-price ratio. Our way of decomposition also allows us to re-examine the forward premium puzzle, as noted earlier. This experiment is infeasible when the decomposition is applied otherwise. In terms of assumptions, we only require that the interest rate does not hit a bubble territory, while the exact decomposition in Froot and Ramadorai (2005) enforces the purchasing power parity (PPP) to hold (on expectations) in the long run. Then, as in the literature on equity returns, our decomposition indicates that the foreign interest rate contains the sum of future discounted change of exchange rate plus foreign interest rate alone over successive periods, while the exact decomposition shows that the real exchange rate involves the sum of non-discounted real interest rate differential between two countries over the same period. Our research design is also related to a vast body of work that analyzes equity markets, bond markets, international trade, real estate, and fiscal surplus through the lens of the present-value approach.[5] Our own

[5]See, e.g., Campbell and Shiller (1988), Campbell and Mei (1993), Cochrane (2011), van Binsbergen and Koijen (2010), Lettau and Ludvigson (2001), Gourinchas and Rey (2007), Plazzi, Torous, and Valkanov (2010), and Berndt, Lustig, and Yeltekin (2012).

decomposition in the context of currency return predictability is novel.

The rest of the paper proceeds as following. Section 2 implements the log-linearization and motivates tests on currency return predictability and interest rate parities. Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes. Additional results are reported in the Appendix.

2 Theory

In this theoretical section, we first decompose un-hedged currency investment return along the lines of the present-value approach, then describe model-implied predictive regressions and VAR models that will be implemented in the empirical section that follows, and finally motivate the re-examination of the forward premium puzzle in the presence of currency predictability.

In what follows, lower case letter variables represent the log of their upper case counterparts. Then, let the direct rate between the USD and foreign currency unit (FCU) be $s_t = \log S_t$ (i.e., S_t=1.5USD/£ or 1£=1.5USD) for the spot rate, let $f_t = \log F_t$ for the forward rate, and let the domestic and foreign interest rates between time $t-1$ and time t be $I_{t-1\to t}$ and $I^*_{t-1\to t}$, respectively. Out notation follows the extant literature on exchange rates: we add asterisks to denote the corresponding foreign variables, use ∇ as the cross country difference (i.e., $\nabla I_{t\to t+1} = I_{t\to t+1} - I^*_{t\to t+1}$), and use Δ as the time-series first difference (i.e., $\Delta s_{t+1} = s_{t+1} - s_t$).

2.1 Decomposing un-hedged foreign investment return

Consider an investment in foreign currencies. The un-hedged currency total return R_{t+1} is calculated through converting 1 USD to FCU at S_t, depositing the converted value at $I^*_{t\to t+1}$, then converting back at S_{t+1}. Thus,

$$R_{t+1} = \frac{S_{t+1} + D_{t+1}}{S_t} \tag{1}$$

where the cash flow component of investment return is given by

$$D_{t+1} \quad = \quad S_{t+1} I^*_{t \to t+1}. \tag{2}$$

The cash-flow-to-price ratio $\frac{D_{t+1}}{S_{t+1}}$ is the foreign exchange equivalent to the dividend-to-price ratio. It is equal to the lagged foreign interest rate $I^*_{t \to t+1}$ and is observable already at time t.

Taking logs from both sides of the total return equation (1) yields

$$\begin{aligned} r_{t+1} &= \log\left(S_{t+1} + D_{t+1}\right) - \log\left(S_t\right) \\ &= s_{t+1} - s_t + \log\left(1 + \frac{D_{t+1}}{S_{t+1}}\right) \\ &= s_{t+1} - s_t + \log\left(1 + I^*_{t \to t+1}\right). \end{aligned} \tag{3}$$

We are now ready to conduct the log-linearization. In particular,

$$\begin{aligned} \log\left(1 + I^*_{t \to t+1}\right) &= \log\left(1 + \exp\left(i^*_{t \to t+1}\right)\right) \\ &\simeq \log\left(1 + \exp\left(\bar{\imath}^*\right)\right) + \frac{\exp\left(\bar{\imath}^*\right)}{1 + \exp\left(\bar{\imath}^*\right)}\left(i^*_{t \to t+1} - \bar{\imath}^*\right) \\ &\simeq k + (1 - \rho)\, i^*_{t \to t+1} \end{aligned} \tag{4}$$

where k is a log-linearization constant, $\rho = \frac{1}{1+\exp(\bar{\imath}^*)}$, and $\bar{\imath}^*$ is the unconditional mean of the log foreign interest rate.

Substituting the log-linearization outcome (4) into the log total return equation (3) yields

$$\begin{aligned} r_{t+1} &= s_{t+1} - s_t + k + (1 - \rho)\, i^*_{t \to t+1} \\ &= s_{t+1} - s_t + k + (1 - \rho)\left(d_{t+1} - s_{t+1}\right). \end{aligned} \tag{5}$$

Rearranging equation (5), the log spot rate can be re-expressed as

$$s_t = \rho s_{t+1} + (1 - \rho)\, d_{t+1} - r_{t+1} + k. \tag{6}$$

Moreover, the currency-market equivalent to the log price-to-dividend ratio is given by

$$s_t - d_t = \rho\left(s_{t+1} - d_{t+1}\right) + k + \Delta d_{t+1} - r_{t+1}. \tag{7}$$

Iterating equation (7) forward and precluding the possibility of bubbles in foreign exchange rates, we get

$$s_t - d_t = \frac{k}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1}\left(\Delta d_{t+j} - r_{t+j}\right). \tag{8}$$

As $s_t - d_t = -i^*_{t-1\to t}$, equation (8) can be rewritten as

$$-i^*_{t-1\to t} \;=\; \frac{k}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1}\left(\Delta d_{t+j} - r_{t+j}\right). \tag{9}$$

While the above derived relations hold ex post they also apply ex ante. In particular, taking conditional expectations form both sides of equation (9), we get

$$-i^*_{t-1\to t} \;=\; \frac{k}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1} E_t\left(\Delta d_{t+j} - r_{t+j}\right). \tag{10}$$

Equation (10) establishes the log-linearization of foreign un-hedged investment return. Similar to the stock return decomposition, it suggests that $i^*_{t-1\to t}$, the currency market equivalent to the dividend-to-price ratio, should predict currency return or cash-flow change (or both). In addition, while the dividend-to-price ratio used to predict the time $t+1$ equity return is observed at time t , in the currency market context, the risk-free foreign interest rate is known already at time $t-1$.

2.2 Testing currency return predictability by the foreign interest rate

We cast the decomposition (10) through return and growth predictive regressions

$$r_{t+1} \;=\; a_r + b_r i^*_{t-1\to t} + v_{1,t+1} \tag{11}$$

$$\Delta d_{t+1} \;=\; a_r + b_d i^*_{t-1\to t} + v_{2,t+1}. \tag{12}$$

The return predictive regression (11) departs from the extant literature on currency return predictability in two important ways. First, past work typically considers a regression of excess currency return ($r^e_{t+1} = \log R^e_{t+1} \approx \Delta s_{t+1} - \nabla I_{t\to t+1}$) on the interest-rate differential (carry) $\nabla I_{t\to t+1} = I_{t\to t+1} - I^*_{t\to t+1}$. Here, the total currency return decomposition suggests that the dependent variable is total return r_{t+1} instead of excess return r^e_{t+1}. Second, our predictor is available already at time $t-1$ to predict time $t+1$ return. In comparison, carry is available at time t, and is already part of the excess return at time t: $\underbrace{\log(S_{t+1}) - \log(S_t) + \log(1 + I^*_{t\to t+1})}_{\text{total return}} - \underbrace{\log(1 + I_{t\to t+1})}_{\text{risk free rate}}$.

Beyond predictive regressions, we also employ first-order VAR specifications. We first study a restricted VAR version with the foreign interest rate as the single predictor

$$
\begin{aligned}
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \epsilon_{1,t+1} \\
\Delta d_{t+1} &= a_d + b_d i^*_{t-1\to t} + \epsilon_{2,t+1} \\
i^*_{t\to t+1} &= a_i + b_{i^*} i^*_{t-1\to t} + \epsilon_{3,t+1}.
\end{aligned}
\tag{13}
$$

Then, the log-linearization implies the constraint

$$
b_r - b_d + \rho b_{i^*} = 1. \tag{14}
$$

We then consider an unrestricted VAR

$$
\begin{aligned}
r_{t+1} &= a_r + b_{r,i^*} i^*_{t-1\to t} + b_{r,r} r_t + b_{r,d}\Delta d_t + \varepsilon_{1,t+1} \\
\Delta d_{t+1} &= a_d + b_{d,i^*} i^*_{t-1\to t} + b_{d,r} r_t + b_{d,d}\Delta d_t + \varepsilon_{2,t+1} \\
i^*_{t\to t+1} &= a_{i^*} + b_{i^*,i^*} i^*_{t-1\to t} + b_{i^*,r} r_t + b_{i^*,d}\Delta d_t + \varepsilon_{3,t+1}.
\end{aligned}
\tag{15}
$$

Cross-equation constraints are given by

$$\begin{aligned} b_{r,i^*} - b_{d,i^*} + \rho b_{i^*,i^*} &= 1 \\ b_{r,r} - b_{d,r} + \rho b_{i^*,r} &= 0 \\ b_{r,d} - b_{d,d} + \rho b_{i^*,d} &= 0. \end{aligned} \tag{16}$$

In the empirical analysis, we estimate restricted and unrestricted VAR models with versus without cross-equation constraints along with time-series predictive regressions.

Before proceeding, we make three remarks about the proposed currency return decomposition. First, Froot and Ramadorai (2005) implement a present-value type decomposition to the identity: change in the real exchange rate= the real excess return minus the real interest rate differential. They show that the current real spot rate is the difference between the infinite sum of real interest rate differential and excess return. Their decomposition implies that the current nominal spot rate may contain information about future excess return. Our approach points to the lagged foreign interest rate, a cash-flow-to-price ratio, as the predictor of future total return. While Froot and Ramadorai (2005) enforces the real spot rate to converge to zero in the long run (i.e., PPP holds in expectations), we only require that the interest rate is bounded from above in the long run.

Second, as $E_t \Delta s_{t+1}$ can vary with other macro variables, beyond the foreign interest rate, we also consider multiple predictive regressions including the lagged currency return, the forward premium, carry, and the depreciation rate. We note upfront that the predictive power of the lagged interest rate is independent and complementary to that of any other predictor.

Third, while we take the perspective of a U.S. investor, our framework applies broadly to any other global investor. For example, consider an Australian agent who invests in the US dollar. The log-linearization holds, except that the foreign interest rate would be that of the US. While our empirical analysis pays special attention to the United States as the home country, we also run the analysis from the perspective of any other global investor.

2.3 Testing uncovered interest rate parity

Past work employs the log-linearization formula to study the expected value of total return (capital gain plus dividend yield) among various asset classes. In the context of currency markets, the decomposition delivers meaningful implications for uncovered interest rate parity (UIP). In particular, observe from equation (5) that having at hand an estimate for expected currency return $\mu_t = E_t(r_{t+1})$, the conditional expected rate of depreciation (the capital gain) can be backed out, as the foreign interest rate (the dividend-to-price equivalent) is at the time t information set. This important property allows us to reexamine UIP using the expected, rather than the realized, rate of depreciation as the dependent variable in forward premium regressions.

For perspective, a brief background on interest rate parities is in order. Covered interest rate parity (CIP) reflects the theoretical condition where interest rates as well as spot and forward currency values of two countries are in equilibrium: there are no interest rate arbitrage opportunities between the two currencies. Thus, CIP requires that $\frac{1+I_{t\to t+1}}{1+I^*_{t\to t+1}} = \frac{F_t}{S_t}$. While CIP formulates the forward rate, UIP refers to a condition that the difference in interest rates between two countries is equal to the expected change in exchange rates. Specifically, UIP requires that

$$\frac{1 + I_{t\to t+1}}{1 + I^*_{t\to t+1}} = \frac{E_t S_{t+1}}{S_t}. \tag{17}$$

Testing UIP can then rely on the regression specification (e.g., Chin and Meredith (2004))

$$s_{t+1} - s_t = \alpha + \beta \left(\log(1 + I_{t\to t+1}) - \log(1 + I^*_{t\to t+1})\right) + e_{t+1}. \tag{18}$$

If CIP holds, then $\log(1 + I_{t\to t+1}) - \log(1 + I^*_{t\to t+1})$ can be replaced by $f_t - s_t$. Therefore, the following regression is typically used to test UIP (e.g., Fama (1984), Backus, Gregory, and Telmer (1993), and Froot and Frankel (1989)):

$$s_{t+1} - s_t = \alpha + \beta (f_t - s_t) + w_{t+1}. \tag{19}$$

Indeed, if interest rate parities hold, the regression (19) should deliver a slope coefficient β equal to unity. Empirically, however, numerous studies have found that the expected depreciation rate of a high interest rate currency is negatively related to the interest rate differential. To illustrate, Froot and Thaler (1990) find that the average estimate of β based on 75 published articles is about -0.88. Froot and Frankel (1989) decompose the deviation of $\hat{\beta}$ from unity into two components related to (i) risk premium and (ii) forecast errors. They argue that violations of UIP are due to systematic forecast errors. Bekaert and Hodrick (1993), however, test the model misspecification channel and find only little empirical support. Bansal and Dahlquist (2000) argue that the puzzle exists only in high income economies. Similarly, Frankel and Poonawala (2010) demonstrate that emerging markets tend to exhibit smaller, albeit negative, coefficients.[6]

These studies typically employ the ex post rate of depreciation as the dependent variable in forward premium regressions.[7] Averaging through ex post realizations, however, could establish a poor proxy for expected value. Recall, UIP essentially maintains that the expected spot rate should be equal to the forward rate. To reinforce this important point, notice that Pastor, Sinha, and Swaminathan (2008) show that while the risk-return relation in equity markets is mostly negative based on regressing realized return on conditional volatility, it turns positive when the dependent variable is the implied value of expected return. In our context, it is useful to consider the model-based expected depreciation rate in forward premium regressions.

