Beyond Carry: The Prospective Interest Rate Differential and Currency Excess Returns

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Abstract

We use a Beveridge-Nelson decomposition to link expected foreign currency excess returns to the "prospective interest rate differential" – the infinite sum of expected future interest rate differentials. Empirically, we find that the prospective interest rate differential is a stronger predictor of currency excess returns than carry, in both portfolio sorts and Fama-MacBeth regressions. A factor based on the prospective interest rate differential is also useful in explaining the returns of a broad set of currency test portfolios.

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1 Introduction

The uncovered interest parity (UIP) hypothesizes that a high-interest-rate foreign currency is expected to depreciate by the interest rate differential between the foreign and home countries. Numerous empirical studies strongly reject the UIP (e.g., Fama (1984) and Hodrick and Srivastava (1984)) and find that the realized depreciation rate of a high-interest-rate currency is at best weakly related to the interest rate differential.[1] Moreover, foreign currency excess returns are known to be predictable by the interest rate differential (Burnside (2012), Bekaert and Hodrick (1992), and Verdelhan (2010)), and high-interest-rate currencies typically appreciate, generating a profitable trading strategy (the so-called "carry trade"). Diversification further boosts the risk-return trade-off of such currency speculations (Burnside et al. (2008)). The empirical evidence thus suggests that returns are highly predictable in the foreign currency market.

In this paper, we follow Engel (2016) and Jiang et al. (2021, 2023) and conduct a Beveridge and Nelson (1981) decomposition of the exchange rate into a permanent and a transitory component. This decomposition reveals that the sum of expected future excess returns equals the sum of expected future detrended interest rate differentials – the *prospective* interest rate differential – minus the transitory component of the exchange rate. Because the transitory component is not expected to have a fundamental or permanent effect on the riskiness of the foreign currency, an increase in the prospective interest rate differential therefore signals higher expected foreign currency excess returns. Hassan and Mano (2019) suggest that a positive cross-sectional covariance between future excess returns and the current interest rate differential corresponds to the investment payoff from the carry trade. We draw on this insight and demonstrate that the covariance between future excess returns and the prospective interest rate differential should be even larger, implying a greater investment payoff than the carry trade.

We measure the prospective interest rate differential by separately estimating the infinite sum of detrended expected future foreign short rates and domestic short rates. We use the historical sample average as the proxy for the long-run trend of interest rates. Estimating the persistence parameter of short rates is empirically more challenging. In the Beveridge-Nelson

[1] For a complete survey, see Engel (1996).

decomposition, the short rate is assumed to be stationary. However, using a simple AR(1) model to characterize the short rate is problematic for the following reasons. The short rate could exhibit I(1) behavior empirically (see Campbell and Shiller (1991) and Mishkin (1992)), which may result in the prospective interest rate not being properly defined. On the other hand, when the initial sample size is small, an AR(1) model could suffer from the well-known "Hurwicz bias": the point estimate for a country with a short interest rate sample will be more severely downward biased than that for the US, which has a long interest rate sample. This bias could unduly amplify the asymmetry in the persistence parameters between foreign and domestic short rates, confounding the return predictability results. We overcome these empirical challenges with the following approach.

In a no-arbitrage framework, the rate of depreciation between two currencies is related to the pricing kernels in the two countries (Brandt et al. (2006)).[2] Following this intuition, we use a parsimonious term structure model to decompose the pricing kernel into a transitory and a permanent component.[3] We then demonstrate that the short rate and government bond returns in a country share the same persistence parameter, which allows us to exploit the panel of government bond returns in addition to the short rates in each country to estimate the persistence parameter using a Kalman filter.

Incorporating additional information from government bond returns across multiple maturities proves valuable in obtaining a more precise estimate of the short-rate persistence parameter. We find significant variation in this parameter across countries, resulting in considerable cross-country differences in the prospective interest rate differential. Therefore, incorporating the dynamics of the short rate amplifies the current interest rate differential and allows us to better track the expected currency excess returns in the future.

We study an unbalanced panel of 31 currencies with adequate government bond returns data from January 1980 to July 2023. Following the carry trade literature, we construct currency portfolios using the equal weighting, high-minus-low, and ranking methods. We find that portfolios based on the prospective interest rate differential achieve higher average returns compared to carry

[2] When market is complete, the rate of depreciation equals the difference in the pricing kernels.

[3] Prior research (e.g., Backus et al. (2001) and Lustig et al. (2011)) has demonstrated the importance of asymmetries between foreign and domestic pricing kernels for understanding the carry trade.

portfolios while also reducing volatilities. As a result, the Sharpe ratios of the equal-weighted, high-minus-low, and rank-based portfolios are 21%, 74%, and 35%, respectively, higher than the corresponding carry portfolios.[4] In addition, currency crashes are a significant risk for the carry trade (Farhi et al. (2009) and Jurek (2014)). Our analysis confirms that carry portfolios exhibit negative skewness. In contrast, portfolios based on the prospective interest rate differential exhibit much smaller skewness values (the equal-weighted portfolio actually displays positive skewness). Moreover, these portfolios were more resilient than carry portfolios during the Global Financial Crisis.

Can existing currency market risk factors explain the performance of the portfolios based on the prospective interest rate differential? Lustig et al. (2011) show that a currency market slope factor successfully explains the excess returns of carry portfolios. Menkhoff et al. (2012) show that large return spreads are generated by currency momentum strategies. We regress the returns of the equal-weighted, high-minus-low, and rank-based portfolios formed on the prospective interest rate differential on the carry and momentum factors. We find that existing currency market factors cannot explain the excess returns of these portfolios, with all intercepts being highly significant. In addition, currency-level Fama-MacBeth cross-sectional regressions show that the prospective interest rate differential predicts individual currency excess returns up to 12 months ahead, after controlling for carry, past returns, and other common currency predictors.

We then use the high-minus-low portfolio formed on the prospective interest rate differential as a novel slope factor to explain the cross section of currency excess returns. We use a comprehensive set of one- and two-way-sorted test portfolios formed on the prospective interest rate differential, carry, and momentum, to evaluate competing currency market factor models. Our proposed model is a two-factor model that combines the currency market level factor and the slope factor based on the prospective interest rate differential. We also examine two alternative two-factor models using carry or momentum as the slope factor and an all-inclusive four-factor model that nests all three two-factor models, including our new factor model. Our proposed two-factor model outperforms all the other models considered. It is the only model to pass the GRS test at conventional significance levels, regardless of which test assets we use. In addition, our proposed

[4] We observe an even greater improvement in performance when comparing portfolios based on the prospective interest rate differential with currency momentum portfolios.

model successfully explains the excess returns of all high-minus-low spread portfolios and generates the smallest average pricing errors compared to all the other models.

Our paper is related to two strands of literature: permanent-transitory components decomposition and currency return predictability. Regarding the first literature, Engel (2016) applies Beveridge-Nelson decomposition to spot exchange rate to study the relation between future excess returns and the current interest rate differential (carry). Jiang et al. (2021, 2023) use the same Beveridge-Nelson decomposition framework to study the convenience yield in holding USD. Froot and Ramadorai (2005) decompose unexpected currency returns into permanent intrinsic-value news and transitory expected-return news, and study the relation between innovations in expected future real interest rate differentials and currency excess returns. Our paper also follows Alvarez and Jermann (2005) and Bakshi and Chabi-Yo (2012) and decomposes the pricing kernel into a permanent and a transitory component. In our model, the transitory component follows an exogenous autoregressive process that simultaneously determines the dynamics of the short rate as well as government bond returns.

Regarding the literature on currency return predictability, Ang and Chen (2010) use yield curve variables to predict currency excess returns. Menkhoff et al. (2012) document momentum in currency returns. Bakshi and Panayotov (2013) use commodity index returns and currency volatility to forecast currency returns. Lustig et al. (2014) design a "dollar carry trade" strategy that takes long (short) positions in currencies from countries with a higher (lower) short rate than the US. He et al. (2017) construct an aggregate capital ratio for the intermediary sector by matching the New York Fed's primary dealers with CRSP/Compustat and Datastream data on their publicly traded holding companies, and show that this capital ratio captures risk exposure for assets across multiple financial markets. Bartram et al. (2024) find that excess money demand could predict the cross section of currency returns. Our paper not only introduces a novel and strong return predictor but also proposes a factor model that can better explain the cross section of currency excess returns.

The rest of the paper is organized as follows. In Section 2, we present the Beveridge-Nelson decomposition and describe how we measure the prospective interest rate differential. Section 3 introduces the data and summarizes the empirical properties of the prospective interest rate differential. Section 4 presents the results on currency return predictability and its asset pricing implications. Section 5 concludes.

2 Model and Estimation

We analyze the nominal foreign exchange rate, taking USD as the home currency. Let the direct exchange rate between the USD and the foreign currency unit (FCU) be $s_t = \log S_t$ (e.g., S_t=1.5USD/£), and the US and foreign interest rates be i_t and i_t^*, respectively. We follow the literature and add asterisks to denote the corresponding foreign variables, use ∇ to denote cross-country differences (e.g., $\nabla i_t = i_t^* - i_t$), and use Δ to denote time-series first differences (e.g., $\Delta s_{t+1} = s_{t+1} - s_t$). The foreign currency excess return is then $\lambda_{t+1} = s_{t+1} - s_t + \nabla i_t$. We denote the expected value of the currency excess return $l_t \equiv E_t \lambda_{t+1}$, such that $s_t - E_t s_{t+1} = \nabla i_t - E_t \lambda_{t+1} = \nabla i_t - l_t$.

Next, we define $\bar{\imath}^* = \lim_{j\to\infty} i_{t+j}^*$, $\bar{\imath} = \lim_{j\to\infty} i_{t+j}$, and $\bar{l} = \lim_{j\to\infty} l_{t+j}$. Further, let $\tau = \bar{l} - (\bar{\imath}^* - \bar{\imath})$. By iterating forward and summing up, we then obtain

$$s_t - \lim_{j\to\infty} E_t s_{t+j} + j\tau = \sum_{j=0}^{\infty} \left(E_t \left[i_{t+j}^* - \bar{\imath}^* \right] - E_t \left[i_{t+j} - \bar{\imath} \right] \right) - \sum_{j=0}^{\infty} E_t \left(l_{t+j} - \bar{l} \right). \tag{1}$$

To derive the above equation, we perform the Beveridge-Nelson decomposition, following Engel (2016) and Jiang et al. (2021, 2023). This involves subtracting the permanent component s_t^{BN} from the spot rate s_t ($s_t - s_t^{BN} = s_t - \lim_{j\to\infty} E_t s_{t+j} + j\tau = s_t^T$), ensuring both sides of the equation remain stationary. In Engel (2016), the term $\sum_{j=0}^{\infty} \left(E_t[i_{t+j}^* - \bar{\imath}^*] - E_t \left[i_{t+j} - \bar{\imath} \right] \right)$ is referred to as the prospective interest rate differential. Note that this term is still about the infinite sum of expected short interest rates, not the rates of long-term bonds. Rearranging the terms, we have

$$\sum_{j=0}^{\infty} E_t \left(l_{t+j} - \bar{l} \right) = \sum_{j=0}^{\infty} \left(E_t \left[i_{t+j}^* - \bar{\imath}^* \right] - E_t \left[i_{t+j} - \bar{\imath} \right] \right) - s_t^T. \tag{2}$$

Conceptually, the permanent component s_t^{BN} represents the present value of expected future domestic and foreign money stocks, real incomes, inflation rates, and current account balances

(Mussa (1982) and Engel et al. (2010)). They have lasting effects on the level of the exchange rate. In contrast, the transitory component, s_t^T, reflects infrequent central bank interventions, microstructure phenomena such as bubbles and rumors, the effects of technical trading by noise traders (Baum et al. (2001)), or portfolio reallocations among international investors (Evans and Lyons (2002)). These effects typically have only temporary impacts on the exchange rate and should not affect the riskiness of a foreign currency. Therefore, expected foreign currency excess returns should comove much more closely with the prospective interest rate differential than with s_t^T.

This comovement indicates strong return predictability of the prospective interest rate differential, which has direct portfolio implications. In a study of active mutual fund trading, Pástor et al. (2017) point out that the covariance between available information and future returns is equivalent to an investment payoff. Furthermore, Hassan and Mano (2019) provide an analytic framework for the carry trade, demonstrating that the cross-sectional covariance between future foreign currency excess returns and the current interest rate differential corresponds to a carry trade investment payoff. This involves taking a long (short) position in a foreign currency when its interest rate differential is above (below) the cross-sectional average. A profitable carry trade thus implies

$$Cov_t\left(\lambda_{t+1}, i_t^* - i_t\right) = Cov_t\left(l_t, i_t^* - i_t\right) > 0. \tag{3}$$

The investment payoff, based on the prospective interest rate differential, is given by the following

$$\begin{aligned} & Cov_t\left(l_t, \sum_{j=0}^{\infty}\left[E_t\left[i_{t+j}^* - \bar{\imath}^*\right] - E_t\left[i_{t+j} - \bar{\imath}\right]\right]\right) \\ = \; & Cov_t\left(l_t, \left[i_t^* - \bar{\imath}^*\right] - \left[i_t - \bar{\imath}\right]\right) + Cov_t\left(l_t, \left[E_t\left[i_{t+1}^* - \bar{\imath}^*\right] - E_t\left[i_{t+1} - \bar{\imath}\right]\right]\right) + ... \\ & + Cov_t\left(l_t, \left[E_t\left[i_{t+\infty}^* - \bar{\imath}^*\right] - E_t\left[i_{t+\infty} - \bar{\imath}\right]\right]\right). \end{aligned} \tag{4}$$

Comparing equations (3) and (4) highlights two differences. First, in equation (4), the cross-sectional covariances are between detrended interest rate differentials and expected future excess returns. Second, equation (4) involves an infinite sum of covariances. Despite these differences, the magnitudes of both equations can still be compared. If the detrended carry trade is as profitable as the carry trade itself, meaning that $Cov_t\left(l_t, [i_t^* - \bar{\imath}^*] - [i_t - \bar{\imath}]\right)$ is similar in magnitude to $Cov_t\left(l_t, i_t^* - i_t\right)$, and if the covariances between expected future detrended interest rate differentials and expected excess returns are also positive, we can conclude that

$$Cov_t\left(l_t, \sum_{j=0}^{\infty}\left[E_t\left[i_{t+j}^* - \bar{\imath}^*\right] - E_t\left[i_{t+j} - \bar{\imath}\right]\right]\right) \geq Cov_t\left(l_t, i_t^* - i_t\right). \tag{5}$$

We confirm that these two conditions hold true. First, we are able to verify empirically that the detrended carry trade generates profits similar to the regular carry trade. Second, interest rates are known to be persistent, and high (low) current short rates tend to be followed by similarly high (low) short rates in the future for certain countries. For example, commodity-producing countries tend to have higher interest rates, while countries that export finished goods tend to have lower interest rates (Ready et al. (2017)). In addition, monetary policy strongly influences short rates, and some countries tend to have a higher interest rate policy than others.[5] Furthermore, currency momentum suggests that the persistence of excess returns reflects the persistence of short rates (Menkhoff et al. (2012)). The reason is that the excess return is the sum of the rate of depreciation and the interest rate differential, and the rate of depreciation is only weakly autocorrelated. Therefore, the persistence of excess returns primarily mirrors that of short rates. Taken together, the above evidence suggests that the additional covariance terms in equation (4) are likely to be positive. As a result, the prospective interest rate differential should have a larger covariance with expected future excess returns than the current interest rate differential. In other words, the prospective interest rate differential should generate a larger investment payoff compared to the carry trade.

