What drives exchange rates? Time-series and cross-sectional evidence

Pedro Barroso[1] Paulo Maio[2]

This version: December 2018[3]

[1]University of New South Wales Business School. E-mail: p.barroso@unws.edu.au
[2]Hanken School of Economics, Department of Finance and Statistics. E-mail: paulofmaio@gmail.com
[3]We thank John Campbell, John Cochrane, and participants at the IIFT Conference on Empirical Issues in International Trade & Finance (New Delhi), 2015 MFA meeting, 2015 FMA European Meeting, and the 2015 MFS annual conference for helpful comments. We are grateful to Lucio Sarno and Adrien Verdelhan for providing data on currency factor returns. Previous drafts were titled "What drives exchange rates?" and "What drives exchange rates? Reassessing currency return predictability". All remaining errors are ours.

Abstract

We compute variance decompositions for nominal exchange rates (based on a present-value relation) in both the time-series and cross-sectional dimensions. At long horizons, return predictability drives the variation in the exchange rate while predictability of interest rate differentials plays a secondary role. At short horizons, the dominant force is predictability of the future spot rate. An alternative VAR-based decomposition produces qualitatively similar results. In the cross-section, the dispersion in the average appreciation rate of foreign currencies is due to predictability of interest rate spreads. By decomposing the cross-sectional return channel, pricing errors outweigh currency risk premia in explaining currency appreciation.

Keywords: exchange rates, currency return predictability, interest rate differentials, variance decomposition, present-value relation, carry trade, uncovered interest rate parity

JEL classification: F31, G12, G15, G17

1 Introduction

The international finance literature has widely documented the empirical failure of the uncovered interest rate parity (UIP), i.e. the fact that interest rate differentials fail to predict offsetting changes in spot rates. As a result, forward exchange rates are biased predictors of the future spot rate. See, for some examples in the literature, Hansen and Hodrick (1980), Bilson (1981), Meese and Rogoff (1983), Fama (1984), Hodrick (1987) and more recently Engel (1996) and Sarno (2005). The empirical rejection of the UIP is commonly known as the "forward premium puzzle" and it motivates currency speculation strategies that exploit this apparent arbitrage opportunity. The carry trade, one of the most popular strategies, consists of borrowing low-interest-rate currencies and lending high-interest-rate currencies. It has received a great deal of attention in the academic literature for its profitability.[1]

Our paper contributes to this branch of the literature by defining a variance decomposition for the nominal spot exchange rate based on a present-value relation (see, for example, Froot and Ramadorai (2005)) in both the time-series and cross-sectional dimensions. In the time-series, this present-value relation is similar to the widely used decomposition of the dividend yield derived by Campbell and Shiller (1988), although here it is exact and not approximate. According to this dynamic present-value relation, variation in the current spot exchange rate results from variation in future currency returns, future interest rate differentials, and/or the spot exchange rate at some terminal date. Specifically, the current log exchange rate is positively correlated with future multiperiod log interest rate spreads and the exchange rate at some terminal date, and negatively correlated with future multiperiod log currency returns.

By using this present-value relation, we define a variance decomposition for the log exchange rate where the slopes obtained from weighted long-horizon regressions represent the fraction of the variance of the current exchange rate attributable to interest spread, return, and future exchange rate predictability. This approach is similar to the analysis conducted for the dividend-to-price in Cochrane (2008, 2011), for the book-to-market ratio in Cohen, Polk, and Vuolteenaho (2003), for the earnings yield in both Chen, Da, and Priestley (2012) and Maio and Xu (2018), or the net

[1]Papers that study this strategy include Lustig and Verdelhan (2007), Brunnermeier, Nagel, and Pedersen (2009), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov, and Verdelhan (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012), Dobrynskaya (2014), Jurek (2014), and Barroso and Santa-Clara (2015).

payout yield in Larrain and Yogo (2008). We estimate a term-structure of variance decompositions in order to account for the different predictability patterns at short, intermediate, and long forecasting horizons. We use the G10 currencies in the analysis—Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR)—spanning the period from 1985:01 to 2015:06.

Our results can be summarized as follows. First, what drives the variation in the nominal exchange rate at long horizons is currency return predictability. Specifically, at the 120-month horizon the return slopes vary between -1.16 (SEK) and -2.27 (AUD). This means that the shares of return predictability over the variance of the exchange rate are always above 100% and as large as 227%. Second, at short horizons, there is mainly predictability about the future exchange rates itself, consistent with their large persistence. This is especially notable in the cases of JPY and CHF, the two currencies typically associated with the short-side of the carry trade strategy.[2] Third, predictability about future interest rate differentials plays a rather marginal role in driving the current exchange rate and this pattern is especially true at intermediate and long horizons.[3] Specifically, at long horizons, the interest differential coefficient estimates are negative for most currencies, varying between -0.12 (EUR) and -0.37 (DKK). The few exceptions hold for CAD and SEK with weights associated with interest rate spread predictability of 19% and 40%, respectively (at the 120-month horizon).

Following Cochrane (2008), we estimate an alternative time-series variance decomposition for the log exchange rate based on a first-order VAR. Under this approach the coefficients for future returns, interest rate spreads, and exchange rate at multiple horizons are mechanically related with the one-period corresponding slopes. The results indicate that the VAR-based framework leads to qualitatively similar results than the long-horizon regressions, which means that the VAR does represent a valid approximation to the predictability relation at multiple horizons. However, there is a larger amount of interest spread predictability at long horizons in comparison to the direct approach. Similarly, there is more exchange rate predictability at both short and middle

[2]See Galati, Heath, and McGuire (2007) for a discussion on carry trade implementation.

[3]This finding is consistent with related results in the literature. For example, Della Corte, Ramadorai, and Sarno (2016) find that the returns to a currency strategy based on currency volatility are mainly generated by movements in spot exchange rates rather than interest rate differentials.

horizons under the VAR approach compared to the long-horizon regressions. These results are roughly confirmed by a Monte-Carlo simulation, which shows that the interest spread coefficients are statistically significant at intermediate and long horizons for several currencies.

A major innovation in this paper is that we explore the cross-sectional dimension of currencies by deriving and estimating a cross-sectional variance decomposition for the log growth in exchange rates. Similarly to the cross-sectional variance decomposition for the dividend yield in Cochrane (2011), we decompose the cross-sectional dispersion in the appreciation rate of foreign currencies into cross-sectional return predictability and cross-sectional interest spread predictability. By estimating OLS cross-sectional regressions we find that cross-sectional predictability of average interest rate spreads drives the cross-sectional dispersion in the average rate of appreciation of foreign currencies, while there seems to exist no significant role for cross-sectional return predictability. Indeed, more than 130% of the cross-sectional dispersion in the average rate of appreciation of foreign currencies is due to predictability of interest rate spreads. Further, currencies with a higher rate of appreciation against the U.S. Dollar tend to be those currencies showing lower interest rate spreads relative to the median currency. These results are in contrast with the currency-specific variance decompositions in the time-series dimensions discussed above.

In the last part of the paper, we compute an alternative cross-sectional variance decomposition for the growth in exchange rates by splitting the currency return into a systematic (risk premium) component and an idiosyncratic (pricing error) component. To compute the risk premiums and pricing errors (alphas) associated with each currency, we use the time-series regression approach widely used in the asset pricing literature. We employ six alternative factor models of currency returns that have been proposed in the literature, including the two-factor models of Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and the three-factor model of Della Corte, Riddiough, and Sarno (2016). The results from cross-sectional regressions suggest that higher cross-sectional dispersion in the appreciation rate of currencies (against the U.S. Dollar) is associated with higher (cross-sectional) correlation between exchange rate growth and currency pricing errors while cross-sectional covariance with systematic risk premiums does not seem to play a relevant role. Still, the interest spread channel is the most important in both economic and statistical terms.

1.1 Related literature

Our work is directly related to the long literature that analyses time-series predictability of currency returns or exchange rate changes at multiple forecasting horizons. A large portion of this literature has focused on the relation between exchange rates and macro fundamentals, such as nominal money supply and real GDP. Examples include Meese and Rogoff (1983), Mark (1995), Kilian (1999), Mark and Sul (2001), Rapach and Wohar (2002), Groen (2005), and Engel and West (2005). The evidence in these studies usually consists of a weak relation between currencies and macro fundamentals. This is often interpreted as a fundamental failure of standard models of exchange rates and it has even been described as the major weakness of international macroeconomics (Bacchetta and Van Wincoop (2006)). Yet, Engel, Mark, and West (2007) show that theoretical models imply near-random walk behaviour for short-term exchange rates. This is natural since exchange rates, as asset prices, should be mostly driven by changes in expectations. Furthermore, they show that the forecasting power of these models improves considerably when using panel regressions and long-horizon forecasts. Also, Gabaix and Maggiori (2015) provide a theory of the determination of exchange rates based on capital flows in imperfect financial markets, which helps to rationalize the apparent empirical disconnect between exchange rates and traditional macroeconomic fundamentals. In turn, Della Corte, Sarno, and Tsiakas (2009) show that bayesian forecast combinations improve substantially the economic case for short-horizon predictive ability of economic fundamentals.

Our work is also related to a growing literature, which finds evidence that the cross-section of currency returns is exposed to priced risk factors. Lustig and Verdelhan (2007) find that consumption growth risk is priced in the cross-section of currencies. That risk is further heightened in times of crisis (Lustig and Verdelhan (2011)). Volatility risk is the focus of various other studies: Lustig, Roussanov, and Verdelhan (2011) provide empirical evidence that a common risk factor in currency markets is related to changes in global equity market volatility; Della Corte, Sarno, and Tsiakas (2011) investigate the economic value of volatility predictability in foreign exchange markets; Menkhoff, Sarno, Schmeling, and Schrimpf (2012) consider exposures to a global FX volatility risk factor; Bakshi and Panayotov (2013) look at both currency volatility and commodity returns; and Della Corte, Ramadorai, and Sarno (2016) use the predictive capability of currency volatility risk premia for currency returns to develop a new currency strategy with desirable return and diversification properties. Other known predictors of exchange rates or currency returns focus on interest rate variables and macroeconomic fundamentals. Boudoukh, Richardson, and Whitelaw (2016) revisit the uncovered interest parity and show that past forward interest rate differentials have strong forecasting power for exchange rates. Other papers use variables related with the term structure of bond yields to forecast currency returns (e.g., Clarida and Taylor (1997), Clarida, Sarno, Taylor, and Valente (2003), Diez de los Rios (2009), Ang and Chen (2010), and Chen and Tsang (2013), and Lustig, Stathopoulos, and Verdelhan (2018)). Della Corte, Riddiough, and Sarno (2016) show that a global imbalance risk factor explains excess returns in a broad cross-section of portfolios formed on momentum, value, interest rates, and other currency characteristics.

In contrast with some of these studies, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) find no role for standard risk factors in explaining the carry trade and therefore argue for a peso problem explanation. Burnside (2012) argues that systematic risk is not sufficient to explain the carry puzzle and so a peso problem remains a plausible explanation. Brunnermeier, Nagel, and Pedersen (2009) find supporting evidence for this possibility. They show that high interest rate currencies are exposed to sudden crashes when carry trades unwind, suggesting that abnormal currency returns are a compensation for funding liquidity risk in the presence of financial frictions. Their evidence is also supported by the findings in Filipe and Suominen (2014), who use stock volatility and crash risk from low interest rate countries as a proxy for funding risk. Lettau, Maggiori, and Weber (2014) and Dobrynskaya (2014) argue that, as high interest rate currencies have high market exposures in bad states, a downside risk model can price the cross-section of currency returns. Daniel, Hodrick, and Lu (2017) also study the carry trade in terms of exposure to risk factors and drawdowns distribution. On the other hand, Jurek (2014) studies crash-neutral option-hedged carry trades and find crash risk premia can account for at most one third of the excess return of carry. More generally, Engel (2016) discusses in a recent paper the relationship of foreign exchange risk premium and interest-rate differentials. Whereas high interest rate countries have higher expected returns in the short run, they also have a stronger currency in levels. Engel (2016) argues that existing models are unable to account for both stylized facts and discusses a framework that might reconcile the two findings, by embedding liquidity risk within a standard open-economy macroeconomic model.

We contribute to the literature above by studying the term structure of exchange rate predictability and showing that the current nominal exchange rate captures time variation in both currency risk premia and the future spot rate, with the relative weights depending on the time horizon considered. Our methodology is in line with the branch of the literature that applies the return decomposition of Campbell and Shiller (1988) in the context of the foreign exchange market. Froot and Ramadorai (2005) employ a decomposition of the real exchange rate into cumulated future real interest differentials (the permanent component) and future expected return innovations (the transitory component). By expressing unexpected currency returns as the difference between "cash-flow" news and "expected return" news, their goal is to study the interaction between exchange rates, investor flows, and fundamentals. They find that investor flows are important in understanding transitory elements of currency returns, but not the long-run currency value. More recently, Atanasov and Nitschka (2015) also use the Campbell and Shiller (1988) decomposition to understand currency returns. They first decompose the return on the stock market into cash-flow and discount-rate news and then calculate the sensitivities of currency returns to these two stock return components. They find that the sensitivities to aggregate cash-flow news are significantly related to average excess returns on foreign currency portfolios. More directly related to our paper is the work of Balduzzi and Chiang (2017), who also extend the analysis of Cochrane (2008) to currency returns. However, there are three key differences between the two papers. First, we compute a variance decomposition for the nominal exchange rate, while they focus on the real exchange rate. Second, we derive and estimate a cross-sectional variance decomposition for the change in exchange rates linking the cross-sectional dispersion in currency appreciation rates to cross-sectional dispersion in currency returns and interest rate spreads, which is absent from their study. Third, we use the findings of the recent literature on the cross-section of currency returns to disentangle risk premiums and mispricing in the observed long term exchange rate appreciation.

The rest of the paper is organized as follows. Section 2 discusses the methodology. Section 3 describes the data. Section 4 presents the main results based on long-horizon regressions. Section 5 presents the alternative VAR-based variance decomposition. Section 6 derives and estimates a cross-sectional variance decomposition for the growth in exchange rates. In Section 7, we estimate an alternative cross-sectional variance decomposition. Finally, Section 8 concludes.

2 Methodology

Consider the gross return associated with a zero-cost investment strategy in foreign currency,[4]

$$1 + R_{t+1} = \frac{\frac{S_{t+1}}{S_t}(1 + i^*_{t+1})}{1 + i_{t+1}}, \tag{1}$$

where S_t denotes the spot exchange rate at time t (units of domestic currency per unit of foreign currency), i_{t+1} is the domestic short-term interest rate between t and $t+1$, which is known at the beginning of the period, and i^*_{t+1} stands for the foreign interest rate.