Specifically, we estimate the predictive regression (11), substitute the fitted value into the expected currency return, and then recover the expected rate of depreciation, $E_t(s_{t+1} - s_t)$.[8] We then consider the forward premium regression

$$E_t(s_{t+1} - s_t) = \alpha + \beta_2 (f_t - s_t) + \varepsilon_{t+1}. \tag{20}$$

[6] This evidence is consistent with the notion that emerging markets have higher inflation and their currency follows the medium horizon trend more readily. However, the evidence is inconsistent with the notion that emerging markets should command a higher risk premium.

[7] Froot and Frankel (1989) use three set of economic surveys to test the UIP puzzle.

[8] Engel (2016) measures the expectation of future multi-period excess return from the difference between the transitory component of the exchange rate and the infinite sum of expected interest rate differentials using a vector error correction model.

Indeed, while we use the estimated value of expected depreciation in regression (20), the errors-in-variables (EIV) bias should not apply in our setup. EIV emerges when an estimated quantity, rather than the true value, serves as the regression independent variable. (See, e.g., Greene (2008).) While our dependent variable is estimated with errors in the first step, there is no a-priori reason to believe that such errors are systematically correlated with the current forward premium in the second step.[9] Our results are also robust to considering VAR models and long-horizon regressions in the first-step estimation.

As discussed in the empirical section below, we document stronger support for UIP. In particular, the regression (20) generates positive and significant slope estimates using both individual countries and the aggregate.

3 Data

We obtain data on foreign exchange rates from Datastream over the sample period from December 1979 to September 2017 (452 months). Our sample spans 25 countries/regions, including Australia, Germany, Belgium, Canada, Czech, Denmark, Euro (economic and monetary union), Spain, Finland, France, Greece, Hungry, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Austria, Poland, Portugal, South Africa, Sweden, Switzerland, United Kingdom, while the United States serves as the home country.

The risk-free rate is proxied by the one-month Eurocurrency deposit rate. Spot and forward exchange rates are monthly and are mostly from WM/Reuters (WMR). To maximize data availability, we use Barclays Bank International (BBI) whenever WMR is unavailable. Further, following Burnside (2012) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), when necessary, we complement the BBI data with Reuters currency rates quoted against the British Pound, assuming no violations of triangular arbitrage.

[9] See also Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006) who employ estimates of expected returns as dependent variables in asset pricing regressions.

In studies of equity return predictability, the dividend-to-price ratio cannot record negative values. Here, we do encounter a few episodes of negative nominal foreign short interest rates. For example, from 2002:09, Japan often realized negative nominal short rates. Similarly, after 2015:01, the Euro area consistently recorded negative short rates. While we exclude such non-positive foreign short rates when using the variables in logs, we show that our predictive regression results are quantitatively similar upon using levels, wherein negative rates do not establish any hurdle.

Panel A of Table 1 summarizes the total returns for all 25 currencies through the sample period from January 1980 to September 2017. The mean currency return ranges from 0.246% (Euro) to 0.828% (New Zealand) per month and there is little serial correlation for most currencies. About 19 of the 25 currencies exhibit negative skewness in realized returns. Comparing the min and max monthly returns reveals similar patterns. The magnitude of the largest monthly loss exceeds that of the biggest monthly gain for 13 of the 25 currencies.

Table 1 about here.

Panel B of Table 1 reports the correlations between each country's lagged interest rate ($I^*_{t-1\to t}$) and future currency return, R_{t+1}, interest rate differential $\nabla I_{t\to t+1}$, forward premium fp_t, and realized rate of depreciation, $\Delta S_{t+1}/S_t$. On average, lagged interest rate is positively related to future currency return, suggesting that higher foreign interest rates are associated with higher future investment payoffs for U.S. investors. Also, the lagged interest rate is negatively related to carry and forward premium, with an average correlation coefficient of about -0.5. This evidence thus rules out the possibility that the foreign interest rate is a mere proxy for carry or forward premium. Finally, the rate of depreciation records an average correlation of -0.020.

4 Results

We employ our setup to examine the evidence on predictability in currency returns as well UIP violations. We start with a predictive regression analysis. We then cast the present value decomposition using various VAR models. We finally evaluate performance of investment strategies that exploit the predictive power of foreign interest rate.

4.1 Predictive regressions

Table 2 presents the slope and R^2 estimates of the predictive regressions (11) and (12), where b_r and b_d are multiplied by 100. To adjust for serial correlation, we use a six-lag Newey-West standard error. The present-value decomposition indicates that the foreign interest rate should forecast positive return and negative cash-flow growth. For the most part, out findings are supportive.

Starting with the return predictive regression, slope coefficients are positive for 24 foreign currencies (with Greece as the only exception), while significance is recorded for 18 economies. The evidence also shows cross-country dispersion in the ability of lagged foreign interest rate to predict future currency return: the regression R^2-s are greater than 1% for 13 currencies, and greater than 2% for three currencies (Ireland, Japan, and Norway). The R^2 estimates may not look large enough. Notice, however, that Kandel and Stambaugh (1996) and Cochrane (2011), among others, discuss the meaningful economic implications of apparently small goodness-of-fit measures in time-series regressions. In addition, we show below that the regression R^2 increases with the investment horizon, and we further reinforce the notion that currency return predictability based on the foreign interest rate is economically significant through currency trading strategies.[10]

Switching to growth predictive regressions, there are more negative than positive slopes, albeit estimates are mostly insignificant. Moreover, except for three economies (Greece, Hungary, and South Africa), most of the adjusted R^2-s are below 1%, providing less supportive evidence for cash-flow growth predictability.

Consistent with the evidence from short-run predictive regressions, we later show that the long-horizon variance of foreign interest rate is mostly attributable to its co-variation with expected

[10] As acknowledged by Engel (2016), "it seems plausible that there were some changes in the driving processes for interest rates and exchange rates during the turbulent period from late 2008 until early 2013 because of the global financial crisis and the European debt crisis". We indeed find that when the foreign interest rate is particularly low and stable in the recent years, the evidence on return predictability becomes weaker. Nevertheless, the economic significance in that period still stands out.

currency return, while substantially smaller fraction emerges from co-variation with cash-flow growth. Therefore, to extract the expected rate of depreciation in forward premium regressions, we rely on currency return predictive regressions, rather than growth regressions.

Table 2 about here.

If lagged foreign interest rate could predict future return, then it would be natural to examine whether currency return predictability is carried over for the long run, as economic cycles are long lasting. We thus examine the long-horizon predictive regression

$$r_{t\to t+k} = a_{r,k} + b_{r,k} i^*_{t-1\to t} + \eta_{t+k} \tag{21}$$

where $k = 3, 6, 12$. We use six-lag Newey-West standard errors to conduct statistical inference.

Table 3 presents the results, where $b_{r,3}$, $b_{r,6}$, and $b_{r,12}$ are multiplied by 100. For almost all currencies, as the investment horizon gets longer, the regression slopes grow in magnitude and become more significant. Likewise, the regression R^2 grows with increasing investment horizons, recording a cross-country average of 10% for the 12-month horizon. Take Australia for example. For one-month ahead total return, the recorded slope coefficient is 0.440 (t=1.535). For the three, six, and twelve month ahead cumulative returns, the slope coefficient grows up to 1.414 (t=1.832), 3.310 (t=2.517), and 7.409 (t=3.718). The regression R^2 also increases to 1.748% (three month), 4.507% (six month), and 10.375% (twelve month), comparing to 0.544% for the one-month predictive regression.

Table 3 about here.

As elaborated earlier, our log-linearization approach is different from the exact decomposition implemented by Froot and Ramadorai (2005). Empirically, it is also imperative to distinguish the return predictive power of lagged foreign interest rate from that of carry, the focus of a tremendous body of the existing work. Hence, we examine the following regressions

$$\begin{aligned} r_{t+1} &= a_r + b_r i^*_{t-1\to t} + && +\upsilon_{1,t+1} \\ r_{t+1} &= a_r + && +b_c(\log(1+I_t) - \log(1+I^*_t)) + \upsilon_{2,t+1} \\ r_{t+1} &= a_r + b_r i^*_{t-1\to t} && + b_c(\log(1+I_t) - \log(1+I^*_t)) + \upsilon_{3,t+1} \end{aligned} \quad (22)$$

The results are reported in Table A.1. Briefly, of the 25 economies, there are 18 and 14 countries where the lagged interest rate and carry, respectively, predict future currency return on a stand alone basis. When we consider both variables jointly in a multiple regression, the corresponding figures are 9 and 8. Aggregating the evidence through all countries in our sample, both variables are highly significant predictors with t values of 6.37 (foreign interest rate) and -4.98 (carry). Overall, the lagged foreign interest rate is incremental to carry in predicting future returns.

We also include the lagged currency return, the forward premium, and the rate of depreciation as additional explanatory variables in currency return predictive regressions (results are reported in Table A.2). Altogether, the predictive power of the lagged foreign interest rate remains intact in multiple regressions. Beyond the evidence from predictive regressions, the argument of Cochrane (2008) also applies in our context: if lagged foreign interest rate cannot predict cash-flow growth, then return must be predictable, to generate the observed variation in foreign interest rate.

4.2 Testing uncovered interest rate parity

Given the solid evidence on currency return predictability, we are now ready to re-examine uncovered interest rate parity. In table 4, we first estimate the conventional Fama regression in equation (19), where the dependent variable is the realized rate of depreciation. We confirm the violation of UIP: 15 of the regression slopes are negative, including four of G6 currencies (except for France and Italy).

We then use the expected rate of depreciation as the dependent variable in forward premium regressions, as formulated in equation (20). Strikingly, there is only one negative slope coefficient

(South Africa). Otherwise, among all other currencies, predictive regressions produce considerably larger slope estimates, often even near unity, the required value under the null hypothesis of uncovered interest rate parity.

From an aggregate perspective, the average slope estimate of the 25 currencies using the pooling conventional Fama regression with country fixed effects amounts to -0.247 ($t = -2.950$, with Newey-West standard error calculated using 6 lags, and R^2 of 0.32%). However, the counterpart based on the expected rate of depreciation is about 0.145, with $t = 2.800$ and R^2 of 29.90%. Even more so, the average of G6 country slope estimates is -0.646 using the ex-post realized rate of depreciation (Engel (2016) obtains -1.467 from 1979:06 to 2009:10), while it is 0.358 using the ex-ante measure, as prescribed by the log-linearization formula.

Table 4 about here.

Our results on UIP are robust to various considerations. First, positive slopes are also recorded for VAR models, as discussed below. Second, UIP can also be tested using levels rather than logs (Engel (1996)). We confirm that the overall evidence remains unchanged using levels. Third and most importantly, our analysis employs the whole-sample to estimate investors' expected rate of depreciations. To circumvent concerns related to look-ahead bias, we also conduct a purely out-of-sample analysis. In particular, starting from month 31, we use expanding windows with all the past available data to estimate predictive regression intercept and slope coefficients, and then generate out-of-sample estimates of expected depreciation rate. We confirm that the evidence supporting positive slopes is equally strong.