To measure the prospective interest rate differential, we assume that both the foreign and domestic (US) short rates follow simple AR(1) processes such that $i_{t+1}^* - \bar{\imath}^* = \phi^*\left(i_t^* - \bar{\imath}^*\right) + \varepsilon_{t+1}^*$ and $i_{t+1} - \bar{\imath} = \phi\left(i_t - \bar{\imath}\right) + \varepsilon_{t+1}$. We can then rewrite the prospective interest rate differential as

$$\sum_{j=0}^{\infty}\left[E_t\left[i_{t+j}^* - \bar{\imath}^*\right] - E_t\left[i_{t+j} - \bar{\imath}\right]\right] = \frac{i_t^* - \bar{\imath}^*}{1 - \phi^*} - \frac{i_t - \bar{\imath}}{1 - \phi}. \tag{6}$$

[5]Based on this observation, Backus et al. (2014) argue the UIP puzzle can be restated in terms of monetary policies.

If investors expect no time variation in interest rates, then currency returns can only be predicted based on the interest rate differential. However, if investors update their beliefs whenever they receive new information, interest rates are expected to exhibit different degrees of persistence and fluctuate around their averages. Therefore, by incorporating parameters related to the dynamics of interest rates, the prospective interest rate differential could be a stronger return predictor, and implementable trading strategies can be developed with ex ante estimates of the persistence and long-run trends of both foreign and domestic interest rates.

Empirically, we estimate the long-run trend of the short rate by using its historical sample average. Estimating the persistence parameter of the short rate, on the other hand, is not as straightforward. First, simple OLS estimates of the persistence parameter could be downward biased during the early sample period when the number of observations is small – the well-known "Hurwicz bias." Second, the short rate may empirically exhibit I(1) behavior (see Campbell and Shiller (1991) and Mishkin (1992)), and an estimated persistence parameter greater than one means that the prospective interest rate differential is not properly defined.

To overcome these empirical challenges, we use a parsimonious one-country model to decompose the exogenously specified pricing kernel into a permanent and a transitory component. The essence of this model is that, in each country, government bonds of all maturities are driven by transitory shocks to the pricing kernel for that country (see, e.g., Kazemi (1992), Alvarez and Jermann (2005), and Bakshi and Chabi-Yo (2012)). More importantly, the persistence of the transitory shocks determines the persistence of the short rate and long-term bond returns. Because the transitory component of the pricing kernel is not directly observable, we follow the term structure literature and use each country's available government bond returns, across different maturities, to estimate the persistence parameter via a Kalman filter.

Specifically, we follow Alvarez and Jermann (2005) and consider the following discrete-time model of the log pricing kernel (i.e., the marginal utility of wealth for the representative agent), $m_t \equiv \log M_t$:

$$m_{t+1} - \mu_{t+1} = \phi (m_t - \mu_t) + u_{0,t+1}; \ \ |\phi| < 1, \tag{7}$$

$$\mu_{t+1} = -\nu + \mu_t + u_{1,t+1}, \tag{8}$$

where $u_{0,t+1}$ ~i.i.d.$N\left(0,\sigma_0^2\right)$ and $u_{1,t+1}$ ~i.i.d.$N\left(0,\sigma_1^2\right)$ are Gaussian white noise processes.

The long-run mean of the log pricing kernel, μ_t, follows a random walk with drift (equation (8)), which characterizes the "stochastic trend" of the log pricing kernel. Equation (7) describes the transitory variation of the log pricing kernel (m_t) around μ_t. Hence, our model represents a two-factor setup of the pricing kernel, where $u_{0,t+1}$ and $u_{1,t+1}$ are the transitory and permanent factors, respectively, with their correlation equal to σ_{01}.

We then guess the default-free zero-coupon bond log price $b_t^n = \log B_{t,n}$ (at time t with maturity n) to be an exponential function of $x_t = E_t \Delta m_{t+1}$ with maturity-dependent coefficients g_n and f_n:

$$b_t^n = g_n + f_n x_t. \tag{9}$$

Then, from the Euler equation

$$E_t\left[M_{t+1} B_{t+1,n-1}\right] = M_t B_{t,n} \tag{10}$$

we can guess and verify that

$$f_n = \frac{1-\phi^n}{1-\phi}. \tag{11}$$

And the dynamics of x_t are

$$x_{t+1} = -\nu(1-\phi) + \phi x_t + (\phi - 1) u_{0,t+1}. \tag{12}$$

The one-period (log) holding return of the zero-coupon bond with maturity n, $r_{t+1,n}^b = b_{t+1}^{n-1} - b_t^n$ is then

$$r_{t+1,n}^b = i_t + \frac{1}{2}\left[2\left(1-\phi^{n-1}\right)\sigma_{01} + \left(1-\phi^{2(n-1)}\right)\sigma_0^2\right] - \left(1-\phi^{n-1}\right)u_{0,t+1}. \tag{13}$$

The unexpected return is driven by the transitory shock to the pricing kernel, depending only on ϕ,

$$r_{t+1,n}^b - E_t r_{t+1,n}^b = -\left(1-\phi^{n-1}\right)u_{0,t+1}. \tag{14}$$

Finally, the short rate is obtained by setting $n = 1$:

$$i_{t+1} = \phi i_t + a - (\phi - 1)\, u_{0,t+1}. \tag{15}$$

This model implies that the persistence of the transitory component, ϕ, equals the persistence of the short rate. In addition, because both interest rates and bond returns are driven by transitory shocks to the pricing kernel, the term structure of discount bond returns is informative of the dynamics – particularly the persistence property – of the transitory component of the pricing kernel.

Next, we follow the term structure literature to estimate ϕ via a Kalman filter.[6] To obtain a state-space representation, let $y_{t+1} = r^b_{t+1,n}$. Then, for a certain maturity n, the measurement equation is

$$y_t = -\tfrac{1}{2} Var_t \left[\phi^{T-1} u_{0,t+1} + u_{1,t+1}\right] + \begin{bmatrix} 0 & -1 & -\left(1 - \phi^{T-1}\right) \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ u_{0,t} \end{bmatrix} + \sqrt{\tau_i}\varepsilon_t, \tag{16}$$

where ε_t is an error term. We assume that bond returns contain measurement errors that are proportional to the maturity date following the affine term structure literature. The transition equation is

$$\begin{bmatrix} x_{t+1} \\ x_t \\ u_{0,t+1} \end{bmatrix} = \begin{bmatrix} -\nu\,(1-\phi) \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \phi & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ u_{0,t} \end{bmatrix} + \begin{bmatrix} \phi - 1 \\ 0 \\ 1 \end{bmatrix} u_{0,t+1}. \tag{17}$$

The above linear state space formulation allows us to recursively make inferences about the unobserved state variables using a log-likelihood function, which can be maximized via a Kalman filter. We can then obtain the optimal parameter estimates.

[6] We do not model market incompleteness, and our estimation is conducted country-by-country. For discussion of currency risk premiums in a multi-country or global affine term structure model, see Backus et al. (2001) and Sarno et al. (2012).

There are two benefits to using a simple term structure model in our context. First, short rates are closely tied to government bond returns, both theoretically and empirically. In classical bond pricing models (e.g., Vasicek (1977) and Cox et al. (1985)), the short rate is the only state variable in the economy and thus the only source of variation for bond prices. This suggests that the additional information embedded in government bond returns allows the true dynamics of the short rate to reveal themselves more effectively than by narrowly focusing on the time series of the short rate alone, especially when the number of observations is limited. Our approach also complements past studies that demonstrate term structure variables contain useful information about currency excess returns (Ang and Chen (2010) and Bekaert et al. (2007)).

Second, in our model, the short rate inherits its stationary property from the transitory component of the pricing kernel. Empirically, however, the short rate may appear to follow a unit root process when studied in isolation, due to structural breaks, regime switching, or stochastic volatility. Examining the joint dynamics with government bond returns mitigates this concern and effectively reduces the noise in estimating the persistent parameter of the short rate.

The primary objective of our AR(1) specification is to use a simple model to link the persistence of the pricing kernel to that of the short rate in a single country, rather than developing a multi-factor model to price the cross section of government bonds. For simplicity and tractability, we do not model stochastic volatility of the pricing kernel, impose any relations between pricing kernels of different countries, or consider international asset market incompleteness. Explaining why currency risk premiums exist in equilibrium would require a full-fledged model that incorporates these features, which is outside the scope of our paper.

3 Data and Summary Statistics

3.1 Data

We obtain monthly zero-coupon government bond index returns, short interest rates, and foreign exchange rates, over the sample period from December 1979 to July 2023 (523 months), from Datastream. Our sample consists of 31 foreign countries/regions: Australia, Austria, Belgium, Canada, China, Czech, Denmark, EMU (EURO), Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Mexico, the Netherlands, Norway, New Zealand, Poland, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, and the UK. The US is the home country. We mainly rely on Barclays Bank International (BBI) for spot and forward exchange rates, and augment with WM/Reuters (WMR) when BBI data are not available.

For zero-coupon government bond indices, we use all available maturities for each country. Table 1 reports the maturities and the first month when a country's government bond indices become available in our sample. China, France, and the UK have bond data for all nine maturities (2, 3, 5, 7, 10, 15, 20, 30, and 50 years), while Germany, the Netherlands, the UK, and the US have the earliest starting date (December 1979) in our sample.

Table 1 about here.

For short interest rates, we use one-month Eurocurrency deposit rates following the literature and interbank rates if the former are not available. To match the sample coverage of bond indices, we augment the short rate and foreign exchange data in the following ways. In cases where the short rate is missing but the exchange rate against USD is available, we back out the short rate via the covered interest rate parity. In cases where the short rate is available but the exchange rate against USD is missing, we assume no triangular arbitrage and back out the FCU/$ rate as (FCU/£)/($/£).

Our final sample consists of an unbalanced panel of government bond returns, spot and forward exchange rates, and short interest rates for the 31 countries/regions. Our main empirical results are based on 30 currencies that are available before the euro was introduced in 1999 and 20 currencies thereafter. They represent the most actively traded currencies during our sample period.

3.2 Summary statistics and parameter estimates

Table 2 summarizes the excess returns of the 31 currencies from January 1980 to July 2023, subject to data availability. The mean monthly excess returns range from -0.05% (Finland) to 0.45%

(South Africa), and most currencies exhibit little serial correlation. Out of the 31 currencies, 24 exhibit negative skewness in their returns, and 23 show a greater magnitude for the largest monthly loss than the largest monthly gain. These features highlight the risk of currency crashes as emphasized in Brunnermeier et al. (2008).

Table 2 about here.

Panel A of Table 3 presents the estimated OLS AR(1) coefficient (ϕ) for the short rate in each country to serve as a baseline. We first report the full-sample (FS) estimate for each country. Next, we report the summary statistics of the estimates using extending backward-looking windows. Specifically, ϕ is initially estimated using the first 30 monthly observations for each country, and then each month, one more observation is added for re-estimation. The bottom row reports the cross-country averages of the full-sample estimates, the median and standard deviation, and the minimum (maximum) of the time-series minimum (maximum) estimates based on extending windows. The cross-country averages of the full-sample and time-series median estimates are 0.969 and 0.971, respectively, suggesting that short rates are highly persistent. Importantly, the time-series estimates based on extending windows exhibit more extreme values across countries than the full-sample estimates. Estimates such as 0.029 (Norway) and 0.100 (New Zealand), when compared with the full-sample estimates of 0.910 (Norway) and 0.961 (New Zealand), suggest a severe downward bias during the early sample period when the number of observations is small. On the other hand, larger-than-unit estimates also appear occasionally in our sample. For example, Czech, Denmark, EMU, Greece, Hungary, Ireland, South Africa, South Korea, Mexico, and Singapore have their largest time-series estimates at 1.071, 1.165, 1.001, 1.004, 1.004, 1.134, 1.001, 1.002, 1.133, and 1.056, respectively, which make the prospective interest rate (infinite sum) not properly defined. These sporadic occurrences of extreme estimates suggest that they may be caused by estimation noise.

Table 3 about here.

Panel B of Table 3 presents the persistence parameters estimated using the Kalman filter. Again, we first report the full-sample estimates. Compared to their OLS counterparts in Panel

A, the average value of ϕ across countries decreases slightly from 0.969 to 0.956. Next, we report the ϕ estimates using extending backward-looking windows. Similar to the OLS estimation, ϕ is initially estimated with the first 30 monthly observations for each country using the Kalman filter. We then expand the estimation window with every additional monthly observation and obtain a time series of the ϕ estimates. Our Kalman-filter procedure produces much less extreme and better behaving estimates than the OLS estimates reported in Panel A. The cross-country minimum and maximum of the time-series minimum and maximum ϕ estimates are 0.476 and 0.993, respectively, which are far less extreme than their OLS counterparts (0.029 and 1.165, respectively). The average within-country time-series standard deviation is 0.028, which is less than a third of the OLS value (0.093).

Table 4 presents the summary statistics of the prospective interest rate differentials (in percent) using the time series of OLS ϕ and Kalman filter (KF) ϕ, with the long-run expected short rate proxied by its historical sample average. We exclude estimates when ϕ is larger than unit because the infinite sum is not properly defined. For comparison, we also present the summary statistics of the current interest rate differential (carry). The table shows that more than half of the countries have higher interest rates than the US during our sample period, with the cross-country average of the monthly mean (median) carry value at 0.09% (0.00%). India and South Africa have the largest carry, with means (medians) of 0.48% (0.46%) and 0.47% (0.44%), respectively, whereas Japan and Switzerland have the smallest carry, with means (medians) of −0.17% (−0.15%) and −0.15% (−0.14%), respectively.