By applying logs to the previous identity, we obtain:

$$r_{t+1} = s_{t+1} - s_t + d_{t+1}, \tag{2}$$

where r_{t+1} is the log currency return, s_{t+1} denotes the log exchange rate at the end of $t+1$, and $d_{t+1} \equiv \ln(1 + i^*_{t+1}) - \ln(1 + i_{t+1})$ represents the log interest rate differential.

The previous equation can be interpreted as a difference equation in s_t. By solving forward for s_t, we obtain the following dynamic decomposition for the log exchange rate:

$$s_t = \sum_{j=1}^{K} d_{t+j} - \sum_{j=1}^{K} r_{t+j} + s_{t+K}. \tag{3}$$

According to this dynamic present value relation, variation in the current log spot exchange rate results from variation in future currency log returns, future log interest rate differentials, or the log exchange rate at some future date. Specifically, the current log exchange rate is positively correlated with future multiperiod log interest rate spreads and the exchange rate at some terminal date, and negatively correlated with future log currency returns. Hence, this relation represents a valid benchmark to analyse predictability in currency markets, and is similar to the Campbell and Shiller (1988) decomposition associated with the log dividend-to-price ratio, except the fact that it holds exactly rather than approximately. Campbell and Clarida (1987), Froot and Ramadorai (2005), and Engel (2016) derive similar present-value relations for the real exchange rate at an infinite horizon.

[4] More specifically, $1 + R$ represents the ratio of the gross return of investing in the foreign currency to the gross return of investing in the domestic currency.

As shown in Appendix A, by employing the present-value relation above we can define a variance decomposition for the log exchange rate,

$$1 = b_d^K - b_r^K + b_s^K, \tag{4}$$

where b_d^K, b_r^K, and b_s^K represent the fraction of the variance of the current exchange rate attributable to interest spread, return, and future exchange rate predictability, respectively.[5] Estimating a term-structure of variance decompositions, that is one decomposition for each forecasting horizon K, enables us to account for the different predictability patterns at short and long horizons. Under this variance decomposition, if the shares associated with the predictability of interest rate spreads and future exchange rates are small or close to zero, this reinforces the evidence of return predictability from the exchange rate since the three slopes have to sum to one. In other words, since the nominal exchange rate varies over time, there must be at least one of these three sources of predictability in driving the exchange rate. Cochrane (2008, 2011) and Maio and Xu (2018) use similar variance decompositions for the market dividend yield and earnings yield, respectively, while Maio and Santa-Clara (2015) apply a variance decomposition for portfolio dividend yields.

The predictive coefficients above are obtained from the following long-horizon forecasting regressions:

$$\sum_{j=1}^{K} d_{t+j} = a_d^K + b_d^K s_t + \varepsilon_{t+K}^d, \tag{5}$$

$$\sum_{j=1}^{K} r_{t+j} = a_r^K + b_r^K s_t + \varepsilon_{t+K}^r, \tag{6}$$

$$s_{t+K} = a_s^K + b_s^K s_t + \varepsilon_{t+K}^s. \tag{7}$$

The t-statistics associated with the predictive slopes are based on Newey and West (1987) standard errors with K lags to account for the overlapping in the residuals that is caused by the overlapping in the predicted variables.

Following Cochrane (2008), an alternative approach to study predictability uses a restricted

[5] In contrast to the variance decomposition for the dividend-to-price ratio (or alternative stock market ratios), which holds approximately, this variance decomposition holds exactly.

first-order VAR,

$$r_{t+1} = a_r + b_r s_t + \varepsilon^r_{t+1}, \tag{8}$$

$$d_{t+1} = a_d + b_d s_t + \varepsilon^d_{t+1}, \tag{9}$$

$$s_{t+1} = a_s + \phi s_t + \varepsilon^s_{t+1}, \tag{10}$$

to obtain the following variance decomposition for s:

$$\begin{aligned} 1 &= b_d^K - b_r^K + b_s^K, \\ b_d^K &\equiv \frac{b_d(1-\phi^K)}{1-\phi}, \\ b_r^K &\equiv \frac{b_r(1-\phi^K)}{1-\phi}, \\ b_s^K &\equiv \phi^K. \end{aligned} \tag{11}$$

The full derivation of this alternative variance decomposition is shown in Appendix B. The t-statistics for the predictive coefficients, b_d^K, b_r^K, b_s^K, are based on the t-statistics associated with the VAR slopes above by using the Delta method. The standard error formulas are presented in Appendix B.

In the very long-run ($K \to \infty$), the VAR-based variance decomposition is given by

$$\begin{aligned} 1 &= b_d^{lr} - b_r^{lr}, \\ b_d^{lr} &\equiv \frac{b_d}{1-\phi}, \\ b_r^{lr} &\equiv \frac{b_r}{1-\phi}, \end{aligned} \tag{12}$$

which stems from the assumption that the share of future exchange rate predictability dies off in the very long-run, $\lim_{K\to\infty} \phi^K = 0$.

In comparison to the direct approach, the VAR method allows us to cope with the sharp decrease in the number of usable observations under the direct approach at long horizons (and the resulting low statistical power of the long-horizon regressions). On the other hand, the first-order VAR represents only an approximation of the true long-run dynamics that govern the variables, and thus, may produce wrong estimates of the predictive slopes at long horizons. Therefore, ideally the two approaches should provide similar variance decompositions.[6]

3 Data and variables

We use monthly data on spot and one-month forward exchange rates (amounts of U.S. dollars per unit of foreign currency) associated with ten currencies—Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). As common practice defining returns for the set of G10 currencies we splice the series of Germany with the Euro in January 1999.[7] The sample is from 1985:01 to 2015:06.[8] The exchange data are originally from Datastream and represent a subset of the data employed in Barroso, Kho, Rouxelin, and Yang (2018).

The log interest rate spread is computed as

$$d_{t+1} = s_t - f_{t+1}, \tag{13}$$

where f_{t+1} is the log forward exchange rate for $t+1$, which is known at time t. Based on the data for s and d, the monthly currency log returns are computed from equation (2) above.

The descriptive statistics for the log exchange rate (s), log return (r), and log interest rate differential (d) associated with the ten currencies are shown in Table 1. Currency returns are substantially more volatile than the corresponding interest rate differentials across all currencies. On the other hand, the interest rate spreads are relatively persistent variables (with autoregressive slopes above 0.70 for most currencies), as opposed to currency returns (with autocorrelation coefficients close to zero in all cases). Yet, the most persistent series are the log exchange rates with autoregressive coefficients above 0.93 in all cases (above 0.97 in the cases of CAD, CHF, JPY, SEK, AUD, and NZD). In terms of contemporaneous correlations, d and s are positively correlated for most currencies with the largest correlations holding for CHF, SEK, and EUR (correlations above

[6] See Cochrane (2008) and Maio and Xu (2018) for a related discussion.

[7] Examples of studies splicing the German mark with the euro include Christiansen, Ranaldo, and Söderlind (2011), Jordà and Taylor (2012), Kroencke, Schindler, and Schrimpf (2013), and Ready, Roussanov, and Ward (2017).

[8] The starting date is constrained by the availability on the forward exchange rate data for these ten currencies.

20%). On the other hand, r and d show weak positive correlations (around or above 10%) for most currencies. r and s are also positively correlated with the most relevant correlations occurring in the cases of GBP, SEK, and AUD.

4 Long-horizon regressions

In this section, we compute the variance decomposition based on direct regressions for the log exchange rate presented in Section 2.

The term-structure of predictive slopes, and the associated t-statistics, are presented in Figures 1 (for CAD, CHF, GBP, JPY, and SEK) and 2 (for the remaining currencies). Due to large disparity in scale, we do not graph the t-ratios for the slopes in the regressions for the future exchange rate.

For all ten currencies it turns out that at both intermediate and long horizons the bulk of variation in the current log exchange rate is predictability of future currency returns with interest spread predictability playing a rather marginal role. At the longest horizon ($K = 120$), the return slopes are below -1 in all cases, varying between -1.16 (SEK) and -2.27 (AUD). This means that the share of return predictability over the variance of the current exchange rate varies between 116% and 227% at that horizon. Across all currencies the return slopes are statistically significant at the 5% level at most forecasting horizons. The exceptions are the cases of CAD, CHF, SEK, and AUD in which these estimates are not significant for a few short or intermediate horizons.

The return slope estimates above 100% in magnitude implies that either the coefficients associated with interest rate spreads or the future exchange rate have the wrong sign (negative). Indeed, at the longest horizon the interest differential coefficient estimates are negative for most currencies, varying between -0.12 (EUR) and -0.37 (DKK). The few exceptions hold for CAD and SEK with weights associated with interest rate spread predictability of 19% and 40%, respectively (at the 120-month horizon). Yet, these estimates are substantially smaller than the corresponding shares of return predictability (above 100%). At intermediate horizons there is also some degree of interest spread predictability (with the right sign) for these two currencies. However, only in the case of SEK (and only at some horizons) are these estimates statistically significant. At short horizons, the interest coefficients associated with CAD, CHF, SEK, AUD, and EUR are positive and statistically significant, albeit the magnitudes are quite small.

The predictive slopes at long-horizons associated with the future exchange rate have the wrong sign (negative) for all ten currencies, and there is statistical significance in the cases of CAD, SEK, DKK, NOK, AUD, and EUR. At short horizons (until 20 months ahead), the dominant source of variation in the current exchange rate tends to be predictability of the future exchange rate itself. This pattern is especially notable in the cases of CAD, CHF, JPY, and AUD where the coefficients for future s converge to zero rather slowly. At middle horizons there is also significant exchange rate predictability in the cases of CHF and JPY. This is a consequence of the fact that these four exchange rates tend to be the more persistent ones, as shown in the previous section. On the other hand, the currency for which the slopes associated with future s converge faster to zero is clearly GBP, in light of the lowest autoregressive coefficient among all currencies.

In sum, we can summarize the results of this section as follows: First, what drives the variation in the nominal exchange rate at long horizons is currency return predictability. Second, at short horizons, there is mainly predictability about the future exchange rates itself, consistent with their large persistence. Third, predictability about future interest rate differentials plays a rather marginal role in driving the current exchange rate and this pattern is especially true at intermediate and long horizons.

5 VAR-based predictability

In this section, we estimate the VAR-based variance decomposition for the log exchange rate.

5.1 Main results

The term-structure of predictive coefficients based on the first-order VAR, and the respective t-statistics, is displayed in Figures 3 and 4. The first-order VAR estimates are presented in Table 2.

At long horizons, it turns out that return predictability is the main driver of variation in the current log exchange rate for all currencies. This pattern is better illustrated by the long-run (infinite horizon) coefficients presented in Table 2: the long-run return slopes vary between -0.75 (SEK) and -1.05 (both NOK and NZD), while the long-run interest differential slopes vary between -0.05 (NOK and NZD) and 0.25 (SEK). With the exception of SEK and AUD, the long-run return slope estimates are below -0.90 for all currencies, which implies that more than 90% of the variation in s is attributable to long-run return predictability. The return slopes are statistically significant at most forecasting horizons across all currencies. The few exceptions take place for CAD, SEK, and AUD in which cases these estimates are not significant at very short horizons as a result of insignificant one-period VAR estimates. On the other hand, there is statistical significance for the interest spread slopes at all horizons in the cases of CHF, SEK, AUD, and EUR. This stems from the significant VAR interest slopes in the cases of these four currencies. Hence, there is stronger significance for the coefficients associated with interest differentials than in the direct regression approach conducted in the last section.

In comparison to the benchmark variance decomposition based on the long-horizon regressions, the slopes associated with d have the correct sign for more currencies. The exceptions are DKK, NOK, and NZD for which the respective slopes are negative at all horizons as a result of negative one-month ahead slopes from the VAR. For eight out of the ten currencies (CAD, GBP, JPY, SEK, DKK, NOK, AUD, and NZD), we clearly reject (at the 5% level) the null that the long-run return slope is zero, and do not reject the null that such estimate is -1 (marginally so in the case of SEK). In other words, we cannot reject the proposition that what drives all the variation in the exchange rates of these eight currencies happens to be long-run return predictability. In the cases of CHF and EUR, while the null $b_r^{lr} = 0$ is strongly rejected it is the case that the null $b_r^{lr} = -1$ is also rejected. Hence, we can not rule out that long-run interest spread predictability plays a role in statistical terms for these two currencies. In the cases of SEK and AUD the null that $b_r^{lr} = -1$ is not rejected at the 5% level, but it is rejected at the 10% level.

At short forecasting horizons, the key driving force of the exchange rate is predictability of the future exchange rate, and this pattern is particularly strong in the cases of CAD, CHF, and JPY. Even at intermediate horizons (between 40 and 60 months), the shares of exchange rate predictability are economically significant for most currencies (above 30%). Hence, in comparison to the benchmark variance decomposition, the coefficients associated with future s decay to zero on a slower pace. This is a consequence of the fact that the multi-period VAR-based slopes are mechanically related with the one-month VAR estimated slopes, which have relative high magnitudes across most currencies.

Overall, the results of this subsection indicate that the VAR-based framework produces qualitatively similar results to the long-horizon regressions. However, there is a larger amount of interest spread predictability at long horizons in comparison to the direct approach. Similarly, there is more exchange rate predictability at both short and middle horizons under the VAR approach.

5.2 Simulation

In the asset return predictability literature, substantial attention has been devoted to the poor small-sample properties of long-horizon predictability (see Valkanov (2003), Torous, Valkanov, and Yan (2004), and Boudoukh, Richardson, and Whitelaw (2008), among others). To address this issue, we conduct a Monte-Carlo simulation of the VAR model associated with the log exchange rate estimated above.

To assess the statistical significance of currency return predictability, we impose a null hypothesis where the log exchange rate does not forecast the future return. That is, under this null, all the variation of the log exchange rate comes from predicting the future interest rate differential. Thus, we simulate the first-order VAR by imposing the restrictions (in the predictive slopes and residuals) associated with this null hypothesis:

$$\begin{pmatrix} r_{t+1} \\ d_{t+1} \\ s_{t+1} \end{pmatrix} = \begin{pmatrix} 0 \\ 1-\phi \\ \phi \end{pmatrix} s_t + \begin{pmatrix} \varepsilon^s_{t+1} + \varepsilon^d_{t+1} \\ \varepsilon^d_{t+1} \\ \varepsilon^s_{t+1} \end{pmatrix}, \tag{14}$$

where all the variables are demeaned.