To further understand the sign of the slope coefficient in model-implied forward premium regressions, we express the slope coefficient as (see details in the appendix):

$$\beta_2 = \frac{b_r Cov\left(i^*_{t-1\to t}, I_{t\to t+1}\right) - Cov\left(I^*_{t\to t+1}, I_{t\to t+1}\right) - b_r Cov\left(i^*_{t-1\to t}, I^*_{t\to t+1}\right) + Var\left(I^*_{t\to t+1}\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)}. \quad (23)$$

The regression slope depends on the presence of currency return predictability (through b_r), the cross correlation between the log foreign interest rate and the level of US interest rate, the contemporaneous correlation between foreign and U.S. rates, the cross correlation between the log and the level of the foreign interest rate, and finally the variance of the foreign interest rate. We are unaware of any economic theory that enforces positive sign over the numerator in equation (23). Thus, whether the slope is negative or positive remains an empirical question. Past works focuses on $b_r = 0$. Then the resulting slope turns out to be negative. With the positive b_r documented here, the slope turns, for the most part, positive.

For comparison, we also show in the appendix the condition for a positive slope when the expected depreciation rate is based on predictive regressions that rely on carry, rather than the lagged foreign interest rate. In untabulated tests, we show that such forward premium regressions yield negative slope estimates. This evidence reinforces the notion that using model-implied depreciation rate could mitigate UIP violations.

We next examine whether the newly documented relationship between the expected rate of depreciation and the forward premium (interest rate differential) extends for the long run. In particular, for each country, we run long-horizon predictive regressions using the expected depreciation rate

$$E_t r_{t\to t+k} - \log\left(1 + I^*_{t-1\to t+k-1}\right) = \alpha + \beta_k \left(f_t - s_t\right) + \varepsilon_{t+k}; \quad k = 3, 6, 12 \tag{24}$$

where $E_t r_{t\to t+k}$ is the fitted value of k-th period ahead return from the long-horizon return predictive regression.

Table 5 about here.

The test results are presented in Table 5. The evidence is consistent with the notion that when the foreign interest rate is higher than the domestic one, the foreign currency rate should depreciate in the long run. To illustrate, take Australia for example. For one month-ahead expected rate of depreciation, the slope coefficient is 0.463, while for three, six, and twelve month ahead expected rate of depreciation, the slope coefficient grows to 1.401, 1.831, and 1.574, respectively. We also report cross-country long-horizon estimates by pooling countries with country fixed effects. The joint estimate is 0.368 (three month), 0.668 (six month), and 1.182 (twelve month), compared to 0.145 for the one-month regression.

4.3 Addressing the small-sample bias

As the foreign interest rate $i^*_{t \to t+1}$ is highly persistent, a potential concern is that slope coefficients in predictive regressions are subject to the small-sample bias (see, e.g., Stambaugh (1999)). In the presence of such bias, slope estimates and their t-ratios could be inflated and thus our UIP tests could also be affected. In response, we follow the approach outlined in Amihud and Hurvich (2004) and Amihud, Hurvich, and Wang (2009) to address the small-sample bias. Bias-corrected results of return predictability and UIP tests are reported in Table 6.

Table 6 about here.

We first examine the bias-corrected estimates of return predictive regressions. For perspective, in the case where the dividend-to-price ratio is the equity return predictor, contemporaneous innovations in the dividend-to-price ratio and equity return are negatively correlated. Such negative correlations inflate the slope estimates and their t-values. In contract, we find that for the vast majority of currencies, the correlation between the innovations in the foreign interest rate and currency return are positive. Only seven currencies record negative correlations, while the average correlation is 0.022. This positive correlation mitigates concerns that the return predictability evidence is spurious, while it further reinforces the notion that cash-flow growth is unpredictable.

It is evident from Table 6 that the bias-corrected slope estimates are fairly close to those reported in Table 2. For example, the G6 countries, Germany, Canada, France, Italy, Japan, and UK, exhibit slopes of 0.233, 0.268, 0.247, 0.244, 0.310, and 0.259, compared to 0.232, 0.258, 0.244, 0.237, 0.310, and 0.252 from Table 2. The cross country average is 0.313, slightly larger than 0.303 the estimated value prior to the bias correction. Considering a country fixed effect regression, the point estimate is 0.270 (t=8.878), similar to 0.266 (t=8.750) reported in Table 2.

Then, using the bias-corrected estimates to back out the expected value of depreciation rate, the overall evidence is unchanged. In UIP tests, Germany, Canada, France, Italy, Japan, and UK record slopes of 0.076, 0.373, 0.587, 0.733, 0.087, and 0.234, compared to 0.073, 0.358, 0.616, 0.771, 0.086, and 0.242 from Table 4. In addition, the regression coefficient with fixed effects is 0.135 (t=2.753). The evidence thus indicates that the small-sample bias plays virtually no role in model implied return predictive regressions.

4.4 VAR

Thus far, our analysis relies on time-series predictive regressions with the future currency total return and lagged foreign interest rate as dependent and independent variables, respectively. The log-linearization essentially implies that economic quantities can better be estimated through expanding the regression system into a VAR setup. In our context, not only does the present value model motivate a predictive variable, i.e., the foreign interest rate, but it also imposes tight restrictions on VAR slope coefficients.

We consider three VAR models to account for the present-value formula. Model 1 is the single predictive variable version in (13) along with the constraint in (14). In models 2 and 3, we estimate the first-order unrestricted VAR with all lagged values in the state vector, as described in equation (15). We estimate unrestricted VAR coefficients both excluding (Model 2) and including (Model 3) the constraints formulated in equation (16).

Table 7 presents the empirical evidence, where the estimate of the slope coefficient b_r is multiplied by 100. Starting with model 1, we observe that the magnitude and sign of the slope estimates generally line up with those reported in Table 2. Combined, the significance level for all countries (excluding Poland) increases in a VAR setup. For example, consider Australia. The new estimate is 0.400 (t=1.631), compared to 0.440 (t=1.535). Moreover, there are 19 currencies with significantly positive slopes.

Table 7 about here.

The evidence is fairly robust to considering models 2 and 3. Again, for Australia, the new estimate is 0.478 (t=1.605) without cross equation constraints, and 0.370 (t=1.227) with constraints. Overall, including all state variables as predictors and either imposing or disregarding constraints on the VAR coefficients does not alter the base results. Thus, we provide strong support to the notion that currency returns are predictable by the lagged foreign interest rate.

We also reexamine forward premium regressions using the three VAR specifications. In model 1, the expected depreciation rate is estimated imposing the constraint $b_r - b_d + \rho b_{i^*} = 1$. In models 2 and 3, the expected rate of depreciation is estimated using $E_t r_{t+1} - \log\left(1 + I^*_{t\to t+1}\right)$, where

$$\begin{aligned} E_t r_{t+1} &= E_t\left(s_{t+1} - s_t + \log\left(1 + I^*_{t\to t+1}\right)\right) \\ &= \hat{a}_r + \hat{b}_{r,i^*} i^*_{t-1\to t} + \hat{b}_{r,r} r_t + \hat{b}_{r,d} \Delta d_t. \end{aligned} \tag{25}$$

Table 8 about here.

Table 8 reports the evidence on forward premium regressions with expected rate of depreciation. Incorporating the VAR structure confirms our previous finding that the UIP puzzle can be substantially mitigated. In model 1, South Africa is yet again the only country that produces a negative slope at −0.005 (t=−1.695). The magnitudes of other slope estimates are close to those reported in Table 4. Turning to models 2 and 3, we show that while there are more negative slope estimates, their magnitudes are fairly small and they are statistically insignificant except for South Africa. In contrast, the positive slopes are, for the most part, statistically significant.

4.5 Considering other base currencies

The econometric setup developed here goes beyond the United States as the home country and extends to any other global investor. Thus, we re-run the major analysis to consider each of the other economies as the home country, or, equivalently, each of the other currencies as the base currency. To ensure that our results are easily comparable, we rely on the triangular relationship for the implied cross rates to obtain a sample whose length is identical for every base currency.

As any domestic agent considers 25 investable foreign currencies, we have conducted 25×25 tests in total. To economize the disposition, table 9 reports only one set of results, the all-country averages, each of which summarizes 25 individual-country regressions. Specifically, we pool all the variables together and run time-series regressions with country individual fixed effects. We only report the small-sample bias corrected results and use 6-lags Newey-West standard error to conduct statistical inference.

For example, an Australian agent would consider an investment in any of the other 25 countries, including the US, as risky. In untabulated tests, we have found that there is strong return predictability in 21 of 25 foreign currencies for that Australian investor. Then, when we aggregate all the evidence from every single country's perspective, there is significant return predictability in an average of 17 of 25 foreign currencies. Therefore, our findings from either an Australian or a US investor's perspective are largely representative.

Table 9 about here.

As shown in table 9, slope estimates in currency return predictive regressions are mostly positive and highly significant. Take, for example, an Australian investor. When we pool all the observations together (investing in 25 foreign currencies), the estimated b_r^c is 0.362 (t=9.673). Japan is an obvious exception, with the b_r^c of 0.033 (t=0.860). The t-stats are smaller in Czech (2.514) and EUR (2.819). Overall, the evidence strongly supports return predictability by the lagged foreign interest rate in global currency markets.

Table 9 also reports the all-country average tests on UIP. We generally document strong evidence supporting UIP. The empirical support is particularly prominent for other major currencies beyond USD: Canadian dollar, Japanese yen, and UK pound. There are also country heterogeneities. For an investor from Czech, Euro zone, or Greece, it is fair to conclude that UIP is generally violated as the β_2^c values are -0.031, -0.042, and -0.023, respectively, all of which are significant. β_2^c is also not different from zero in Finland, Hungary, Poland, or Portugal. Still, the slope in forward premium regressions with expected depreciation rate is significantly positive for all other countries.

Moreover, with the realized rate of depreciation, Fama regressions produce supporting evidence in favor of UIP only for Spain.

4.6 Slope decomposition

To further understand the implications of the present-value model for long-run exchange rates, we attribute the long-run variation in foreign interest rate to its covariation with (i) long-run future currency return, (ii) long-run future cash-flow growth, and (iii) long-run future foreign interest rate. In particular, we start from equation (7) and iterate forward for k periods to obtain

$$i^*_{t-1\to t} = \sum_{j=1}^{k} \rho^{j-1} r_{t+j} - \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} + \rho^k i^*_{t+k-1\to t+k}. \quad (26)$$

We then run the following long-run predictive regressions

$$\begin{aligned} \sum_{j=1}^{k} \rho^{j-1} r_{t+j} &= a + b^k_r i^*_{t-1\to t} + \eta_{1,t+k} \\ \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} &= a + b^k_d i^*_{t-1\to t} + \eta_{2,t+k} \\ \rho^k i^*_{t+k-1\to t+k} &= a + b^k_{i^*} i^*_{t-1\to t} + \eta_{3,t+k}. \end{aligned} \quad (27)$$

Multiplying both sides of the long-run restriction $1 = b^k_r - b^k_d + \rho^k b^k_{i^*}$ by $\text{Var}(i_{t-1\to t})$ yields

$$Var(i^*_{t-1\to t}) = Cov(i^*_{t-1\to t}, \sum_{j=1}^{k} \rho^{j-1} r_{t+j}) - Cov(i^*_{t-1\to t}, \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}) + \rho^k Cov(i^*_{t-1\to t}, i^*_{t+k-1\to t+k}). \quad (28)$$

In words, if foreign interest rates vary, they must forecast long-run currency returns, long-run cash-flow growth, or a "bubble" in future foreign interest rate. To quantify the relative importance of each component, we examine its contribution to the total variation of foreign interest rate.

Following Cochrane (2011), we first conduct direct currency return regressions for investment horizons of ten years. We then use one-year vector auto-regression estimates to obtain implied ten-year horizon slope coefficients. Finally, we infer the infinite-horizon slope coefficients from one-year estimates.

Table 10 about here.

Table 10 reports the results. In panels A and B, we consider currency exchange rates. For comparison and to gain additional perspective, we also report in Panels C and D regression results for equities. Panel A uses the annualized currency data to produce currency total return, cash-flow growth, and foreign interest rate. We pool the country year observations and then run panel regression to obtain coefficient estimates.

As the log-linearization is an approximation, the three estimated slopes do not add up exactly to unity. Therefore, in Panel B, we impose exactly the Campbell-Shiller decomposition: $-i^*_{t-1\to t} = -\rho i^*_{t\to t+1} + k + \Delta d_{t+1} - r_{t+1}$. In Panel C, we estimate the regression using the annual CRSP value weighted stock index data to produce stock return, cash-flow growth, and dividend yield. In Panel D, we use the expected cash-flow growth, imposing the constraint again to ensure summing up to unity. The sample period is 1981∼2016 for both the currency and equity data.

We start with currency markets. Considering the ten-year forecasting horizon, while more than 30% of the foreign interest rate variance can be attributed to the expected return variation, there is about 60% variance attributable to the future foreign interest rate. This ten-year horizon evidence highlights the persistence in foreign interest rates, which may appear more pronounced than that of the dividend yield in equity markets. However, since the interest rate is stationary, its remote distance value in the future time j discounted by ρ^j, would eventually dye out. Indeed, in the infinite horizon case, about 81.2% of the variance of foreign interest rates is due to variation in expected return, only 18.8% is due to variation in cash-flow growth, and virtually none is related to "bubbles."