More importantly, Table 4 shows that accounting for the persistence of short rates significantly increases the cross-country variation of the prospective interest rate differential compared to that of carry. Conceptually, the prospective interest rate differential contains carry, plus the sum of expected carry over future periods. Therefore, its variation should exceed that of carry, provided that short rates are highly persistent. Indeed, the median prospective interest rate differential based on KF ϕ ranges from −3.26% (Sweden) to 7.14% (Singapore), whereas the median carry ranges from −0.15% (Japan) to 0.46% (India). Moreover, OLS ϕ tends to produce much more extreme estimates of the prospective interest rate differential than KF ϕ, likely due to the estimation noise in OLS ϕ. The range for the median prospective interest rate differential based on OLS ϕ (from -35.47% for Italy to 21.02% for China) is almost six times the range based on KF ϕ (from -3.26% for Sweden to 7.14% for Singapore). For the remainder of the paper, we focus on the estimates based on KF ϕ in our empirical tests.[7]

4 Empirical Analysis

4.1 Portfolio analysis

Following the convention in the currency market literature, we examine the return predictability of the prospective interest rate differential using both portfolio analysis and Fama-MacBeth regressions. Because we use the first 30 monthly observations to construct the initial estimate of the prospective interest rate differential, our return predictability tests start from July 1982. Afterwards, we expand the monthly estimation window up to the most recent month to avoid any look-ahead bias. We form currency portfolios using the prospective interest rate differential based on the Kalman filter persistence estimates ($\frac{i_t^*-\bar{\imath}^*}{1-\phi^*} - \frac{i_t-\bar{\imath}}{1-\phi}$, denoted as χ hereafter) and compare their performance with that of the currency carry and momentum portfolios.

We form three sets of portfolios at the beginning of each month. The first set of portfolios takes long or short positions in individual currencies depending on the sign of the selected predictor (e.g., the prospective interest rate differential). For example, when a foreign currency's prospective interest rate differential is positive, we take a long position in the foreign currency and a short position in USD. When the prospective interest rate differential is negative, we perform the opposite transactions. We then combine all individual currency positions into an equal-weighted (EW) portfolio. Because the number of currencies that we take long versus short positions in may vary over time, we scale the sum of weights accordingly to ensure the long and short bets are equal such that one USD is always at stake.

We also construct high-minus-low (HML) portfolios following Lustig et al. (2011). Each month, all available currencies in our sample are sorted into quartiles according to their predictor values.

[7] To compare with the predictive power of carry, we follow the literature and construct the prospective interest rate differential using discrete short interest rates. Using continuous compounding short rate generates almost identical results.

When the predictor is the prospective interest rate differential, for example, the lowest quartile contains the currencies with the lowest values of the prospective interest rate differential and the highest quartile contains the currencies with the highest values of the prospective interest rate differential. The HML portfolio then takes an equal-weighted long position in the highest quartile and a short position in the lowest quartile. This procedure is equivalent to executing a trade in which the investor borrows in the currencies in the lowest quartile to invest in the currencies in the highest quartile.

The third set of portfolios is based on the ranks of predictor values in the same fashion as Asness et al. (2013). In the case of the prospective interest rate differential, this rank-based (RNK) portfolio takes long positions in currencies with positive values of the prospective interest rate differential and short positions in currencies with negative values of the prospective interest rate differential, with the weight given to a particular currency determined by its relative rank across currencies. We again scale to maintain that one USD is always at stake and long and short bets are equal when both positions are traded.

Table 5 about here.

Panel A of Table 5 presents the results for the full sample period. For each predictor, we report the return characteristics (in percent) for all three portfolios: EW, HML, and RNK. The results show that the portfolios formed on the prospective interest rate differential χ offer superior risk-return tradeoffs than the corresponding carry and momentum portfolios. For example, the EW portfolio based on χ generates an average monthly return of 0.182% and outperforms the EW carry and momentum portfolios, which return 0.158% and 0.163%, respectively. The standard deviation of the EW χ portfolio is 1.381% per month, which is lower than that of the carry portfolio (1.456%) and the momentum portfolio (1.633%). The annualized Sharpe ratio of the EW χ portfolios is 0.456, which is 21% higher than that of the carry portfolio at 0.377 and 32% higher than that of the momentum portfolio at 0.346. Furthermore, the EW χ portfolio shows a positive skewness of 0.805, and the largest monthly gain of 8.875% is larger in magnitude than the largest monthly loss of −8.202%. This is in contrast to the carry and momentum portfolios, which display negative skewness of -0.468 and -0.023, with the largest monthly gains at 7.199% and 7.852% and monthly losses at -8.202% and -8.875%, respectively.

The HML portfolios differ from the EW portfolios along two dimensions. First, the long and short currency positions are determined by the relative rankings of a predictor across currencies, rather than by the signs of the predictor. Second, the HML portfolios only trade currencies with extreme values of the predictor and therefore take more aggressive positions than the EW portfolios. When comparing the HML portfolio based on the prospective interest rate differential with those based on carry and momentum, we again observe that the χ portfolio outperforms. The average monthly return of the HML χ portfolio is 0.412%, which is significantly higher than that of the HML carry portfolio (0.311%) and the HML momentum portfolio (0.067%). The standard deviation of the HML χ portfolio is 1.828% per month, lower than that of the carry portfolio at 2.393% and the momentum portfolio at 2.235%. The annualized Sharpe ratio of the HML χ portfolio, 0.781, is much higher than that of the carry portfolio (0.450) and the momentum portfolio (0.104).

Similar to the HML portfolios, the RNK portfolios exploit relative rankings in a predictor and invest more in currencies with more extreme predictor values. Unlike the HML portfolios, however, the RNK portfolios invest in all currencies, rather than only those with extreme predictor values. The average return, standard deviation, and annualized Sharpe ratio of the RNK χ portfolio are 0.312%, 1.536%, and 0.704, respectively, which again compare favorably to those of the corresponding carry portfolio (0.298%, 1.981%, and 0.521, respectively) and momentum portfolio (0.082%, 1.839%, and 0.155, respectively).

We also plot the cumulative returns of the χ, carry, and momentum portfolios in Figure 1. Panels A, B, and C plot the EW, HML, and RNK portfolios, respectively. The figures show that, regardless of the portfolio construction method, the χ portfolios outperform the carry and momentum portfolios over the entire sample period. Even during the Global Financial Crisis (GFC), the χ portfolios performed relatively well compared to the carry portfolios, which suffered visibly large losses. Although some research (e.g., Burnside et al. (2011)) attributes carry trade profits to a peso problem or crash risk, this explanation seems less applicable to the performance of the χ portfolios. The momentum portfolios exhibited strong performance during the GFC;

however, their cumulative returns have turned negative in the years since.

Figure 1 about here.

To examine whether our findings are influenced by the introduction of the euro – which led to the elimination of several European currencies – we analyze the sample periods before and after the euro's adoption separately. The results from the pre-euro period, as presented in Panel B of Table 5, closely align with our full-sample results in Panel A. The χ portfolios based on the prospective interest rate differential are nearly always associated with higher average returns, lower volatility, and higher Sharpe ratios than the corresponding carry and momentum portfolios. For example, during the pre-euro period, the Sharpe ratios of the EW, HML, and RNK χ portfolios are 0.579, 0.722, and 0.575, respectively. In comparison, the Sharpe ratios are 0.441, 0.301, and 0.366 for the corresponding carry portfolios and 0.478, 0.435, and 0.521 for the momentum portfolios, respectively. Panel C of Table 5 shows that, during the post-euro period, the Sharpe ratios of the EW, HML, and RNK χ portfolios are 0.328, 0.846, and 0.845, respectively. In comparison, the corresponding carry portfolios' Sharpe ratios are 0.303, 0.570, and 0.664, and the momentum portfolios' Sharpe ratios are 0.193, -0.179, and -0.172, respectively. Although the average returns of the χ portfolios do not necessarily surpass those of their carry and momentum counterparts during the post-euro sample period, they consistently display lower volatility and thus higher Sharpe ratios than both the carry and momentum portfolios.

4.2 Factor model regressions

Next, we investigate whether existing factor models can explain the performance of portfolios formed on the prospective interest rate differential. To answer this question, we regress the monthly returns of the EW, HML, and RNK χ portfolios on existing equity market and currency market factors and report the results in Table 6. For equity factor models, we follow Burnside (2012) and consider the CAPM (MKT), Fama-French three-factor model (MKT, SMB, and HML), and Carhart four-factor model (MKT, SMB, HML, and UMD). For currency factor models, we consider two different two-factor models that each combine a common level factor with a distinct slope factor. The level factor is a simple average of the excess returns of all our sample currencies.[8] The first slope factor, HML_{FX}, is the carry trade risk factor from Lustig et al. (2011). The second slope factor, HML_{MOM}, is the high-minus-low momentum return spread from Menkhoff et al. (2012). In addition, we include these two slope factors together with the level factor in a three-factor model.[9] The average monthly premiums of the level, HML_{FX}, and HML_{MOM} factors are 0.182% (t=2.88), 0.412% (t=4.95), and 0.312% (t=4.46), respectively.

Table 6 about here.

Panels A, B, and C of Table 6 present the factor model regression results for the EW, HML, and RNK χ portfolios, respectively. We first examine the explanatory power of equity factor models (columns 1, 2, and 3 of each panel). Previous studies show that equity market factors cannot explain carry portfolio returns (Lustig and Verdelhan (2007), Lustig et al. (2011), and Burnside (2012)). Consistent with their findings, the alphas of the χ portfolios range from 0.167% (t=2.58) to 0.399% (t=4.56), compared with the average returns ranging from 0.182% (t=2.88) to 0.412% (t=4.95). Moreover, most of the equity factor loadings are insignificant, and all of the regression R^2's are less than 1%, indicating that equity market factors also fail to explain the return variation of portfolios formed on the prospective interest rate differential.

Next, we examine the ability of currency factor models to explain the returns of the χ portfolios (columns 4, 5, and 6 of each panel). Except for the EW portfolio, all loadings on the level factor are insignificant. This observation is consistent with Lustig et al. (2011), who find that the level factor mainly captures the average magnitude of currency excess returns but fails to explain the differences in excess returns across currencies. Additionally, the loadings on the HML_{MOM} factor are consistently insignificant, suggesting minimal comovement between the χ portfolios and currency momentum. As a result, the two-factor model with the level and HML_{MOM} factors leaves sizable unexplained alphas: 0.147% (t=2.84), 0.411% (t=4.75), and 0.318% (t=4.62) for the EW, HML, and RNK χ portfolios, respectively.

[8] This level factor is highly correlated with the RX factor in Lustig et al. (2011), with a correlation of 98.6%.

[9] The two slope factors are downloaded from the authors' websites. The momentum portfolios in Menkhoff et al. (2012) end in January 2010, and we follow their methodology and sample of currencies to update the momentum slope factor to July 2023.

Because the prospective interest rate differential is related to carry, examining the explanatory power of the models with the carry slope factor, HML_{FX}, is more relevant. For the EW, HML, and RNK χ portfolios, the loadings on HML_{FX} are 0.027 (t=0.66), 0.220 (t=3.36), and 0.210 (t=4.14), respectively, in the two-factor model. When we control for HML_{MOM} in the three-factor model, the loadings on HML_{FX} are 0.027 (t=0.67), 0.221 (t=3.45), and 0.211 (t=4.28), respectively. Overall, the regression R^2's range from 9% to 20%, suggesting that currency market factors – HML_{FX} in particular – capture sizable return variation of the χ portfolios.

However, despite the improved explanatory power, these models still cannot explain the excess returns of the portfolios formed on the prospective interest rate differential. In the two-factor model with HML_{FX}, the alpha is 0.133% (t=2.06) for the EW χ portfolio, 0.278% (t=2.90) for the HML χ portfolio, and 0.202% (t=2.71) for the RNK χ portfolio. In the three-factor model with both HML_{FX} and HML_{MOM}, the alpha is 0.130% (t=2.10) for the EW χ portfolio, 0.270% (t=2.83) for the HML χ portfolio, and 0.183% (t=2.48) for the RNK χ portfolio. In sum, existing equity and currency market factors fail to capture the returns of portfolios based on the prospective interest rate differential.

4.3 Fama-MacBeth regressions

In this section, we employ Fama-MacBeth (1973) cross-sectional regressions to directly compare the predictive power of the prospective interest rate differential against carry and momentum. The cross-sectional regressions allow us to examine the predictability of currency returns over different horizons, to use individual currencies instead of portfolios, and to control for additional predictors of currency returns.

Each month, we regress the (average) monthly currency excess returns over the next one, three, six, and 12 months on the prospective interest rate differential and control variables. In addition to carry, our control variables include the one-month lagged currency excess return r_{t-1} (Menkhoff et al. (2012)), the two-to-six-month lagged cumulative excess return $r_{t-6,t-2}$ (Menkhoff et al. (2012)), the inflation rate differential ∇inf (Jordà and Taylor (2012)), and the quarterly change in log real exchange rate ΔRER (Jordà and Taylor (2012), Asness et al. (2013), and

Menkhoff et al. (2017)). To ensure a sufficiently large sample size for each cross section, we begin the regressions in July 1984 and require a minimum of 10 monthly observations.

Table 7 about here.

Table 7 reports the Fama-MacBeth regression coefficients and their associated t-stats. The results indicate that both the prospective interest rate differential and carry are significant predictors of currency excess returns across all four horizons when considered individually. For example, in the univariate regressions at the one-month horizon, the coefficient on χ is 0.055 with a t-stat of 3.93, and the coefficient on carry is 0.852 with a t-stat of 3.91. In terms of economic significance, a one standard deviation increase in χ (3.546%) or carry (0.264%) predicts an increase of 0.195% (0.055 $\times$ 3.546%) or 0.225% (0.852 $\times$ 0.264%) in next month's excess return, both economically sizable. Interestingly, while the predictive power of carry diminishes gradually over time, that of χ remains relatively stable. At the 12-month horizon, the coefficient on χ decreases slightly to 0.049 with a t-stat of 5.98, whereas the coefficient on carry drops by almost 20% to 0.693 with a t-stat of 4.48.

Turning to the control variables, the one-month lagged excess return (r_{t-1}) significantly predicts three- and 12-month-ahead future excess returns and marginally predicts one- and six-month-ahead excess returns. However, the two-to-six-month lagged excess return ($r_{t-6,t-2}$) only marginally predicts excess returns at the one- and three-month horizons. The inflation rate differential (∇inf) significantly predicts future excess returns at all but the one-month horizon. In contrast, the quarterly change in log real exchange rate ΔRER does not show significant predictive power at any horizon.

More importantly, when we include both carry and the prospective interest rate differential in the same regression along with other control variables, the coefficient on carry weakens and becomes insignificant at the one- and three-month horizons. On the other hand, the coefficient on χ remains highly significant at all horizons. Specifically, at the one-, three-, six, and 12-month horizons, the coefficients on carry are 0.417 (t=1.29), 0.403 (t=1.59), 0.454 (t=1.97), and 0.408 (t=2.05), respectively, whereas those on χ are 0.028 (t=2.88), 0.023 (t=2.91), 0.020 (t=2.73), and 0.025 (t=3.84), respectively. These results underscore the significant predictive power of the prospective interest rate differential above and beyond carry (the current interest rate differential).

