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Exchange Rates and Unobservable Fundamentals: A New Approach to Out-of-sample Forecasting

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Exchange Rates and Unobservable Fundamentals: A New Approach to Out-of-sample Forecasting

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Abstract

Traditional exchange rate models are based on differences in macroeconomic fundamentals. However, despite being well grounded in economic theory they have a rather poor out-of-sample forecasting record. This empirical failure may be a result of the overly restrictive choice of macroeconomic fundamentals. We suggest using the sovereign yield spread level and slope as proxies of the market's expectations for current and future fundamentals and find promising results when we investigate the out-of-sample forecasting accuracy of these variables. Using the yield spread level and slope as a set of unobservable fundamentals, our approach outperforms traditional exchange rate models for most considered currencies and horizons. It is also superior to a random walk in terms of direction of change forecasts and profitability.

Key words: Exchange Rates, Forecasting, Macroeconomic Fundamentals, Yield Spreads

JEL: F31, F37, E43, G15, G17

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1 Introduction

Traditional exchange rate models, e.g. the monetary model or the purchasing power parity approach, are based on differences in macroeconomic fundamentals such as monetary supply, inflation and output. However, these standard fundamental-based models have a rather poor out-of-sample forecasting performance. Starting with the seminal contribution of Meese and Rogoff (1983), a vast body of empirical research finds that models based on macroeconomic fundamentals cannot outperform a naive random walk model in terms of the root mean squared error (RMSE), see e.g., Cheung et al. (2005); Molodtsova and Papell (2009); Rossi (2013), just to name a few.

The literature has put forth several reasons for this dismal record. The sole focus on the traditional RMSE metric may not be entirely appropriate for exchange rates (Cheung et al., 2005; Moosa and Burns, 2014). Existing structural models may also be overly restrictive in their choice of macroeconomic fundamentals (Engel and West, 2005; Balke et al., 2013). The empirical failure may further be a result of using inappropriate proxies for the market expectations of future fundamentals which become highly important when the exchange rate is understood as an asset price (Mark, 1995; Bacchetta and van Wincoop, 2013).

Instead of applying traditional observable fundamentals, we therefore suggest using the level and slope of sovereign yield spread curves between economies[2] as market-based proxies for current and future macroeconomic fundamentals to forecast exchange rates. We find that this approach delivers promising forecasting results based on statistical and economic evaluation measures when compared against the random walk and commonly used fundamental exchange rate models.

The motivations for our innovative approach are twofold. First, interpreted as an asset price, exchange rates are now commonly considered to equal the sum of discounted future macroeconomic fundamentals. The yield spread level

[2]Sovereign yield spreads are the difference between two sovereign bond yields of equal maturity. The sovereign yield spread level $L^{\Delta sy}$ is defined as an average of short, medium and long term spreads and the spread slope $S^{\Delta sy}$ denotes the difference between long and short term yield spreads.

and slope are forward-looking financial indicators which summarize long-term macroeconomic information contained in the term structure of yield spreads – the difference between the yield curves of two different economies. Thus, these variables naturally contain unobservable information about the same expected macroeconomic differentials that drive exchange rates (Chen and Tsang, 2013; Bui and Fisher, 2016). Second, because bond yields and foreign exchanges are susceptible to the same macroeconomic risk, the expected risk premiums that investors require for holding these assets might closely relate to each other.

Our approach has several further advantages compared to traditional fundamental models. The yield spread approach is market based, as expectations about future economic fundamentals reflect the view of a large number of market participants in highly liquid sovereign bond markets. Yield data is also readily and easily available on a daily basis as opposed to monthly and quarterly macroeconomic data which is often published with a considerable time lag, while being revised afterwards. Finally, our parsimonious model is straightforward to implement and therefore an appealing approach for investment practitioners.

To assess the accuracy of our approach we conduct an extensive out-of-sample forecasting exercise for time horizons of one, three, six and twelve months against the random walk and several traditional fundamental exchange rate models based on interest rate, price, monetary and Taylor rule fundamentals. We use major currencies of advanced countries with free floating exchange rates and highly liquid bond markets with little to no credit risk (the Australian Dollar, the Canadian Dollar, the Swiss Franc, the Japanese Yen, the British Pound and the US Dollar).

We assess the forecasting accuracy of the investigated models based on several different evaluation methods to provide a multifaceted assessment of the performance of our approach and the benchmark models. In addition to the RMSE, we thus apply a measure of direction accuracy and assess the forecasting uncertainty based on density forecasts.

Since statistical evidence of superior exchange rate forecasting accuracy does not necessarily guarantee an investor to make a profit when exploiting this predictability, the ultimate test of forecasting power is to examine the economic viability of the predictions (Abhyankar et al., 2005; Corte et al., 2009; Moosa and Burns, 2014). We thus also implement a period-by-period trading strategy to assess the profitability of the forecasts produced by the implemented models.

Considering all of the applied statistical and economic evaluation metrics, we find promising results for our yield spread approach. Using the spread level and slope is generally superior in terms of the RMSE and direction accuracy, when being compared to traditional fundamental models. The approach typically also provides better results in terms of density forecasts. While neither our approach nor the benchmark models are able to consistently beat the random walk in terms of the RMSE – which should hardly be surprising given the findings in previous literature – the suggested yield spread approach clearly outperforms the random walk in forecasting the direction of exchange rate changes. We also find that our approach consistently yields higher (lower) risk-adjusted profits (losses) than the considered fundamental benchmark models and also outperforms the random walk in terms of profitability for several currencies.

Overall, these results drawn from different statistical and economic evaluation measures are encouraging with regards to the forecasting ability of our approach. The promising out-of-sample results also confirm previous studies which have investigated the predictive power of financial variables for exchange rates. Guo and Savickas (2008), for example, show that financial variables that have been commonly used as predictors of stock or bond returns also have the ability to forecast exchange rates. Evans and Lyons (2007) and Rime et al. (2010) show that order flow helps to forecast exchange rates because it contains information about current and future macroeconomic fundamentals. Our results also support the view that financial variables may be an intuitive and promising forecasting approach when exchange rates are understood as an asset price and equal the sum of expected future fundamentals.

It is important to note that our results do not imply that the macroeconomic fundamentals applied in traditional models cannot forecast exchange rates. Quite the opposite, our findings are consistent with the view that the principal drivers of exchange rates are standard macro fundamentals. The difference between our approach and traditional fundamental models is that we apply the spread level and spread slope as proxies for *unobservable* fundamentals instead of using selected, often restricted *observable* macroeconomic variables directly in the forecasting equation.