The evidence from equity markets is qualitatively similar to that from currency markets. To illustrate, for the ten-year forecasting horizon, about 84.5% of the variance of dividend yield is due to variation in expected returns. In the infinite horizon, about 108.7% of the variance of dividend yield is due to variation in expected returns, echoing the finding of Cochrane (2011) that all price-dividend ratio volatility corresponds to variation in expected stock returns.

In sum, we reinforce our findings from predictive regressions. The foreign short interest rate $i^*_{t-1\to t}$, or the "dividend yield" in foreign currency investment, is predictive of future currency returns.

4.7 Using expected volatility of foreign interest rate to predict return

Past work has focused on the first-order Taylor expansion in log-linearizing investment return. The first-order approximation is accurate if the log dividend-to-price ratio is not too volatile. There are also data limitations on monthly higher moments of the dividend-to-price ratio that could establish a nontrivial hurdle for considering such moments. Still, it remains an empirical question whether, at least, the second-order term is incremental in predicting return. The foreign exchange market provides an ideal setting for assessing the predictive power of the second order term, as the volatility of interest rate could be estimated using high frequency data.

In particular, consider the log-linearization of currency return with second-order Taylor expansion

$$E_t r_{t+1} = \kappa + (1 - \rho b_{i*})\, i^*_{t-1\to t} + E_t \Delta d_{t+1} + \frac{1}{2}\rho\,(1-\rho)\, E_t \sigma^2_{i^*,t+1} \tag{29}$$

where b_{i*} is the AR(1) coefficient of $i^*_{t-1\to t}$. The derivation motivates a regression with realized return r_{t+1} as the dependent variable, and both the level of lagged foreign interest rate ($i^*_{t-1\to t}$) and the conditional expectation of foreign interest rate volatility ($E_t \sigma^2_{i^*,t+1}$) as predictive variables. The second-order component should play a bigger role in governing expected return variation when $i^*_{t-1\to t}$ drifts away from its long-term trend.

To account for the second-order term, we estimate the regression

$$r_{t+1} \quad = \quad a_r + b_r i^*_{t-1\to t} + b_{r,v} vol_{t-1\to t} + v_{1,t+1}. \tag{30}$$

where $vol_{t-1\rightarrow t}$ is the volatility of daily sampled interest rate in month t.[11]

Table 11 about here.

Table 11 reports regression coefficients. The volatility estimate is a significant predictor in 9 countries. In some cases, volatility has an independent role in predicting returns. Take Denmark as an example. The slope b_r is not different from zero, while $b_{r,v}$ is strongly significant. There are six countries where both level and volatility have significant slopes (Germany, Belgium, Czech, Finland, France, Japan). While there is evidence that the second-order term has some role in predicting currency market return, the all-country significance of level is considerably higher that than of volatility (7.495 versus -1.714). After all, volatility is a second-order determinant. Still, understanding the role of other volatility estimates as well as higher-order terms is left for future research.

4.8 Dollar-trade strategies

In this section, we assess the economic significance of currency return predictability. To set the stage, we average across N countries and estimate the time-series regression:

$$\bar{R}_{t+1} - 1 \quad = \quad -0.0010 + \underbrace{1.4692}_{t=2.2735} \bar{I}^*_{t-1\rightarrow t} \tag{31}$$

where $\bar{R}_{r+1} = \frac{1}{N}\sum R_{t+1}$, $\bar{I}^*_{t-1\rightarrow t} = \frac{1}{N}\sum I^*_{t-1\rightarrow t}$. There are 24 currencies prior to Jan 1999 and 14 following the adoption of Euro. These two periods are of roughly equal lengths: 1980:01∼1998:12; and 1999:01∼2017:09. To assess significance, we use the Newey-West standard error with 6 lags. The evidence shows that the slope coefficient is positive and significant at conventional levels. We also estimate the log version of the predictive regression:

$$\bar{r}_{r+1} \quad = \quad 0.0250 + \underbrace{0.0035}_{t=2.0594} \bar{\imath}^*_{t-1\rightarrow t} \tag{32}$$

[11] We also examine the predictive power of the second order terms on a stand-alone basis. In Table A.3 of the appendix, we report simple regression results with the standard deviation and the variance as return predictors.

where $\bar{r}_{t+1} = \log\left(\bar{R}_{t+1}\right)$ and $\bar{\imath}^*_{t-1\to t} = \log(\bar{I}^*_{t-1\to t})$. The slope coefficient is, again, positive and significant. The results based on the single regression of average currency return are generally consistent with the evidence from pooled regressions. Statistically, there is solid evidence on return predictability in joint and individual tests.

Is the statistical evidence translated into economically significant investment payoffs? To evaluate economic significance, we draw on the dollar-trade strategy of Lustig, Roussanov, and Verdelhan (2014). This strategy buys (sells) a basket of foreign currencies and sells short (buys) the dollar whenever the average foreign short-term interest rate is above (below) the corresponding U.S. rate.

Similarly, we propose trading strategies using various signals emerging from return predictive regressions. The strategies are detailed in the next paragraph. While carry is observable, our signals require the estimation of regression intercept and slope coefficients to deliver the estimate of expected currency return. For this purpose, we use the first 30 months of the sample period to obtain a first estimate of expected currency return. We use an expanding window such that in every month we add one more observation in estimating the predictive regression and regenerating the investment signal. Similar to the dollar strategy, the signal sign dictates whether to buy all foreign currencies and sell short the U.S. dollar or instead to buy the U.S. dollar and sell short all foreign currencies.

For comparison, we first generate an investment strategy based on average carry (the time t observed foreign vs. domestic interest rate differential $\overline{I^*_{t\to t+1} - I_{t\to t+1}}$). We then generate three dollar strategies that exploit the log-linearization implied predictive variable. The proposed strategies are based on the following signals: (ii) the lagged average foreign vs. domestic interest rate differential $\overline{I^*_{t-1\to t} - I_{t-1\to t}}$, (iii) the average value of N expected returns from N country return predictive regressions $\overline{E_t R_{t+1}} = 1/N(\sum E_t R_{t+1})$ using country lagged foreign interest rate as the single regressor, and (iv) the predicted return $E_t\bar{R}_{t+1}$ from a single predictive regression with the average of N returns as the dependent variable and the average of N lagged foreign interest rates $1/N\sum(i^*_{t-1\to t})$ as the explanatory variable.

The four zero-cost strategies generate time-series of excess returns, and the results are summarized in Table 12. In Panel A, figures are monthly percentage points except for the Sharpe ratio (SR) that is annualized. We report the average monthly return, the standard deviation, the Sharpe ratio (SR), the max return, the min return, skewness, AR(1), and the information ratio (IR) relative to the conventional "dollar" strategy with the current interest rate differential as the investment signal.

Both strategies (ii) and (iv) generate higher excess return, smaller volatility, and ultimately higher Sharpe ratios than the benchmark dollar strategy. While the correlation between the lagged average carry and average carry can be fairly high, it is still noteworthy that using the lagged information can deliver a slightly outperforming strategy with an information ratio of 0.217 relative to the benchmark dollar carry trade strategy. The most notable performance is that of strategy (iv) that uses a single predictive regression. It generates a Sharpe ratio of 0.481 per year and information ratio of 0.343 relative to the benchmark carry-trade dollar strategy. The evidence highlights the economic significance of currency return predictability: using the lagged foreign interest rate is beneficial in currency investing.

Table 12 about here.

In unreported tests, we show that during the out-of-sample period 2001:07 ∼2017:09, our proposed investment strategies are robust. In that period, the carry dollar strategy records annualized Sharpe ratio of only 0.126, while ours generate annualized Sharpe ratios that range between 0.227 to 0.380.

We then examine risk-adjusted payoffs for the four dollar strategies proposed here. Panels B, C and D of Table 12 report the evidence. In conducting risk adjustment, we first consider the carry dollar strategy as the benchmark. Unsurprisingly, the strategy (ii), using the lagged carry, heavily loads (0.946) on the benchmark. The other two strategies display smaller benchmark loadings. The fourth dollar strategy, which conditions only on the lagged foreign rate using a single regression, produces annualized alpha about 1.9% (t=2.289, with 6 lags Newey-West standard error).

We then follow Lustig, Roussanov, and Verdelhan (2011) and construct currency factors. We start through sorting currencies by their interest rates. To adjust for the changing number of investable currencies (when there are more than 20/15/10 investable currencies) we sort into 5/4/3 buckets. We then obtain the two factors, namely, the level and slope factors, which are the average and the high-minus-low returns of these buckets of currencies.

In Panel C, we regress returns of all four dollar strategies on the slope factor first, which is known to explain most of the cross section of carry trades. The $E_t\bar{R}_{t+1}$ dollar strategy, which conditions only on the lagged foreign rate, produces annualized alpha that exceeds 3% and is significant at 10%, using a Newey-West standard error of 6 lags. This strategy loads slightly more heavily on the slope factor ($\beta_S = 0.262$, relative to 0.247 from the carry dollar strategy).

In panel D, we consider both level and slope factors. Alphas record stronger statistical significance. The annualized alpha is about 2% (t=2.132) for $E_t\bar{R}_{t+1}$ dollar strategy. Also, this strategy loads less on the level factor ($\beta_L = 0.757$, relative to 0.790 from the carry dollar strategy), and more on the slope factor ($\beta_S = 0.094$, relative to 0.072 from the carry dollar strategy).

In sum, the evidence from investment strategies further supports currency return predictability by the lagged foreign interest rate. That is, not only does the foreign rate predict currency returns to statistically significant degrees, but also it can be employed to design dollar-trade strategies that outperform the well studied carry. The newly proposed dollar strategy, bases on a single regression, delivers investment payoffs that are unexplained by traditional currency factors.

5 Conclusion

We find strong evidence on currency return predictability by the lagged foreign interest rate. The predictive ability of the foreign rate goes beyond carry. Currency return predictability is robust to including control variables, adjusting for the small-sample bias in predictive regressions, as well as imposing cross equation constraints implied by the present-value decomposition. We further show that most of the long-run foreign interest rate volatility is attributable to its co-variation with expected currency return.

As expectation is notoriously difficult to estimate, past studies mainly rely on the realized rate of appreciation to test uncovered interest rate parity. It is often concluded that high interest rate currencies do appreciate. Fairly strong evidence on currency return predictability allows us to utilize the expected rate of appreciation, recovered from return predictive regressions, and re-examine forward premium regressions. We consistently reveal positive slope estimates for both individual counties and the aggregate.

We finally propose currency trading strategies to assess the economic significance of return predictability by the lagged foreign interest rate. A conditional dollar-trade strategy that exploits the documented predictability outperforms the dollar-carry trade strategy. Moreover, our proposed strategy generates investment payoffs that are unexplained by conventional currency market factors.

References

Amihud, Y. and C. M. Hurvich (2004). Predictive regressions: A reduced-bias estimation method. *The Journal of Financial and Quantitative Analysis 39*(4), 813–841.

Amihud, Y., C. M. Hurvich, and Y. Wang (2009). Multiple-predictor regressions: Hypothesis testing. *The Review of Financial Studies 22*(1), 413–434.

Avramov, D. and T. Chordia (2006). Asset pricing models and financial market anomalies. *The Review of Financial Studies 19*(3), 1001–1040.

Bacchetta, P. and E. v. Wincoop (2010). Infrequent portfolio decisions: A solution to the forward discount puzzle. *The American Economic Review 100*(3), pp. 870–904.

Backus, D. K., A. W. Gregory, and C. I. Telmer (1993). Accounting for forward rates in markets for foreign currency. *The Journal of Finance 48*(5), 1887–1908.

Bansal, R. and M. Dahlquist (2000). The forward premium puzzle: different tales from developed and emerging economies. *Journal of International Economics 51*(1), 115 – 144.

Bansal, R. and I. Shaliastovich (2010). A long-run risks explanation of predictability puzzles in bond and currency markets. Duke University, working paper.

Bekaert, G. and R. J. Hodrick (1993). On biases in the measurement of foreign exchange risk premiums. *Journal of International Money and Finance 12*(2), 115 – 138.

Berndt, A., H. Lustig, and S. Yeltekin (2012). How does the us government finance fiscal shocks? *American Economic Journal: Macroeconomics 4*(1), 69–104.

Brennan, M. J., T. Chordia, and A. Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics 49*(3), 345 – 373.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual 2008 23*, 313–347.

Burnside, C. (2012). *Carry Trades and Risk*. Hoboken: John Wiley & Sons.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2011). Do peso problems explain the returns to the carry trade? *The Review of Financial Studies 24*(3), pp. 853–891.