In sum, the results from Fama-MacBeth regressions support the conclusion from portfolio sorts and factor regressions that the prospective interest rate differential holds significant information about future currency excess returns. Furthermore, consistent with our theoretical framework, its return predictive power remains significant even after accounting for carry and other currency return predictors.

4.4 Asset pricing with a new currency slope factor

Lustig et al. (2011) introduce HML_{FX} as a slope factor to account for the differences in excess returns between high and low interest rate currencies. Given the predictive power of the prospective interest rate differential, we ask whether a similarly constructed slope factor can further improve the pricing of the cross section of currency excess returns. Hou et al. (2018, 2020) emphasize the importance of using a broad set of test assets to draw reliable inferences on competing factor models. Thus, we construct equal-weighted one- and two-way-sorted portfolios based on the prospective interest rate differential, carry, and momentum (one-month lagged return) as our main test assets. At the beginning of each month, we use all available sample currencies with valid predictors (χ, carry, or momentum) to construct each set of test portfolios. We then regress the time series of monthly test portfolio returns on different currency factor models to evaluate their performance in explaining test portfolio returns. We consider three two-factor models that separately combine the level factor with a single HML slope factor based on χ, carry, or momentum (each model named after its slope factor), as well as a four-factor model that combines the level factor with all three slope factors.

We begin with the one-way-sorted portfolios as test assets. Panels A, B, and C of Table 8 present the time-series regression results using quintile portfolios formed on carry, momentum, and χ, respectively. Each panel reports the average excess returns, alphas, factor loadings, and their associated t-stats. To evaluate the overall performance of a model, we report the mean absolute alpha ($|\overline{\alpha}|$) and the p-value of the GRS test (p_{GRS}) for the hypothesis that all quintile alphas are jointly equal to zero. We also pool all three sets of quintile portfolios together and present the result of a joint test in Panel D of Table 8.

Table 8 about here.

In Panel A, the average excess returns of the carry quintile portfolios are monotonically increasing, and the average high-minus-low excess return is 0.412% (t=2.93). The high-minus-low alpha in the HML_χ two-factor model (level plus HML_χ) is only 0.056% (t=0.47), a reduction of more than 85%, largely due to the substantial loading of 0.787 (t=6.61) on HML_χ. The alpha in the HML_{FX} model (level plus HML_{FX}) is even smaller at −0.032% (t=−0.31), thanks to the loading of 0.728 (t=11.22) on HML_{FX}. Compared with these two models, the HML_{MOM} model (level plus HML_{MOM}) performs rather poorly, with a large positive alpha of 0.397% (t=3.04) and a tiny loading of −0.016 (t=−0.33) on HML_{MOM}. Finally, the four-factor model that includes all three slope factors appears to overpredict the excess return of the high-minus-low carry portfolio, leaving a negative and significant alpha at −0.212% (t=−2.09). This result is mostly attributable to the large loadings of 0.545 (t=6.08) on HML_χ and 0.603 (t=9.47) on HML_{FX}.

The mean absolute alphas in the HML_χ, HML_{FX}, HML_{MOM}, and four-factor models are 0.039%, 0.056%, 0.144%, and 0.048%, respectively, compared with the mean absolute excess return of the carry quintile portfolios at 0.188%. Consistent with Lustig et al. (2011), the HML_{FX} model performs well in pricing the carry portfolios. Nevertheless, the HML_χ model does an even better job with a smaller mean absolute alpha. The HML_{MOM} model performs poorly with a much larger mean absolute alpha, whereas the four-factor model performs slightly better than the HML_{FX} model but worse than the HML_χ model. The GRS test rejects the HML_{MOM} (p-value=0.017) and HML_{FX} (p-value=0.062) models at the 5% and 10% levels, respectively, but fails to reject the HML_χ (p-value=0.813) or the four-factor model (p-value=0.173) at any conventional significance level.

Next, we present the results for the momentum test portfolios in Panel B of Table 8. Due to our data requirement for government bond returns, our currency sample is smaller than that used by Menkhoff et al. (2012). As a result, the average excess return of the high-minus-low momentum quintile portfolio is insignificant at 0.103% (t=0.94). The high-minus-low alphas in the HML_{χ}, HML_{FX}, HML_{MOM}, and four-factor models are 0.117% (t=0.99), 0.159% (t=1.28), −0.428% (t=−3.61), and −0.404% (t=−3.28), respectively. Notably, both the HML_{MOM} and four-factor models overpredict the excess return of the high-minus-low momentum portfolio, primarily due to the large loadings on HML_{MOM} in both models.

The mean absolute alphas in the HML_{χ}, HML_{FX}, HML_{MOM}, and four-factor models are 0.047%, 0.087%, 0.092%, and 0.110%, respectively, compared with the mean absolute excess return of 0.192% for the momentum quintile portfolios. Thus, the HML_{χ} model remains the best performing model, while the four-factor model is the worst performing model. Finally, the GRS test easily rejects the HML_{FX}, HML_{MOM}, and four-factor models at the 5% significance level but fails to reject the HML_{χ} model (p-value=0.588).

Panel C of Table 8 presents the results for the test portfolios sorted on the prospective interest rate differential. The quintile excess returns increase monotonically from 0.052% for Quintile 1 to 0.470% for Quintile 5. The average high-minus-low excess return is 0.419% (t=3.99), and the alphas in the HML_{χ}, HML_{FX}, HML_{MOM}, and four-factor models are −0.020% (t=−0.46), 0.248% (t=2.31), 0.408% (t=4.45), and −0.055% (t=−1.22), respectively. The HML_{χ} and four-factor models are able to explain the returns of the high-minus-low χ portfolio due to the large loadings of 1.052 (t=35.13) and 1.035 (t=32.79), respectively, on HML_{χ} in the two models. Conversely, the HML_{FX} and HML_{MOM} models leave significant high-minus-low alphas unexplained because the HML_{FX} loading in the former model is only moderate, while the HML_{MOM} loading in the latter model is tiny. Compared with the mean absolute excess return of 0.189% for the χ quintile portfolios, the mean absolute alphas in the HML_{χ}, HML_{FX}, HML_{MOM}, and four-factor models are 0.070%, 0.076%, 0.134%, and 0.064%, respectively. Finally, the GRS test easily rejects the HML_{FX} and HML_{MOM} models at the 1% significance level but fails to reject the HML_{χ} and four-factor models (p-values of 0.202 and 0.240, respectively).

In Panel D of Table 8, we pool all three sets of quintile portfolios and perform a joint test. The mean absolute alphas across all 15 test portfolios in the HML_{χ}, HML_{FX}, HML_{MOM}, and four-factor models are 0.052%, 0.071%, 0.123%, and 0.074%, respectively. The HML_{χ} model again produces the smallest pricing errors, while the HML_{MOM} model has the largest. Moreover, all but the HML_χ model are rejected by the GRS test at the 1% significance level, with p-values of 0.440, 0.005, 0.000, and 0.005 for the HML_χ, HML_{FX}, HML_{MOM}, and four-factor models, respectively.

Overall, the results in Table 8 show that the HML_χ model performs the best in explaining the excess returns of one-way-sorted test portfolios based on carry, momentum, and the prospective interest rate differential. The high-minus-low alphas in the HML_χ model are always insignificant, and the GRS test fails to reject the model for all three sets of test portfolios as well as in the joint test. By comparison, the HML_{FX} model leaves a significant high-minus-low alpha for the χ test portfolios and is rejected by the GRS test for the momentum and χ test portfolios and in the joint test. The HML_{MOM} model leaves significant high-minus-low alphas for all three sets of test portfolios and is rejected by the GRS test for all of them as well as in the joint test. Finally, the four-factor model leaves significant high-minus-low alphas for the carry and momentum test portfolios and is rejected by the GRS test for the momentum test portfolios, as well as in the joint test.

Table 9 about here.

Next, in Table 9, we compare the performance of different models in explaining the excess returns of two-way-sorted test portfolios. At the beginning of each month, we first sort all sample currencies into terciles based on one variable (carry, momentum, or χ) and then further divide each tercile into three portfolios based on another variable. We also average the high-minus-low portfolios based on one sorting variable across the terciles of the other sorting variable, denoting as H-L_c for carry, H-L_m for momentum, and H-L_χ for χ. Panels A, B, and C of Table 9 report the results for the 3×3 portfolios based on carry and momentum, carry and χ, and momentum and χ, respectively.[10] Panel D reports the joint test, which pools all three sets of two-way-sorted portfolios.

Panel A shows that, consistent with the results from the one-way sorts, the HML_χ model continues to explain the returns of the high-minus-low carry and momentum portfolios in the two-way sorts. The H-L_m and H-L_c alphas in the HML_χ model are -0.059% (t=-0.77) and

[10] Our results are robust to using independent two-way-sorted portfolios.

0.066% (t=0.73), compared to the average excess returns of −0.046% (t=−0.66) and 0.316% (t=2.87), respectively. The HML_{FX} model also performs fairly well, with H-L_m and H-L_c alphas of −0.017% (t=−0.22) and −0.035% (t=−0.44), respectively. In contrast, the H-L_m and H-L_c alphas in the HML_{MOM} model are −0.306% (t=−3.81) and 0.280% (t=2.80), respectively, both highly significant. Similarly, the four-factor model also fails to explain the high-minus-low returns, leaving an H-L_m alpha of −0.300 (t=−3.55) and an H-L_c alpha of −0.142 (t=−1.87).

The mean absolute alphas in the HML_χ, HML_{FX}, HML_{MOM}, and four-factor models are 0.073%, 0.086%, 0.168%, and 0.124%, respectively, with the HML_χ model producing the smallest and the HML_{MOM} model producing the largest pricing errors. Additionally, the GRS test fails to reject the HML_χ and HML_{FX} models, but easily rejects the HML_{MOM} and four-factor models at the 1% significance level.

In Panel B, for the two-way-sorted test portfolios based on carry and χ, the average excess returns of the high-minus-low portfolios H-L_χ and H-L_c are 0.224% (t=3.47) and 0.345% (t=3.11), respectively. Notably, the prospective interest rate differential still generates a significant return spread even after controlling for carry in the two-way sorts. The HML_χ model reduces the H-L_χ and H-L_c alphas to insignificant 0.054% (t=1.01) and 0.091% (t=0.96), respectively. The HML_{FX} model leaves a significant H-L_χ alpha of 0.182% (t=2.96) but insignificant H-L_c alpha of −0.006% (t=−0.08). The HML_{MOM} model is again the worst performing model, with significant H-L_χ and H-L_c alphas of 0.198% (t=3.17) and 0.304% (t=3.01), respectively. Finally, the four-factor model also reduces the H-L_χ and H-L_c alphas to insignificant 0.053% (t=1.02) and −0.120% (t=−1.48), respectively. The mean absolute alphas in the HML_χ, HML_{FX}, HML_{MOM}, and four-factor models are 0.060%, 0.080%, 0.124%, and 0.067%, respectively. Again, the HML_χ model produces the smallest and the HML_{MOM} model the largest pricing errors. The GRS test fails to reject the HML_χ and four-factor models but does reject the HML_{FX} and HML_{MOM} models at the 5% significance level.

In Panel C, for the test portfolios sorted by momentum and χ, the average excess returns of the high-minus-low portfolios H-L_χ and H-L_m are 0.243% (t=3.35) and 0.075% (t=0.87), respectively. The HML_χ model lowers the H-L_χ and H-L_m alphas to insignificant 0.038% (t=0.84) and 0.046% (t=0.49), respectively. By comparison, the H-L_χ and H-L_m alphas are, respectively, 0.125%

(t=1.99) and 0.093% (t=0.97) in the HML$_{FX}$ model, 0.246% (t=3.37) and −0.300% (t=−3.12) in the HML$_{MOM}$ model, and 0.022% (t=0.40) and −0.319% (t=−3.18) in the four-factor model. The mean absolute alphas in the HML$_{\chi}$, HML$_{FX}$, HML$_{MOM}$, and four-factor models are 0.077%, 0.094%, 0.154%, and 0.131%, respectively. Finally, the GRS test rejects the HML$_{FX}$, HML$_{MOM}$, and four-factor models at the 10%, 1%, and 1% significance levels, respectively, but fails to reject the HML$_{\chi}$ model.

Panel D reports the results of the joint test using all three sets of two-way-sorted test portfolios. The mean absolute alphas in the HML$_{\chi}$, HML$_{FX}$, HML$_{MOM}$, and four-factor models are 0.070%, 0.087%, 0.149%, and 0.107%, respectively, with the HML$_{\chi}$ model again producing the smallest pricing errors, followed by the HML$_{FX}$ and four-factor models, and the HML$_{MOM}$ model producing the largest pricing errors. Only the HML$_{\chi}$ model is not rejected by the GRS test, with a p-value of 0.144. In contrast, the HML$_{FX}$, HML$_{MOM}$, and four-factor models are rejected at the 5%, 1%, and 5% significance levels with p-values of 0.037, 0.000, and 0.019, respectively.

Overall, by comparing the results from the two-way-sorted test portfolios with those from the one-way-sorted test portfolios, we reach the same conclusion: The HML$_{\chi}$ model is the best performing model among all the models we have considered. It successfully explains the excess returns of all high-minus-low portfolios, generates the smallest pricing errors, and is not rejected by the GRS test at any conventional significance level.

5 Conclusion

In this paper, we introduce a novel predictor of foreign currency excess returns. We link expected future excess returns to the prospective interest rate differential (the sum of all expected future foreign and domestic detrended interest rate differentials) and the transitory component of the spot exchange rate. Since the transitory component is not expected to have a permanent impact on the riskiness of the foreign currency, the prospective interest rate differential should predict future currency excess returns. To test this prediction, we estimate the prospective interest rate differential using information embedded in the term structure of government bond returns through a pricing-kernel decomposition approach.

During the sample period from July 1982 to July 2023, the prospective interest rate differential systematically outperforms the conventional carry signal in portfolio analysis and Fama-MacBeth regressions. In addition, the excess returns of portfolios formed on the prospective interest rate differential cannot be explained by existing currency market factors. Finally, a new two-factor model that includes a slope factor based on the prospective interest rate differential can explain the cross section of currency excess returns better than existing currency factor models.

References

Alvarez, F. and Jermann, U. J. (2005). Using asset prices to measure the persistence of the marginal utility of wealth. *Econometrica*, 73(6):1977–2016.

Ang, A. and Chen, J. (2010). Yield curve predictors of foreign exchange returns. Columbia University working paper.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, 68(3):929–985.