With this study, we thus contribute to the literature of exchange rate forecasting in several dimensions. First, we present an innovative, parsimonious, market driven approach to exchange rate forecasting based on readily and easily available data. This makes it a promising proposition in particular for market practitioners. Second, we provide further evidence that financial variables are useful indicators to be considered in exchange rate forecasting and thus hope that our findings contribute to the renewed interest in exchange rate forecasting models based on financial variables. Finally, we confirm that the random walk is beatable by models using observable and unobservable models if appropriate evaluation criteria and measures of trading profitability are applied. The difference in conclusions for the implemented evaluation metrics also further highlights the importance of applying various measures to provide a conclusive assessment of a model's forecasting ability. As Rossi (2013) suggests, "the choice of the evaluation method matters, and matters a lot."

The remainder of this paper is structured as follows. The next section provides an overview of traditional exchange rate models and their empirical forecasting performance. Section 3 introduces our forecasting approach based on the empirical sovereign yield spread level and slope. In Section 4 reviews the applied forecasting evaluation criteria, while Section 5 provides empirical results for the conducted out-of-sample forecasting study. In Section 6 we implement a simple trading strategy to investigate the profitability of our forecasts. Section 7 concludes and provides suggestions for future work.

2 Exchange Rate Determination and Forecasting

2.1 Traditional Fundamental Exchange Rate Models

Economic theory states that the exchange rate is determined by differences between macroeconomic fundamentals such as money supply, inflation, output and interest rates. This relationship between the exchange rate and its fundamentals can be described by different models based on varying economic variables and econometric techniques such as error correction models (ECM), time-varying parameter (TVP) models and – still most commonly applied – linear models, see, e.g., Rossi (2013), for an excellent recent overview.
For expositional purposes, let the basic model be linear with a constant term. Assume that s_t denotes the log of the nominal exchange rate (home currency price per unit of foreign currency) and f_t the (potentially multivariate) fundamental(s) of the exchange rate. The general relationship can then be expressed as:

$$s_t = \alpha + \beta f_t. \tag{1}$$

This framework gives way for the most commonly used models tying floating exchange rates to differences in interest rates and macroeconomic fundamentals:

Interest Rate Differentials

Traditionally, the relation between differences in interest rates and exchange rates is expressed in the uncovered interest rate parity (UIRP) condition. The UIRP relates exchange rate changes to interest rate differentials between two economies over the same horizon:

$$\Delta s_{t+h} = \alpha + \beta(i_t^h - i_t^{h,*}), \tag{2}$$

where Δs_{t+h} is the h-horizon exchange rate change and i_t^h and i_t^{h*} are the domestic and foreign interest rates of maturity h. If uncovered interest rate parity holds, α and β should be 0 and 1 respectively.

Price Level Fundamentals

According to Purchasing Power Parity (PPP), the real price of comparable commodity baskets in two countries should be the same. Thus, the price level in the home country should equal the price level of the foreign country converted to the currency of the foreign country. It follows that a unit of currency in the home country will have the same purchasing power in the foreign country. Accordingly, PPP implies that

$$s_t = \alpha + \beta(p_t - p_t^*), \tag{3}$$

where p_t and p_t^* denote the logarithm of the price index in the home and foreign country, respectively.

Monetary and Output Fundamentals

The frequently used monetary model builds upon PPP and UIP but assumes additional restrictions. It models exchange rate behavior in terms of relative demand for and supply of money in the two economies. To start with, real money demand is viewed as a function of income and interest rates:

$$m_t - p_t = \eta i_t + \phi y_t, \tag{4}$$

where m_t is the log of nominal money demand, i_t denotes the interest rate, y_t is the logarithm of real output and η and ϕ are coefficients. Assuming that a similar equation holds for the foreign country with symmetric coefficients and taking the difference between the two gives the relative money demand equation:

$$m_t - m_t^* - (p_t - p_t^*) = \eta(i_t - i_t^*) + \phi(y_t - y_t^*). \tag{5}$$

The 'flexible price version' of the monetary model (valid if prices and exchange rates are completely flexible) assumes that PPP holds at every point in time. Substituting the PPP relation into the relative money demand equation, we get

$$s_t = \eta(i_t - i_t^*) - \phi(y_t - y_t^*) + (m_t - m_t^*). \tag{6}$$

In the presence of sticky price adjustment, either the relative price level or inflation differentials are included to obtain the 'sticky price version' of the monetary model:

$$s_t = \eta(i_t - i_t^*) - \phi(y_t - y_t^*) + (m_t - m_t^*) + \upsilon(p_t - p_t^*). \tag{7}$$

In this case it is assumed that PPP holds in the long run but does not hold in the short run.

Taylor Rule Fundamentals

Recently, studies have proposed fundamentals based on a Taylor rule for monetary policy (Engel and West, 2005; Molodtsova and Papell, 2009). At the core of models using Taylor rule fundamentals is the idea that if two economies set interest rates based on a Taylor rule, their bilateral exchange rate will reflect their relative interest rates through UIRP.

Consequently, this approach assumes that both central banks adjust the target rate i_t^T according to a Taylor rule in response to changes in the output gap and deviation from target inflation:

$$i_t^T = \pi_t + \phi(\pi_t - \pi^T) + \gamma y_t^{gap} + r, \tag{8}$$

where π_t is the inflation rate, π^T is the target level of inflation, y_t^{gap} is the output gap[3] and r is the equilibrium level of the real interest rate.

Assuming that a similar condition applies to the foreign country with equal coefficients ϕ and γ (symmetric Taylor rule with homogeneous coefficients) and further assuming that UIRP and PPP hold, then yields:[4]

$$\Delta s_{t+h} = (1 + \phi)(\pi_t - \pi_t^*) + \gamma(y_t^{gap} - y_t^{gap*}). \tag{9}$$

Hence, under this basic Taylor rule approach, the fundamentals that determine the exchange rate are the country differentials in inflation and output gap.[5]

[3]The output gap is the difference between actual output and potential output $y_t^{gap} = y_t - \bar{y}_t$ at time t, where y_t is the logarithm of real output and $\bar{y}_t$ is the logarithm of potential output measured e.g. by a linear time trend.

[4]See Giacomini and Rossi (2010) for a more detailed derivation.

[5]Under different assumptions, e.g heterogenous coefficients or central banks also considering the real exchange rate, other fundamentals such as the country differentials in interest rates and price levels may be included as well. Molodtsova and Papell (2009) provide a

2.2 Empirical Evidence

The empirical validation for these theoretical frameworks remains rather elusive. In a large body of empirical out-of-sample forecasting studies the random walk model has proven almost unbeatable by models with traditional macroeconomic predictors. Meese and Rogoff (1983) first established this result in their seminal paper. They evaluated the out-of-sample fit of several exchange rate models in the short run and concluded that a random walk predicts exchange rates better than macroeconomic models in terms of the RMSE.