Burnside, C., B. Han, D. Hirshleifer, and T. Y. Wang (2011). Investor overconfidence and the forward premium puzzle. *The Review of Economic Studies 78*(2), 523–558.

Campbell, J. Y. and R. H. Clarida (1987). The dollar and real interest rates. *Carnegie-Rochester Conference Series on Public Policy 27*, 103 – 139.

Campbell, J. Y. and J. Mei (1993). Where do betas come from? asset price dynamics and the sources of systematic risk. *The Review of Financial Studies 6*(3), 567–592.

Campbell, J. Y. and R. J. Shiller (1988). Stock prices, earnings, and expected dividends. *The Journal of Finance 43*(3), pp. 661–676.

Chen, Y. and K. Rogoff (2003). Commodity currencies. *Journal of International Economics 60*(1), 133 – 160. Emperical Exchange Rate Models.

Chin, M. and G. Meredith (2004). Monetary policy and long-horizon uncovered interest rate parity. *IMF Staff Papers 51*(3).

Cochrane, J. (2008). State-space vs. var models for stock returns. University of Chicago Working paper.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance 66*(4), 1047–1108.

Engel, C. (1996). The forward discount anomaly and the risk premium: A survey of recent evidence. *Journal of Empirical Finance 3*(2), 123 – 192.

Engel, C. (2016). Exchange rates, interest rates, and the risk premium. *American Economic Review 106*, 436–474.

Engel, C. and K. D. West (2005). Exchange rates and fundamentals. *Journal of Political Economy 113*(3), 485–517.

Fama, E. M. (1984). Forward and spot exchange rates. *Journal of Monetary Economics 14*(3), 319–338.

Farhi, E., S. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan (2009). Crash risk in currency markets. MIT working paper.

Frankel, J. and C. M. Engel (1984). Do asset-demand functions optimize over the mean and variance of real returns? a six-currency test. *Journal of International Economics 17*(3), 309 – 323.

Frankel, J. and J. Poonawala (2010). The forward market in emerging currencies: Less biased than in major currencies. *Journal of International Money and Finance 29*(3), 585 – 598.

Froot, K. A. and J. A. Frankel (1989). Forward discount bias: Is it an exchange risk premium? *The Quarterly Journal of Economics 104*(1), 139–161.

Froot, K. A. and T. Ramadorai (2005). Currency returns, intrinsic value, and institutional-investor flows. *The Journal of Finance 60*(3), 1535–1566.

Froot, K. A. and R. H. Thaler (1990). Anomalies: Foreign exchange. *The Journal of Economic Perspectives 4*(3), 179–192.

Gourinchas, P. and H. Rey (2007). International financial adjustment. *Journal of Political Economy 115*(4), 665–703.

Gourinchas, P.-O., H. Rey, and N. Govillot (2010). Exorbitant privilege and exorbitant duty. IMES Discussion Paper Series 10-E-20, Institute for Monetary and Economic Studies, Bank of Japan.

Greene, W. (2008). *Econometric Analysis* (6 ed.). Pearson.

Hansen, L. P. and R. J. Hodrick (1980). Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *Journal of Political Economy 88*(5), 829–853.

Hassan, T. and R. Mano (2015). Forward and spot exchange rates in a multi-currency world. Working paper, University of Chicago.

Jurek, J. W. (2014). Crash-neutral currency carry trades. *Journal of Financial Economics 113*(3), 325 – 347.

Kandel, S. and R. F. Stambaugh (1996). On the predictability of stock returns: An asset-allocation perspective. *The Journal of Finance 51*(2), 385–424.

Lettau, M. and S. Ludvigson (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance 56*(3), 815–849.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common risk factors in currency markets. *The Review of Financial Studies 24*(11), 3731–3777.

Lustig, H., N. Roussanov, and A. Verdelhan (2014). Countercyclical currency risk premia. *Journal of Financial Economics 111*(3), 527 – 553.

Lustig, H. and A. Verdelhan (2007, March). The cross-section of foreign currency risk premia and us consumption growth risk. *American Economic Review 97*(1), 89–117.

Mark, N. C. (1988). Time-varying betas and risk premia in the pricing of forward foreign exchange contracts. *Journal of Financial Economics 22*(2), 335 – 354.

Meese, R. A. and K. Rogoff (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics 14*(1 - 2), 3 – 24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012a). Carry trades and global foreign exchange volatility. *The Journal of Finance 67*(2), pp. 681–718.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012b). Currency momentum strategies. *Journal of Financial Economics 106*(3), 660 – 684.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics 8*(4), 323 – 361.

Pastor, L., M. Sinha, and B. Swaminathan (2008). Estimating the intertemporal risk-return tradeoff using the implied cost of capital. *The Journal of Finance 63*(6), 2859–2897.

Plazzi, A., W. Torous, and R. Valkanov (2010). Expected returns and expected growth in rents of commercial real estate. *The Review of Financial Studies 23*(9), 3469–3519.

Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature 51*(4), 1063–1119.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics 54*(3), 375 – 421.

van Binsbergen, J. H. and R. Koijen (2010). Predictive regressions: A present-value approach. *The Journal of Finance 65*(4), 1439–1471.

Verdelhan, A. (2010). A habit-based explanation of the exchange rate risk premium. *Journal of Finance 65*(1), 123 – 146.

Table 1: Summary statistics

Panel A: Summary of foreign currency market total returns						
	Mean	Std.dev.	Max	Min	skewness	AR(1)
Australia	0.6583	3.3458	9.6351	-15.2276	-0.4305	0.0496
Germany	0.4024	3.1798	9.8917	-10.0343	-0.0102	0.0430
Belgium	0.4457	3.1712	9.8947	-10.4933	0.0029	0.0570
Canada	0.4783	2.0689	9.4550	-11.4329	-0.5098	-0.0149
Czech	0.4608	3.4854	10.3158	-11.4432	-0.1750	0.0237
Denmark	0.5751	3.0771	10.3235	-9.7698	-0.0439	0.0674
EURO	0.2456	2.9038	10.1524	-9.1793	-0.0522	0.0282
Spain	0.4104	3.0741	9.8945	-9.5201	-0.1292	0.0739
Finland	0.3777	3.1172	9.8784	-12.4045	-0.2745	0.0827
France	0.4664	3.1315	9.8946	-9.7377	-0.0129	0.0508
Greece	0.3680	2.9420	9.8017	-9.5154	-0.1504	0.0142
Hungary	0.5828	3.7608	12.0904	-17.1704	-0.8091	0.0149
Ireland	0.5477	3.0783	10.5507	-9.9771	-0.0862	0.0241
Italy	0.5146	3.0768	9.8946	-11.8502	-0.1480	0.0782
Japan	0.4305	3.3546	17.3745	-9.6737	0.6121	0.0620
Netherland	0.4076	3.1730	9.8937	-10.1517	0.0125	0.0571
Norway	0.5748	3.1681	8.3642	-11.6526	-0.2782	0.0493
New Zealand	0.8282	3.5801	13.3604	-12.5826	-0.1368	0.0054
Austria	0.4189	3.1777	9.8741	-10.6437	-0.0553	0.0463
Poland	0.6485	3.7438	10.3572	-14.4162	-0.6257	0.0650
Portugal	0.2911	2.8882	9.8946	-9.3382	-0.1606	0.0461
South Africa	0.5348	4.1782	16.2984	-14.0829	0.0405	0.0583
Sweden	0.5071	3.2299	9.2468	-14.1430	-0.3025	0.1256
Switzerland	0.4035	3.3910	13.7322	-11.0819	0.3148	0.0244
UK	0.4751	2.9805	15.6183	-11.6711	0.0580	0.0812
All country	0.4822	3.2111	11.0275	-11.4877	-0.1340	0.0485

Panel B: Correlations between lagged foreign interest rate and economic variables

	with R_{t+1}	with $\nabla I_{t\to t+1}$	with fp_t	with $\Delta S_{t+1}/S_t$
Australia	0.097	-0.764	-0.741	-0.011
Germany	0.055	0.065	0.038	-0.025
Belgium	0.064	-0.402	-0.492	-0.053
Canada	0.164	-0.390	-0.371	-0.016
Czech	0.025	-0.761	-0.765	-0.082
Denmark	0.171	-0.645	-0.574	0.069
EURO	0.073	-0.046	-0.017	0.025
Spain	0.071	-0.579	-0.655	-0.068
Finland	0.068	-0.775	-0.785	-0.046
France	0.073	-0.564	-0.570	-0.064
Greece	-0.024	-0.671	-0.864	-0.111
Hungary	0.037	-0.938	-0.947	-0.099
Ireland	0.147	-0.654	-0.469	0.030
Italy	0.076	-0.795	-0.772	-0.108
Japan	0.167	0.053	0.056	0.090
Netherland	0.084	0.079	0.024	0.002
Norway	0.139	-0.693	-0.598	0.031
New Zealand	0.153	-0.837	-0.807	0.025
Austria	0.072	0.114	0.075	-0.010
Poland	0.077	-0.970	-0.970	-0.093
Portugal	0.058	-0.778	-0.706	-0.047
South Africa	0.100	-0.659	-0.182	0.026
Sweden	0.122	-0.740	-0.655	0.011
Switzerland	0.083	0.049	0.080	0.015
UK	0.126	-0.455	-0.420	-0.005
All country	0.091	-0.510	-0.484	-0.020

The table reports summary statistics for total currency returns, computed from the perspective of US investors. In particular, consider, for example, Australia. A US investor converts one US dollar into the Australian dollar on the basis of the current exchange rate. The converted amount is deposited in the Australian one-month interest rate. The amount accumulated over the month is then converted back into US dollar on the basis of the next-month exchange rate. In panel A, we report the summary of monthly foreign currency total returns for each country as well as cross-country averages. The mean, std dev, max, and min of returns are expressed in percent per month. In panel B, we report the correlation coefficient ρ between the lagged interest rate $I_{t-1\to t}$ of each country and the following variables: return, R_{t+1}, interest rate differential $\nabla I_{t\to t+1} = I_{t\to t+1} - I^*_{t\to t+1}$, forward premium fp_t, and rate of depreciation $\Delta S_{t+1}/S_t$. The sample period is 1980:01∼2017:09.

Table 2: Using lagged foreign short rate to predict future currency return and cash-flow growth

	b_r	t-stat	R^2	b_d	t-stat	R^2
Australia	0.440	1.535	0.544	-0.838	-1.245	0.283
Germany	0.232	1.703	0.744	0.880	0.634	0.515
Belgium	0.253	1.954	1.053	0.701	0.562	0.298
Canada	0.258	2.545	1.608	-1.005	-1.122	0.516
Czech	0.205	1.564	0.824	-0.024	-0.057	0.001
Denmark	0.494	2.571	1.800	-0.392	-0.331	0.070
EURO	0.183	1.224	0.675	0.500	0.259	0.095
Spain	0.208	1.716	0.850	0.494	0.425	0.161
Finland	0.220	1.674	0.838	1.205	0.839	0.915
France	0.244	2.013	1.076	0.401	0.332	0.089
Greece	-0.163	-0.465	0.086	-2.050	-2.148	3.619
Hungary	0.171	0.913	0.215	1.660	1.308	2.997
Ireland	0.353	2.824	2.319	1.031	0.747	0.535
Italy	0.237	2.069	1.215	0.495	0.453	0.191
Japan	0.310	3.101	2.615	-1.270	-1.468	0.445
Netherland	0.260	1.892	0.963	0.816	0.595	0.446
Norway	0.545	2.768	2.024	-1.496	-1.768	0.562
New Zealand	0.587	1.841	1.109	-1.594	-1.990	0.666
Austria	0.276	2.033	1.043	1.242	0.874	0.798
Poland	0.384	1.995	0.802	-0.468	-0.979	0.398
Portugal	0.212	1.499	1.035	0.457	0.319	0.130
South Africa	0.971	2.123	0.809	-12.343	-1.558	5.790
Sweden	0.382	1.783	1.297	0.835	0.489	0.292
Switzerland	0.056	0.363	0.039	-0.221	-0.199	0.013
UK	0.252	2.046	1.025	0.026	0.069	0.001
All country	0.266	8.750	0.900	0.166	0.610	0.030

The table reports estimates from the regressions:

$$\begin{aligned} r_{t+1} &= a_r + b_r i^*_{t-1\to t} + v_{1,t+1} \\ \Delta d_{t+1} &= a_d + b_d i^*_{t-1\to t} + v_{2,t+1}. \end{aligned}$$

We also report cross-country estimates by pooling the countries with country fixed effects. The dependent variables are log returns and cash-flow growth rates. The sample period is 1980:01∼2017:09. For each regression and for each country, we report the slope estimate, the t-statistic, and the R^2. We use 6 lags Newey-West standard errors to conduct statistical inference. Slope estimates are multiplied by 100.