Backus, D. K., Foresi, S., and Telmer, C. I. (2001). Affine term structure models and the forward premium anomaly. *The Journal of Finance*, 56(1):279–304.

Backus, D. K., Gavazzoni, F., Telmer, C., and Zin, S. E. (2014). Monetary policy and the uncovered interest rate parity puzzle. NYU working paper.

Bakshi, G. and Chabi-Yo, F. (2012). Variance bounds on the permanent and transitory components of stochastic discount factors. *Journal of Financial Economics*, 105(1):191–208.

Bakshi, G. and Panayotov, G. (2013). Predictability of currency carry trades and asset pricing implications. *Journal of Financial Economics*, 110(1):139–163.

Bartram, S., Grinblatt, M., and Xu, Y. (2024). The demand for money, adaptive expectations, and currency movements, UCLA working paper.

Baum, C. F., Caglayan, M., and Barkoulas, J. T. (2001). Exchange rate uncertainty and firm profitability. *Journal of Macroeconomics*, 23(4):565–576.

Bekaert, G. and Hodrick, R. J. (1992). Characterizing predictable components in excess returns on equity and foreign exchange markets. *The Journal of Finance*, 47(2):467–509.

Bekaert, G., Wei, M., and Xing, Y. (2007). Uncovered interest rate parity and the term structure. *Journal of International Money and Finance*, 26(6):1038–1069.

Beveridge, S. and Nelson, C. R. (1981). A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the business cycle. *Journal of Monetary Economics*, 7(2):151–174.

Brandt, M., Cochrane, J., and Santa-Clara, P. (2006). International risk sharing is better than you think, or exchange rates are too smooth. *Journal of Monetary Economics*, 53(4):671–698.

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

Burnside, C. (2012). Carry trades and risk. *Handbook of Exchange Rates (eds J. James, I.W. Marsh and L. Sarno).*

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

Burnside, C., Eichenbaum, M., and Rebelo, S. (2008). Carry trade: The gains of diversification. *Journal of the European Economic Association*, 6(2-3):581–588.

Campbell, J. Y. and Shiller, R. J. (1991). Yield spreads and interest rate movements: A bird's eye view. *The Review of Economic Studies*, 58(3):495–514.

Cox, J. C., Ingersoll Jr, J. E., Ross, S. A., et al. (1985). A theory of the term structure of interest rates. *Econometrica*, 53(2):385–407.

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., Wang, J., and Wu, J. (2010). Long-horizon forecasts of asset prices when the discount factor is close to unity. University of Wisconsin working paper.

Evans, M. D. and Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, 110(1):170–180.

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

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

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

Hassan, T. A. and Mano, R. C. (2019). Forward and spot exchange rates in a multi-currency world. *The Quarterly Journal of Economics*, 134(1):397–450.

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35.

Hodrick, R. J. and Srivastava, S. (1984). An investigation of risk and return in forward foreign exchange. *Journal of International Money and Finance*, 3(1):5–29.

Hou, K., Mo, H., Xue, C., and Zhang, L. (2018). Which factors? *Review of Finance*, 23(1):1–35.

Hou, K., Mo, H., Xue, C., and Zhang, L. (2020). An augmented q-factor model with expected growth. *Review of Finance*, 25(1):1–41.

Jiang, Z., Krishnamurthy, A., and Lustig, H. (2021). Foreign safe asset demand and the dollar exchange rate. *The Journal of Finance*, 76(3):1049–1089.

Jiang, Z., Krishnamurthy, A., and Lustig, H. (2023). Implications of asset market data for equilibrium models of exchange rates. Technical report, National Bureau of Economic Research.

Jordà, Ò. and Taylor, A. M. (2012). The carry trade and fundamentals: Nothing to fear but FEER itself. *Journal of International Economics*, 88(1):74–90.

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

Kazemi, H. B. (1992). An intemporal model of asset prices in a markov economy with a limiting stationary distribution. *The Review of Financial Studies*, 5(1):85–104.

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

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

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

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

Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2017). Currency value. *The Review of Financial Studies*, 30(2):416–441.

Mishkin, F. S. (1992). Is the Fisher effect for real?: A reexamination of the relationship between inflation and interest rates. *Journal of Monetary Economics*, 30(2):195–215.

Mussa, M. (1982). A model of exchange rate dynamics. *Journal of Political Economy*, 90(1):74–104.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2017). Do funds make more when they trade more? *The Journal of Finance*, 72(4):1483–1528.

Ready, R., Roussanov, N., and Ward, C. (2017). Commodity trade and the carry trade: A tale of two countries. *The Journal of Finance*, 72(6):2629–2684.

Sarno, L., Schneider, P., and Wagner, C. (2012). Properties of foreign exchange risk premiums. *Journal of Financial Economics*, 105(2):279–310.

Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of Financial Economics*, 5(2):177–188.

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

Table 1: Government bond indices from Datastream

Country	Start date	Maturity in years									
		2	3	5	7	10	15	20	30	50	Total
Australia	198702	1	1	1	1	1					5
Austria	198412	1	1	1	1	1			1		6
Belgium	198412	1	1	1	1	1	1		1		7
Canada	198412	1	1	1	1	1		1	1		7
China	200706	1	1	1	1	1	1	1	1	1	9
Czech	200004	1	1	1	1	1	1				6
Denmark	198412	1	1	1	1	1		1			6
EMU	199901	1	1	1	1	1	1	1	1		8
Finland	198910		1	1		1					3
France	198412	1	1	1	1	1	1	1	1	1	9
Germany	197912	1	1	1	1	1		1	1		7
Greece	199903	1	1	1		1	1				5
Hungary	199901	1	1	1		1					4
India	200706	1	1	1	1	1	1		1		7
Indonesia	201205	1	1	1	1	1	1		1		7
Ireland	198412		1	1	1	1	1				5
Italy	198812	1	1	1	1	1	1		1		7
Japan	198112	1	1	1	1	1	1	1	1		8
Mexico	201006	1	1	1	1	1	1	1			7
Netherlands	197912	1	1	1	1	1			1		6
Norway	198812			1	1	1					3
New Zealand	198812	1	1	1	1	1					5
Poland	200012	1	1	1	1	1		1			6
Portugal	199212	1	1	1	1	1					5
Singapore	200812	1	1	1	1	1	1	1	1		8
South Africa	200008		1	1	1	1			1		5
South Korea	201203	1	1	1	1	1	1	1	1		8
Spain	198812	1	1	1	1	1	1		1		7
Sweden	198412	1	1	1	1	1	1				6
Switzerland	198012	1	1	1	1	1					5
UK	197912	1	1	1	1	1	1	1	1	1	9
US	197912	1	1	1	1	1			1		6
Total		28	31	32	29	32	17	12	18	3	202

This table summarizes the data availability of government bond indices from Datastream. For each country, we report the first month when the data on bond indices become available for any maturity (start date). We also report a "1" when data for a particular maturity are available.

Table 2: Summary statistics of currency excess returns

Country	Min	Mean	Median	Max	SD	Skew	AR(1)
Australia	-15.64	0.19	0.25	9.59	3.23	-0.30	0.02
Austria	-10.28	0.05	0.11	9.69	2.90	-0.13	0.08
Belgium	-11.07	0.07	0.14	9.71	2.91	-0.15	0.07
Canada	-11.85	0.07	0.12	9.41	2.12	-0.35	-0.04
China	-3.89	0.19	0.30	3.88	1.21	-0.72	0.32
Czech	-11.48	0.23	0.27	10.24	3.40	-0.18	0.02
Denmark	-10.32	0.12	0.10	10.08	2.86	-0.07	0.08
EMU	-9.64	0.05	-0.01	10.03	2.72	-0.01	0.03
Finland	-12.82	-0.05	0.00	9.78	2.98	-0.22	0.06
France	-10.32	0.08	0.22	9.71	2.87	-0.16	0.06
Germany	-10.61	0.01	0.03	9.71	3.01	-0.00	0.05
Greece	-9.93	0.19	0.09	9.62	2.74	-0.06	0.02
Hungary	-17.20	0.33	0.63	12.06	3.95	-0.61	0.03
India	-7.20	0.20	0.23	8.23	2.22	0.14	-0.03
Indonesia	-11.79	0.18	0.22	10.01	2.48	-0.08	-0.11
Ireland	-26.51	0.11	0.29	33.87	3.50	0.89	0.03
Italy	-12.13	0.01	0.10	9.71	2.85	-0.25	0.08
Japan	-10.04	-0.02	-0.04	17.02	3.14	0.51	0.06
Mexico	-15.22	0.29	0.33	8.13	3.40	-0.77	-0.03
Netherlands	-10.73	0.01	0.02	9.71	3.01	0.01	0.06
Norway	-12.07	0.04	0.14	7.90	3.23	-0.17	0.05
New Zealand	-12.62	0.26	0.43	13.31	3.33	-0.20	-0.02
Poland	-14.45	0.25	0.27	10.23	3.85	-0.48	0.04
Portugal	-9.75	0.00	0.00	9.71	2.71	-0.01	0.04
Singapore	-7.59	0.02	-0.04	4.43	1.60	-0.46	-0.06
South Africa	-14.50	0.45	0.62	13.48	4.70	-0.22	-0.02
South Korea	-7.03	-0.04	0.08	8.22	2.50	0.20	0.02
Spain	-9.78	0.01	0.10	9.71	2.88	-0.21	0.07
Sweden	-14.41	0.02	0.13	9.22	3.14	-0.22	0.11
Switzerland	-11.09	0.06	-0.02	13.73	3.17	0.24	0.01
UK	-11.93	0.04	-0.05	14.88	2.90	0.03	0.08

This table reports the summary statistics of foreign currency excess returns. The sample period is from January 1980 to July 2023. For each country, we report the minimum (min), mean, median, maximum (max), standard deviation (SD), skewness (skew), and AR(1) autocorrelation of excess returns.

Table 3: Summary statistics of ϕ estimates

Country	Panel A: OLS estimation of ϕ					Panel B: Kalman filter estimation of ϕ				
	FS	Min	Median	Max	SD	FS	Min	Median	Max	SD
Australia	0.977	0.758	0.967	0.979	0.044	0.947	0.768	0.919	0.968	0.029
Austria	0.992	0.768	0.983	0.993	0.049	0.959	0.716	0.938	0.992	0.032
Belgium	0.989	0.810	0.981	0.990	0.043	0.970	0.692	0.950	0.973	0.037
Canada	0.989	0.732	0.983	0.990	0.053	0.958	0.853	0.933	0.958	0.014
China	0.704	0.533	0.673	0.704	0.038	0.947	0.813	0.947	0.987	0.025
Czech	0.988	0.974	0.988	1.071	0.011	0.967	0.857	0.955	0.973	0.023
Denmark	0.954	0.430	0.895	1.165	0.129	0.964	0.755	0.926	0.964	0.041
EMU	0.996	0.954	0.996	1.001	0.009	0.971	0.813	0.956	0.986	0.038
Finland	0.980	0.432	0.972	0.981	0.082	0.960	0.863	0.949	0.970	0.017
France	0.974	0.594	0.945	0.975	0.103	0.969	0.745	0.933	0.984	0.041
Germany	0.991	0.725	0.983	0.993	0.029	0.959	0.808	0.938	0.985	0.027
Greece	0.966	0.966	0.967	1.004	0.006	0.943	0.850	0.920	0.968	0.030
Hungary	0.991	0.916	0.960	1.004	0.022	0.931	0.869	0.925	0.941	0.010
India	0.959	0.917	0.933	0.965	0.013	0.963	0.898	0.939	0.970	0.010
Indonesia	0.952	0.882	0.929	0.970	0.028	0.960	0.859	0.970	0.979	0.014
Ireland	0.892	0.500	0.827	1.134	0.101	0.934	0.476	0.895	0.940	0.067
Italy	0.992	0.613	0.992	0.997	0.073	0.955	0.890	0.947	0.970	0.018
Japan	0.993	0.342	0.994	0.999	0.123	0.962	0.804	0.954	0.990	0.020
Mexico	1.019	0.831	1.006	1.133	0.035	0.943	0.889	0.962	0.975	0.017
Netherlands	0.987	0.795	0.976	0.989	0.023	0.963	0.755	0.947	0.988	0.021
Norway	0.910	0.029	0.834	0.910	0.213	0.930	0.825	0.913	0.954	0.024
New Zealand	0.961	0.100	0.905	0.963	0.093	0.947	0.788	0.930	0.968	0.021
Poland	0.961	0.945	0.951	0.970	0.005	0.953	0.750	0.941	0.972	0.031
Portugal	0.972	0.787	0.960	0.973	0.033	0.945	0.800	0.945	0.972	0.032
Singapore	1.024	0.482	0.980	1.056	0.225	0.971	0.939	0.976	0.993	0.006
South Africa	0.983	0.940	0.985	1.001	0.007	0.976	0.670	0.935	0.980	0.027
South Korea	0.994	0.924	0.976	1.002	0.011	0.967	0.925	0.971	0.977	0.008
Spain	0.984	0.375	0.974	0.985	0.109	0.963	0.800	0.949	0.977	0.039
Sweden	0.966	0.652	0.930	0.967	0.097	0.963	0.887	0.952	0.978	0.017
Switzerland	0.987	0.913	0.978	0.988	0.023	0.951	0.787	0.934	0.953	0.019
UK	0.990	0.858	0.983	0.991	0.024	0.957	0.752	0.938	0.964	0.015
US	0.981	0.680	0.971	0.983	0.041	0.948	0.822	0.926	0.954	0.021
Cross-country	0.969	0.029	0.971	1.165	0.093	0.956	0.476	0.933	0.993	0.028

This table reports the summary statistics of ϕ estimated via OLS in Panel A, and Kalman filter in Panel B. For each country and each estimation method, we report the full-sample (FS) estimate and the minimum (min), median, maximum (max), and standard deviation (SD) of ϕ estimated from extending backward-looking windows. The sample period is from January 1980 to July 2023.