Many studies have subsequently claimed to find success for various versions of fundamentals-based models. Kilian and Taylor (2003), for example, find that exchange rates can be predicted from economic models at horizons of two to three years after taking into account the possibility of nonlinear exchange rate dynamics. Bjørnland and Hungnes (2006) combine the purchasing power parity condition with the interest rate differential in the long run and show that their approach outperforms a random walk in an out-of-sample forecasting exercise for several horizons. Molodtsova and Papell (2009) investigate the predictability of models that incorporate Taylor rule fundamentals and provide evidence of short-run exchange rate predictability.

However, the success of these models has not proven to be universally reliable and robust. Models that work well in one period or for one currency do not necessarily work well in another period or for other currencies. The study by Cheung et al. (2005) examines the out-of-sample performance of several popular fundamentals-based models and finds that none of the models consistently outperforms the random walk. More recently, Rossi (2013) also concludes in a comprehensive survey that forecasting success largely depends on the choice of predictor, forecast horizon, sample period, model, and forecast evaluation method. Thus, even after more than 30 years, the Meese and Rogoff (1983) results have not yet been convincingly overturned.

comprehensive overview of different approaches applying Taylor rule fundamentals.

Several reasons have been put forward for the empirical out-of-sample forecasting failure of traditional exchange rate models. The poor forecasting performance may for example reflect, at least in part, econometric issues. In their original paper, Meese and Rogoff (1983) attribute the failure to underlying econometrics such as a simultaneous equations bias, sampling errors, stochastic movements in the true underlying parameters, misspecification and nonlinearities. Moosa (2013) also demonstrates that failure to outperform the random walk should be the rule rather than the exception due to the characteristics of the underlying processes.

The empirical failure may further be a result of using inappropriate proxies for the market expectations of future fundamentals rather than the failure of the models themselves. It has long been suggested, see, e.g., Frenkel (1983) for an early survey, that exchange rates should be viewed as an asset price determined in financial markets, similar to stock, bond and commodity markets, in which current prices reflect the market's expectations about the present and the future. Following Mark (1995) and Engel and West (2005), the exchange rate is now commonly modeled as an asset price, where the nominal exchange rate is determined as the present value of the discounted sum of current and expected fundamentals:

$$s_t = (1-\omega)f_t + \omega E_t(s_{t+1}), \tag{10}$$

where ω is a discount factor less than one. Iterating this equation forward then leads to

$$s_t = (1-\omega)f_t + (1-\omega)\sum_{j=1}^{\infty}\omega^j E_t(f_{t+j}). \tag{11}$$

This approach implies that the exchange rate is determined by the weighted average of fundamentals such as economic growth, inflation or money supply which are determined by the chosen model. It also follows that within the present value framework exchange rates rely more on expectations about the future than on current fundamentals. Properly measuring expectations about fundamentals and model parameters thus becomes especially important in empirical studies on exchange rate dynamics (Bacchetta and van

Wincoop, 2013). Standard empirical approaches, however, often reduce the sum of expected future fundamentals to equal current fundamentals (Chen and Gwati, 2014).

Existing structural models grounded in economic theory may also be overly restrictive in their choice of observable macroeconomic fundamentals. Engel and West (2005), for example, argue that exchange rates are not only affected by observable fundamentals. Balke et al. (2013) also show that it is difficult to obtain sharp inferences about the relative contribution of fundamentals using only data on observed fundamentals.

Finally, it has been suggested that the use of the RMSE and similar statistical criteria solely based on minimizing the loss function may not be entirely appropriate to measure exchange rate forecasting accuracy. A correct prediction of the direction of change can often be more important than the magnitude of the error (Cheung et al., 2005), for example when it comes to hedging decisions. Moosa and Burns (2014) demonstrate that the conventional monetary model can outperform the random walk in out-of-sample forecasting if forecasting power is measured by direction accuracy. Several studies also argue that it is important to asses the uncertainty of exchange rate forecasts (Diebold et al., 1999; Rapach and Wohar, 2006). Wang and Wu (2012), for example, find that Taylor rule models can outperform the random walk, especially at long horizons, based on interval forecasting criteria. Researchers have further suggested that the ultimate test of forecasting power is the ability to make profits based on predicted exchange rate movements (Corte et al., 2009).

We take these arguments into account and evaluate the forecasting accuracy of the applied models based on several different statistical measures. We further implement a trading strategy to asses the profitability of the derived forecasts.

2.3 Alternative Approaches

The perceived failure of traditional fundamentals-based exchange rate models in empirical out-of-sample forecasting has motivated numerous alternative approaches to model and forecast the exchange rate. Engel et al. (2008), for example, include expectations of fundamentals drawn from survey data and demonstrate that the predictive power of the models can be greatly increased by using panel techniques. Engel (2014) construct factors from a cross-section of exchange rates and use the idiosyncratic deviations from these factors to beat the random walk benchmark.

One recent stream of literature also investigates financial variables as predictors for exchange rates. Evans and Lyons (2007) and Rime et al. (2010) for example show that order flow forecasts exchange rates because it contains information about future fundamentals. Christiansen (2011) use a smooth transition model to show that typical FX carry trade strategies have a high exposure to the stock market. Molodtsova and Papell (2013) incorporate indicators of financial stress to improve the forecasting performance of models based on Taylor rule fundamentals. Ferraro et al. (2015) further document the relationship between commodity prices and exchange rates.

We follow a similar path by applying the level and slope of cross-country yield spread curves as forward-looking financial variables which reflect expectations of future and unobservable macroeconomic fundamentals. This approach is further described in the subsequent section.