Table 3: Predicting long horizon currency return

	b_3	t-stat	R^2	b_6	t-stat	R^2	b_{12}	t-stat	R^2
Australia	1.414	1.832	1.748	3.310	2.517	4.507	7.409	3.718	10.375
Germany	0.612	1.723	1.532	1.099	1.747	2.142	1.951	2.093	2.962
Belgium	0.648	1.890	2.001	1.220	1.936	3.030	2.373	2.320	4.907
Canada	0.819	3.067	5.271	1.637	3.453	9.507	3.354	3.887	16.759
Czech	0.613	1.661	2.276	1.263	1.909	4.344	2.856	2.824	11.547
Denmark	1.769	2.719	5.552	3.497	2.717	9.275	6.516	3.155	13.900
EURO	0.488	1.165	1.443	0.918	1.236	2.351	1.713	1.561	3.966
Spain	0.508	1.566	1.443	0.899	1.490	1.938	1.641	1.631	2.593
Finland	0.600	1.512	1.666	1.127	1.559	2.597	2.015	1.815	3.918
France	0.642	1.985	2.189	1.170	1.989	3.108	2.094	2.260	4.420
Greece	-0.382	-0.400	0.153	-0.629	-0.382	0.203	-0.746	-0.306	0.157
Hungary	0.395	0.676	0.336	1.308	1.220	1.447	3.687	2.044	4.710
Ireland	0.974	2.718	5.076	1.845	2.640	7.289	3.683	3.245	12.777
Italy	0.633	2.063	2.452	1.164	2.085	3.552	2.121	2.424	5.401
Japan	0.911	3.178	6.448	1.755	3.457	10.959	3.323	4.033	18.380
Netherland	0.687	1.881	1.924	1.237	1.877	2.669	2.103	2.093	3.358
Norway	1.624	2.867	5.208	3.453	3.481	10.451	6.976	4.282	19.093
New Zealand	1.672	1.886	2.970	3.681	2.381	6.057	6.796	2.893	9.173
Austria	0.724	1.926	2.049	1.280	1.854	2.621	2.335	2.228	3.816
Poland	1.038	1.937	1.769	2.107	2.200	3.262	4.804	3.065	9.149
Portugal	0.504	1.378	1.794	0.866	1.333	2.346	1.745	1.817	4.470
South Africa	2.737	2.246	1.928	5.472	2.599	3.962	11.499	3.573	8.632
Sweden	1.000	1.625	2.357	1.874	1.668	3.518	3.063	1.671	4.479
Switzerland	0.156	0.375	0.089	0.209	0.275	0.073	0.627	0.505	0.304
UK	0.770	2.243	2.736	1.538	2.487	4.756	3.224	3.335	10.142
All country	0.741	8.450	2.040	1.451	8.710	3.390	2.875	9.570	5.930

The table reports estimates from the long-horizon regression:

$$r_{t\to t+k} \quad = \quad a_{r,k} + b_{r,k} i^*_{t-1\to t} + \eta_{t+k} \quad k = 3, 6, 12.$$

We also report cross-country estimates by pooling the countries with country fixed effects. The sample period is 1980:01$\sim$2017:09. We use 6 lags Newey-West standard errors to conduct statistical inference. Slope estimates are multiplied by 100.

Table 4: Using expected rate of depreciation to test Uncovered Interest rate parity

	β_1	t-stat	R^2	β_2	t-stat	R^2
Australia	-0.598	-1.109	0.171	0.463	6.578	50.705
Germany	-1.078	-1.333	0.630	0.073	1.107	1.116
Belgium	-0.609	-0.827	0.182	0.439	3.171	16.950
Canada	-0.812	-1.521	0.355	0.358	2.859	8.257
Czech	0.571	1.280	0.318	0.574	5.764	53.787
Denmark	-0.569	-0.770	0.251	0.112	1.503	1.617
EUR	-2.307	-1.329	0.792	0.019	0.174	0.024
Spain	0.696	1.350	0.783	0.327	4.575	27.186
Finland	0.688	0.633	0.314	0.575	10.675	46.591
France	0.031	0.045	0.001	0.616	4.733	34.959
Greece	1.211	1.153	0.712	1.493	14.725	78.017
Hungary	0.550	1.393	0.405	0.850	14.887	85.978
Ireland	0.097	0.086	0.008	0.293	2.839	7.140
Italy	0.345	0.659	0.151	0.771	7.769	53.065
Japan	-0.436	-0.572	0.143	0.086	0.810	0.542
Netherland	-1.412	-1.641	0.976	0.075	1.187	0.848
Norway	0.904	1.224	0.744	0.033	0.425	0.237
New Zealand	-0.948	-2.401	1.006	0.492	6.504	60.095
Austria	-1.068	-1.320	0.534	0.067	1.035	0.577
Poland	0.598	1.692	0.672	0.629	18.313	87.026
Portugal	0.126	0.160	0.013	0.427	6.268	31.201
South Africa	-0.338	-4.207	2.318	-0.006	-1.856	0.351
Sweden	-0.318	-0.322	0.070	0.204	3.389	9.234
Switzerland	-1.172	-1.598	0.924	0.050	0.576	0.739
UK	-1.925	-2.149	1.850	0.242	2.086	7.482
All country	-0.247	-2.950	0.320	0.145	2.800	29.90

The table reports estimates from the two regressions:

$$
\begin{aligned}
s_{t+1} - s_t &= \alpha + \beta_1 (f_t - s_t) + e_{t+1} \\
E_t r_{t+1} - \log\left(1 + I^*_{t \to t+1}\right) &= \alpha + \beta_2 (f_t - s_t) + \varepsilon_{t+1}.
\end{aligned}
$$

The first is the conventional forward premium regression, while the second is already exploiting currency return predictability by the lagged foreign interest rate. The expected rate of depreciation is estimated as $E_t r_{t+1} - \log\left(1 + I^*_{t \to t+1}\right)$, where $E_t r_{t+1}$ is the fitted value from return predictive regressions. We also report cross-country estimate by pooling the countries with country fixed effects. The sample period is 1980:01∼2017:09. Reported are slope estimates, t-statistics, and goodness-of-fit measures. We use 6 lags Newey-West standard errors to conduct statistical inference.

Table 5: Using expected rate of depreciation in long horizons

	β_3	t-stat	R^2	β_6	t-stat	R^2	β_{12}	t-stat	R^2
Australia	1.401	8.803	53.998	1.831	5.693	28.230	1.574	2.063	4.502
Germany	0.095	0.359	0.225	-0.068	-0.115	0.032	-0.746	-0.608	0.933
Belgium	0.957	2.444	8.999	1.398	1.655	4.823	1.059	0.556	0.683
Canada	1.063	2.040	5.835	1.504	1.401	2.896	1.254	0.547	0.499
Czech	1.576	11.528	44.182	2.772	8.211	36.248	4.206	4.727	20.528
Denmark	-0.174	-0.885	0.375	-0.605	-1.576	1.296	-1.550	-1.805	2.615
EURO	-0.194	-0.631	0.385	-0.951	-1.673	2.784	-4.112	-3.987	14.189
Spain	1.570	5.448	30.466	3.121	4.852	27.949	5.593	4.040	21.911
Finland	1.792	9.926	52.234	3.484	8.336	48.531	6.628	6.063	40.274
France	1.691	4.972	27.250	2.715	3.922	17.899	4.425	2.470	11.568
Greece	3.480	4.974	47.484	6.626	5.012	47.684	11.998	5.052	48.630
Hungary	2.776	18.743	86.082	4.529	13.675	80.010	6.987	10.005	69.793
Ireland	1.125	4.208	17.505	1.538	2.945	10.609	1.476	1.342	2.794
Italy	2.447	10.668	54.160	4.522	9.970	45.379	8.621	8.922	41.244
Japan	0.282	0.571	0.412	0.331	0.347	0.158	-0.207	-0.114	0.018
Netherland	0.086	0.342	0.146	-0.118	-0.207	0.082	-1.034	-0.823	1.667
Norway	-0.022	-0.096	0.010	-0.781	-1.775	2.646	-2.731	-3.093	7.467
New Zealand	1.422	10.751	60.395	2.029	6.029	37.338	3.587	5.540	31.218
Austria	0.080	0.327	0.117	-0.166	-0.308	0.167	-0.971	-0.908	1.457
Poland	2.040	19.081	87.887	3.884	15.586	83.798	6.212	9.519	68.214
Portugal	1.636	12.360	56.385	3.231	11.982	59.624	5.415	9.366	49.302
South Africa	0.165	0.824	0.935	-0.164	-0.398	0.212	-2.400	-2.285	8.010
Sweden	0.961	5.819	22.632	1.906	5.816	22.260	4.315	6.105	24.626
Switzerland	0.152	0.446	0.596	0.058	0.078	0.019	-0.206	-0.156	0.071
UK	0.742	1.807	6.515	1.217	1.418	4.450	1.045	0.635	0.858
All country	0.368	2.150	13.990	0.668	2.120	13.520	1.182	2.100	13.080

The table reports estimates from the regressions:

$$E_t r_{t\to t+k} - \log\left(1 + I^*_{t-1\to t+k-1}\right) = \alpha + \beta_k\left(f_t - s_t\right) + \varepsilon_{t+k}; \quad k = 3, 6, 12.$$

In the last line we also report cross-country estimate by pooling the countries with country fixed effects. In calculating the expected long-horizon rate of depreciation, $E_t r_{t\to t+k}$ is the fitted value of k-period return from return predictive regressions. The sample period is 1980:01∼2017:09. We report slope estimates, t-statistics, and goodness-of-fit measures. We use 6 lags Newey-West standard errors to conduct statistical inference.

Table 6: Correcting for small sample bias

	b_r	t-stat	β_2	t-stat
Australia	0.460	1.585	0.395	6.362
Germany	0.233	1.688	0.076	1.150
Belgium	0.253	1.939	0.439	3.188
Canada	0.268	2.612	0.373	3.051
Czech	0.245	1.911	0.332	2.728
Denmark	0.489	2.472	0.143	1.631
EURO	0.167	1.057	-0.073	-0.621
Spain	0.213	1.757	0.321	4.574
Finland	0.221	1.670	0.576	10.755
France	0.247	2.026	0.587	4.733
Greece	-0.151	-0.397	1.459	14.940
Hungary	0.226	1.201	0.862	8.956
Ireland	0.343	2.589	0.361	2.657
Italy	0.244	2.139	0.733	7.649
Japan	0.310	3.066	0.087	0.817
Netherland	0.260	1.857	0.074	1.161
Norway	0.536	2.664	0.093	0.723
New Zealand	0.611	1.885	0.297	4.264
Austria	0.272	1.953	0.063	0.970
Poland	0.458	2.303	0.617	15.874
Portugal	0.216	1.515	0.432	6.519
South Africa	0.978	2.229	-0.011	-5.548
Sweden	0.384	1.810	0.194	3.279
Switzerland	0.076	0.493	0.187	1.915
UK	0.259	2.128	0.234	2.037
All country	0.270	8.878	0.135	2.753

The table reports estimates from the regressions:

$$\begin{aligned} r_{t+1} &= a_r + b_r i^*_{t-1\to t} + v\_c_{t+1} + u_{t+1} \\ E_t r_{t+1} - \log\left(1 + I^*_{t\to t+1}\right) &= \alpha + \beta_2 \left(f_t - s_t\right) + \varepsilon_{t+1}. \end{aligned}$$

We correct for the small sample bias following the procedure outlined in Amihud and Hurvich (2004), where $v\_c_{t+1} = i^*_{t+1} - \hat{\theta}^c - \rho^c i^*_t$, and $\rho^c = \hat{\rho} + (1 + 3\hat{\rho})/T + 3(1 + 3\hat{\rho})/T^2$, with $\hat{\theta}^c$ and $\hat{\rho}$ obtained by regressing i^* on its lagged value. We also report cross-country estimate by pooling the countries with country fixed effects. The expected rate of depreciation is calculated as $E_t r_{t+1} - \log\left(1 + I^*_{t\to t+1}\right)$, where $E_t r_{t+1}$ is the fitted value from return predictive regressions. The sample period is 1980:01∼2017:09. We report slope estimates and t-statistics. We use 6 lags Newey-West standard errors to conduct statistical inference.