Table 4: Summary statistics of the prospective interest rate differential

Country	Panel A: Carry					Panel B: Prospective interest rate differential based on OLS ϕ					Panel C: Prospective interest rate differential based on KF ϕ				
	Min	Mean	Median	Max	SD	Min	Mean	Median	Max	SD	Min	Mean	Median	Max	SD
Australia	-0.13	0.16	0.15	0.81	0.17	-9.78	3.13	1.99	15.84	6.20	-6.36	0.85	0.68	5.60	2.58
Austria	-0.37	-0.04	-0.06	0.52	0.16	-34.72	-5.98	-3.11	17.06	13.08	-35.44	-0.18	0.72	8.41	7.03
Belgium	-0.26	-0.02	-0.05	0.69	0.17	-25.49	-4.39	-4.48	14.19	8.98	-9.33	-0.48	-0.76	8.38	2.82
Canada	-0.21	0.04	0.02	0.44	0.11	-19.66	-5.10	-5.04	9.70	6.38	-3.96	0.92	0.85	5.55	1.54
China	-0.25	0.22	0.23	0.64	0.16	-4.24	18.02	21.02	23.03	6.16	-3.10	5.58	5.95	15.67	3.51
Czech	-0.45	-0.05	-0.00	0.22	0.13	-438.88	5.86	6.59	134.98	30.96	-4.66	2.65	3.08	7.42	2.13
Denmark	-0.32	0.03	-0.03	1.82	0.25	-6.13	8.47	8.25	18.82	5.76	-6.54	0.61	0.49	14.23	2.87
EMU	-0.26	-0.04	-0.04	0.28	0.11	-579.68	-13.64	-16.29	1300.86	101.09	-1.97	2.60	2.68	8.64	2.10
Finland	-0.30	-0.02	-0.05	1.12	0.20	-9.02	1.52	2.64	14.19	5.62	-5.38	-0.96	-1.00	5.98	2.28
France	-0.26	-0.00	-0.03	0.99	0.19	-5.27	5.79	5.50	14.49	4.89	-18.73	-1.05	-1.23	10.11	3.41
Germany	-0.54	-0.07	-0.09	0.54	0.18	-38.17	-7.94	-4.86	19.29	13.18	-20.65	0.25	-0.05	8.74	3.08
Greece	-0.24	0.10	0.14	0.22	0.14	-5258.12	-6.58	15.40	197.93	326.19	-2.18	4.02	4.38	7.53	2.28
Hungary	-0.22	0.33	0.31	1.06	0.32	-31.20	6.43	6.54	143.71	27.46	-4.95	1.85	1.68	15.75	3.96
India	0.11	0.48	0.46	0.89	0.20	-3.63	17.09	17.69	30.43	6.95	-1.85	5.21	4.66	11.77	3.42
Indonesia	0.07	0.35	0.33	0.66	0.13	-2.80	15.16	17.16	26.54	6.42	-1.73	4.07	3.78	13.58	3.28
Ireland	-0.26	0.03	-0.01	3.28	0.28	-7.42	10.05	9.59	27.66	6.64	-3.06	1.42	1.15	37.13	3.03
Italy	-0.26	0.05	-0.01	1.22	0.24	-123.66	-26.74	-35.47	188.01	24.56	-7.79	-1.44	-1.47	6.28	2.65
Japan	-0.55	-0.17	-0.15	0.33	0.18	-367.56	-22.70	-12.38	12.08	34.47	-11.45	-0.09	0.43	8.22	3.30
Mexico	0.20	0.40	0.42	0.54	0.10	-146.94	6.40	10.51	116.94	34.41	2.79	7.43	6.57	14.12	2.98
Netherlands	-0.55	-0.06	-0.08	0.54	0.18	-41.22	-2.31	-1.95	15.14	7.74	-26.52	-0.86	-0.43	8.32	4.71
Norway	-0.21	0.09	0.05	1.79	0.22	-4.52	11.42	11.64	20.01	6.29	-2.82	1.95	2.21	6.92	2.11
New Zealand	-0.17	0.18	0.20	0.51	0.14	-3.74	9.64	9.47	18.64	5.47	-5.56	1.34	1.95	6.67	2.62
Poland	-0.11	0.16	0.18	0.55	0.16	-2.94	11.07	12.28	20.73	6.26	-4.84	1.51	1.95	12.07	2.88
Portugal	-0.26	-0.04	-0.04	0.28	0.12	-3.95	6.09	7.46	14.53	5.16	-6.25	-0.30	-0.26	4.74	2.29
Singapore	-0.13	-0.01	0.00	0.05	0.03	-32.90	13.98	19.46	24.65	12.81	4.08	7.17	7.14	10.29	1.19
South Africa	0.17	0.47	0.44	1.05	0.17	-240.62	2.22	4.42	43.51	21.14	-9.81	2.10	2.70	10.19	3.61
South Korea	-0.16	0.02	0.03	0.17	0.07	-11.25	15.07	15.00	55.34	5.67	2.17	3.76	3.55	6.46	0.95
Spain	-0.26	0.04	-0.01	1.32	0.25	-16.25	-2.04	-2.27	13.25	6.31	-12.57	-2.21	-2.14	7.63	3.19
Sweden	-0.45	0.06	0.01	1.00	0.23	-7.18	6.34	5.76	15.79	5.28	-16.52	-2.63	-3.26	9.95	3.76
Switzerland	-0.70	-0.15	-0.14	0.52	0.19	-13.81	1.41	1.70	18.12	5.77	-3.29	1.51	1.75	9.26	2.26
UK	-0.24	0.11	0.04	0.60	0.17	-42.32	-15.09	-10.47	8.21	15.55	-9.03	-2.01	-2.74	5.58	2.74
Cross-country	-0.70	0.09	0.00	3.28	0.06	-5258.12	2.05	5.76	1300.86	58.87	-35.44	1.44	1.15	37.13	1.12

This table reports the summary statistics of carry, the prospective interest rate differential based on OLS ϕ, and the prospective interest rate differential based on Kalman filter (KF) ϕ. For each country, we report the minimum (min), mean, median, maximum (max), and standard deviation (SD) of the three variables estimated from extending backward-looking windows. The sample period is from January 1980 to July 2023.

Table 5: Summary statistics of currency portfolios

	χ			Carry			Momentum		
	EW	HML	RNK	EW	HML	RNK	EW	HML	RNK
Panel A: Full sample, 493 months									
Mean	0.182	0.412	0.312	0.158	0.311	0.298	0.163	0.067	0.082
SD	1.381	1.828	1.536	1.456	2.393	1.981	1.633	2.235	1.839
SR	0.456	0.781	0.704	0.377	0.450	0.521	0.346	0.104	0.155
Max	8.875	9.017	5.946	7.199	6.570	7.367	7.852	11.225	9.008
Min	-8.202	-8.064	-7.367	-8.202	-12.092	-9.756	-8.875	-6.570	-5.165
Skew	0.805	-0.077	-0.365	-0.468	-0.944	-0.760	-0.023	0.484	0.505
AR(1)	0.016	-0.040	0.042	0.153	0.052	0.069	0.009	-0.007	-0.029
Panel B: Pre-euro, 229 months									
Mean	0.309	0.401	0.273	0.222	0.207	0.212	0.271	0.292	0.284
SD	1.851	1.925	1.644	1.748	2.380	2.008	1.968	2.326	1.889
SR	0.579	0.722	0.575	0.441	0.301	0.366	0.478	0.435	0.521
Max	8.875	9.017	5.946	5.226	6.570	7.367	7.852	9.330	6.740
Min	-8.202	-6.029	-7.367	-8.202	-9.330	-6.928	-8.875	-6.570	-4.892
Skew	0.576	0.317	-0.150	-0.584	-0.703	-0.399	-0.526	0.288	0.375
AR(1)	0.017	0.066	0.173	0.138	0.063	0.107	-0.081	0.031	-0.020
Panel C: Post-euro, 264 months									
Mean	0.071	0.426	0.350	0.100	0.395	0.374	0.071	-0.110	-0.088
SD	0.745	1.745	1.435	1.140	2.400	1.954	1.265	2.144	1.778
SR	0.328	0.846	0.845	0.303	0.570	0.664	0.193	-0.179	-0.172
Max	2.709	7.910	5.764	7.199	5.851	5.523	7.199	11.225	9.008
Min	-3.142	-8.064	-6.772	-7.258	-12.092	-9.756	-3.210	-5.699	-5.165
Skew	-0.413	-0.516	-0.626	-0.185	-1.143	-1.101	1.309	0.644	0.610
AR(1)	-0.039	-0.145	-0.109	0.179	0.040	0.030	0.189	-0.061	-0.060

This table reports the summary statistics of three sets of portfolios (equal-weighted (EW), high-minus-low (HML), and rank-based (RNK)) for different currency return predictors (the prospective interest rate differential χ, carry, and momentum), for the full sample period (July 1982 to July 2023, Panel A), pre-euro period (July 1982 to July 2001, Panel B), and post-euro period (August 2001 to July 2023, Panel C). We report the mean, standard deviation (SD), annualized Sharpe ratio (SR), maximum (max), minimum (min), skewness (skew), and AR(1) autocorrelation of each portfolio.

Table 6: Explaining χ portfolio returns

	Panel A: EW χ portfolio						Panel B: HML χ portfolio						Panel C: RNK χ portfolio					
$\bar{R}$	0.182						0.412						0.312					
	(2.88)						(4.95)						(4.46)					
α	0.172	0.170	0.167	0.133	0.147	0.130	0.399	0.386	0.377	0.278	0.411	0.270	0.315	0.307	0.286	0.202	0.318	0.183
	(2.66)	(2.61)	(2.58)	(2.06)	(2.84)	(2.10)	(4.56)	(4.42)	(4.28)	(2.90)	(4.75)	(2.83)	(4.46)	(4.31)	(3.98)	(2.71)	(4.62)	(2.48)
MKT	0.013	0.018	0.019				0.018	0.020	0.024				0.018	0.018	0.027			
	(0.90)	(1.19)	(1.16)				(0.71)	(0.77)	(0.88)				(0.81)	(0.81)	(1.17)			
SMB		-0.034	-0.034					0.031	0.031					0.023	0.023			
		(-1.40)	(-1.41)					(0.95)	(0.97)					(0.90)	(0.93)			
HML		0.000	0.002					0.054	0.058					0.034	0.044			
		(0.01)	(0.08)					(1.67)	(1.77)					(1.24)	(1.60)			
UMD			0.004						0.014						0.031			
			(0.32)						(0.74)						(2.04)			
level				0.259	0.264	0.260				0.055	0.092	0.056				0.038	0.073	0.039
				(4.99)	(5.35)	(5.00)				(0.94)	(1.57)	(0.95)				(0.83)	(1.53)	(0.85)
HML_{FX}				0.027		0.027				0.220		0.221				0.210		0.211
				(0.66)		(0.67)				(3.36)		(3.45)				(4.14)		(4.28)
HML_{MOM}					0.001	0.002					-0.009	0.006					-0.001	0.013
					(0.04)	(0.13)					(-0.26)	(0.17)					(-0.04)	(0.50)
R^2	-0.000	0.001	-0.001	0.199	0.197	0.198	-0.000	0.005	0.004	0.092	0.010	0.090	0.001	0.003	0.009	0.126	0.010	0.125

This table reports the results from time-series regressions of the returns of EW, HML, and RNK χ portfolios on different equity and currency market factors. We consider three equity factor models: the CAPM, Fama-French three-factor model, and Carhart four-factor model. We also consider three currency factor models that combine the currency market level factor with two slope factors HML_{FX} and HML_{MOM}. The t-stats (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample period is from July 1982 to July 2023.

Table 7: Fama-MacBeth regressions

	Panel A: 1-month							Panel B: 3-month						
χ	0.055					0.033	0.028	0.047					0.027	0.023
	(3.93)					(2.66)	(2.88)	(3.43)					(2.43)	(2.91)
carry		0.852				0.602	0.417		0.770				0.592	0.403
		(3.91)				(2.48)	(1.29)		(3.61)				(2.58)	(1.59)
r_{t-1}			0.046				-0.020			0.035				0.005
			(1.67)				(-0.56)			(2.15)				(0.28)
r_{t-6t-2}			0.102				0.028			0.067				0.026
			(1.90)				(0.32)			(1.37)				(0.47)
∇inf				0.096			0.060				0.095			0.081
				(1.62)			(1.10)				(2.07)			(2.09)
ΔRER					-0.001		0.010					0.002		-0.002
					(-0.09)		(0.39)					(0.20)		(-0.13)
	Panel C: 6-month							Panel D: 12-month						
χ	0.047					0.028	0.020	0.049					0.032	0.025
	(3.99)					(3.06)	(2.73)	(5.98)					(4.00)	(3.84)
carry		0.759				0.615	0.454		0.693				0.567	0.408
		(3.93)				(2.97)	(1.97)		(4.48)				(3.31)	(2.05)
r_{t-1}			0.019				0.006			0.018				0.011
			(1.70)				(0.48)			(2.08)				(1.05)
r_{t-6t-2}			0.077				0.044			0.020				0.002
			(1.74)				(1.01)			(0.64)				(0.04)
∇inf				0.092			0.055				0.072			0.049
				(2.39)			(1.75)				(2.34)			(1.77)
ΔRER					0.004		-0.004					0.003		-0.008
					(0.51)		(-0.40)					(0.51)		(-1.02)

This table reports monthly Fama-MacBeth regression results. The dependent variable is the (average) monthly currency excess returns over the next one, three, six, and 12 months. The independent variables include χ (the prospective interest rate differential), carry, the lagged one-month return (r_{t-1}), the lagged return from six months to two months ago ($r_{t-6,t-2}$), the inflation rate differential (∇inf), and the quarterly change in log real exchange rate (ΔRER). The t-stats (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample period is from July 1984 to July 2023.