3 A Market Driven Approach using the Sovereign Spread Level and Slope

3.1 Financial Variables and Exchange Rates

One of the main findings of the previous Section 2 suggests that the failure of empirical exchange rate forecasting models may be due to using inappropriate proxies for market expectations of future and non-observable fundamentals. The fact that plausible models now consider the exchange rate as an asset price means that short-run movements in exchange rates are primarily determined by changes in expectations and that unobservable fundamentals play a significant part in this process. However, future expectations and unob-

servable fundamentals both are difficult to capture with traditional empirical models which commonly reduce the sum of expected future fundamentals to equal current fundamentals (Chen and Gwati, 2014) and are too stylized to be successfully applied to forecasting exchange rates (Rossi, 2013).
In this context, financial variables may be an intuitive, promising resolution. Through their forward-looking character many financial variables incorporate market expectations of future economic conditions (Stock and Watson, 2003). Share and bond prices, for instance, reflect discounted future cash flows based on expectations about the firm level and macroeconomic environment. When exchange rates are understood as an asset price and equal the sum of expected future fundamentals, financial variables may thus naturally have predictive power for exchange rates.
Furthermore, financial variables such as stock or bond returns might also be related to exchange rates because the expected risk premiums that investors require for holding stocks, bonds, and foreign currencies might closely relate to each other. Guo and Savickas (2008) investigate whether financial variables that have been commonly used as predictors of stock or bond returns also forecast exchange rates. Their findings document in particular a strong relation between idiosyncratic stock volatility and exchange rates.

3.2 Yield Curves and Macroeconomic Fundamentals

While the exchange rate literature has so far focused more on the relation between stock prices and exchange rates (Evans and Lyons, 2007; Rime et al., 2010; Cenedese et al., 2015), bond yields are another obvious choice. Yield curves are well known to summarize expectations about future paths of short interest rates and thus contain information about expected future economic conditions such as output, inflation, recessions and monetary policy (Stock and Watson, 2003; Ang et al., 2006; Rudebusch and Wu, 2008; Favero et al., 2012; Erdogan et al., 2015).
Findings in previous studies suggest that this macroeconomic information entailed in the yield curve is summarized in the level, slope and curvature of the term structure. Estrella and Mishkin (1998), for example, argue that

the yield curve slope is a serious candidate as predictor of output growth and recessions. Diebold et al. (2006) find that an increase in the US yield curve level factor raises capacity utilization, the US fund rate and inflation. Dewachter and Lyrio (2006) suggest that the level factor reflects long run inflation expectations. Rudebusch and Wu (2007) also contend that the level factor incorporates long-term inflation expectations and the slope factor captures the business cycle. Moench (2012) finds that a rising yield curve slope factor is associated with a future decline of output while surprise surges of the yield curve level are followed by a strong and persistent increase of inflation rates.

The shape and movements of the yield curve have therefore long been used to provide readings of market expectations about the same fundamentals whose differentials are commonly used to model and forecast exchange rates (see Section 2).

3.3 Macroeconomic Fundamentals and Sovereign Spread Factors

We thus argue that the term structure of sovereign yield spreads – the difference between two economies' respective yield curves – can be considered as a natural candidate for exchange rate forecasting.

Sovereign yield spreads are the difference between two government bond yields of equal maturity. The τ-maturity sovereign yield spread Δsy_t^m is thus calculated as:

$$\Delta sy_t^\tau = sy_t^\tau - sy_t^{\tau,*}, \tag{12}$$

where sy_t^τ and $sy_t^{\tau,*}$ are τ-maturity home and foreign country sovereign yields respectively.

As sovereign spreads can be calculated for any maturity, they exhibit a term structure – or spread curve – of their own. We conjecture that this spread curve naturally contains valuable information about market expectations of differences in macroeconomic conditions that determine exchange rates. The findings in the yield curve literature described above further suggest that the information about macroeconomic differentials entailed in sovereign spread curves will be reflected in the spread level, spread slope and spread curvature. Recent research comprising the term structure of sovereign yield spreads confirms this suspected link between spread curve factors and exchange rates. In a cross-country setting based on portfolio strategies, Ang and Chen (2010) find an economically and statistically significant ability of the yield level and slope factors of the term structure to predict exchange rate profitability. Chen and Tsang (2013) find in-sample that cross-country Nelson-Siegel factors which are related to the sovereign spread level, slope and curvature can predict future exchange rate changes and excess currency returns. Bui and Fisher (2016) support their findings for the relative yield curves of the US and Australia. Trück and Wellmann (2016) investigate the term structure of sovereign yield spreads for six advanced economies. They estimate the latent factors driving the spread term structure and find that these factors are highly correlated with the empirical yield spread level, slope and curvature. Most importantly, they also show that in particular the spread level and slope factors have predictive power for exchange rate dynamics in an in-sample setting.

3.4 Using the Sovereign Spread Level and Slope to Forecast Exchange Rates

Encouraged by these promising results we propose to exploit the fundamental information contained in sovereign yield spread curves between economies to forecast exchange rates out-of-sample. To make this information applicable within a parsimonious forecasting model, we suggest using the empirical[6]

[6]We decide to use the empirical rather than estimated factors as applied in Trück and Wellmann (2016), because applying the empirical factors in an out-of-sample forecasting framework is intuitive and less computationally intensive. It is thus straightforward to apply such an approach in practice. Robustness tests comparing the forecasting accuracy between empirical and estimated factors (results available upon request) also indicate that there is no considerable difference in the overall forecasting accuracy.

sovereign yield spread curve level $L_t^{\Delta sy}$ and slope $S_t^{\Delta sy}$ as a set of financial proxies which summarize the information of the spread curve and reflect market expectations of future and unobservable fundamentals.

Following the common approach in the yield curve literature (Diebold et al., 2006; Afonso and Martins, 2012), the sovereign spread level $L_t^{\Delta sy}$ is defined as an average of short, medium and long term spreads:

$$L_t^{\Delta sy} = \frac{\Delta sy_t^{short} + \Delta sy_t^{medium} + \Delta sy_t^{long}}{3}, \tag{13}$$

and the spread slope $S_t^{\Delta sy}$ denotes the difference between long and short term spreads:

$$S_t^{\Delta sy} = \Delta sy_t^{long} - \Delta sy_t^{short}. \tag{14}$$

Note, that we do not use the spread curvature which is commonly identified as a third factor in the yield curve literature (Diebold and Li, 2006; Moench, 2012). We opt not to include it in our approach because previous in-sample results (see in particular Trück and Wellmann (2016)) indicate that the additional predictive power of the curvature factor for exchange rates is rather limited. Robustness tests with the spread curvature (results available upon request) also confirm that including curvature as a third factor does not improve the overall out-of-sample forecasting accuracy.

Our innovative approach has several advantages compared to traditional fundamental models. First, the sovereign yield spread level and slope are driven by the sentiment of highly liquid financial markets. Sovereign bond markets are amongst the largest and most liquid financial markets in the world and therefore summarize the expectations of a large number of market participants. This also means that changes in expectations about future economic fluctuations are quickly incorporated into the variables. Second, yield data is readily and easily available on a daily basis as opposed to monthly or quarterly macroeconomic data used for fundamental models which is often published with a significant delay and revised in hindsight. Finally, our approach is parsimonious, which makes it straightforward to apply in practice.