Table 7: Using lagged foreign short rate to predict currency return: log-linearization and VAR models

	Model 1		Model 2		Model 3	
	b_r	t-stat	b_r	t-stat	b_r	t-stat
Australia	0.400	1.631	0.478	1.605	0.370	1.227
Germany	0.257	2.413	0.243	1.825	0.265	2.003
Belgium	0.272	2.789	0.247	2.026	0.266	2.195
Canada	0.254	3.282	0.271	2.824	0.273	2.864
Czech	0.183	1.650	0.200	1.450	0.186	1.363
Denmark	0.511	3.122	0.522	2.441	0.491	2.395
EURO	0.190	1.446	0.197	1.178	0.199	1.207
Spain	0.233	2.603	0.186	1.677	0.210	1.902
Finland	0.226	2.115	0.197	1.435	0.206	1.514
France	0.259	2.778	0.232	1.996	0.244	2.112
Greece	-0.227	-0.785	-0.172	-0.474	-0.269	-0.757
Hungary	0.209	1.129	0.062	0.262	0.088	0.377
Ireland	0.369	3.799	0.354	2.870	0.368	3.013
Italy	0.252	2.961	0.222	2.099	0.236	2.242
Japan	0.294	3.686	0.295	2.950	0.276	2.778
Netherland	0.286	2.722	0.252	1.917	0.275	2.108
Norway	0.531	3.397	0.540	2.766	0.508	2.622
New Zealand	0.530	2.321	0.594	2.094	0.519	1.844
Austria	0.302	2.824	0.274	2.025	0.296	2.206
Poland	0.322	1.521	0.350	1.324	0.315	1.211
Portugal	0.213	2.049	0.204	1.567	0.211	1.642
South Africa	0.959	2.138	0.778	1.364	0.775	1.367
Sweden	0.384	2.667	0.284	1.590	0.273	1.543
Switzerland	0.060	0.505	0.100	0.674	0.088	0.597
UK	0.268	2.823	0.228	1.935	0.247	2.116
All country	0.261	1.880	0.235	9.000	0.250	1.910

The table reports slope coefficient b_r of three VAR models. In the first model, the restricted VAR, we regress the currency return on the lagged foreign interest rate, imposing the cross-equation constraint implied by the log-linearization $b_r - b_d + \rho b_{i*} = 1$. In the second model, we additionally include the lagged return and lagged cash-flow growth as predictive variables (unrestricted VAR) without imposing present-value restrictions. In the third model, we impose the cross-equation constraints and run the unrestricted VAR. The sample period is 1980:01∼2017:09. We report slope estimates and t-statistics for each country. We use 6 lags Newey-West standard error to conduct statistical inference. Slope estimates are multiplied by 100.

Table 8: Using lagged foreign short rate to test UIP: log-linearization and VAR

	Model 1		Model 2		Model 3	
	β_2	t-stat	β_2	t-stat	β_2	t-stat
Australia	0.524	6.928	0.322	3.829	0.482	4.910
Germany	0.088	1.445	-0.005	-0.061	0.006	0.076
Belgium	0.409	2.999	0.288	1.948	0.259	1.776
Canada	0.366	2.893	0.351	2.522	0.350	2.495
Czech	0.628	7.234	0.626	3.692	0.663	4.086
Denmark	0.091	1.195	0.052	0.566	0.081	0.881
EURO	0.024	0.205	-0.083	-0.624	-0.078	-0.582
Spain	0.284	4.186	0.307	4.539	0.270	4.055
Finland	0.561	10.432	0.581	6.842	0.560	6.663
France	0.591	4.572	0.520	3.847	0.499	3.708
Greece	1.630	14.849	1.466	9.715	1.683	10.756
Hungary	0.781	11.716	0.938	7.489	0.888	6.782
Ireland	0.270	2.426	0.274	2.621	0.258	2.273
Italy	0.736	7.328	0.699	7.276	0.672	6.973
Japan	0.082	0.849	-0.012	-0.116	-0.014	-0.154
Netherland	0.089	1.468	-0.051	-0.611	-0.041	-0.518
Norway	0.053	0.680	0.003	0.034	0.049	0.518
New Zealand	0.557	7.850	0.454	7.638	0.545	9.647
Austria	0.084	1.337	-0.016	-0.208	-0.004	-0.052
Poland	0.724	22.622	0.670	18.472	0.729	21.320
Portugal	0.425	6.236	0.373	4.003	0.373	4.096
South Africa	-0.005	-1.695	-0.023	-3.145	-0.023	-3.074
Sweden	0.199	3.320	0.190	1.459	0.213	1.648
Switzerland	0.053	0.615	-0.067	-0.710	-0.072	-0.745
UK	0.206	1.875	0.036	0.251	0.005	0.040
All country	0.179	8.170	0.165	7.130	0.154	7.010

The table reports estimated slope coefficients from regressing the expected rate of depreciation on interest rate differentials. The expected rate of depreciations are derived from the three VAR models that are described in the previous Table. The sample period is 1980:01∼2017:09. We report slope estimate and t-statistics for each country. We use 6 lags Newey-West standard error to conduct statistical inference. Slope estimates are multiplied with 100.

Table 9: Tests with other base currencies

	b_r^c	t-stat	β_2^c	t-stat	β_1	t-stat
Australia	0.362	9.673	0.044	1.906	-0.048	-0.521
Germany	0.195	10.226	0.206	2.959	-0.024	-0.258
Belgium	0.223	11.158	0.122	2.686	-0.032	-0.342
Canada	0.262	9.379	0.116	2.648	-0.137	-1.738
Czech	0.071	2.514	-0.031	-4.193	-0.098	-1.104
Denmark	0.161	8.773	0.094	2.623	-0.053	-0.595
EUR	0.152	2.819	-0.042	-4.000	-0.208	-2.033
Spain	0.294	13.831	0.077	2.911	0.256	1.754
Finland	0.232	10.315	0.043	1.595	0.030	0.260
France	0.238	11.839	0.097	2.696	0.050	0.463
Greece	0.144	6.710	-0.023	-2.871	-0.029	-0.280
Hungary	0.223	7.373	0.016	0.862	0.056	0.524
Ireland	0.199	10.348	0.079	2.702	0.124	0.933
Italy	0.293	13.679	0.078	2.778	0.021	0.224
Japan	0.033	0.860	0.281	3.665	0.211	1.323
Netherland	0.196	10.180	0.197	2.865	-0.042	-0.465
Norway	0.181	7.276	0.084	2.787	0.126	0.881
New Zealand	0.369	12.257	0.052	2.322	0.108	1.089
Austria	0.192	10.141	0.202	2.877	-0.011	-0.112
Poland	0.231	7.309	0.012	0.731	-0.058	-0.714
Portugal	0.181	8.392	0.029	1.332	-0.009	-0.085
South Africa	0.337	9.093	0.016	5.647	-0.212	-10.010
Sweden	0.281	11.748	0.069	2.257	-0.051	-0.533
Switzerland	0.282	11.013	0.131	2.879	-0.131	-1.602
UK	0.299	12.113	0.160	2.693	-0.193	-2.362

The table repeats the main procedures from the perspective of individual investors from every single country in our sample. For each country, we pool all the variables and run regressions with country individual effects. b_r^c is the small sample bias corrected predictive regression slope, β_2^c is the small sample bias corrected expected depreciation regression slope, and β_1 is the conventional Fama regression slope. We report the coefficient estimates and t-statistics based on 6 lags Newey-West standard error to conduct statistical inference. The coefficient estimate b_r is multiplied by 100. The sample period is 1980:01∼2017:09.

Table 10: Slope decomposition

	b_r^k	b_d^k	$\rho^k b_{dp}^k$	b_r^k	b_d^k	$\rho^k b_{dp}^k$
	Currencies					
	Panel A: real			Panel B: implied		
Direct regression, $k = 10$	0.157	-0.248	0.603	0.157	-0.239	0.603
Implied by VAR, $k = 10$	0.308	-0.059	0.621	0.308	-0.071	0.621
Implied by VAR, $k = \infty$	0.812	-0.155	0	0.812	-0.188	0
	Equities					
	Panel C: real			Panel D: implied		
Direct regression, $k = 10$	0.821	-0.062	-0.038	0.821	-0.217	-0.038
Implied by VAR, $k = 10$	0.845	0.268	0.223	0.845	0.068	0.223
Implied by VAR, $k = \infty$	1.087	0.344	0	1.087	0.087	0

The table reports the long-horizon regression coefficients from:

$$\begin{aligned}
\sum_{j=1}^{k} \rho^{j-1} r_{t+j} &= a + b_r^k i_{t-1\to t}^* + \eta_{1,t+k} \\
\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} &= a + b_d^k i_{t-1\to t}^* + \eta_{2,t+k} \\
\rho^k i_{t+k-1\to t+k}^* &= a + b_{dp}^k i_{t-1\to t}^* + \eta_{3,t+k}
\end{aligned}$$

"Direct" estimates are based on ten-year ex-post returns. The "VAR" estimates infer long-run coefficients from one-year regression coefficients. In Panel A, we use the real annual currency data on log return, cash-flow growth, and lagged foreign interest rate. We pool country-year observations then run panel regression to obtain the coefficient estimates. In Panel B, we use the expected cash-flow growth from the Campbell-Shiller decomposition: $s_t - d_t = \rho\,(s_{t+1} - d_{t+1}) + k + \Delta d_{t+1} - r_{t+1}$. Similarly, in Panel C, we use the real annual CRSP value weighted stock index data on log return, cash-flow growth, and lagged foreign interest rate. In Panel D, we use the expected cash-flow growth from the Campbell-Shiller decomposition. The sample period is 1981∼2016 for both the currency and equity data.

Table 11: Predicting return and growth with both level and volatility

	b_r	t-stat	$b_{r,v}$	t-stat
Australia	-0.525	-0.640	5.699	1.319
Germany	0.259	1.920	-1.432	-6.942
Belgium	0.296	2.299	-0.031	-3.181
Canada	0.246	2.353	0.207	0.759
Czech	0.231	1.786	-0.028	-6.112
Denmark	0.171	0.516	31.439	3.183
EUR	0.180	1.184	1.620	0.142
Spain	0.182	1.296	-1.096	-2.923
Finland	0.238	1.672	-16.327	-2.422
France	0.262	2.092	-0.017	-2.011
Greece	-0.667	-1.471	0.108	0.175
Hungary	0.139	0.728	0.736	1.352
Ireland	0.349	2.735	0.003	1.273
Italy	0.248	2.121	-0.017	-0.935
Japan	0.268	2.644	2.194	1.769
Netherland	0.271	1.952	-0.740	-0.356
Norway	0.341	1.009	0.478	0.896
New Zealand	-0.593	-0.960	0.121	0.044
Austria	0.275	1.846	-7.860	-0.876
Poland	0.369	1.624	0.164	0.153
Portugal	0.240	1.781	-0.345	-0.475
South Africa	1.665	2.236	-0.183	-0.660
Sweden	0.144	0.429	4.789	2.397
Switzerland	0.095	0.592	-1.317	-0.747
UK	0.187	1.537	2.521	1.225
All country	0.240	7.495	-0.016	-1.714

This table estimates the predictive regression

$$r_{t+1} \quad = \quad a_r + b_r i^*_{t-1\to t} + +b_{r,v} vol_{t-1\to t} + v_{1,t+1}.$$

We report the coefficient estimates and t-statistics based on 6 lags Newey-West standard error to conduct statistical inference. The regression coefficient estimates are multiplied by 100. The sample period is 1980:01∼2017:09.

Table 12: Trading strategies: performance and risk adjustment

	$I^*_{t\to t+1} - I_{t\to t+1}$	$I^*_{t-1\to t} - I_{t-1\to t}$	$\overline{E_t R_{t+1}}$	$E_t \bar{R}_{t+1}$
Panel A: Summary of portfolios				
Mean	0.253	0.301	0.280	0.351
Std dev	2.604	2.599	2.602	2.531
SR	0.337	0.401	0.372	0.481
Max	7.843	7.843	7.170	7.170
Min	-9.798	-9.798	-9.798	-9.798
Skew	-0.269	-0.282	-0.418	-0.408
AR(1)	0.041	0.047	0.051	0.050
IR		0.217	0.158	0.343
Panel B: One factor model: benchmark				
α		0.062	0.280	0.156
t-stat		1.330	1.147	2.289
β		0.946	0.771	0.768
t-stat		35.529	8.619	10.118
Panel C: One factor model: slope factor				
α	0.160	0.205	0.181	0.253
t-stat	1.054	1.344	1.211	1.690
β_S	0.247	0.255	0.262	0.262
t-stat	2.073	2.145	2.231	2.222
Panel D: Two factor model: level and slope factors				
α	0.069	0.118	0.092	0.166
t-stat	0.889	1.308	1.104	2.132
β_L	0.790	0.759	0.774	0.757
t-stat	110.795	9.972	7.570	8.461
β_S	0.072	0.086	0.091	0.094
t-stat	1.869	1.984	2.248	2.259

The table proposes several investment strategies, based on the return predictive regression results. In Panel A, we report the portfolio performances of four strategies. Each strategy employs the sign of the signal to decide whether to invest in foreign currencies or the USD. The signals are: (i) the current interest rate differential (carry) $I^*_{t\to t+1} - I_{t\to t+1}$, (ii) the lagged interest rate differential $I^*_{t-1\to t} - I_{t-1\to t}$, (iii) the average value of expected return from country return predictive regression $\overline{E_t R_{t+1}}$ with country lagged foreign interest rate as regressor, and (iv) the predicted average return $E_t \bar{R}_{t+1}$ from a return predictive regression with the average lagged foreign interest rate as regressor. We report the average monthly percentage return, the standard deviation, the Sharpe ratio (SR), the max return, the min return, skewness, AR(1), and the information ratio (IR) relative to the conventional "dollar" strategy with the current interest rate differential as signal. In the remaining panels, we implement risk adjustment of these strategies. In Panel B, the factor is the strategy (i) itself. Then we use the slope alone, then both the level and slope factors in Panel C and D. The level and slope are the average and the high-minus-low returns of conventional carry trades. We report the coefficient estimates and t-statistics based on 6 lags Newey-West standard error to conduct statistical inference. The regression intercept α estimates are multiplied by 100. The sample period is 1980:01$\sim$2017:09.