Table 8: Explaining one-way-sorted currency portfolio returns

Panel A: Carry

	1	2	3	4	5	H-L	$\overline{\lvert\alpha\rvert}$	p_{GRS}
$\bar{R}$	-0.010	0.071	0.165	0.292	0.402	0.412		
	(-0.08)	(0.50)	(1.15)	(1.82)	(2.59)	(2.93)		
α	-0.011	-0.050	-0.046	0.045	0.044	0.056	0.039	0.813
	(-0.14)	(-0.92)	(-0.88)	(0.76)	(0.68)	(0.47)		
level	0.936	1.081	1.111	1.125	1.091	0.155		
	(18.65)	(33.75)	(41.11)	(28.65)	(27.19)	(2.15)		
HML_{χ}	-0.387	-0.162	0.041	0.123	0.400	0.787		
	(-5.14)	(-3.29)	(0.93)	(3.08)	(5.82)	(6.61)		
R^2	0.686	0.837	0.868	0.841	0.786	0.314		
α	0.096	0.014	0.054	0.050	0.064	-0.032	0.056	0.062
	(1.35)	(0.28)	(0.99)	(0.71)	(0.94)	(-0.31)		
level	0.990	1.110	1.141	1.120	1.077	0.088		
	(24.91)	(31.14)	(39.86)	(27.09)	(22.57)	(1.21)		
HML_{FX}	-0.473	-0.232	-0.148	0.080	0.255	0.728		
	(-12.67)	(-8.65)	(-4.92)	(1.83)	(6.11)	(11.22)		
R^2	0.797	0.867	0.884	0.840	0.769	0.450		
α	-0.210	-0.169	-0.057	0.095	0.187	0.397	0.144	0.017
	(-2.56)	(-3.27)	(-1.13)	(1.55)	(2.56)	(3.04)		
level	0.909	1.073	1.117	1.134	1.124	0.215		
	(13.63)	(28.22)	(40.09)	(26.96)	(20.78)	(2.00)		
HML_{MOM}	0.029	0.037	0.019	-0.000	0.013	-0.016		
	(1.10)	(1.60)	(1.19)	(-0.01)	(0.43)	(-0.33)		
R^2	0.619	0.828	0.868	0.835	0.729	0.035		
α	0.147	-0.004	0.005	0.017	-0.065	-0.212	0.048	0.173
	(1.96)	(-0.08)	(0.09)	(0.25)	(-1.11)	(-2.09)		
level	0.998	1.115	1.138	1.117	1.068	0.069		
	(30.53)	(35.71)	(42.79)	(28.32)	(27.02)	(1.31)		
HML_{χ}	-0.217	-0.075	0.111	0.100	0.328	0.545		
	(-4.23)	(-1.35)	(2.89)	(2.09)	(4.54)	(6.08)		
HML_{FX}	-0.422	-0.212	-0.173	0.057	0.181	0.603		
	(-12.56)	(-5.57)	(-5.84)	(1.26)	(3.77)	(9.47)		
HML_{MOM}	0.006	0.026	0.012	0.004	0.026	0.020		
	(0.33)	(1.46)	(0.94)	(0.20)	(1.04)	(0.63)		
R^2	0.817	0.870	0.889	0.843	0.804	0.572		

Panel B: Momentum

	1	2	3	4	5	H-L	$\overline{\lvert\alpha\rvert}$	p_{GRS}
$\bar{R}$	0.065	0.170	0.237	0.317	0.169	0.103		
	(0.44)	(1.19)	(1.56)	(2.18)	(1.29)	(0.94)		
α	-0.129	-0.022	0.018	0.055	-0.011	0.117	0.047	0.588
	(-1.71)	(-0.39)	(0.36)	(1.07)	(-0.15)	(0.99)		
level	1.030	1.115	1.117	1.140	0.981	-0.049		
	(24.58)	(37.59)	(41.78)	(35.02)	(20.60)	(-0.66)		
HML_{χ}	0.002	-0.041	0.022	0.115	-0.010	-0.011		
	(0.02)	(-1.06)	(0.65)	(2.21)	(-0.17)	(-0.11)		
R^2	0.666	0.836	0.851	0.849	0.714	0.002		
α	-0.119	0.004	0.094	0.176	0.040	0.159	0.087	0.015
	(-1.52)	(0.07)	(1.76)	(3.77)	(0.55)	(1.28)		
level	1.033	1.125	1.140	1.174	0.998	-0.035		
	(23.77)	(34.62)	(41.51)	(34.86)	(21.56)	(-0.46)		
HML_{FX}	-0.016	-0.076	-0.121	-0.135	-0.100	-0.084		
	(-0.35)	(-1.96)	(-4.67)	(-5.38)	(-2.39)	(-1.11)		
R^2	0.667	0.840	0.861	0.857	0.722	0.008		
α	0.130	0.005	0.017	-0.012	-0.298	-0.428	0.092	0.001
	(1.54)	(0.08)	(0.34)	(-0.24)	(-4.75)	(-3.61)		
level	1.012	1.108	1.119	1.157	0.999	-0.013		
	(24.55)	(37.72)	(41.10)	(33.50)	(24.21)	(-0.19)		
HML_{MOM}	-0.180	-0.030	0.007	0.079	0.197	0.377		
	(-4.41)	(-1.41)	(0.44)	(4.00)	(7.77)	(6.33)		
R^2	0.706	0.837	0.850	0.852	0.771	0.233		
α	0.148	0.058	0.071	0.017	-0.256	-0.404	0.110	0.007
	(1.73)	(0.82)	(1.33)	(0.30)	(-3.62)	(-3.28)		
level	1.017	1.123	1.138	1.173	1.012	-0.005		
	(24.94)	(35.35)	(41.70)	(42.05)	(25.67)	(-0.07)		
HML_{χ}	0.008	-0.011	0.078	0.187	0.034	0.026		
	(0.12)	(-0.26)	(2.80)	(4.17)	(0.69)	(0.26)		
HML_{FX}	-0.034	-0.077	-0.139	-0.172	-0.090	-0.056		
	(-0.74)	(-1.75)	(-5.87)	(-7.61)	(-2.39)	(-0.80)		
HML_{MOM}	-0.181	-0.034	0.001	0.073	0.193	0.374		
	(-4.45)	(-1.72)	(0.07)	(3.77)	(7.82)	(6.33)		
R^2	0.707	0.842	0.863	0.876	0.777	0.235		

Panel C: χ

	1	2	3	4	5	H-L	$\overline{\lvert\alpha\rvert}$	p_{GRS}
$\bar{R}$	0.052	0.072	0.137	0.213	0.470	0.419		
	(0.40)	(0.51)	(0.93)	(1.38)	(3.20)	(3.99)		
α	0.098	-0.061	-0.085	-0.028	0.077	-0.020	0.070	0.202
	(1.77)	(-1.08)	(-1.49)	(-0.49)	(2.00)	(-0.46)		
level	0.959	1.109	1.166	1.142	0.956	-0.003		
	(27.90)	(41.99)	(41.96)	(36.71)	(33.87)	(-0.11)		
HML_{χ}	-0.511	-0.147	0.044	0.101	0.541	1.052		

Table 8 – Continued on next page

	1	2	3	4	5	H-L	$\overline{\|\alpha\|}$	p_{GRS}
	(-11.22)	(-3.42)	(1.11)	(3.03)	(17.19)	(35.13)		
R^2	0.822	0.849	0.869	0.856	0.883	0.844		
α	0.032	-0.037	-0.008	0.023	0.281	0.248	0.076	0.001
	(0.47)	(-0.65)	(-0.15)	(0.37)	(4.42)	(2.31)		
level	0.964	1.124	1.188	1.153	0.994	0.030		
	(18.46)	(40.99)	(40.89)	(34.94)	(20.67)	(0.34)		
HML_{FX}	-0.252	-0.148	-0.105	-0.018	0.028	0.280		
	(-6.66)	(-6.46)	(-2.96)	(-0.56)	(0.64)	(3.92)		
R^2	0.747	0.857	0.876	0.852	0.749	0.111		
α	-0.150	-0.144	-0.110	0.009	0.258	0.408	0.134	0.000
	(-2.46)	(-2.52)	(-2.12)	(0.15)	(4.11)	(4.45)		
level	0.922	1.100	1.173	1.150	1.002	0.079		
	(15.27)	(39.78)	(41.68)	(34.22)	(21.14)	(0.86)		
HML_{MOM}	0.028	0.017	0.030	0.003	0.026	-0.002		
	(1.02)	(0.94)	(1.40)	(0.14)	(1.24)	(-0.06)		
R^2	0.693	0.841	0.869	0.852	0.749	0.008		
α	0.133	-0.025	-0.072	-0.012	0.078	-0.055	0.064	0.240
	(2.58)	(-0.41)	(-1.28)	(-0.20)	(2.12)	(-1.22)		
level	0.982	1.128	1.187	1.148	0.975	-0.008		
	(32.39)	(42.21)	(40.84)	(36.57)	(39.36)	(-0.30)		
HML_{χ}	-0.451	-0.096	0.095	0.119	0.584	1.035		
	(-9.27)	(-2.15)	(2.54)	(3.25)	(16.10)	(32.79)		
HML_{FX}	-0.147	-0.125	-0.125	-0.046	-0.105	0.042		
	(-5.81)	(-4.22)	(-3.50)	(-1.42)	(-4.52)	(2.01)		
HML_{MOM}	0.016	0.009	0.025	0.002	0.028	0.012		
	(0.94)	(0.57)	(1.35)	(0.10)	(2.07)	(0.90)		
R^2	0.840	0.860	0.880	0.857	0.892	0.846		

Panel D: Joint test

Model	HML_{χ}	HML_{FX}	HML_{MOM}	Four-factor
$\overline{\|\alpha\|}$	0.052	0.071	0.123	0.074
p_{GRS}	0.440	0.005	0.000	0.005

This table reports the results from time-series factor regressions using one-way-sorted portfolios as test assets. In Panels A, B, and C, we sort sample currencies into quintiles based on carry, momentum, and χ, respectively. Panel D reports the joint test, which pools all three sets of test portfolios together. We consider three two-factor models: the level factor plus a single slope factor (HML_{χ}, HML_{FX}, or HML_{MOM}). We also examine a four-factor model that combines the level factor with all three slope factors. The t-stats (in parentheses) are adjusted for heteroscedasticity and autocorrelation. We also report the mean absolute alpha ($\overline{|\alpha|}$) and the p-value for the GRS test (p_{GRS}). The sample period is from July 1982 to July 2023.

Table 9: Explaining 3×3 two-way-sorted currency portfolio returns

	Low			Medium			High					$\overline{\lvert\alpha\rvert}$	p_{GRS}
						Panel A: Carry-momentum							
	Low	Medium	High	Low	Medium	High	Low	Medium	High	H-L$_m$	H-L$_c$		
$\bar{R}$	-0.107	0.043	-0.033	0.162	0.029	0.168	0.367	0.333	0.149	-0.046	0.316		
	(-0.69)	(0.32)	(-0.25)	(1.09)	(0.19)	(1.19)	(2.12)	(1.93)	(0.96)	(-0.66)	(2.87)		
α	-0.110	-0.006	-0.018	0.065	-0.130	0.017	0.095	0.091	-0.124	-0.059	0.066	0.073	0.224
	(-1.25)	(-0.07)	(-0.19)	(0.82)	(-1.98)	(0.25)	(1.06)	(1.07)	(-1.38)	(-0.77)	(0.73)		
level	1.008	1.005	0.941	1.061	1.121	1.126	1.161	1.144	1.066	-0.032	0.139		
	(22.57)	(19.90)	(14.98)	(25.57)	(34.34)	(27.78)	(24.04)	(24.20)	(18.41)	(-0.75)	(2.31)		
HML$_\chi$	-0.340	-0.214	-0.365	-0.105	0.041	0.018	0.331	0.259	0.369	0.045	0.626		
	(-6.12)	(-2.31)	(-5.13)	(-1.86)	(0.93)	(0.30)	(6.34)	(4.90)	(4.85)	(0.73)	(9.71)		
R^2	0.657	0.653	0.627	0.729	0.805	0.789	0.705	0.733	0.656	0.004	0.354		
α	-0.067	0.111	0.083	0.088	-0.068	0.078	0.062	0.088	-0.128	-0.017	-0.035	0.086	0.166
	(-0.78)	(1.42)	(1.00)	(1.19)	(-1.05)	(1.12)	(0.64)	(1.01)	(-1.60)	(-0.22)	(-0.44)		
level	1.052	1.073	1.013	1.078	1.146	1.153	1.123	1.124	1.038	-0.016	0.049		
	(17.99)	(25.14)	(16.54)	(24.24)	(33.63)	(28.59)	(24.07)	(23.59)	(15.70)	(-0.36)	(0.80)		
HML$_{FX}$	-0.292	-0.344	-0.413	-0.106	-0.083	-0.097	0.270	0.171	0.242	-0.046	0.578		
	(-6.32)	(-10.01)	(-11.05)	(-3.38)	(-2.58)	(-2.99)	(4.81)	(3.42)	(4.54)	(-1.19)	(11.09)		
R^2	0.670	0.716	0.694	0.733	0.809	0.794	0.710	0.728	0.646	0.006	0.498		
α	-0.142	-0.069	-0.343	0.121	-0.086	-0.075	0.325	0.158	-0.196	-0.306	0.280	0.168	0.000
	(-1.55)	(-0.80)	(-3.74)	(1.49)	(-1.29)	(-1.11)	(2.90)	(1.77)	(-2.25)	(-3.81)	(2.80)		
level	0.969	0.983	0.923	1.043	1.123	1.136	1.183	1.170	1.118	-0.006	0.198		
	(16.78)	(18.18)	(12.86)	(23.11)	(33.22)	(27.07)	(22.35)	(22.22)	(16.30)	(-0.14)	(2.39)		
HML$_{MOM}$	-0.062	-0.010	0.133	-0.064	-0.020	0.068	-0.076	0.018	0.141	0.181	0.007		
	(-1.99)	(-0.38)	(3.72)	(-2.53)	(-0.88)	(2.98)	(-1.83)	(0.77)	(5.00)	(5.77)	(0.20)		
R^2	0.618	0.636	0.598	0.731	0.805	0.795	0.680	0.712	0.636	0.150	0.051		
α	0.079	0.147	-0.065	0.198	-0.054	-0.035	0.121	0.016	-0.402	-0.300	-0.142	0.124	0.001
	(0.89)	(1.75)	(-0.74)	(2.26)	(-0.78)	(-0.49)	(1.09)	(0.18)	(-4.75)	(-3.55)	(-1.87)		
level	1.048	1.072	1.030	1.072	1.142	1.159	1.112	1.123	1.050	0.002	0.045		
	(21.24)	(25.15)	(20.86)	(23.64)	(35.44)	(31.27)	(25.29)	(24.49)	(18.38)	(0.06)	(0.95)		
HML$_\chi$	-0.223	-0.043	-0.179	-0.059	0.100	0.080	0.227	0.202	0.288	0.082	0.387		
	(-2.96)	(-0.52)	(-2.38)	(-0.81)	(2.25)	(1.32)	(4.09)	(3.27)	(3.10)	(1.12)	(6.10)		
HML$_{FX}$	-0.229	-0.332	-0.353	-0.092	-0.114	-0.117	0.199	0.112	0.164	-0.061	0.463		
	(-4.11)	(-8.00)	(-8.82)	(-2.24)	(-3.27)	(-3.39)	(3.34)	(1.95)	(2.85)	(-1.21)	(8.87)		
HML$_{MOM}$	-0.069	-0.019	0.123	-0.067	-0.022	0.066	-0.069	0.022	0.147	0.180	0.022		
	(-2.51)	(-0.92)	(3.91)	(-2.69)	(-1.04)	(3.08)	(-1.66)	(0.99)	(5.56)	(5.53)	(0.84)		
R^2	0.692	0.717	0.728	0.740	0.813	0.802	0.727	0.739	0.691	0.161	0.597		
						Panel B: Carry-χ							
	Low	Medium	High	Low	Medium	High	Low	Medium	High	H-L$_\chi$	H-L$_c$		
$\bar{R}$	-0.195	-0.051	0.100	0.057	0.152	0.128	0.209	0.164	0.515	0.224	0.345		
	(-1.42)	(-0.37)	(0.72)	(0.40)	(1.02)	(0.89)	(1.29)	(0.89)	(3.12)	(3.47)	(3.11)		
α	-0.105	-0.054	0.004	-0.002	0.000	-0.068	0.046	-0.093	0.164	0.054	0.091	0.060	0.317
	(-1.19)	(-0.75)	(0.06)	(-0.04)	(0.01)	(-0.99)	(0.45)	(-0.92)	(2.39)	(1.01)	(0.96)		
level	0.928	1.006	1.023	1.105	1.150	1.085	1.217	1.174	1.001	-0.047	0.145		