Naturally, our approach is somewhat related to the UIRP inspired fundamental model based on interest rate differentials described in Section 2.1. However, while the interest rate differential model only uses yield spreads of one specific maturity, the spread level and slope naturally exploit forward-looking information contained in the entire spread curve and thus seem to better reflect the idea that exchange rates are now considered as asset prices. Purists may further criticize a lack of a clear theoretical foundation. The results from the yield curve literature described above suggest that the level factor can be seen as a long-run inflation expectation factor while the slope factor reflects business cycle and output growth dynamics, see also Chen and Tsang (2013). Still, the factors cannot clearly be tied to specific macroeconomic variables as they may reflect a range of latent, unobservable fundamentals. However, in empirical forecasting, this should rather be considered as an advantage as it allows for parsimonious yet flexible modeling compared to often overly restrictive structural models and is therefore less prone to the omitted variable bias.

4 Out-of-sample Forecasting Framework

4.1 Forecating Specifications

To investigate the forecasting accuracy of our approach, we conduct an extensive out-of-sample forecasting exercise using the major currencies of advanced countries with free floating exchange rates and highly liquid bond markets with little to no credit risk. We thus include the Australian Dollar (AUD), the Canadian Dollar (CAD), the Swiss Franc (CHF), the Japanese Yen (JPY) and the British Pound (GBP). All currencies are measured against the US Dollar (USD), following the typical convention in the exchange rate literature, see, e.g., Molodtsova and Papell (2009); Giacomini and Rossi (2010); Rossi (2013). We do not include the Euro because there is no Euro yield curve which reflects the macroeconomic prospects of the entire Euro area. Using, e.g. German yields as a proxy does not appear to be reasonable for our approach, especially as our sample includes the recent Euro crisis. To ensure that our conclusions are not driven by USD specific effects, we also examine the three major cross-rates CHF/GBP, GBP/JPY and JPY/CHF.[7] Our analysis covers the time period from January 1995 to December 2014. To evaluate the out-of-sample forecasting ability, the sample of size $T = 240$ monthly observations is split into an in-sample period, consisting of observations from $t = 1$ to R, and an out-of-sample portion of size $P = T - R$. We adopt the convention, see, e.g., Wang and Wu (2015), in the empirical exchange rate forecasting literature of implementing 'rolling windows'[8] and use a rolling window of size $R = 60$. This means that the models are estimated over an initial in-sample window from January 1995 - December 1999 to produce h-months ahead forecasts and then the in-sample window is moved up or 'rolled' forward one observation before the procedure is repeated. We thus produce h-months ahead forecasts for the period $R+h-1, ..., T$ for the forecast horizons $h = 1$, $h = 3$, $h = 6$ and $h = 12$ months.

4.2 Forecasting Models

Yield Spread Model

As described in the previous section, our approach considers the empirical yield spread level $L_t^{\Delta sy}$ and spread slope $S_t^{\Delta sy}$ as market driven indicators reflecting unobservable fundamentals. Applying both variables to forecast exchange rate changes, the forecasting equation thus becomes:

$$\widehat{s_{t+h}} - s_t = \alpha + \beta_t^L L_t^{\Delta sy} + \beta_t^S S_t^{\Delta sy} + \epsilon_{t+h} \tag{15}$$

where $L_t^{\Delta sy} = (L_t^{sy} - L_t^{sy*})$ and $S_t^{\Delta sy} = (S_t^{sy} - S_t^{sy*})$ are the differences in yield curve level and slope between home and foreign country. Following the convention in the yield curve literature, see, e.g., Diebold et al. (2006); Afonso and Martins (2012), we calculate the empirical spread level $L_t^{\Delta sy}$ as

[7] We note, that our findings also hold for other cross exchange rates.

[8] While the rolling regressions do not incorporate the possible efficiency gains of 'recursive windows' as the sample moves forward through time, the procedure has the potential benefit of alleviating parameter instability effects over time, which is a commonly conceived phenomenon in exchange rate forecasting.

the average of the 3-months, the 36-months and the 120-months yield spread:

$$L_t^{\Delta sy} = \frac{\Delta sy_t^{\tau=3} + \Delta sy_t^{\tau=36} + \Delta sy_t^{\tau=120}}{3}, \tag{16}$$

and the empirical spread slope $S_t^{\Delta sy}$ as the difference between the 120-months and 3-months yield spread:

$$S_t^{\Delta sy} = \Delta sy_t^{\tau=120} - \Delta sy_t^{\tau=3}. \tag{17}$$

In the following, we denote this model as **YLDSPRD**.

Macroeconomic Benchmark Models

We are particularly interested in how the proposed yield spread model performs against traditional fundamental exchange rate models. With the wide variety of these models being used in the literature[9] one necessarily has to be selective with respect to model choice in order to keep the results manageable. We thus include one prominent version for any of the major fundamental models described in Section 2:

Empirically, the most common approach to evaluating traditional fundamental exchange rate models out-of-sample (following Mark (1995)) is to represent a change in the log of the nominal exchange rate as a function of its deviation from its fundamental value (see also Molodtsova and Papell (2009); Giacomini and Rossi (2010)). Thus, the h-period-ahead change in the log exchange rate can be denoted as:

$$\widehat{s_{t+h}} - s_t = \alpha + \beta z_t + \epsilon_{t+h}, \tag{18}$$

where $\widehat{s_{t+h}}$ is the h-period forecast of the log exchange rate s and $z_t = f_t - s_t$ with f_t being the long-run equilibrium level of the nominal exchange rate determined by its fundamentals. The choice of fundamentals f_t is then determined by the respective model.

Interest Rate Differentials: To apply differences in interest rates, the UIRP relation is often directly used in forecast equations. However, empirical

[9] Molodtsova and Papell (2009) for example test 48 variations of the model based on Taylor rule fundamentals.

evidence indicates that, while exchange rate movements may be consistent with UIRP in the long-run, it clearly does not hold in the short-run, see, e.g., Sarno (2005); Engel (2014). Following Clark and West (2006), we thus implement a more flexible specification with:

$$f_t^{IRD} = (i_t^h - i_t^{h*}) + s_t, \tag{19}$$

and do not restrict $\alpha = 0$ and $\beta = 1$ in the forecasting equation (18).[10] We denote the interest rate differential model as **IRD**.

Price Fundamentals: If market participants believe that the future exchange rate is formed in line with PPP, the fundamental f_t is specified as:

$$f_t^{PPP} = (p_t - p_t^*). \tag{20}$$

This model is denoted as **PPP**.