To assess predictability of future interest rate differentials, we simulate an alternative VAR:

$$\begin{pmatrix} r_{t+1} \\ d_{t+1} \\ s_{t+1} \end{pmatrix} = \begin{pmatrix} \phi-1 \\ 0 \\ \phi \end{pmatrix} s_t + \begin{pmatrix} \varepsilon^s_{t+1} + \varepsilon^d_{t+1} \\ \varepsilon^d_{t+1} \\ \varepsilon^s_{t+1} \end{pmatrix}. \tag{15}$$

In this VAR, we impose a null hypothesis where the log exchange rate does not forecast the future interest rate differential. In other words, all the variation of the log exchange rate comes from predicting the future currency return.[9]

[9] Cochrane (2008) and Maio and Santa-Clara (2015) conduct similar Monte-Carlo simulations to assess the predictability of the dividend yield for future stock returns and dividend growth.

In drawing the VAR residuals (10,000 times) in both simulations, we assume that they are jointly normally distributed and use their sample covariances. We use the same sample size as in the original sample. The log exchange rate for the base period is simulated as $s_1 \sim N\left[0, \mathrm{Var}(\varepsilon^s_{t+1})/(1-\phi^2)\right]$. We compute the empirical p-values associated with the implied VAR return slopes for each horizon, which represent the fraction of simulated estimates for the return coefficients (from the first simulation) that are lower than the estimates found in the data. Likewise, the p-values for the interest spread slopes represent the fraction of pseudo estimates of the interest coefficient (obtained from the second simulation) that are higher than the sample estimates.[10]

The p-values at selected forecasting horizons ($K = 40, 80, 120$) are presented in Table 3. In Panel A, we can see that the return coefficients are statistically significant (at the 5% level) at $K = 80$ and $K = 120$ for all currencies, except CAD. Hence, the key difference relative to the inference based on the asymptotic t-ratios occurs for CAD since there is no significance at long horizons, in contrast to the asymptotic p-values below 5%.

The p-values associated with the interest spread coefficients (shown in Panel B) indicate significance (at the 5% level) in the cases of CAD, CHF, SEK, AUD, and EUR at all three forecasting horizons. Hence, in comparison with the inference based on the asymptotic t-ratios it turns out that the interest slopes in the case of CAD become statistically significant at long horizons.

With 5 out of 10 coefficients for d significant at the 5% level, the combined evidence suggests expectations of currency fundamentals are likely a more important partial determinant of the exchange rate than the evidence provided in the last subsection would suggest. This result confirms Engel and West (2005), Sarno and Sojli (2009), and Sarno and Schmeling (2014), among others. Still, the null of no return predictability is rejected with even more clarity. This suggests time-varying expected returns are an even more important determinant of time-series variation in nominal exchange rates.

6 Cross-sectional variation in exchange rates

In this section, we explore the cross-sectional variation of exchange rates, which complements the time-series analysis conducted in the previous sections. Specifically, we derive and estimate a

[10]The full details of the Monte-carlo simulations are available upon request.

cross-sectional variance decomposition for the growth in exchange rates.

By reorganizing the definition of excess currency return, we can write the log growth in the exchange rate for currency n as

$$\Delta s_{n,t+1} = r_{n,t+1} - d_{n,t+1}, \tag{16}$$

and by taking unconditional expectations, we obtain,

$$\overline{\Delta s}_n = \overline{r}_n - \overline{d}_n, \tag{17}$$

where $\overline{\Delta s}_n \equiv \mathrm{E}(\Delta s_{n,t+1})$, and similarly for the other variables. This equation postulates that the currencies that register a higher average appreciation against the U.S. Dollar (higher values of $\overline{\Delta s}_n$) are those currencies with higher average excess returns and/or lower interest rate differentials.

Next, we compute the cross-sectional covariance with $\overline{\Delta s}_n$, which leads to

$$\mathrm{Var}\left(\overline{\Delta s}_n\right) = \mathrm{Cov}\left(\overline{r}_n, \overline{\Delta s}_n\right) - \mathrm{Cov}\left(\overline{d}_n, \overline{\Delta s}_n\right). \tag{18}$$

By dividing both sides of the previous equation by $\mathrm{Var}\left(\overline{\Delta s}_n\right)$, we obtain

$$1 = b_r^{cs} - b_d^{cs}, \tag{19}$$

where

$$b_r^{cs} \equiv \frac{\mathrm{Cov}\left(\overline{r}_n, \overline{\Delta s}_n\right)}{\mathrm{Var}\left(\overline{\Delta s}_n\right)}, \tag{20}$$

$$b_d^{cs} \equiv \frac{\mathrm{Cov}\left(\overline{d}_n, \overline{\Delta s}_n\right)}{\mathrm{Var}\left(\overline{\Delta s}_n\right)}. \tag{21}$$

This equation represents a cross-sectional variance decomposition for the log growth in nominal exchange rates. Under this decomposition, the cross-sectional dispersion in the appreciation rate of foreign currencies is attributable to cross-sectional return predictability (captured by the term b_r^{cs}) or cross-sectional interest spread predictability (given by b_d^{cs}).[11]

The parameters in the variance decomposition are obtained from the following cross-sectional

[11] Cochrane (2011) uses a similar cross-sectional variance decomposition for the dividend yield.

regressions,

$$\overline{r}_n = a_r^{cs} + b_r^{cs}\overline{\Delta s}_n + \zeta_n^r, \tag{22}$$

$$\overline{d}_n = a_d^{cs} + b_d^{cs}\overline{\Delta s}_n + \zeta_n^d. \tag{23}$$

Given the low dimension of the cross-section (ten currencies), we use OLS t-ratios (instead of GMM-based t-ratios) to infer the statistical significance of both b_r^{cs} and b_d^{cs}. Yet, in addition to the OLS t-ratios, we compute empirical p-values obtained from a Bootstrap simulation. The objective is to relax some of the restrictive assumptions underlying the OLS standard errors and provide a more robust assessment of the statistical significance of the slope estimates. The data generating process is simulated under the assumption that all three variables in the cross-sectional regressions $(\overline{r}_n, \overline{d}_n, \overline{\Delta s}_n)$ are mutually independent. Details on the bootstrap simulation are provided in Appendix D.

Table 4 presents the results for the cross-sectional variance decomposition. We can see that the interest spread slope is negative and strongly statistically significant (t-ratio$= -2.69$ and empirical p-value around zero). In comparison, the return coefficient estimate has the wrong sign (negative) and is largely insignificant. The difference of the slope estimates is around one, which indicates that the cross-sectional variance decomposition is quite accurate. The explanatory ratio in the regression for $\overline{d}_n$ is also substantially larger than the corresponding estimate for $\overline{r}_n$ (48% versus 6%). Hence, since the return coefficient has the wrong sign (negative), more than 130% of the cross-sectional dispersion in the average rate of appreciation of foreign currencies is due to predictability of interest rate spreads. Further, currencies with a higher rate of appreciation against the U.S. Dollar tend to be those currencies showing lower interest rate spreads relative to the median currency.

This finding can be interpreted in light of related results in the literature. For example, Brunnermeier, Nagel, and Pedersen (2009) show that high interest rate differentials predict negative skewness in the cross-section. This implies that currencies that have high interest rate differentials (i.e. typically the investment currencies in the long side of the carry trade) are subject to crash risk. The reverse is true for the funding currencies such as CHF and JPY. Brunnermeier, Nagel, and Pedersen (2009) argue that the carry trade returns are a compensation for the crash risk, which is related to the availability of funding liquidity in the market. As the returns to the carry trade are on average positive, the cross-sectional dispersion in the appreciation of foreign currencies is (by construction) mainly related to the cross-sectional dispersion in interest rates spreads. Therefore we argue that our results for the cross-sectional variance decomposition capture this effect.

We find that differences in expected appreciation rates line up consistently with interest rate fundamentals in the G10. This is the strongest component driving long-term appreciation in currencies. It is noteworthy that the relation has the correct sign according to the UIP: currencies with higher interest rates tend to depreciate.[12] Nevertheless, this does not overturn previous findings showing that UIP fails in the cross-section of currency returns (see Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011), among others). While high interest rate currencies depreciate the most on average, they are still the ones producing higher returns.

Overall, the results of this section indicate that cross-sectional predictability of average interest rate spreads drives the cross-sectional dispersion in the average rate of appreciation of foreign currencies, while there seems to exist no significant role for cross-sectional return predictability.

7 Decomposing currency risk premia

In this section, we compute an alternative cross-sectional variance decomposition for the growth in exchange rates by splitting the currency return into a systematic component and an idiosyncratic component.

7.1 Methodology

Following the asset pricing literature, we assume the following return generating process for currency returns,

$$R_{n,t+1} = \alpha_n + \sum_{j=1}^{J} \beta_{n,j} f_{j,t+1} + \varepsilon_{n,t+1}, \tag{24}$$

where $f_j, j = 1, ..., J$ denotes the realization on the common risk factor j and $\beta_{n,j}$ represents the corresponding factor loading or beta for currency n, which represents the quantity of risk. The

[12] This is perhaps more surprising as Frankel and Poonawala (2010) show UIP is generally more successful as a predictor of spot rates in emerging currencies and not so much in developed markets.

systematic realized return for currency n is given by

$$RP_{n,t+1} = \sum_{j=1}^{J} \beta_{n,j} f_{j,t+1}, \tag{25}$$

while the residual or idiosyncratic return is equal to $\alpha_n + \varepsilon_{n,t+1}$.

Hence, the decomposition for the log exchange rate is given by

$$\Delta s_{n,t+1} \simeq R_{n,t+1} - d_{n,t+1} = RP_{n,t+1} + \alpha_n + \varepsilon_{n,t+1} - d_{n,t+1}, \tag{26}$$

where we decompose the total currency return in its systematic and idiosyncratic components. Since $\mathrm{E}(\varepsilon_{n,t+1}) = 0$, by taking unconditional expectations, we obtain,

$$\overline{\Delta s}_n = \overline{RP}_n + \alpha_n - \overline{d}_n, \tag{27}$$

in which

$$\overline{RP}_n \equiv \sum_{j=1}^{J} \beta_{n,j} \, \mathrm{E}(f_{j,t+1}), \tag{28}$$

represents the systematic risk premium, that is, the component of the currency risk premium explained by the linear factor model. α_n represents the model's pricing error, that is, the part of the currency risk premium not explained by the J common factors in the following asset pricing equation:

$$\mathrm{E}(R_{n,t+1}) = \alpha_n + \sum_{j=1}^{J} \beta_{n,j} \, \mathrm{E}(f_{j,t+1}). \tag{29}$$

If the asset pricing model is true ($\alpha_n = 0$), the previous expected return-beta equation is equivalent to the following fundamental pricing equation

$$0 = \mathrm{E}_t(M_{t+1} R^e_{n,t+1}), \tag{30}$$

where M is the stochastic discount factor (SDF) that prices assets, $\mathrm{E}_t(\cdot)$ is the conditional expectation at time t, and R^e_n represents the difference between the gross returns of investing in the foreign currency n and the domestic currency:

$$R^e_{n,t+1} \equiv \frac{S_{n,t+1}}{S_{n,t}}(1+i^*_{n,t+1}) - (1+i_{t+1}). \tag{31}$$

In comparison to R, it turns out that R^e represents a more conventional excess return (difference of two returns). Yet, as shown in Appendix C, the pricing implications are the same for both R and R^e.

It follows that the cross-sectional covariance with $\overline{\Delta s}_n$ is

$$\mathrm{Var}\left(\overline{\Delta s}_n\right) = \mathrm{Cov}\left(\overline{RP}_n, \overline{\Delta s}_n\right) + \mathrm{Cov}\left(\alpha_n, \overline{\Delta s}_n\right) - \mathrm{Cov}\left(\overline{d}_n, \overline{\Delta s}_n\right), \tag{32}$$

which leads to the following variance decomposition for $\overline{\Delta s}_n$,

$$1 = b^{cs}_{RP} + b^{cs}_{\alpha} - b^{cs}_{d}, \tag{33}$$

in which

$$b^{cs}_{RP} \equiv \frac{\mathrm{Cov}\left(\overline{RP}_n, \overline{\Delta s}_n\right)}{\mathrm{Var}\left(\overline{\Delta s}_n\right)}, \tag{34}$$

$$b^{cs}_{\alpha} \equiv \frac{\mathrm{Cov}\left(\alpha_n, \overline{\Delta s}_n\right)}{\mathrm{Var}\left(\overline{\Delta s}_n\right)}, \tag{35}$$

$$b^{cs}_{d} \equiv \frac{\mathrm{Cov}\left(\overline{d}_n, \overline{\Delta s}_n\right)}{\mathrm{Var}\left(\overline{\Delta s}_n\right)}. \tag{36}$$

The parameters in this variance decomposition are obtained from the following cross-sectional regressions:

$$\overline{RP}_n = a^{cs}_{RP} + b^{cs}_{RP}\overline{\Delta s}_n + \zeta^{RP}_n, \tag{37}$$

$$\alpha_n = a^{cs}_{\alpha} + b^{cs}_{\alpha}\overline{\Delta s}_n + \zeta^{\alpha}_n, \tag{38}$$

$$\overline{d}_n = a^{cs}_{d} + b^{cs}_{d}\overline{\Delta s}_n + \zeta^{d}_n. \tag{39}$$

Essentially, the new variance decomposition breaks the total return slope (from the decomposition in the previous section) into a systematic risk premium coefficient and a mispricing coefficient:[13]

$$b_r^{cs} = b_{RP}^{cs} + b_{\alpha}^{cs}. \tag{40}$$

The objective of this analysis is to assess which of these slopes are economically and statistically significant (if any). In other words, is it dispersion in systematic risk premiums or is it dispersion in alphas that drives cross-sectional dispersion in exchange rate appreciation? The insignificant total return slope obtained in the previous section could be a consequence of those two effects cancelling out.

7.2 Results

To compute currency risk premia, we use several factor models that have been proposed in the related literature.

The first model represents a version of the CAPM of Sharpe (1964) and Lintner (1965) for the currency market,

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}), \tag{41}$$

in which RX represents the currency "market" return in U.S. Dollars for a U.S. investor, also known as the dollar factor.[14]

The second model is the two-factor model proposed by Lustig, Roussanov, and Verdelhan (2011) (hereafter denoted by LRV2),

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}) + \beta_{n,HML}\,\mathrm{E}(HML_{t+1}), \tag{42}$$

in which HML represents a zero-cost portfolio that goes long in high interest rate currencies and goes short in low interest rate currencies. In other words, HML represents a carry factor.