Appendix

We use the fitted value of expected currency return $E_t r_{t+1} = a + b_r i^*_{t-1\to t}$ to back out the expected rate of depreciation

$$E_t(s_{t+1} - s_t) \;=\; E_t r_{t+1} - \log\left(1 + I^*_{t\to t+1}\right) \approx a + b_r i^*_{t-1\to t} - I^*_{t\to t+1}.$$

Thus, in the Fama regression with expected rate of depreciation

$$E_t(s_{t+1} - s_t) = \alpha + \beta_2 \left(I_{t\to t+1} - I^*_{t\to t+1}\right) + error$$

the slope is given by

$$\begin{aligned}\beta_2 &= \frac{Cov\left(b_r i^*_{t-1\to t} - I^*_{t\to t+1}, I_{t\to t+1} - I^*_{t\to t+1}\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)} \\ &= \frac{b_r Cov\left(i^*_{t-1}, I_t\right) - Cov\left(I^*_t, I_t\right) - b_r Cov\left(i^*_{t-1}, I^*_t\right) + Var\left(I^*_t\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)}.\end{aligned}$$

The sign of β_2 depends on the

1. return predictability b_r
2. the cross correlation between the log of the foreign interest rate and the level of the US interest rate $Cov\left(i^*_{t-1}, I_t\right)$
3. the contemporaneous correlation between two interest rates $Cov\left(I^*_t, I_t\right)$
4. the cross correlation between the log and the level of the foreign interest rate $Cov\left(i^*_{t-1}, I^*_t\right)$
5. the variance of foreign interest rate $Var\left(I^*_t\right)$.

What if we use carry to predict return and then implement forward premium regressions? Consider the predictive regression of return on carry: $E_t r_{t+1} = a + b_r\left(I_{t\to t+1} - I^*_{t\to t+1}\right)$. This regression generally yields $b_r < 0$. The expected depreciation rate is given by

$$E_t(s_{t+1} - s_t) = a + b_r\left(I_{t\to t+1} - I^*_{t\to t+1}\right) - I^*_{t\to t+1}$$

Thus, in the Fama regression with expected rate of depreciation, the slope coefficient is given by

$$\begin{aligned}\beta_2 &= \frac{Cov\left(b_r\left(I_{t\to t+1} - I^*_{t\to t+1}\right) - I^*_{t\to t+1}, I_{t\to t+1} - I^*_{t\to t+1}\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)} \\ &= b_r - \frac{Cov\left(I^*_{t\to t+1}, I_{t\to t+1} - I^*_{t\to t+1}\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)}\end{aligned}$$

To generate $\beta_2 > 0$, this requires $\frac{Cov\left(I^*_{t\to t+1}, I_{t\to t+1} - I^*_{t\to t+1}\right)}{Var\left(I_{t\to t+1} - I^*_{t\to t+1}\right)}$ to be more negative than b_r.
We have experimented with this regression specification. We find that 13 currencies show significantly negative slope β_2, while only 8 show significantly positive slope. These results are untabulated but available upon request.

Table A.1: Foreign interest rate versus carry

	(1)		(2)		(3)			
	b_r	t-stat	b_c	t-stat	b_r	t-stat	b_c	t-stat
Australia	0.440	1.535	-2.047	-3.518	-0.131	-0.321	-2.267	-2.649
Germany	0.232	1.703	-0.857	-1.081	0.258	1.898	-1.045	-1.269
Belgium	0.253	1.954	-1.737	-2.514	0.201	1.523	-1.472	-2.094
Canada	0.258	2.545	-2.066	-3.328	0.203	1.907	-1.592	-2.524
Czech	0.205	1.564	-0.631	-1.191	0.191	1.231	-0.130	-0.221
Denmark	0.494	2.571	-1.346	-1.972	0.407	2.033	-0.735	-1.079
EUR	0.183	1.224	-1.588	-0.829	0.195	1.268	-1.786	-0.907
Spain	0.208	1.716	-1.422	-1.792	0.115	0.940	-1.192	-1.450
Finland	0.220	1.674	-0.232	-0.211	0.250	2.004	0.347	0.298
France	0.244	2.013	-1.338	-2.017	0.176	1.334	-1.031	-1.405
Greece	-0.163	-0.465	0.680	0.604	-0.007	-0.019	0.668	0.519
Hungary	0.171	0.913	-0.446	-1.233	0.070	0.223	-0.315	-0.475
Ireland	0.353	2.824	-0.421	-0.468	0.369	2.717	0.194	0.239
Italy	0.237	2.069	-0.962	-1.746	0.162	1.159	-0.560	-0.848
Japan	0.310	3.101	-1.546	-2.146	0.320	3.228	-1.665	-2.413
Netherland	0.260	1.892	-1.443	-1.779	0.298	2.159	-1.667	-1.902
Norway	0.545	2.768	-0.802	-0.801	0.611	2.399	0.365	0.322
New Zealand	0.587	1.841	-2.216	-6.023	-0.434	-1.405	-2.733	-5.897
Austria	0.276	2.033	-0.868	-1.036	0.304	2.252	-1.126	-1.287
Poland	0.384	1.995	-0.600	-1.685	0.373	0.585	-0.021	-0.019
Portugal	0.212	1.499	-0.796	-0.999	0.183	1.235	-0.392	-0.485
South Africa	0.971	2.123	-1.983	-2.260	0.320	0.592	-1.715	-1.632
Sweden	0.382	1.783	-1.004	-0.855	0.353	1.608	-0.204	-0.158
Switzerland	0.056	0.363	-1.768	-2.298	0.118	0.774	-1.855	-2.343
UK	0.252	2.046	-2.840	-2.843	0.081	0.718	-2.626	-2.505
All country	0.266	8.750	-1.138	-6.980	0.202	6.370	-0.853	-4.980

This table compares the return predictive power between the lagged foreign interest rate and current interest rate differential (carry).

$$
\begin{aligned}
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \upsilon_{1,t+1} \\
r_{t+1} &= a_r + b_c(\log(1+I_t) - \log(1+I^*_t)) + \upsilon_{2,t+1} \\
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + b_c(\log(1+I_t) - \log(1+I^*_t)) + \upsilon_{3,t+1}
\end{aligned}
$$

We report the coefficient estimates and t-statistics based on 6 lags Newey-West standard error to conduct statistical inference. The regression slope estimate b_r is multiplied by 100. The sample period is 1980:01∼2017:09.

Table A.2: Using lagged foreign short rate to predict return and growth: Robustness

	Model 1		Model 2		Model 3		Model 4	
	b_r	t-stat	b_r	t-stat	b_r	t-stat	b_r	t-stat
Australia	0.417	1.484	-0.003	-0.007	0.446	1.628	-1.164	-0.681
Germany	0.224	1.705	0.258	1.897	0.231	1.755	0.380	1.654
Belgium	0.242	1.936	0.200	1.505	0.254	2.052	0.438	2.131
Canada	0.267	2.579	0.201	1.904	0.256	2.441	-0.115	-0.532
Czech	0.200	1.524	0.204	1.301	0.204	1.594	0.491	2.559
Denmark	0.480	2.519	0.393	1.930	0.490	2.588	-0.074	-0.258
EURO	0.180	1.236	0.195	1.304	0.182	1.243	0.265	0.921
Spain	0.195	1.708	0.275	2.005	0.214	1.875	0.299	1.605
Finland	0.205	1.634	0.233	1.830	0.222	1.814	0.338	1.916
France	0.234	2.017	0.195	1.475	0.246	2.107	0.332	1.837
Greece	-0.161	-0.462	-0.494	-0.848	-0.155	-0.436	-1.186	-1.251
Hungary	0.170	0.911	-0.080	-0.251	0.173	0.924	0.075	0.222
Ireland	0.351	2.807	0.338	2.573	0.353	2.836	0.204	1.134
Italy	0.221	2.034	0.150	1.074	0.245	2.280	0.318	1.936
Japan	0.296	3.078	0.313	3.168	0.303	3.154	0.087	0.401
Netherland	0.249	1.886	0.287	2.085	0.258	1.956	0.282	1.276
Norway	0.531	2.632	0.761	3.397	0.543	2.812	0.064	0.132
New Zealand	0.596	1.829	-0.402	-1.336	0.586	1.806	-0.922	-1.572
Austria	0.267	2.046	0.300	2.229	0.274	2.097	0.375	1.689
Poland	0.360	1.949	0.296	0.419	0.404	2.192	0.450	0.629
Portugal	0.205	1.512	0.188	1.284	0.213	1.558	0.484	2.042
South Africa	0.919	2.043	0.648	1.514	0.965	2.187	-4.729	-1.567
Sweden	0.343	1.691	0.281	1.333	0.381	1.959	-0.047	-0.110
Switzerland	0.053	0.350	0.102	0.674	0.059	0.393	-0.072	-0.221
UK	0.232	1.943	0.084	0.730	0.253	2.181	-0.047	-0.220

The table reports slope coefficients b_r from the following regression models with control variables:

$$
\begin{aligned}
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \theta r_t + e_{1,t+1} \\
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \theta(f_t - s_t) + e_{2,t+1} \\
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \theta(\Delta s_t) + e_{3,t+1} \\
r_{t+1} &= a_r + b_r i^*_{t-1\to t} + \theta_1 r_t + \theta_2(f_t - s_t) + \theta_3(I_{t\to t+1} - I^*_{t\to t+1}) + \theta_4 \Delta s_t + e_{4,t+1}
\end{aligned}
$$

for each country. The sample period is 1980:01∼2017:09. We report the slope estimate and t-statistics for each country. We use 6 lags Newey-West standard error to conduct statistical inference. The slope estimates are multiplied with 100.

Table A.3: Predicting return and growth using volatility

	b_r^σ	t-stat	b_d^σ	t-stat
Australia	1.630	0.684	5.376	1.288
Germany	-1.923	-2.093	-1.258	-8.425
Belgium	-0.215	-1.433	-0.027	-2.899
Canada	1.031	2.638	0.579	1.792
Czech	-0.168	-1.760	-0.022	-5.847
Denmark	11.727	3.432	32.621	3.371
EUR	2.337	0.684	4.501	0.397
Spain	-1.570	-2.088	-0.995	-2.719
Finland	-3.130	-1.046	-14.281	-2.119
France	-0.048	-0.546	-0.006	-0.823
Greece	-1.608	-1.750	-0.949	-2.079
Hungary	1.124	1.728	0.803	1.491
Ireland	0.134	1.059	0.008	3.602
Italy	0.109	0.609	-0.000	-0.004
Japan	2.971	2.222	3.037	3.050
Netherland	0.309	0.206	0.355	0.175
Norway	0.713	0.824	0.670	1.342
New Zealand	-1.098	-0.627	-0.657	-0.257
Austria	1.331	0.470	-4.468	-0.514
Poland	1.201	1.334	0.876	0.920
Portugal	0.227	0.189	-0.196	-0.272
South Africa	1.765	1.553	0.137	0.427
Sweden	2.799	1.479	4.771	2.396
Switzerland	-0.467	-0.334	-1.029	-0.596
UK	2.323	1.364	2.801	1.402
All country	0.001	0.009	-0.012	-1.252

This table presents regressions results using the standard deviation and variance of foreign interest rate to predict future return and cash-flow growth. We use the standard deviation (σ) to run return and growth predictive regression

$$r_{t+1} = a_r^\sigma + b_r^\sigma \sigma_t^* + e_{1,t+1}$$

We also use variance (vol) to run return predictive regression

$$r_{t+1} = a_r^v + b_r^v vol_t^* + e_{2,t+1}$$

We report the coefficient estimates and t-statistics based on 6 lags Newey-West standard error to conduct statistical inference. The regression intercept α estimates are multiplied by 100. The sample period is 1980:01∼2017:09.