Monetary Model: We follow Molodtsova and Papell (2009) and apply a version of the flexible-price monetary model, where the fundamental f_t is expressed as:

$$f_t^{MON} = (m_t - m_t^*) - \eta(y_t - y_t^*). \tag{21}$$

We fix $\eta = 3$ which is successfully applied by Molodtsova and Papell (2009) and denote the model as **MON**.

Taylor Rule Fundamentals: We consider a symmetric Taylor rule with homogeneous coefficients, see Giacomini and Rossi (2010). Assuming that UIRP and PPP hold leads to the following forecast equation:

$$\widehat{s_{t+h}} - s_t = (1 + \phi)(\pi_t - \pi_t^*) + \gamma(y_t^{gap} - y_t^{gap*}) + s_t. \tag{22}$$

Note that we estimate the coefficients instead of using Taylor's original coefficients of $\phi = 0.5$ and $\gamma = 0.5$.[11] The model based on Taylor rule fundamentals is indicated as **TR**.

[10] Note, that this approach yields the standard h-period ahead forecasting equation $\Delta s_{t+h} = \alpha + \beta(i_t^h - i_t^{h,*}) + \epsilon_{t+h}$ for maturity h.

[11] We have tested both alternatives for our analysis and find that estimating the coefficients yields a higher forecasting accuracy. We thus use this approach as a benchmark.

Random Walk

The traditional benchmark model for exchange rate forecasting studies is the random walk. We therefore also include the commonly used random walk without drift which stipulates that the best predictor of next period's exchange rate is the current exchange rate. Thus, the random walk always predicts 'no change' for the h-months horizon exchange rate:

$$\widehat{s_{t+h}} - s_t = 0. \tag{23}$$

In the following, the random walk will be denoted as **RW**.

4.3 Data

To construct the yield spread level $L_t^{\Delta sy}$ and slope $S_t^{\Delta sy}$ we use $\tau = 3$, $\tau = 36$ and $\tau = 120$ months sovereign bonds zero-coupon yields available from Bloomberg. The sovereign yield spreads Δsy_t^{τ} are then calculated as the difference between yields of equal maturity τ. Bloomberg yields are available from January 1995 onwards, so we use the time period from 1995:01-2014:12 for our analysis.

The corresponding nominal exchange rates are also taken from Bloomberg and measured as the domestic price per unit of foreign currency (domestic currency/foreign currency). Therefore, a rise in the nominal exchange rate represents a depreciation of the home currency and a lower value an appreciation of the home currency.

The primary source of data used to construct the macroeconomic fundamentals for the benchmark models is the IMF's International Financial Statistics (IFS) database. We follow Molodtsova and Papell (2009) in selecting the data and calculating the fundamental differentials. We use the seasonally adjusted industrial production index as a proxy for output since GDP data is available only at the quarterly frequency.[12] The output gap is calculated as a percentage deviation of actual output from a linear trend. We use the

[12] Industrial production data for Australia and Switzerland are also only available at quarterly frequency and hence are transformed from quarterly to monthly observations using the quadratic-match average method as applied by Molodtsova and Papell (2009).

money market rate as a measure of the short-term ($\tau = 1$ month) interest rate and Bloomberg sovereign yields (see above) equivalent in maturity to the remaining forecast horizons to implement the IRD approach and the trading strategy. The price level is measured by the consumer price index (CPI).[13] The inflation rate is the annual inflation rate, measured as the 12-month difference of the CPI. Finally, we use M1 to measure the money supply for all countries.[14]

We provide descriptive statistics of foreign exchange rates, macroeconomic variables and yield spreads for the considered sample period in Appendix A.1.

4.4 Forecasting Evaluation Measures

As indicated in Section 2, we examine the predictive power of the various models along different criteria. Each of the selected evaluation metrics has a different focus and we thus consider the use of these criteria as complementary. Considered jointly, they provide a multifaceted picture of the forecasting performance of the tested models. Naturally, depending on the purpose of a specific exercise one may favour one metric over the other.

RMSE The most commonly used measure of predictive ability in the out-of-sample exchange rate forecasting literature is the root-mean-square error (RMSE). The RMSE is a measure of global forecasting performance and summarizes the forecasting errors of a specific model M over the entire forecasting period P:

$$RMSE^M = \sqrt{\frac{1}{T-R-h} \sum_{t=R+h}^{T} (\widehat{\Delta s}^M_{t+h/t} - \Delta s^M_{t+h})^2}. \tag{24}$$

The lower the RMSE, the more accurate the forecast. To facilitate comparison between the yield spread models and the benchmarks models, we

[13]Australian CPI data is also only available at quarterly frequency, and hence transformed from quarterly to monthly observations applying the same quadratic-match average interpolation.

[14]M1 data for the UK is not provided by the IMF so we use M1 data provided by Datastream.

report the relative forecasting accuracy with the ratio of the RMSE from the respective yield spread model and the benchmark model M:[15]

$$RMSE\,ratio^{M} = \frac{RMSE^{YLDSPRD}}{RMSE^{M}}. \tag{25}$$

Accordingly, if $RMSE\,ratio^{M} < 1$, forecasts from the yield spread model are more accurate than the benchmark model.

Direction Accuracy From a market timing perspective it is often more important to correctly predict the direction of the exchange rate change. We therefore also apply a measure of direction accuracy (DA). The DA is computed as the number of correct predictions of the direction of change over the total number of predictions:

$$DA^{M} = \frac{1}{T-R-h} \sum_{t=R+h}^{T} a_t, \tag{26}$$

where $a_t = 1$ if the direction of change in period t is predicted correctly and $a_t = 0$ otherwise. The higher the DA the better the model predicts the direction of change.

Density Forecasts Recently, the literature has suggested that it is also important to asses the uncertainty around point forecasts (Sarno et al., 2006; Rapach and Wohar, 2006; Inoue and Rossi, 2008; Hong et al., 2007). One way to achieve this is to use density forecasts. A density forecast is an estimate of the probability distribution of the point forecast, conditional on the information available at time t and thus represents a complete characterization of the uncertainty associated with the forecast (Rossi, 2015).