Next, we estimate the three-factor model of Della Corte, Riddiough, and Sarno (2016) (DCRS3),

[13] This represents an approximation since the variance decomposition presented in the previous section is valid for log returns instead of simple returns. However, untabulated results indicate that this has a negligible effect on the estimated variance decomposition.

[14] RX is similar to a "market" return in the sense that it captures co-movement between all currencies denominated in USD. It is different from the market though as it does not necessarily coincide with the portfolio held by the representative investor.

which adds a global imbalance factor (IMB) to LRV2:

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}) + \beta_{n,HML}\,\mathrm{E}(HML_{t+1}) + \beta_{n,IMB}\,\mathrm{E}(IMB_{t+1}). \tag{43}$$

IMB is the return of a factor of currencies with low net foreign wealth (e.g. high debt) and/or high level of liabilities issued in foreign currencies (e.g. Brazilian debt issued in USD). Habib and Stracca (2012) show that currencies with strong external positions tend to behave as safe havens in times of crisis while the currencies of indebted nations suffer the most in those periods. Eichengreen, Hausmann, and Panizza (2007) posit that issuing debt in foreign denominations is the 'original sin' of currency crisis. The IMB factor combines these two dimensions of global risk, resulting in a portfolio that produces bad returns in periods of turmoil in currency markets and a positive unconditional risk premium.

The fourth model is the two-factor model of Menkhoff, Sarno, Schmeling, and Schrimpf (2012) (MSSS2),

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}) + \beta_{n,VOL}\,\mathrm{E}(VOL_{t+1}), \tag{44}$$

which contains a global currency volatility factor (VOL) in addition to RX. The long (short) leg of the VOL factor consists of currencies with high (low) co-movement with volatility in FX markets. Hence, the volatility factor produces high returns when volatility increases. As investors dislike volatility in currency markets, the factor provides a hedge against bad times, implying its unconditional risk premium is negative.

Next, we estimate the following three-factor model (denotes as LRV2+HMLV),

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}) + \beta_{n,HML}\,\mathrm{E}(HML_{t+1}) + \beta_{n,HMLV}\,\mathrm{E}(HMLV_{t+1}), \tag{45}$$

which adds the currency value factor ($HMLV$) of Menkhoff, Sarno, Schmeling, and Schrimpf (2017) to the LRV2 model.

Finally, we estimate the following three-factor model (LRV2+MOM),

$$\mathrm{E}(R_{n,t+1}) = \beta_{n,RX}\,\mathrm{E}(RX_{t+1}) + \beta_{n,HML}\,\mathrm{E}(HML_{t+1}) + \beta_{n,MOM}\,\mathrm{E}(MOM_{t+1}), \tag{46}$$

which augments LRV2 by the currency momentum factor (MOM) of Menkhoff, Sarno, Schmeling, and Schrimpf (2012). We include momentum and value as factors in our study given the extensive evidence documenting its pervasive premiums in currencies and other asset classes (Kroencke, Schindler, and Schrimpf (2013), Barroso and Santa-Clara (2015), Asness, Moskowitz, and Pedersen (2013), among others). In all six models, the factor risk prices are equal to the corresponding factor means since all of these factors are traded (see, for example, Cochrane (2005) and Lewellen, Nagel, and Shanken (2010)).

The data on both RX and HML are obtained from the webpage of Adrien Verdelhan. The data on IMB and VOL are obtained from Lucio Sarno. The returns for value and momentum factors are obtained from Barroso, Kho, Rouxelin, and Yang (2018). These consist of returns of high-minus-low quintiles of a set of 15 developed currencies sorted according to value (5-year change in the real exchange rate) and (3-month return) momentum. We refer to that paper for details of the data construction. Where possible, the factors are constructed from developed markets to be consistent with the set of currencies used in our tests. The sample employed in the section is 1985:01 to 2014:06 in which the ending date is defined by the data availability on some of the factors.

Table 5 presents summary statistics for the six currency factors presented above. The factor with the largest mean return (in magnitude) is HML (0.45% per month) followed by both IMB and $HMLV$ (average returns above 0.30%). At the other extreme, VOL has the lowest average return (0.10% in absolute value). HML, $HMLV$, and MOM are the most volatile factors as indicated by the monthly volatilities close to 3%. At the other end of the spectrum, the volatility factor shows the smallest volatility by a good margin (0.35%). Most factors are close to be serially uncorrelated as indicated by the autocorrelation coefficients around or below 10% in magnitude. The highest persistence occurs for VOL with an autocorrelation of 0.25.

The contemporaneous correlations among the six factors are displayed in Table 6. We can see that the volatility factor is negatively correlated with RX, HML, and IMB as indicated by the correlations ranging between -0.30 (RX) and -0.68 (HML). Moreover, HML and IMB show a significant positive correlation (0.66). The strong correlations of HML with both IMB and VOL are not surprising as these two factors are proposed as risk-based explanations for the cross section of carry portfolios in Della Corte, Riddiough, and Sarno (2016) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012), respectively. All the other correlations are substantially smaller in magnitude (below 0.20 in most cases).

The asset pricing estimation results associated with the six factor models and ten currencies are displayed in Table 7. To compute the pricing errors (alphas) associated with each testing asset (currency), we use the time-series regression approach widely used in the asset pricing literature (e.g., Fama and French (1993, 1996, 2015). In this method, the (implied) risk price estimates are equal to the factor means and the intercepts (alphas) from the time-series regressions correspond to the pricing errors. The two-step regression approach (e.g., Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), Brennan, Wang, and Xia (2004), and Cochrane (2005)) is not appropriate to estimate factor models containing only traded factors since the estimated risk prices (obtained from the second-pass cross-sectional regression) can be significantly different to the respective sample means (see Cochrane (2005), Lewellen, Nagel, and Shanken (2010), and Maio (2018)).

We can see that the pricing errors associated with all ten currencies are statistically indistinguishable from zero in most cases as indicated by the small t-ratios. Yet, there are substantial differences in the magnitudes and sign of pricing errors across currencies. Specifically, the pricing errors associated with SEK tend to assume large relatively negative values and these estimates are significant (at the 5% or 10% level) under the DCRS3, MSSS2, and LRV2+HMLV models. On the other hand, the alphas associated with JPY tend to assume relatively large positive values, and these estimates are significant under the DCRS3, MSSS2, and LRV2+HMLV models. We can also see that the pricing errors associated with NZD (EUR) under the single-factor model are positive (negative), and those estimates are statistically significant.

The results for the cross-sectional variance decomposition associated with each factor model are reported in Table 8, which is similar to Table 4. As in the last section, the cross-sectional regressions are estimated by OLS. We also compute p-values for the slope estimates, which are obtained from an alternative bootstrap simulation. This simulation differs from the one described in the last section in that we impose each factor model in the data generating process for currency returns. Hence, this simulation accounts for the additional sampling error associated with the estimated pricing errors and risk premiums for each currency. The details of this bootstrap experiment are presented in Appendix E.

The slopes in the regressions associated with $\overline{RP}_n$ have the wrong sign (negative) for most factor models. The sole exception is the single-factor model containing RX, although the positive slope estimate is insignificant at the 10% level based on the OLS t-ratio. In comparison, apart from the case of the single-factor model, the slope estimates associated with α_n have the correct sign (positive). These coefficient estimates are significant based on the OLS inference (at the 5% or 10% level) when the pricing errors are based on the DCRS3, MSSS2, and LRV2+HMLV models. Based on the bootstrap inference, the estimates for b_{α}^{cs} are significant at the 5% level in the case of those three models and at the 10% level in the cases of the RX and LRV2 models. Hence, larger risk-adjusted returns tend to be associated with a higher appreciation rate of foreign currencies in the cross-section.

In the case of DCRS3, MSSS2, and LRV2+HMLV, the explanatory ratios in the cross-sectional regressions associated with α_n are around or above 30%. This is clearly above the fit in the regression for total average returns in the last section (6%), although it still lags behind the fit of the regression associated with interest rate differentials (48%). The results for the regression corresponding to interest rate spreads are similar to those in the benchmark decomposition (over a different sample). The value of $b_{RP}^{cs} + b_{\alpha}^{cs} - b_{d}^{cs}$ is around 1.05 in all cases, which shows that the alternative variance decomposition is relatively accurate.

Therefore, these results suggest that higher cross-sectional dispersion in the appreciation rate of currencies (against the U.S. Dollar) is associated with higher (cross-sectional) correlation between exchange rate growth and currency pricing errors while cross-sectional covariance with systematic risk premiums does not seem to play a relevant role. Actually, this effect goes in the wrong direction in light of the relationship in Eq. (27), and explains why the total average currency returns do not matter for cross-sectional dispersion in currency appreciation, as shown in the last section. Still, the interest spread channel is the most important in both economic and statistical terms as indicated by the magnitudes of the slopes and R^2 in the corresponding cross-sectional regressions.

The recent literature on currency risk factors has considerably advanced our understanding of this important cross-section in the global economy. Besides unconditional risk premiums it has underpinned the co-movement of exchange rates with sources of risk such as volatility in FX markets, crashes, and macroeconomic fundamentals such as external imbalances. Yet, our results in this section show this advancement is not paralleled by a similar advance in understanding the long-run determinants of currency appreciation. The same factors that explain well the cross-section of expected currency returns do not seem to tell us much on expected long-run currency appreciations.

8 Conclusion

We derive and estimate a variance decomposition for the nominal spot exchange rate based on a present-value relation in both the time-series and cross-sectional dimensions. In the time-series, variation in the current spot exchange rate results from variation in future currency returns, future interest rate differentials, and/or the spot exchange rate at some terminal date. Specifically, the current log exchange rate is positively correlated with future multiperiod log interest rate spreads and the exchange rate at some terminal date, and negatively correlated with future multiperiod log currency returns.

By using this present-value relation, we define a variance decomposition for the log exchange rate where the slopes obtained from weighted long-horizon regressions represent the fraction of the variance of the current exchange rate attributable to interest spread, return, and future exchange rate predictability. We estimate a term-structure of variance decompositions in order to account for the different predictability patterns at short, intermediate, and long forecasting horizons. We use ten currencies in the analysis—Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR)—spanning the period from 1985:01 to 2015:06. Our results can be summarized as follows. First, what drives the variation in the nominal exchange rate at long horizons is currency return predictability. Second, at short horizons, there is mainly predictability about the future exchange rates itself, consistent with their large persistence. Third, predictability about future interest rate differentials plays a rather marginal role in driving the current exchange rate and this pattern is especially true at intermediate and long horizons.

Following Cochrane (2008), we estimate an alternative time-series variance decomposition for the log exchange rate based on a first-order VAR. Under this approach the coefficients for future returns, interest rate spreads, and exchange rate at multiple horizons are mechanically related with the one-period corresponding slopes. The results indicate that the VAR-based framework leads to qualitatively similar results than the long-horizon regressions, which means that the VAR does represent a valid approximation to the predictability relation at multiple horizons. However, there is a larger amount of interest spread predictability at long horizons in comparison to the direct approach. Similarly, there is more exchange rate predictability at both short and middle horizons under the VAR approach compared to the long-horizon regressions.

A major innovation of this paper is that we also explore the cross-sectional dimension of currencies by deriving and estimating a cross-sectional variance decomposition for the log growth in exchange rates. We decompose the cross-sectional dispersion in the appreciation rate of foreign currencies into cross-sectional return predictability and cross-sectional interest spread predictability. By estimating OLS cross-sectional regressions we find that cross-sectional predictability of average interest rate spreads drives the cross-sectional dispersion in the average rate of appreciation of foreign currencies, while there seems to exist no significant role for cross-sectional return predictability. Further, currencies with a higher rate of appreciation against the U.S. Dollar tend to be those currencies showing lower interest rate spreads relative to the median currency. These results are in contrast with the currency-specific variance decompositions in the time-series dimensions discussed above.

In the last part of the paper, we compute an alternative cross-sectional variance decomposition for the growth in exchange rates by splitting the currency return into a systematic (risk premium) component and an idiosyncratic (pricing error) component. To compute the risk premiums and pricing errors (alphas) associated with each currency, we use the time-series regression approach widely used in the asset pricing literature. We employ six alternative factor models of currency returns that have been proposed in the literature. The results from cross-sectional regressions suggest that higher cross-sectional dispersion in the appreciation rate of currencies (against the U.S. Dollar) is associated with higher (cross-sectional) correlation between exchange rate growth and currency pricing errors while cross-sectional covariance with systematic risk premiums does not seem to play a relevant role.

References

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

Asness, C.S., T.J. Moskowitz, and L.H. Pedersen, 2013, Value and momentum everywhere, Journal of Finance 68, 929–985.

Atanasov, V., and T. Nitschka, 2015, Foreign currency returns and systematic risks, Journal of Financial and Quantitative Analysis 50, 231–250.

Bacchetta, P., and E. Van Wincoop, 2006, Can information heterogeneity explain the exchange rate determination puzzle? American Economic Review 96, 552–576.

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

Balduzzi, P., and I.E. Chiang, 2017, Real exchange rates and currency risk premia, Working paper, Boston College.

Barroso, P., F. Kho, F. Rouxelin, and L. Yang, 2018, Do external imbalances matter in explaining the cross-section of currency excess returns? Working paper, University of New south Wales.

Barroso, P., and P. Santa-Clara, 2015, Beyond the carry trade: Optimal currency portfolios, Journal of Financial and Quantitative Analysis 50, 1037–1056.

Bilson, J., 1981, Speculative efficiency, Journal of Business 54, 435–451.

Black, F., M.C. Jensen, and M. Scholes, 1972, The capital asset pricing model: Some empirical tests, in M.C. Jensen, ed.: Studies in the Theory of Capital Markets (Praeger, New York).

Boudoukh, J., M. Richardson, and R. Whitelaw, 2008, The myth of long-horizon predictability, Review of Financial Studies 21, 1577–1605.

Boudoukh, J., M. Richardson, and R. Whitelaw, 2016, New evidence on the forward premium puzzle, Journal of Financial and Quantitative Analysis 51, 875–897.

Brennan, M.J., A.W. Wang, and Y. Xia, 2004, Estimation and test of a simple model of intertemporal capital asset pricing, Journal of Finance 59, 1743–1775.

Brunnermeier, M., S. Nagel, and L. Pedersen, 2009, Carry trades and currency crashes, NBER Macroeconomics Annual 23, 313–347.

Burnside, C., 2012, Carry trades and risk in Handbook of Exchange Rates, 283-312.

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

Campbell, J.Y., and R.H. Clarida, 1987, The Dollar and real interest rates, Carnegie-Rochester Conference Series on Public Policy 27, 103–140.