Table 9 – Continued on next page

		Low			Medium			High				$\overline{\lvert\alpha\rvert}$	p_{GRS}
	(16.84)	(22.36)	(21.52)	(32.35)	(33.30)	(33.30)	(20.04)	(20.69)	(21.88)	(-1.80)	(2.34)		
HML_{χ}	-0.560	-0.339	-0.094	-0.222	0.014	0.155	0.020	0.289	0.603	0.475	0.635		
	(-8.81)	(-5.26)	(-1.69)	(-4.35)	(0.28)	(3.90)	(0.28)	(4.75)	(9.61)	(13.16)	(9.20)		
R^2	0.688	0.691	0.727	0.757	0.815	0.792	0.708	0.693	0.727	0.397	0.361		
α	-0.081	-0.004	0.164	-0.017	0.042	0.058	-0.017	-0.132	0.209	0.182	-0.006	0.080	0.045
	(-1.02)	(-0.05)	(2.81)	(-0.28)	(0.71)	(0.85)	(-0.17)	(-1.19)	(2.65)	(2.96)	(-0.08)		
level	0.978	1.053	1.102	1.114	1.168	1.131	1.187	1.136	0.979	-0.022	0.056		
	(14.72)	(20.29)	(27.98)	(33.40)	(33.77)	(33.27)	(19.18)	(22.03)	(16.22)	(-0.49)	(0.85)		
HML_{FX}	-0.400	-0.305	-0.344	-0.115	-0.065	-0.125	0.125	0.253	0.303	0.075	0.577		
	(-10.36)	(-7.22)	(-13.00)	(-4.20)	(-2.16)	(-3.89)	(2.35)	(4.20)	(5.61)	(2.31)	(10.93)		
R^2	0.672	0.710	0.810	0.747	0.817	0.793	0.716	0.701	0.661	0.017	0.493		
α	-0.301	-0.215	-0.070	-0.043	-0.016	-0.027	0.019	-0.060	0.366	0.198	0.304	0.124	0.004
	(-3.43)	(-3.01)	(-1.00)	(-0.64)	(-0.30)	(-0.37)	(0.21)	(-0.54)	(3.96)	(3.17)	(3.01)		
level	0.875	0.978	1.017	1.081	1.153	1.101	1.222	1.208	1.058	-0.001	0.206		
	(10.67)	(17.74)	(21.95)	(30.57)	(32.51)	(32.08)	(19.61)	(20.22)	(15.97)	(-0.01)	(2.37)		
HML_{MOM}	-0.004	0.027	0.028	-0.027	0.015	0.010	0.024	0.049	0.010	0.018	0.010		
	(-0.12)	(1.15)	(1.17)	(-1.16)	(0.67)	(0.40)	(0.82)	(1.45)	(0.27)	(0.89)	(0.29)		
R^2	0.552	0.645	0.725	0.740	0.815	0.783	0.708	0.672	0.609	0.002	0.054		
α	0.020	0.009	0.116	0.064	0.012	-0.002	-0.046	-0.250	0.082	0.053	-0.120	0.067	0.315
	(0.25)	(0.13)	(1.86)	(0.87)	(0.20)	(-0.03)	(-0.45)	(-2.07)	(1.15)	(1.02)	(-1.48)		
level	0.984	1.059	1.103	1.114	1.168	1.128	1.191	1.139	0.972	-0.029	0.052		
	(20.34)	(23.13)	(28.14)	(33.24)	(34.42)	(36.33)	(19.55)	(22.20)	(21.54)	(-1.00)	(1.02)		
HML_{χ}	-0.418	-0.214	0.099	-0.192	0.056	0.259	-0.053	0.187	0.527	0.516	0.398		
	(-6.37)	(-2.77)	(1.66)	(-3.43)	(1.10)	(6.36)	(-0.65)	(2.53)	(7.85)	(13.69)	(5.15)		
HML_{FX}	-0.276	-0.240	-0.372	-0.059	-0.081	-0.202	0.142	0.200	0.147	-0.078	0.459		
	(-7.26)	(-4.93)	(-12.54)	(-1.93)	(-2.47)	(-6.29)	(2.35)	(2.86)	(3.09)	(-2.68)	(8.62)		
HML_{MOM}	-0.015	0.019	0.020	-0.030	0.013	0.007	0.027	0.055	0.018	0.021	0.025		
	(-0.63)	(0.93)	(1.11)	(-1.25)	(0.63)	(0.33)	(0.87)	(1.62)	(0.65)	(1.30)	(0.98)		
R^2	0.736	0.726	0.814	0.760	0.818	0.815	0.717	0.712	0.738	0.416	0.597		
						Panel C: Momentum-χ							
	Low	Medium	High	Low	Medium	High	Low	Medium	High	H-L_{χ}	H-L_m		
$\bar{R}$	-0.121	0.119	0.257	0.093	0.088	0.218	0.131	-0.008	0.357	0.243	0.075		
	(-0.78)	(0.75)	(1.61)	(0.64)	(0.58)	(1.49)	(0.94)	(-0.05)	(2.50)	(3.35)	(0.87)		
α	-0.113	-0.016	0.025	0.064	-0.086	0.002	0.087	-0.177	0.125	0.038	0.046	0.077	0.181
	(-1.38)	(-0.16)	(0.35)	(0.87)	(-1.44)	(0.03)	(1.07)	(-1.68)	(1.70)	(0.84)	(0.49)		
level	1.056	1.121	1.077	1.090	1.145	1.091	1.024	1.136	0.952	-0.016	-0.047		
	(23.55)	(21.09)	(22.67)	(25.97)	(40.74)	(28.03)	(18.37)	(22.60)	(19.87)	(-0.74)	(-0.77)		
HML_{χ}	-0.384	-0.023	0.254	-0.298	0.077	0.205	-0.234	0.064	0.299	0.558	0.094		
	(-6.20)	(-0.41)	(4.39)	(-5.27)	(2.04)	(3.15)	(-3.55)	(0.82)	(5.00)	(16.73)	(1.17)		
R^2	0.698	0.688	0.707	0.739	0.807	0.766	0.658	0.678	0.676	0.514	0.010		
α	-0.150	-0.004	0.060	0.060	-0.019	0.127	0.103	-0.122	0.202	0.125	0.093	0.094	0.056
	(-1.67)	(-0.05)	(0.74)	(0.81)	(-0.29)	(1.88)	(1.18)	(-1.31)	(2.58)	(1.99)	(0.97)		
level	1.066	1.127	1.075	1.109	1.170	1.134	1.048	1.157	0.966	-0.016	-0.032		
	(21.23)	(21.93)	(23.08)	(20.75)	(40.25)	(24.81)	(18.22)	(21.70)	(17.98)	(-0.35)	(-0.50)		

Table 9 – Continued on next page

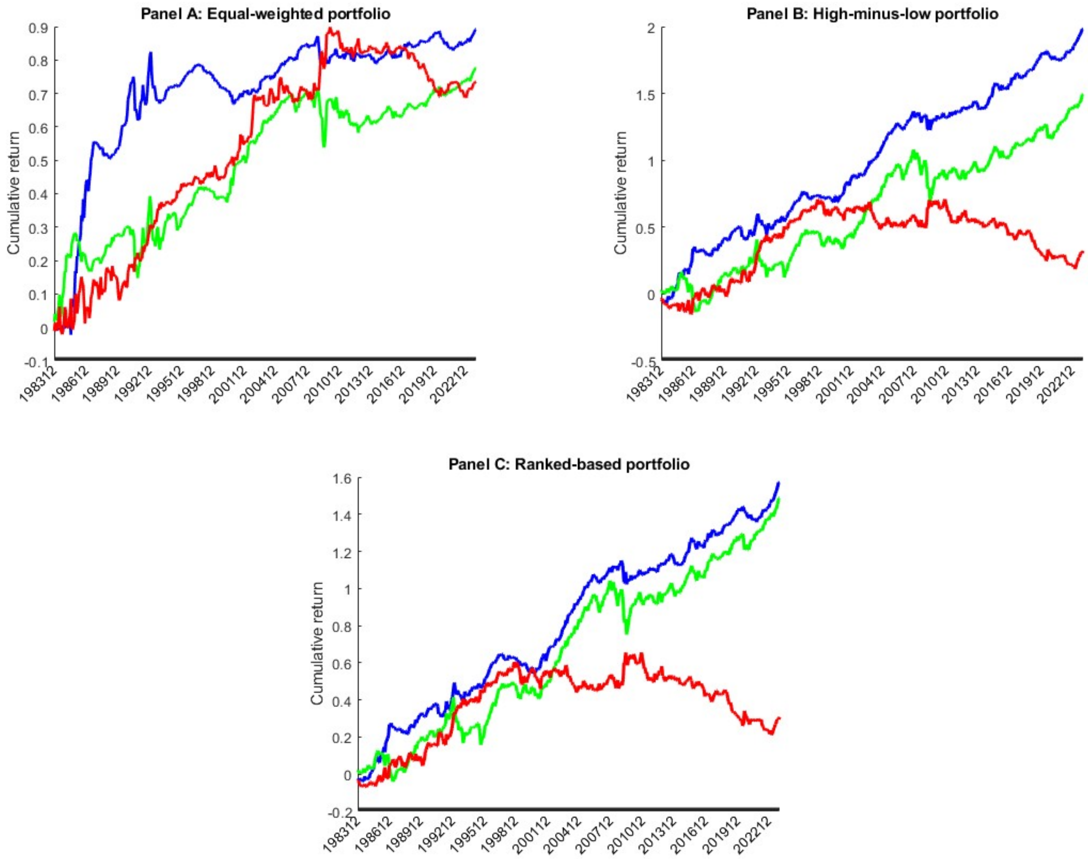
	Low			Medium			High					$\overline{\lvert\alpha\rvert}$	p_{GRS}
HML_{FX}	-0.180	-0.034	0.099	-0.182	-0.071	-0.091	-0.178	-0.058	0.053	0.201	-0.023		
	(-3.55)	(-0.79)	(1.98)	(-5.22)	(-2.28)	(-2.66)	(-4.16)	(-1.59)	(1.14)	(6.06)	(-0.40)		
R^2	0.664	0.688	0.691	0.727	0.808	0.756	0.658	0.679	0.643	0.118	0.003		
α	-0.150	0.193	0.274	-0.044	-0.073	0.054	-0.209	-0.379	0.005	0.246	-0.300	0.154	0.000
	(-1.79)	(1.94)	(2.92)	(-0.55)	(-1.12)	(0.80)	(-2.29)	(-3.72)	(0.07)	(3.37)	(-3.12)		
level	1.011	1.100	1.087	1.062	1.153	1.112	1.020	1.161	0.999	0.035	-0.006		
	(19.54)	(22.25)	(23.96)	(20.76)	(39.55)	(25.09)	(18.12)	(21.33)	(19.97)	(0.72)	(-0.10)		
HML_{MOM}	-0.069	-0.149	-0.109	0.001	0.010	0.015	0.145	0.155	0.156	-0.005	0.261		
	(-2.27)	(-3.89)	(-2.80)	(0.02)	(0.52)	(0.68)	(4.84)	(4.93)	(6.38)	(-0.25)	(5.94)		
R^2	0.650	0.713	0.699	0.706	0.805	0.751	0.666	0.704	0.675	0.004	0.213		
α	0.026	0.219	0.172	0.112	-0.056	0.051	-0.074	-0.371	-0.093	0.022	-0.319	0.131	0.004
	(0.31)	(2.03)	(2.02)	(1.40)	(-0.79)	(0.76)	(-0.77)	(-3.36)	(-1.23)	(0.40)	(-3.18)		
level	1.063	1.111	1.059	1.112	1.169	1.130	1.067	1.172	0.978	-0.025	-0.006		
	(24.35)	(23.48)	(20.91)	(24.31)	(41.32)	(30.18)	(21.47)	(23.35)	(22.50)	(-1.11)	(-0.10)		
HML_{χ}	-0.344	-0.007	0.239	-0.241	0.135	0.298	-0.167	0.112	0.321	0.537	0.126		
	(-5.42)	(-0.12)	(3.18)	(-3.43)	(3.52)	(4.57)	(-2.39)	(1.29)	(6.05)	(14.76)	(1.46)		
HML_{FX}	-0.081	-0.040	0.022	-0.110	-0.111	-0.179	-0.121	-0.083	-0.035	0.040	-0.047		
	(-1.57)	(-0.95)	(0.38)	(-2.49)	(-3.33)	(-4.93)	(-2.38)	(-1.92)	(-0.91)	(1.68)	(-0.73)		
HML_{MOM}	-0.074	-0.150	-0.106	-0.004	0.008	0.013	0.141	0.154	0.158	0.001	0.261		
	(-2.45)	(-3.97)	(-2.83)	(-0.18)	(0.44)	(0.70)	(5.28)	(4.78)	(6.30)	(0.05)	(5.73)		
R^2	0.709	0.714	0.721	0.746	0.814	0.783	0.694	0.708	0.713	0.518	0.225		

Panel D: Joint test

Model	HML_{χ}	HML_{FX}	HML_{MOM}	Four-factor
$\overline{\lvert\alpha\rvert}$	0.070	0.087	0.149	0.107
p_{GRS}	0.144	0.037	0.000	0.019

This table reports the results from time-series factor regressions using 3×3 two-way-sorted portfolios as test assets. In Panel A, we sort sample currencies into terciles by carry first and then further divide each tercile into three portfolios by momentum. In Panel B, we sort by carry first and then by χ. In Panel C, we sort by momentum first and then by χ. Panel D reports the joint test, which pools all three sets of test portfolios together. We consider three two-factor models: the level factor plus a single slope factor (HML_{χ}, HML_{FX}, or HML_{MOM}). We also examine a four-factor model that combines the level factor with all three slope factors. The t-stats (in parentheses) are adjusted for heteroscedasticity and autocorrelation. We also report the mean absolute alpha ($\overline{\lvert\alpha\rvert}$) and the p-value for the GRS test (p_{GRS}). The sample period is from July 1982 to July 2023.

Figure 1: Cumulative returns of different currency portfolios



These figures plot the cumulative returns (in percent) of different currency portfolios formed on the prospective interest rate differential (blue), carry (green), and momentum (red). Panels A, B, and C display the equal-weighted, high-minus-low, and rank-based portfolios, respectively. The sample period is from July 1982 to July 2023.