To evaluate density forecasts, Diebold et al. (1999) have pioneered the use of probability integral transforms (PIT). A PIT is the cumulative probability evaluated at the actual, realized value of the forecasted variable (Rosenblatt, 1952). Diebold et al. (1999) demonstrate that the PIT is uniformly distributed and i.i.d. if the density forecast is correctly specified. In practice, density evaluation is thus implemented with formal tests measuring whether

[15]Note that this ratio is often reported reciprocal as the ratio of a model against the random walk.

an observed PIT is U(0,1): Assume, we are interested in the distribution of the exchange rate change Δs^M_{t+h} which is being forecasted at time t. If the probability density of Δs^M_{t+h} is $f(\Delta s^M_{t+h})$ then its associated cumulative distribution function (CDF) can be expressed as

$$F(\Delta s^M_{t+h}) = \int_{-\infty}^{\Delta s^M_{t+h}} f(x)dx. \tag{27}$$

Following Rossi (2015), we determine the unknown variance of the forecast error with the estimated variance of the in-sample fitted errors and then test for violations of independence and uniformity of $\widehat{F}(\Delta s^M_{t+h})$ within the Rossi and Sekhposyan (2016) framework. This innovative approach comprises two test statistics KS and CM within the class of Kolmogorov-Smirnov and Cramer-von Mises-type tests commonly used in the literature to formally evaluate the correct specification of density forecasts using PITs. Both tests evaluate density forecasts at the estimated parameter values (as opposed to their population values) which is empirically more useful to measure a models' actual forecasting ability in finite samples. The framework is also valid for multiple-step-ahead density forecasts, which is particularly important for our analysis. See Rossi and Sekhposyan (2016) for a detailed derivation of the test statistics.

5 Out-of-sample Forecasting Results

5.1 RMSE

Table 1 reports the RMSEs for all investigated currencies and forecast horizons. The first line shows the results of the yield spread model in absolute terms. As we are mainly interested in the forecasting performance relative to our yield spread models, we present the RMSEs of the other models below as a ratio against both approaches.[16] Hence, numbers smaller than one

[16]Note that this is reciprocal to studies that focus only on the forecasting performance compared to the random walk and thus express the RMSE relative to the random walk.

(reported in bold) indicate a smaller RMSE and accordingly superior forecasting performance of the yield spread model.

We find that the proposed approach performs quite well for several cur-

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	0.039	0.026	0.033	0.029	0.025	0.029	0.038	0.036
IRD	**0.990**	**0.996**	1.007	1.025	1.025	1.037	1.017	**0.971**
PPP	1.004	**0.994**	1.025	1.029	**0.968**	1.028	1.006	1.017
MON	1.006	**0.998**	1.016	**0.995**	**0.988**	1.082	1.038	1.008
TR	**0.979**	**0.985**	**0.998**	1.025	**0.969**	1.059	**0.991**	**0.993**
RW	1.021	1.006	1.044	1.053	1.020	1.090	1.066	1.048
				h = 3				
YLDSPRD	0.073	0.043	0.059	0.058	0.050	0.053	0.082	0.062
IRD	**0.979**	**0.955**	1.036	1.040	1.043	1.023	1.046	1.039
PPP	**0.996**	**0.944**	1.075	1.051	**0.939**	1.071	1.086	**0.998**
MON	1.008	**0.966**	1.050	**0.912**	**0.991**	1.161	1.176	**0.974**
TR	**0.909**	**0.956**	1.025	1.010	**0.898**	1.081	**0.947**	**0.954**
RW	1.056	**0.973**	1.141	1.140	1.068	1.185	1.255	1.112
				h = 6				
YLDSPRD	0.118	0.063	0.091	0.083	0.085	0.087	0.114	0.097
IRD	**0.966**	**0.915**	1.016	1.019	1.091	1.062	1.075	1.020
PPP	**0.992**	**0.922**	1.180	**0.974**	1.078	1.174	**0.948**	**0.959**
MON	1.013	**0.928**	1.112	**0.711**	1.031	1.327	1.041	**0.991**
TR	**0.810**	**0.915**	**0.972**	**0.807**	**0.969**	1.179	**0.911**	**0.970**
RW	1.139	**0.964**	1.273	1.141	1.167	1.383	1.172	1.239
				h = 12				
YLDSPRD	0.197	0.088	0.180	0.162	0.115	0.192	0.217	0.130
IRD	1.073	**0.895**	1.159	1.121	1.064	1.176	1.125	**0.836**
PPP	1.025	**0.808**	1.532	1.134	**0.849**	1.525	1.009	**0.832**
MON	1.060	**0.888**	1.364	**0.765**	**0.914**	1.769	1.137	**0.701**
TR	1.093	**0.625**	1.303	**0.902**	**0.995**	1.408	**0.612**	**0.783**
RW	1.414	**0.973**	1.810	1.584	1.190	2.050	1.561	1.217

Table 1. Root mean squared errors (RMSEs) for the time period from 1995:01 – 2014:12 and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The first line reports the RMSE for the yield spread (YLDSPRD) model. The RMSEs of all other models and the random walk are expressed as the ratio against the yield spread model. Hence, numbers smaller than one (**reported in bold**) indicate a smaller RMSE and accordingly superior forecasting performance of the yield spread model. Numbers larger than one indicate inferior forecasting performance in terms of the RMSE. See Section 4.1 for a detailed description of the models.

rencies, for example the USD/CAD, USD/GBP and the JPY/CHF, where the YLDSPRD model predominantly outperforms the fundamental models across all horizons. However, for some of the currencies it clearly underperforms against the fundamental models, in particular the CHF/GBP exchange rate where our model fails to beat any of the applied fundamental models. It is also obvious that neither our yield spread model nor the traditional models are able to consistently beat the random walk in terms of the RMSE. Except for a few occasions, the random walk consistently yields the lowest RMSE (reflected in the largest RMSE ratios). These results are not entirely surprising based on findings in the previous literature described in Section 2 and provide further evidence to the well documented failure of exchange rate models to outperform the random walk in terms of the RMSE (Cheung et al., 2005; Rossi, 2013). However, this conclusion changes when we turn to further statistical evaluation measures and profitability.

5.2 Direction Accuracy

Our next evaluation metric is the direction of change statistic. Table 2 reports the proportion of forecasts that correctly predict the direction of the exchange rate movement over time horizon h. The first line reports the direction accuracy of the yield spread models. Below, we report the results for the benchmark models. The higher the proportion of correctly forecasted directions of change, the better. Superior direction accuracy of the yield spread models is indicated in bold. Note that compared to a random walk, a value above (below) 0.5 indicates a better (worse) forecasting performance than the naive RW model which has an equal chance of going up or down.[17]

In terms of direction accuracy, we find that our model consistently outperforms both the fundamental models as well as the random walk. The YLDSPRD model is able to predominantly beat the random walk with the DA statistics being typically larger than 0.50 except for the CHF/GBP exchange rate. These results hold across all considered forecasting horizons.