Campbell, J., and R. Shiller, 1988, The dividend price ratio and expectations of future dividends and discount factors, Review of Financial Studies 1, 195–228.

Chen, L., Z. Da, and R. Priestley, 2012, Dividend smoothing and predictability, Management Science 58, 1834–1853.

Chen, Y., and K. Tsang, 2013, What does the yield curve tell us about exchange rate predictability, Review of Economics and Statistics 95, 185–205.

Christiansen, C., A. Ranaldo, and P. Söderlind, 2011, The time-varying systematic risk of carry trade strategies, Journal of Financial and Quantitative Analysis 46, 1107–1125.

Clarida, R., L. Sarno, M. Taylor, and G. Valente, 2003, The out-of-sample success of term structure models as exchange rate predictors: A step beyond, Journal of International Economics 60, 61–83.

Clarida, R., and M. Taylor, 1997, The term structure of forward exchange premiums and the forecastability of spot exchange rates: Correcting the errors, Review of Economics and Statistics 79, 353–361.

Cochrane, J.H., 2005, Asset Pricing, Princeton University Press, Princeton, NJ.

Cochrane, J.H., 2008, The dog that did not bark: A defense of return predictability, Review of Financial Studies 21, 1533–1575.

Cochrane, J.H., 2011, Presidential address: Discount rates, Journal of Finance 66, 1047–1108.

Cohen, R., C. Polk, and T. Vuolteenaho, 2003, The value spread, Journal of Finance 58, 609–641.

Daniel, K., R. Hodrick, and Z. Lu, 2017, The carry trade: Risks and drawdowns, Critical Finance Review 6, 211–262.

Della Corte, P., T. Ramadorai, and L. Sarno, 2016, Volatility risk premia and exchange rate predictability, Journal of Financial Economics 120, 21–40.

Della Corte, P., S. Riddiough, and L. Sarno, 2016, Currency premia and global imbalances, Review of Financial Studies 29, 2161–2193.

Della Corte, P., L. Sarno, and I. Tsiakas, 2009, An economic evaluation of empirical exchange rate models, Review of Financial Studies 22, 3491–3530.

Della Corte, P., L. Sarno, and I. Tsiakas, 2011, Spot and forward volatility in foreign exchange, Journal of Financial Economics 100, 496–513.

Diez de los Rios, A., 2009, Can affine term structure models help us predict exchange rates? Journal of Money, Credit and Banking 41, 755–766.

Dobrynskaya, V., 2014, Downside market risk of carry trades, Review of Finance 18, 1885–1913.

Eichengreen, B., R. Hausmann, and U. Panizza, 2007, Currency mismatches, debt intolerance, and the original sin: Why they are not the same and why it matters, in Capital controls and capital flows in emerging economies: Policies, practices and consequences, 121–170 (University of Chicago Press, Chicago).

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

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

Engel, C., N. Mark, and K. West, 2007, Exchange rate models are not as bad as you think, NBER Macroeconomics Annual 22, 381–441.

Engel, C., and K. West, 2005, Exchange rates and fundamentals, Journal of Political Economy 113, 485–517.

Fama, E.F., 1984, Forward and spot exchange rates, Journal of Monetary Economics 14, 319–338.

Fama, E.F., and K.R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3–56.

Fama, E.F., and K.R. French, 1996, Multifactor explanations of asset pricing anomalies, Journal of Finance 51, 55–84.

Fama, E.F., and K.R. French, 2015, A five-factor asset pricing model, Journal of Financial Economics 116, 1–22.

Fama, E., and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 81, 607–636.

Filipe, S.F., and M. Suominen, 2014, Currency carry trades and funding risk, Working paper, Luxembourg School of Finance.

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

Froot, K., and T. Ramadorai, 2005, Currency returns, intrinsic value, and institutional-investor flows, Journal of Finance 60, 1535–1566.

Gabaix, X., and M. Maggiori, 2015, International liquidity and exchange rate dynamics, Quarterly Journal of Economics 130, 1369–1420.

Galati, G., A. Heath, and P. McGuire, 2007, Evidence of carry trade activity, BIS Quarterly Review.

Groen, J., 2005, Exchange rate predictability and monetary fundamentals in a small multicountry panel, Journal of Money, Credit and Banking 37, 495–516.

Habib, M.M., and L. Stracca, 2012, Getting beyond carry trade: What makes a safe haven currency? Journal of International Economics 87, 50–64.

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

Hodrick, R., 1987, The empirical evidence on the efficiency of forward and futures foreign exchange markets, London: Harwood Academic Publishers.

Jordà, O., and A.M. Taylor, 2012, The carry trade and fundamentals: nothing to fear but FEER itself, Journal of International Economics 88, 74–90.

Jurek, J., 2014, Crash-neutral currency carry trades, Journal of Financial Economics 113, 325–347.

Kilian, L., 1999, Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? Journal of Applied Econometrics 14, 491–510.

Kroencke, T.A., F. Schindler, and A. Schrimpf, 2013, International diversification benefits with foreign exchange investment styles, Review of Finance 18, 1847–1883.

Larrain, B., and M. Yogo, 2008, Does firm value move too much to be justified by subsequent changes in cash flow? Journal of Financial Economics 87, 200–226.

Lettau, M., M. Maggiori, and M. Weber, 2014, Conditional risk premia in currency markets and other asset classes, Journal of Financial Economics 114, 197–225.

Lewellen, J., S. Nagel, and J. Shanken, 2010, A skeptical appraisal of asset-pricing tests, Journal of Financial Economics 96, 175–194.

Lintner, J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics 47, 13–37.

Lustig, H., N. Roussanov, and A. Verdelhan, 2011, Common risk factors in currency markets, Review of Financials Studies 24, 3731–3777.

Lustig, H., A. Stathopoulos, and A. Verdelhan, 2018, The term structure of currency carry trade risk premia, Working paper, Stanford Graduate School of Business.

Lustig, H., and A. Verdelhan, 2007, The cross-section of foreign currency risk premia and consumption growth risk, American Economic Review 97, 89-117.

Lustig, H., and A. Verdelhan, 2011, The cross-section of foreign currency risk premia and consumption growth risk: A reply, American Economic Review 101, 3477–3500.

Maio, P., 2018, Comparing asset pricing models with traded and macro risk factors, Working paper, Hanken School of Economics.

Maio, P., and P. Santa-Clara, 2015, Dividend yields, dividend growth, and return predictability in the cross-section of stocks, Journal of Financial and Quantitative Analysis 50, 33–60.

Maio, P., and D. Xu, 2018, Cash-flow or return predictability at long horizons? The case of earnings yield, Working paper, Hanken School of Economics.

Mark, N., 1995, Exchange rates and fundamentals: evidence on long-horizon predictability, American Economic Review 85, 201–218.

Mark, N., and D. Sul, 2001, Nominal exchange rates and monetary fundamentals: Evidence from a small post-Bretton woods panel, Journal of International Economics 53, 29–52.

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

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf, 2012, Carry trades and global foreign exchange volatility, Journal of Finance 67, 681–718.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf, 2017, Currency value, Review of Financials Studies 30, 416–441.

Newey, W., and K. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica 55, 703–708.

Rapach, D., and M. Wohar, 2002, Testing the monetary model of exchange rate determination: New evidence from a century of data, Journal of International Economics 58, 359–385.

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

Sarno, L., 2005, Viewpoint: Towards a solution to the puzzles in exchange rate economics: Where do we stand? Canadian Journal of Economics 38, 673-708.

Sarno, L., and M. Schmeling, 2014, Which Fundamentals Drive Exchange Rates? A Cross-Sectional Perspective, Journal of Money, Credit and Banking 46, 267–292.

Sarno, L., and E. Sojli, 2009, The feeble link between exchange rates and fundamentals: Can we blame the discount factor? Journal of Money, Credit and Banking 41, 437–442.

Sharpe, W.F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance 19, 425–442.

Torous, W., R. Valkanov, and S. Yan, 2004, On predicting stock returns with nearly integrated explanatory variables, Journal of Business 77, 937–966.

Valkanov, R., 2003, Long-horizon regressions: Theoretical results and applications, Journal of Financial Economics 68, 201–232.

A Derivation of the variance decomposition for s

By multiplying both sides of the present-value relation in equation (3) by $s_t - \mathrm{E}(s_t)$, and taking unconditional expectations, we obtain the following variance decomposition for s_t,

$$\mathrm{Var}(s_t) = \mathrm{Cov}\left(\sum_{j=1}^{K} d_{t+j}, s_t\right) - \mathrm{Cov}\left(\sum_{j=1}^{K} r_{t+j}, s_t\right) + \mathrm{Cov}\left(s_{t+K}, s_t\right), \tag{A.1}$$

and by dividing both sides by $\mathrm{Var}(s_t)$, we have,

$$1 = \beta\left(\sum_{j=1}^{K} d_{t+j}, s_t\right) - \beta\left(\sum_{j=1}^{K} r_{t+j}, s_t\right) + \beta\left(s_{t+K}, s_t\right) \Leftrightarrow \tag{A.2}$$

$$1 = b_d^K - b_r^K + b_s^K, \tag{A.3}$$

where $\beta(y, x)$ denotes the slope from a regression of y on x. This expression represents the variance decomposition for s when the predictive slopes are obtained directly from long-horizon regressions. The variance decomposition associated with the real log exchange rate is obtained in a similar way.

B Derivation of the VAR-based variance decomposition for s

Consider the equation derived above,

$$1 = \beta\left(\sum_{j=1}^{K} d_{t+j}, s_t\right) - \beta\left(\sum_{j=1}^{K} r_{t+j}, s_t\right) + \beta\left(s_{t+K}, s_t\right), \tag{B.4}$$

and by using the property of regression coefficients, $\beta(y + z, x) = \beta(y, x) + \beta(z, x)$, we have:

$$1 = \sum_{j=1}^{K} \beta(d_{t+j}, s_t) - \sum_{j=1}^{K} \beta(r_{t+j}, s_t) + \beta(s_{t+K}, s_t). \tag{B.5}$$

Under the first-order VAR, we have,

$$s_t = \phi^{1-j} s_{t+j-1} - \sum_{l=1}^{j-1} \phi^{-l}(a_s + \varepsilon_{t+l}^s), \tag{B.6}$$

and by combining with the VAR equation for currency returns,

$$r_{t+j} = a_r + b_r s_{t+j-1} + \varepsilon^r_{t+j}, \tag{B.7}$$

implies the following equation for r_{t+j}:

$$r_{t+j} = a_r + \phi^{j-1} b_r s_t + \phi^{j-1} b_r \sum_{l=1}^{j-1} \phi^{-l}(a_s + \varepsilon^s_{t+l}) + \varepsilon^r_{t+j}. \tag{B.8}$$

Since $\mathrm{Cov}(\varepsilon^s_{t+l}, s_t) = 0, l > 0$ and $\mathrm{Cov}(\varepsilon^r_{t+j}, s_t) = 0$, by construction, it follows that

$$\beta(r_{t+j}, s_t) = \phi^{j-1} b_r. \tag{B.9}$$

Similarly, we have,

$$\beta(d_{t+j}, s_t) = \phi^{j-1} b_d. \tag{B.10}$$

On the other hand, given the expanded expression for s_{t+K},

$$s_{t+K} = \phi^K s_t + \phi^K \sum_{l=1}^{j-1} \phi^{-l}(a_s + \varepsilon^s_{t+l}), \tag{B.11}$$

we have

$$\beta(s_{t+K}, s_t) = \phi^K, \tag{B.12}$$

which leads to

$$1 = \sum_{j=1}^{K} \phi^{j-1} b_d - \sum_{j=1}^{K} \phi^{j-1} b_r + \phi^K. \tag{B.13}$$

By simplifying the sums above, we obtain the VAR-based variance decomposition associated with s:

$$\begin{aligned} 1 &= b_d^K - b_r^K + b_s^K, \\ b_d^K &\equiv \frac{b_d(1-\phi^K)}{1-\phi}, \\ b_r^K &\equiv \frac{b_r(1-\phi^K)}{1-\phi}, \\ b_s^K &\equiv \phi^K. \end{aligned} \tag{B.14}$$

To compute the t-statistics for the predictive coefficients, $\mathbf{b}^K \equiv \left(b_d^K, b_r^K, b_s^K\right)'$, we use the Delta method. From the t-statistics associated with the VAR slopes, $\mathbf{b} \equiv (b_d, b_r, \phi)'$, we have:

$$\mathrm{Var}\left(\mathbf{b}^K\right) = \frac{\partial \mathbf{b}^K}{\partial \mathbf{b}'} \mathrm{Var}\left(\mathbf{b}\right) \frac{\partial \mathbf{b}^K}{\partial \mathbf{b}}. \tag{B.15}$$

The matrix of derivatives is given by

$$\frac{\partial \mathbf{b}^K}{\partial \mathbf{b}'} \equiv \begin{bmatrix} \frac{\partial b_d^K}{\partial b_d} & \frac{\partial b_d^K}{\partial b_r} & \frac{\partial b_d^K}{\partial \phi} \\ \frac{\partial b_r^K}{\partial b_d} & \frac{\partial b_r^K}{\partial b_r} & \frac{\partial b_r^K}{\partial \phi} \\ \frac{\partial b_s^K}{\partial b_d} & \frac{\partial b_s^K}{\partial b_r} & \frac{\partial b_s^K}{\partial \phi} \end{bmatrix} = \begin{bmatrix} \frac{1-\phi^K}{1-\phi} & 0 & \frac{-K b_d \phi^{K-1}(1-\phi)+b_d(1-\phi^K)}{(1-\phi)^2} \\ 0 & \frac{1-\phi^K}{1-\phi} & \frac{-K b_r \phi^{K-1}(1-\phi)+b_r(1-\phi^K)}{(1-\phi)^2} \\ 0 & 0 & K\phi^{K-1} \end{bmatrix}. \tag{B.16}$$

C Asset pricing equation

Consider the following SDF equation for a given foreign currency (here, we omit the subscript n to simplify notation):

$$0 = \mathrm{E}_t \left\{ M_{t+1} \left[\frac{S_{t+1}}{S_t}(1 + i_{t+1}^*) - (1 + i_{t+1}) \right] \right\}. \tag{C.17}$$

By multiplying and dividing the right hand side of the previous equation by $1 + i_{t+1}$ and given that i_{t+1} is known at time t and using the linearity of conditional expectations, it follows that

$$0 = \mathrm{E}_t \left\{ M_{t+1} \left[\frac{\frac{S_{t+1}}{S_t}(1 + i_{t+1}^*)}{1 + i_{t+1}} - 1 \right] \right\} = \mathrm{E}_t(M_{t+1} R_{t+1}), \tag{C.18}$$

where R is the currency return defined in the paper.

By using the law of iterated expectations, we have the unconditional pricing equation:

$$0 = \mathrm{E}(M_{t+1} R_{t+1}). \tag{C.19}$$

By expanding the second moment in the previous equation, we obtain the usual unconditional expected return-covariance representation:

$$\mathrm{E}(R_{t+1}) = -\frac{\mathrm{Cov}(R_{t+1}, M_{t+1})}{\mathrm{E}(M_{t+1})}. \tag{C.20}$$

Next, we assume that the SDF is affine in J risk factors:

$$M_{t+1} = 1 + \mathbf{f}'_{t+1}\boldsymbol{\theta} = 1 + \sum_{j=1}^{J} \theta_j f_{j,t+1}. \tag{C.21}$$

By substituting back in the covariance equation, we have

$$\mathrm{E}(R_{t+1}) = -\frac{\mathrm{Cov}(R_{t+1}, \mathbf{f}'_{t+1})\boldsymbol{\theta}}{\mathrm{E}(M_{t+1})}. \tag{C.22}$$

By multiplying by $\mathrm{Var}(\mathbf{f}_{t+1})$ and its inverse, we obtain the expected return-beta representation of the model,

$$\begin{aligned} \mathrm{E}(R_{t+1}) &= -\frac{\mathrm{Cov}(R_{t+1}, \mathbf{f}'_{t+1})\,\mathrm{Var}(\mathbf{f}_{t+1})^{-1}\,\mathrm{Var}(\mathbf{f}_{t+1})\boldsymbol{\theta}}{\mathrm{E}(M_{t+1})}, \\ &= \boldsymbol{\beta}(R_{t+1}, \mathbf{f}'_{t+1})\boldsymbol{\lambda}, \end{aligned} \tag{C.23}$$

in which $\boldsymbol{\beta}(R_{t+1}, \mathbf{f}'_{t+1})$ is the vector of factor betas and $\boldsymbol{\lambda} \equiv -\frac{\mathrm{Var}(\mathbf{f}_{t+1})\boldsymbol{\theta}}{\mathrm{E}(M_{t+1})}$ is the vector of factor risk prices. In scalar form, we have the usual beta equation:

$$\mathrm{E}(R_{t+1}) = \sum_{j=1}^{J} \beta_j \lambda_j, \tag{C.24}$$

where β_j and λ_j denote the beta and risk price for factor j, respectively.

This pricing equation applies to each factor since they represent excess returns. Given that each factor has a (multiple regression) beta of one on itself and zero against all the other factors, it follows from the last equation that the risk price for each factor equals the corresponding unconditional risk premium:

$$\mathrm{E}(f_{j,t+1}) = \lambda_j. \tag{C.25}$$

By substituting the last condition back in the beta equation, we obtain the beta representation used in the paper:

$$\mathrm{E}(R_{t+1}) = \sum_{j=1}^{J} \beta_j\, \mathrm{E}(f_{j,t+1}). \tag{C.26}$$

D Cross-sectional variation in exchange rates: Bootstrap simulation

The bootstrap algorithm associated with the benchmark cross-sectional variance decomposition contains the following steps.

1. The time-series of log currency returns, $r_{n,t}$, interest rate spreads, $d_{n,t}$, and the log growth in exchange rates, $\Delta s_{n,t}$, are saved. The variance decomposition is obtained by estimating the following OLS cross-sectional regressions on the time-series averages:

$$\begin{aligned}\overline{r}_n &= a_r^{cs} + b_r^{cs}\overline{\Delta s}_n + \zeta_n^r, \\ \overline{d}_n &= a_d^{cs} + b_d^{cs}\overline{\Delta s}_n + \zeta_n^d.\end{aligned}$$

   The estimated slopes, b_r^{cs}, b_d^{cs}, are saved.

2. In each replication $b = 1, ..., 10000$, we construct pseudo-samples of the time-series of returns, interest rate spreads, and the log growth in exchange rates for each currency (of size T) by drawing with replacement:

$$\begin{aligned}\{r_{n,t}^b, t &= m_{n,1}^b, m_{n,2}^b, ..., m_{n,T}^b\}, \\ \{d_{n,t}^b, t &= q_{n,1}^b, q_{n,2}^b, ..., q_{n,T}^b\}, \\ \{\Delta s_{n,t}^b, t &= u_{n,1}^b, u_{n,2}^b, ..., u_{n,T}^b\}, n = 1, ..., 10,\end{aligned}$$

   where all the time indices are created randomly from the original time sequence $1, ..., T$. All the pseudo time sequences presented above are mutually independent. We compute the corresponding averages.

3. For each replication, we run the OLS cross-sectional regressions with pseudo data,

$$\begin{aligned}\overline{r}_n^b &= a_r^{cs,b} + b_r^{cs,b}\overline{\Delta s}_n^b + \zeta_n^{r,b}, \\ \overline{d}_n^b &= a_d^{cs,b} + b_d^{cs,b}\overline{\Delta s}_n^b + \zeta_n^{d,b}.\end{aligned}$$

4. The empirical p-value associated with the return slope is computed as

$$p(b_r^{cs}) = \begin{cases} \left[\#\left\{b_r^{cs,b} > b_r^{cs}\right\} + \#\left\{b_r^{cs,b} < -b_r^{cs}\right\}\right]/10000, if\ b_r^{cs} \geq 0 \\ \left[\#\left\{b_r^{cs,b} < b_r^{cs}\right\} + \#\left\{b_r^{cs,b} > -b_r^{cs}\right\}\right]/10000, if\ b_r^{cs} < 0 \end{cases}.$$

and the p-value associated with b_d^{cs} is calculated in a similar way. In the above expression, $\#\left\{b_r^{cs,b} > b_r^{cs}\right\}$ denotes the number of replications in which the pseudo return slope estimate is greater than the corresponding sample estimate.

E Decomposing currency risk premia: Bootstrap simulation

The bootstrap algorithm associated with the alternative variance decomposition contains the following steps. We use the LRV2 model for illustrating purposes.

1. We estimate the time-series regressions to obtain the factor risk premiums and alphas for currency n,

$$R_{n,t} = \alpha_n + \beta_{n,RX} RX_t + \beta_{n,HML} HML_t + \varepsilon_{n,t},$$

with

$$\overline{RP}_n = \beta_{n,RX}\,\mathrm{E}(RX_t) + \beta_{n,HML}\,\mathrm{E}(HML_t).$$

The estimates of α_n, $\beta_{n,RX}$, and $\beta_{n,HML}$ are saved. The fitted residuals, $\varepsilon_{n,t}$, as well as the time-series of RX_t, HML_t, and the log growth in exchange rates, $\Delta s_{n,t}$, are also saved. In a second step, the variance decomposition is obtained by estimating the following OLS cross-sectional regressions:

$$\begin{aligned} \overline{RP}_n &= a_{RP}^{cs} + b_{RP}^{cs}\overline{\Delta s}_n + \zeta_n^{RP}, \\ \alpha_n &= a_{\alpha}^{cs} + b_{\alpha}^{cs}\overline{\Delta s}_n + \zeta_n^{\alpha}. \end{aligned}$$

The estimated slopes, $b_{RP}^{cs}, b_{\alpha}^{cs}$, are saved.

2. In each replication $b = 1, ..., 10000$, we construct a pseudo-sample of the time-series residuals

for each currency (of size T) by drawing with replacement:

$$\{\varepsilon^b_{n,t}, t = m^b_{n,1}, m^b_{n,2}, ..., m^b_{n,T}\}, n = 1, ..., 10,$$

where the time indices $m^b_{n,1}, m^b_{n,2}, ..., m^b_{n,T}$ are created randomly from the original time sequence $1, ..., T$. For each replication $b = 1, ..., 10000$, we construct independent pseudo-sample of the risk factors,

$$\begin{aligned} \{RX^b_t, t &= o^b_1, o^b_2, ..., o^b_T\}, \\ \{HML^b_t, t &= q^b_1, q^b_2, ..., q^b_T\}. \end{aligned}$$

For each replication, we also construct pseudo series for the log growth in exchange rates:

$$\{\Delta s^b_{n,t}, t = u^b_{n,1}, u^b_{n,2}, ..., u^b_{n,T}\}, n = 1, ..., 10,$$

and compute the corresponding average, $\overline{\Delta s}^b_{n,t}$. All the pseudo time sequences presented above are mutually independent.

3. For each replication, the pseudo asset excess returns are constructed by imposing the factor model on the artificial data, but using the sample parameter estimates:

$$R^b_{n,t} = \alpha_n + \beta_{n,RX} RX^b_t + \beta_{n,HML} HML^b_t + \varepsilon^b_{n,t}.$$

4. In each replication, we estimate the factor model, but using the artificial data rather than the original data. The time-series regressions are given by

$$R^b_{n,t} = \alpha^b_n + \beta^b_{n,RX} RX^b_t + \beta^b_{n,HML} HML^b_t + \nu^b_{n,t},$$

with the pseudo currency risk premium equal to

$$\overline{RP}^b_n = \beta^b_{n,RX}\, \mathrm{E}(RX^b_t) + \beta^b_{n,HML}\, \mathrm{E}(HML^b_t).$$

The OLS cross-sectional regressions with pseudo data are as follows

$$\begin{aligned}\overline{RP}_n^b &= a_{RP}^{cs,b} + b_{RP}^{cs,b}\overline{\Delta s}_n^b + \zeta_n^{RP,b}, \\ \alpha_n^b &= a_{\alpha}^{cs,b} + b_{\alpha}^{cs,b}\overline{\Delta s}_n^b + \zeta_n^{\alpha,b}.\end{aligned}$$

5. The empirical p-value associated with the risk premium and pricing error slopes are computed in the same way as in the benchmark bootstrap simulation above.

Table 1: Descriptive statistics

This table reports descriptive statistics for the log currency return (r), log interest rate differential (d), and log exchange rate (s). The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). ϕ designates the first-order autocorrelation coefficient. The columns labeled r–s represent the correlation matrix of the three variables. The sample is 1985:01–2015:06.

	Mean	Stdev.	Min.	Max.	ϕ	r	d	s
				Panel A (CAD)				
r	0.0008	0.0213	−0.1359	0.0807	−0.060	1.00	0.11	0.08
d	0.0007	0.0013	−0.0022	0.0048	0.924		1.00	0.12
s	−0.2231	0.1371	−0.4728	0.0525	0.988			1.00
				Panel B (CHF)				
r	0.0015	0.0342	−0.1198	0.1300	−0.005	1.00	0.11	0.03
d	−0.0013	0.0018	−0.0047	0.0048	0.956		1.00	0.25
s	−0.2742	0.2275	−1.0496	0.2380	0.978			1.00
				Panel C (GBP)				
r	0.0024	0.0294	−0.1260	0.1405	0.070	1.00	0.12	0.10
d	0.0016	0.0017	−0.0027	0.0061	0.954		1.00	0.10
s	0.4900	0.0986	0.0770	0.7311	0.937			1.00
				Panel D (JPY)				
r	−0.0001	0.0327	−0.1108	0.1510	0.050	1.00	0.11	−0.03
d	−0.0020	0.0019	−0.0061	0.0017	0.962		1.00	0.10
s	−4.7538	0.2166	−5.5596	−4.3340	0.971			1.00
				Panel E (SEK)				
r	0.0015	0.0325	−0.1538	0.0913	0.104	1.00	0.03	0.13
d	0.0013	0.0030	−0.0029	0.0363	0.744		1.00	0.31
s	−1.9829	0.1487	−2.3874	−1.6380	0.974			1.00
				Panel F (DKK)				
r	0.0021	0.0316	−0.1086	0.0938	0.034	1.00	0.12	0.01
d	0.0006	0.0024	−0.0103	0.0142	0.761		1.00	−0.04
s	−1.8584	0.1628	−2.4822	−1.5489	0.965			1.00
				Panel G (NOK)				
r	0.0022	0.0325	−0.1279	0.0757	0.014	1.00	0.10	0.09
d	0.0018	0.0025	−0.0110	0.0194	0.760		1.00	−0.09
s	−1.9108	0.1343	−2.2581	−1.6257	0.966			1.00
				Panel H (AUD)				
r	0.0025	0.0348	−0.1800	0.0914	0.066	1.00	0.04	0.12
d	0.0027	0.0037	−0.0103	0.0168	0.366		1.00	0.15
s	−0.2892	0.1722	−0.7169	0.0939	0.979			1.00
				Panel I (NZD)				
r	0.0047	0.0363	−0.1381	0.1286	0.008	1.00	0.13	0.08
d	0.0037	0.0047	−0.0105	0.0296	0.482		1.00	−0.04
s	−0.4813	0.1842	−0.9242	−0.1329	0.978			1.00
				Panel J (EUR)				
r	0.0013	0.0319	−0.1082	0.0915	0.033	1.00	0.05	0.01
d	−0.0003	0.0019	−0.0038	0.0055	0.964		1.00	0.28
s	0.1522	0.1705	−0.5373	0.4603	0.964			1.00

Table 2: VAR estimates

This table reports the one-month restricted VAR estimation results. The variables in the VAR are the log currency return (r), log interest rate differential (d), and log exchange rate (s). $b(\phi)$ denote the VAR slopes associated with lagged s, while t denotes the respective Newey and West (1987) t-statistics (calculated with one lag). $R^2(\%)$ is the coefficient of determination for each equation in the VAR, in %. b^{lr} denote the long-run coefficients (infinite horizon). $t(b_r^{lr} = 0)$ and $t(b_r^{lr} = -1)$ denote the t-statistics associated with the null hypotheses $H_0 : b_r^{lr} = 0, b_d^{lr} = 1$ and $H_0 : b_r^{lr} = -1, b_d^{lr} = 0$, respectively. The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). The sample is 1985:01–2015:06. Italic, underlined, and bold numbers denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$b(\phi)$	t	$R^2(\%)$	b^{lr}	$t(b_r^{lr} = 0)$	$t(b_r^{lr} = -1)$
			Panel A (CAD)			
r	−0.011	−1.39	0.51	−0.91	**−12.13**	1.20
d	0.001	<u>2.25</u>	1.38	0.09	**−12.13**	1.20
s	0.988	**124.43**	97.62			
			Panel B (CHF)			
r	−0.020	<u>−2.54</u>	1.72	−0.91	**−25.85**	<u>2.41</u>
d	0.002	**5.79**	5.31	0.09	**−25.85**	<u>2.41</u>
s	0.978	**126.30**	97.74			
			Panel C (GBP)			
r	−0.061	**−3.28**	4.24	−0.98	**−39.58**	0.89
d	0.001	0.95	0.64	0.02	**−39.58**	0.89
s	0.937	**50.65**	91.27			
			Panel D (JPY)			
r	−0.029	**−3.60**	3.56	−0.97	**−50.86**	1.45
d	0.001	*1.69*	0.91	0.03	**−50.86**	1.45
s	0.971	**123.94**	97.74			
			Panel E (SEK)			
r	−0.019	−1.54	0.79	−0.75	**−5.86**	*1.95*
d	0.006	**3.41**	10.41	0.25	**−5.86**	*1.95*
s	0.974	**75.28**	95.23			
			Panel F (DKK)			
r	−0.036	**−3.51**	3.36	−1.02	**−58.92**	−0.95
d	−0.001	−0.98	0.16	−0.02	**−58.92**	−0.95
s	0.965	**95.55**	96.29			
			Panel G (NOK)			
r	−0.036	**−2.81**	2.22	−1.05	**−29.48**	−1.41
d	−0.002	−1.61	0.85	−0.05	**−29.48**	−1.41
s	0.966	**75.80**	94.24			
			Panel H (AUD)			
r	−0.017	−1.64	0.74	−0.83	**−8.78**	*1.75*
d	0.003	**3.68**	2.64	0.17	**−8.78**	*1.75*
s	0.979	**92.95**	95.94			
			Panel I (NZD)			
r	−0.023	<u>−2.11</u>	1.35	−1.05	**−15.21**	−0.72
d	−0.001	−0.72	0.18	−0.05	**−15.21**	−0.72
s	0.978	**93.19**	**96.19**			
			Panel J (EUR)			
r	−0.033	**−3.45**	3.17	−0.92	**−37.40**	**3.32**
d	0.003	**5.60**	7.09	0.08	**−37.40**	**3.32**
s	0.964	**99.20**	96.51			

Table 3: Monte-Carlo simulation

This table reports the simulated p-values for the VAR-based return (b_r^K) (Panel A) and interest spread (b_d^K) (Panel B) slopes at several forecasting horizons. These are obtained from two Monte-Carlo simulations (with 10,000 replications each) under the nulls of no return and no interest spread predictability in Panels A and B, respectively. The predictive variable is the nominal log exchange rate. The numbers indicate the fraction of pseudo samples under which the return (interest) coefficient is lower (higher) than the corresponding estimates from the original sample. K represents the forecasting horizon (in months). The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR).

K	CAD	CHF	GBP	JPY	SEK	DKK	NOK	AUD	NZD	EUR
					Panel A (b_r^K)					
40	0.39	0.15	0.00	0.02	0.11	0.00	0.00	0.13	0.05	0.00
80	0.29	0.03	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00
120	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
					Panel B (b_d^K)					
40	0.01	0.01	0.14	0.11	0.00	0.59	0.95	0.01	0.79	0.00
80	0.01	0.01	0.15	0.11	0.00	0.60	0.96	0.00	0.81	0.00
120	0.01	0.02	0.15	0.12	0.00	0.60	0.96	0.00	0.81	0.01

Table 4: Cross-sectional regressions: benchmark decomposition

This table reports the results for cross-sectional regressions of average currency returns ($\overline{r}_i$) and average interest rate differentials ($\overline{d}_i$) onto the average log growth in exchange rates. a^{cs} and b^{cs} denote the intercept and slope estimates from the cross-sectional regression, respectively. t denote the respective OLS t-statistics (in parentheses) and R^2 is the coefficient of determination. p represent the empirical p-values (in brackets) for the slope estimates, which are obtained from a bootstrap simulation. The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). The sample is 1985:01–2015:06.

	a^{cs}	t	b^{cs}	t	p	R^2	$b_r^{cs} - b_d^{cs}$
$\overline{r}_i$	0.00	(3.34)	−0.36	(−0.71)	[0.37]	0.06	1.00
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	

Table 5: Descriptive statistics for currency factors

This table reports descriptive statistics for the currency factors. RX, HML, IMB, VOL, $HMLV$, and MOM denote the dollar, carry, imbalances, volatility, value, and momentum factors, respectively. ϕ designates the first-order autocorrelation coefficient. The sample is 1985:01–2014:06.

	Mean(%)	St.dev.(%)	Min.(%)	Max.(%)	ϕ
RX	0.29	2.52	−8.80	7.28	0.05
HML	0.45	2.85	−13.60	10.14	0.10
IMB	0.31	1.96	−6.96	6.95	−0.00
VOL	−0.10	0.35	−1.18	1.24	0.25
$HMLV$	0.34	2.86	−11.52	13.00	0.05
MOM	0.28	2.95	−8.03	11.59	−0.11

Table 6: Correlations among currency factors

This table reports correlation coefficients associated with the currency factors. RX, HML, IMB, VOL, $HMLV$, and MOM denote the dollar, carry, imbalances, volatility, value, and momentum factors, respectively. The sample is 1985:01–2014:06.

	RX	HML	IMB	VOL	$HMLV$	MOM
RX	1.00	0.10	0.15	−0.30	−0.22	0.00
HML		1.00	0.66	−0.68	−0.10	−0.13
IMB			1.00	−0.50	−0.06	−0.10
VOL				1.00	0.07	0.03
$HMLV$					1.00	−0.15
MOM						1.00

Table 7: Alphas estimates

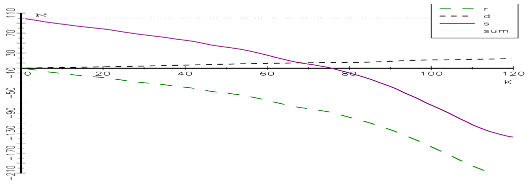
This table presents the pricing errors (alphas) associated with several factor models. The models are the Lustig–Roussanov–Verdelhan two-factor model (LRV2); Della Corte–Riddiough–Sarno three-factor model (DCRS3); Menkhoff–Sarno–Schmeling–Schrimpf two-factor model (MSSS2); LRV2 augmented by the value factor (LRV2+HMLV); LRV2 augmented by the momentum factor (LRV2+MOM); and a single factor model containing the dollar factor (RX). The currencies serving as testing assets are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). For each currency, the first column presents the alpha estimates and the second column reports GMM-based t-ratios. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample is 1985:01–2014:06.

	Panel A: RX		**Panel B: LRV2**		**Panel C: DCRS3**	
	α(%)	t	α(%)	t	α(%)	t
CAD	0.04	0.39	−0.07	−0.70	−0.06	−0.61
CHF	−0.12	−1.35	−0.02	−0.22	−0.01	−0.13
GBP	0.06	0.60	0.02	0.18	0.01	0.13
JPY	−0.10	−0.65	0.18	1.47	0.20	*1.70*
SEK	−0.05	−0.64	−0.13	−1.55	−0.14	*−1.65*
DKK	−0.01	−0.25	0.01	0.11	0.01	0.16
NOK	0.03	0.30	−0.02	−0.25	−0.01	−0.07
AUD	0.15	0.94	−0.09	−0.64	−0.10	−0.74
NZD	0.35	$\underline{2.33}$	0.14	1.07	0.11	0.82
EUR	−0.10	*−1.77*	−0.08	−1.27	−0.07	−1.15
	Panel D: MSSS2		**Panel E: LRV2+HMLV**		**Panel F: LRV2+MOM**	
	α(%)	t	α(%)	t	α(%)	t
CAD	−0.09	−0.82	−0.05	−0.56	−0.05	−0.56
CHF	−0.02	−0.16	−0.00	−0.02	−0.05	−0.56
GBP	−0.01	−0.13	0.01	0.11	0.03	0.28
JPY	0.28	$\underline{2.05}$	0.20	*1.72*	0.15	1.27
SEK	−0.16	*−1.82*	−0.19	$\underline{-2.47}$	−0.11	−1.35
DKK	−0.01	−0.20	−0.00	−0.08	0.00	0.04
NOK	−0.04	−0.45	−0.05	−0.60	−0.00	−0.04
AUD	−0.16	−1.02	−0.16	−1.13	−0.08	−0.60
NZD	0.17	1.04	0.11	0.80	0.15	1.13
EUR	−0.09	−1.52	−0.08	−1.31	−0.08	−1.36

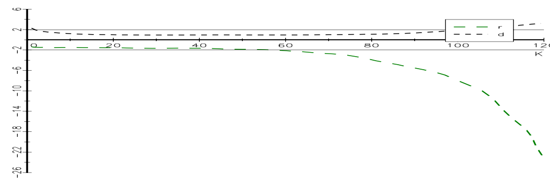
Table 8: Cross-sectional regressions: alternative decomposition

This table reports the results for cross-sectional regressions of currency risk premia ($\overline{RP}_i$), alphas ($\overline{\alpha}_i$), and average interest rate differentials ($\overline{d}_i$) onto the average log growth in exchange rates. a^{cs} and b^{cs} denote the intercept and slope estimates from the cross-sectional regression, respectively. t denote the respective OLS t-statistics (in parentheses) and R^2 is the coefficient of determination. p represent the empirical p-values (in brackets) for the slope estimates, which are obtained from a bootstrap simulation. The pricing errors and risk premia are obtained with six alternative factor models: the Lustig–Roussanov–Verdelhan two-factor model (LRV2); Della Corte–Riddiough–Sarno three-factor model (DCRS3); Menkhoff–Sarno–Schmeling–Schrimpf two-factor model (MSSS2); LRV2 augmented by the value factor (LRV2+HMLV); LRV2 augmented by the momentum factor (LRV2+MOM); and a single factor model containing the dollar factor (RX). The currencies used in the cross-sectional regressions are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), Swedish Krona (SEK), Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). The sample is 1985:01–2014:06.

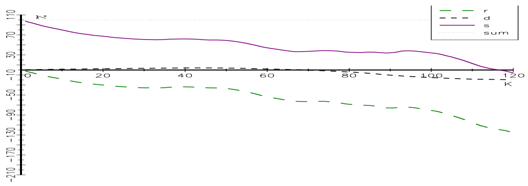
	a^{cs}	t	b^{cs}	t	p	R^2	$b^{cs}_{rp} + b^{cs}_{\alpha} - b^{cs}_{d}$
			Panel A: RX				
$\overline{RP}_i$	0.00	(4.31)	0.40	(1.46)	[0.04]	0.21	1.05
$\overline{\alpha}_i$	0.00	(1.51)	−0.71	(−1.42)	[0.06]	0.20	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	
			Panel B: LRV2				
$\overline{RP}_i$	0.00	(4.59)	−0.85	(−1.61)	[0.03]	0.24	1.05
$\overline{\alpha}_i$	−0.00	(−1.49)	0.54	(1.59)	[0.07]	0.24	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	
			Panel C: DCRS3				
$\overline{RP}_i$	0.00	(4.31)	−0.92	(−1.58)	[0.02]	0.24	1.05
$\overline{\alpha}_i$	−0.00	(−1.69)	0.60	(1.82)	[0.04]	0.29	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	
			Panel D: MSSS2				
$\overline{RP}_i$	0.00	(4.38)	−1.20	(−1.88)	[0.01]	0.31	1.05
$\overline{\alpha}_i$	−0.00	(−1.88)	0.89	(1.94)	[0.03]	0.32	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	
			Panel E: LRV2+HMLV				
$\overline{RP}_i$	0.00	(4.51)	−1.09	(−1.79)	[0.02]	0.29	1.05
$\overline{\alpha}_i$	−0.00	(−2.19)	0.78	(2.11)	[0.02]	0.36	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	
			Panel F: LRV2+MOM				
$\overline{RP}_i$	0.00	(4.43)	−0.69	(−1.33)	[0.05]	0.18	1.05
$\overline{\alpha}_i$	−0.00	(−1.02)	0.37	(1.09)	[0.16]	0.13	
$\overline{d}_i$	0.00	(3.34)	−1.36	(−2.69)	[0.00]	0.48	



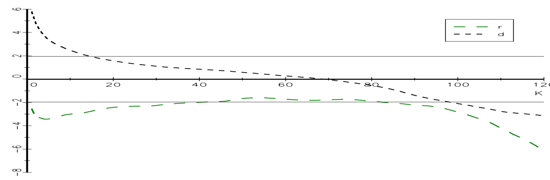
Panel A (CAD)



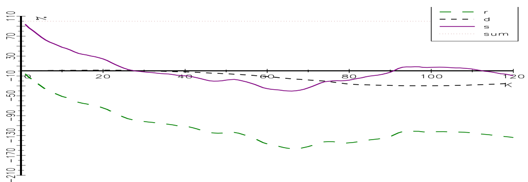
Panel B (CAD, t-ratio)



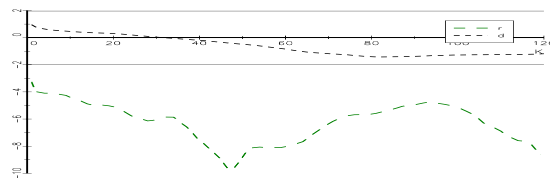
Panel C (CHF)



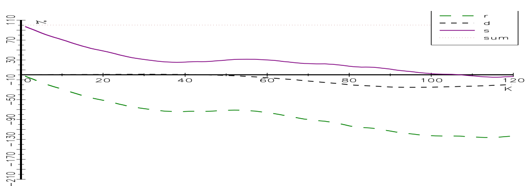
Panel D (CHF, t-ratio)



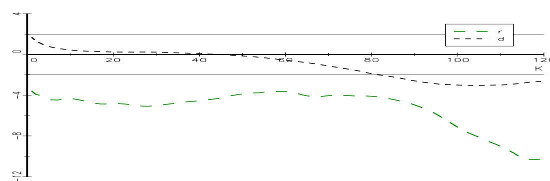
Panel E (GBP)



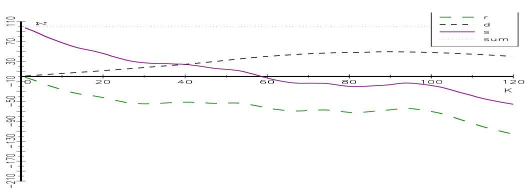
Panel F (GBP, t-ratio)



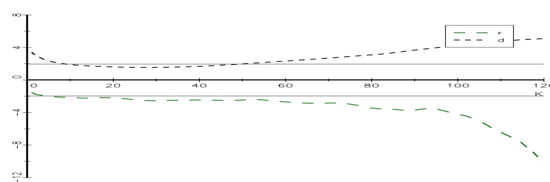
Panel G (JPY)



Panel H (JPY, t-ratio)



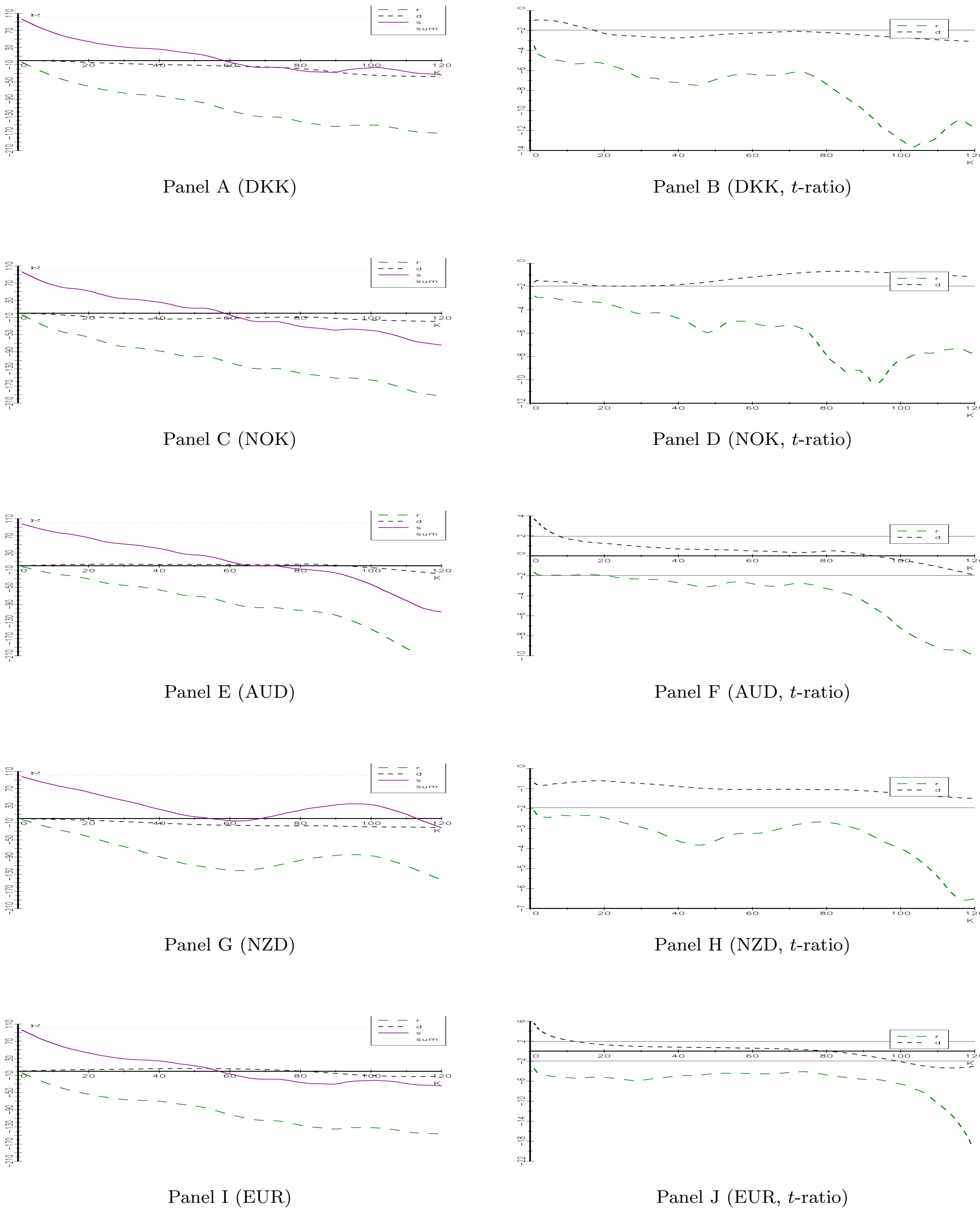
Panel I (SEK)



Panel J (SEK, t-ratio)

Figure 1: Direct long-horizon coefficients: CAD, CHF, GBP, JPY, and SEK

This figure plots the term structure of the direct long-horizon predictive coefficients and respective Newey-West t-statistics. The predictive slopes are associated with the log return (r), log interest rate differential (d), and log spot exchange rate (s). The forecasting variable is the log exchange rate in all three cases. "Sum" denotes the value of the variance decomposition, in %. The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), and Swedish Krona (SEK). The long-horizon coefficients are measured in %, and K represents the number of months ahead. The horizontal lines represent the 5% critical values (-1.96, 1.96). The sample is 1985:01–2015:06.



Panel A (DKK)

Panel B (DKK, t-ratio)

Panel C (NOK)

Panel D (NOK, t-ratio)

Panel E (AUD)

Panel F (AUD, t-ratio)

Panel G (NZD)

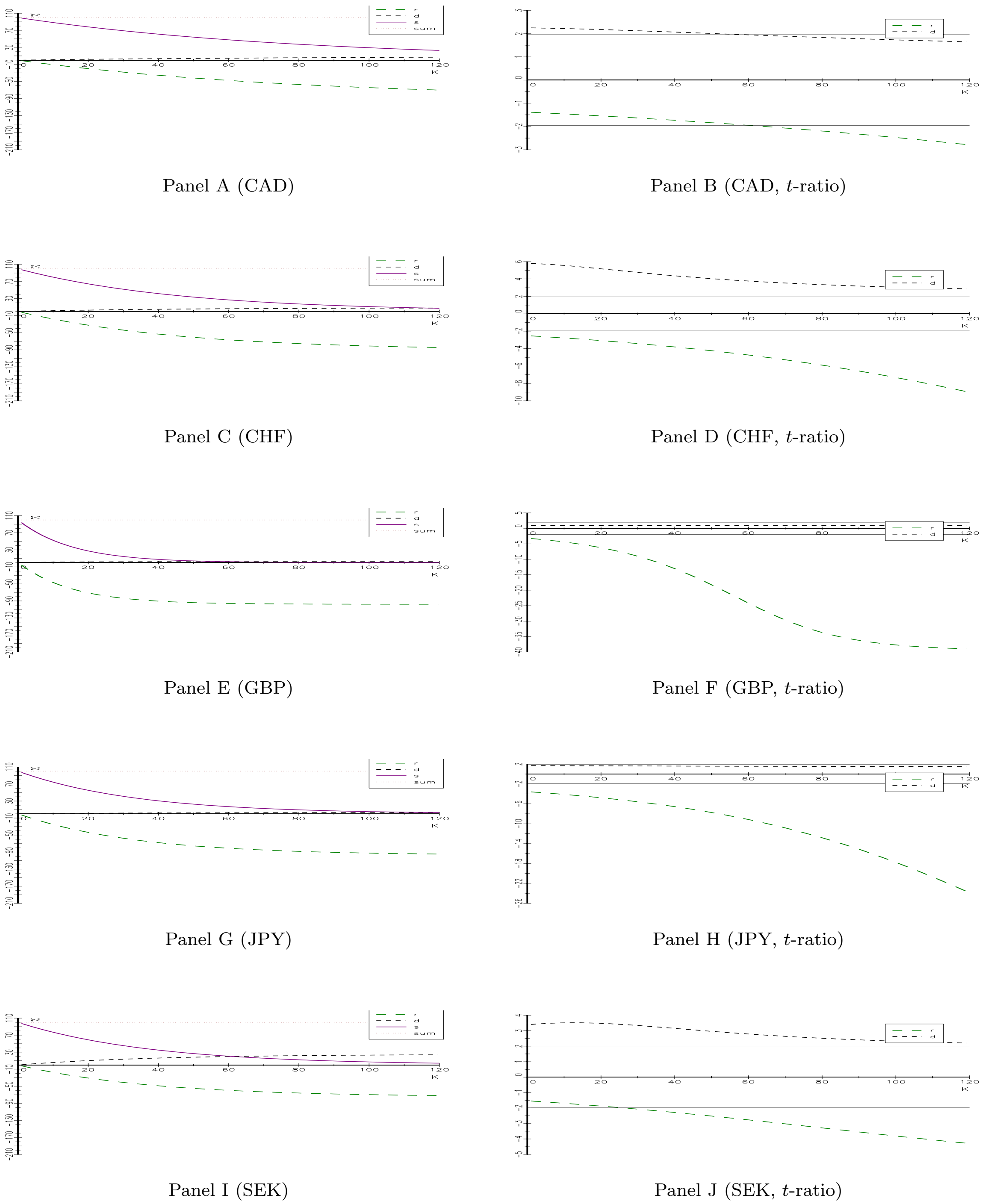
Panel H (NZD, t-ratio)

Panel I (EUR)

Panel J (EUR, t-ratio)

Figure 2: Direct long-horizon coefficients: DKK, NOK, AUD, NZD, and EUR

This figure plots the term structure of the direct long-horizon predictive coefficients and respective Newey-West t-statistics. The predictive slopes are associated with the log return (r), log interest rate differential (d), and log spot exchange rate (s). The forecasting variable is the log exchange rate in all three cases. "Sum" denotes the value of the variance decomposition, in %. The currencies are the Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). The long-horizon coefficients are measured in %, and K represents the number of months ahead. The horizontal lines represent the 5% critical values (-1.96, 1.96). The sample is 1985:01–2015:06.



Panel A (CAD) Panel B (CAD, t-ratio)

Panel C (CHF) Panel D (CHF, t-ratio)

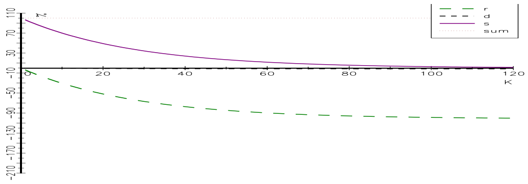
Panel E (GBP) Panel F (GBP, t-ratio)

Panel G (JPY) Panel H (JPY, t-ratio)

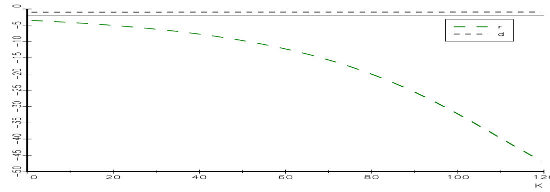
Panel I (SEK) Panel J (SEK, t-ratio)

Figure 3: VAR-based long-horizon coefficients: CAD, CHF, GBP, JPY, and SEK

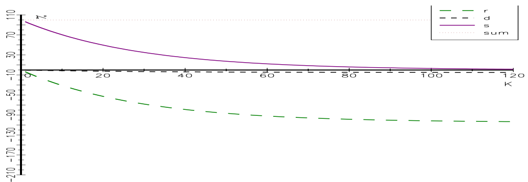
This figure plots the term structure of the VAR-based long-horizon predictive coefficients and respective Newey-West t-statistics. The predictive slopes are associated with the log return (r), log interest rate differential (d), and log spot exchange rate (s). The forecasting variable is the log exchange rate in all three cases. "Sum" denotes the value of the variance decomposition, in %. The currencies are the Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Japanese Yen (JPY), and Swedish Krona (SEK). The long-horizon coefficients are measured in %, and K represents the number of months ahead. The horizontal lines represent the 5% critical values (-1.96, 1.96). The sample is 1985:01–2015:06.



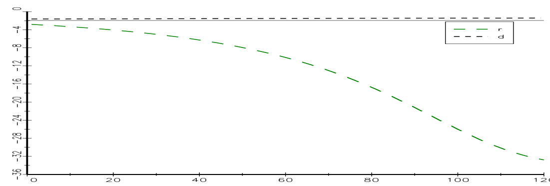
Panel A (DKK)



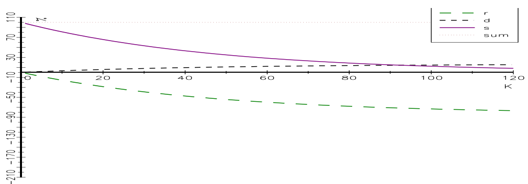
Panel B (DKK, t-ratio)



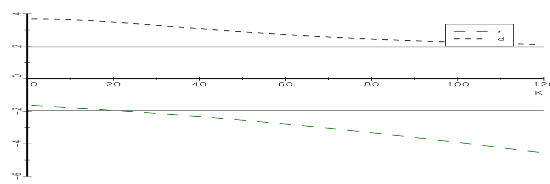
Panel C (NOK)



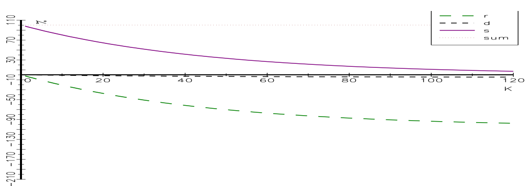
Panel D (NOK, t-ratio)



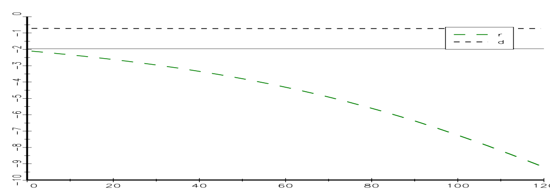
Panel E (AUD)



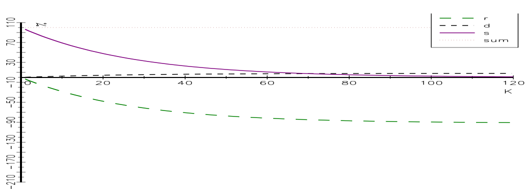
Panel F (AUD, t-ratio)



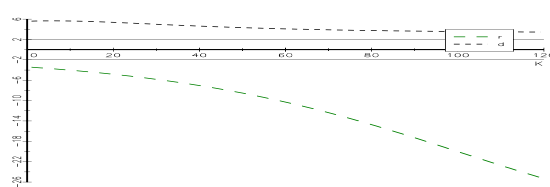
Panel G (NZD)



Panel H (NZD, t-ratio)



Panel I (EUR)



Panel J (EUR, t-ratio)

Figure 4: VAR-based long-horizon coefficients: DKK, NOK, AUD, NZD, and EUR

This figure plots the term structure of the VAR-based long-horizon predictive coefficients and respective Newey-West t-statistics. The predictive slopes are associated with the log return (r), log interest rate differential (d), and log spot exchange rate (s). The forecasting variable is the log exchange rate in all three cases. "Sum" denotes the value of the variance decomposition, in %. The currencies are the Danish Krone (DKK), Norwegian Krone (NOK), Australian Dollar (AUD), New Zealand Dollar (NZD), and Euro (EUR). The long-horizon coefficients are measured in %, and K represents the number of months ahead. The horizontal lines represent the 5% critical values (-1.96, 1.96). The sample is 1985:01–2015:06.