[17] The direction accuracy of the random walk has been the subject of debate in previous literature. Moosa and Burns (2014) for example argue that the random walk has a direction accuracy of zero as the forecast for the exchange rate change is always zero. While this may be technically true, we think that this gives our approach and the fundamental models an unwarranted advantage. In any case, the direction accuracy of a forecast should always be superior to a coin toss. We thus follow, e.g., Cheung et al. (2005), and use 0.5 as the direction accuracy of the random walk.

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	0.56	0.50	0.53	0.57	0.51	0.48	0.56	0.49
IRD	**0.54**	0.51	**0.51**	**0.52**	0.55	**0.45**	**0.56**	**0.46**
PPP	**0.51**	**0.47**	**0.49**	**0.51**	**0.43**	0.49	**0.44**	**0.45**
MON	**0.53**	0.56	**0.49**	**0.51**	**0.49**	0.48	**0.47**	**0.48**
TR	**0.51**	**0.48**	0.54	**0.53**	0.54	**0.42**	**0.55**	**0.48**
RW	**0.50**	0.50	**0.50**	**0.50**	**0.50**	0.50	**0.50**	0.50
				h = 3				
YLDSPRD	0.59	0.60	0.57	0.54	0.48	0.45	0.56	0.48
IRD	**0.56**	**0.53**	0.57	**0.54**	0.56	0.48	**0.52**	0.50
PPP	**0.44**	**0.43**	**0.47**	0.55	**0.43**	0.48	**0.38**	**0.42**
MON	**0.55**	**0.52**	**0.51**	**0.40**	**0.47**	0.55	**0.49**	0.53
TR	**0.51**	**0.58**	**0.50**	**0.49**	0.53	0.51	**0.53**	0.48
RW	**0.50**	**0.50**	**0.50**	**0.50**	0.50	0.50	**0.50**	0.50
				h = 6				
YLDSPRD	0.62	0.66	0.55	0.65	0.46	0.42	0.63	0.58
IRD	**0.58**	**0.51**	0.58	**0.62**	0.54	**0.40**	**0.55**	**0.54**
PPP	**0.45**	**0.44**	0.55	**0.53**	**0.43**	0.46	**0.44**	**0.39**
MON	**0.49**	**0.58**	0.58	**0.40**	**0.45**	0.52	**0.49**	**0.55**
TR	**0.49**	**0.55**	**0.46**	**0.49**	0.57	**0.41**	**0.51**	**0.50**
RW	**0.50**	**0.50**	**0.50**	**0.50**	0.50ˆ	0.50	**0.50**	**0.50**
				h = 12				
YLDSPRD	0.54	0.72	0.50	0.62	0.56	0.49	0.60	0.65
IRD	0.56	**0.57**	0.51	**0.61**	**0.51**	**0.44**	**0.54**	**0.60**
PPP	**0.36**	**0.50**	**0.47**	**0.53**	**0.49**	0.49	**0.31**	**0.40**
MON	**0.46**	**0.55**	0.59	**0.32**	**0.44**	0.57	**0.47**	**0.51**
TR	**0.51**	**0.48**	**0.46**	**0.47**	**0.52**	**0.38**	**0.46**	**0.49**
RW	**0.50**	**0.50**	0.50	**0.50**	**0.50**	0.50	**0.50**	**0.50**

Table 2. Direction accuracy (DA) for the time period from 1995:01 – 2014:12 and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The DA-statistic reports the proportion of forecasts correctly predicting the direction of the exchange rate movement over horizon h. The higher the proportion the better the direction accuracy. The first line reports the direction accuracy of the yield spread (YLDSPRD) model. Direction accuracy smaller than the yield spread model's indicating a superior forecasting performance is **indicated in bold**. A value above (below) 0.5 indicates a better (worse) forecasting accuracy than a random walk. See Section 4.1 for a detailed description of the models.

Comparing the yield spread model to the traditional fundamental models, we also find promising results. Our model is consistently among the models with the highest proportion of forecasts correctly predicting the direction of change for all currencies, except for the CHF/GBP exchange rate. Overall it is the best or second best model for 21 out of the 32 considered horizon/currency combinations. The z-scores of a conventional test of the significance of proportions reported in Apendix A.2 also indicate that the superior direction accuracy of our approach is statistically significant for many cases, especially for the longer forecasting horizons.

5.3 Density Forecasts

Next, we present the results of the evaluation of the density forecasts in Tables 3 and 4 where we summarize the results of the Kolmogorov-Smirnov and Cramer-von-Mises type test-statistics within the Rossi and Sekhposyan (2016) framework. The first line reports the KS and CM test statistic for the yield spread model. The results for the benchmark models are reported below. Note that in both tables a greater value indicates stronger evidence for misspecification of the density forecast for a particular model. Test statistics that are larger for the benchmark models than for our approach therefore indicate a superior forecasting performance of the YLDSPRD model and are highlighted in bold.

We find strong evidence that our approach yields more appropriate density forecasts than the traditional fundamental models. Overall, the YLDSPRD model delivers smaller test statistics than the benchmark models for most of the currencies and forecasting horizons. This observation also holds for the CHF/GBP exchange rate, which has delivered rather poor results for the previous forecasting evaluation measures. The proposed approach is also able to beat the random walk for several of the forecast horizon / currency combinations. For short and medium term forecasting horizons up to $h = 6$ months, the null of uniformity of the PITs based on our model forecasts is only rejected for the USD/GBP exchange rate for $h = 3$-months forecasts, and three additional exchange rates for a $h = 6$-months forecast horizon.

However, we generally find a high number of rejections with lengthening forecasting horizons. For $h = 12$-months ahead forecasts we reject the null of uniformity for all models and currencies indicating that the density forecasts are not correctly specified for all assessed models.

We advocate two potential explanations. First, as described in Section 2, empirical exchange rate forecasting generally is a cumbersome task, espe-

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	0.72	1.06	0.63	0.91	0.93	0.63	0.92	1.02
IRD	0.61	0.96	0.59	0.87	**1.08**	**1.31**	**0.94**	**1.24**
PPP	**0.74**	0.63	**0.88**	**1.34**	0.82	**0.76**	**1.79***	**2.06***
MON	0.70	0.57	**0.86**	0.83	0.74	**1.10**	**1.09**	**1.14**
TR	**1.31**	0.80	**0.78**	**1.05**	0.74	**1.02**	**0.98**	**1.11**
RW	**0.91**	0.89	**0.99**	0.62	0.68	**1.34**	**1.18**	**1.85***
				h = 3				
YLDSPRD	0.97	0.91	1.24	0.76	1.42*	0.65	1.02	0.88
IRD	0.87	0.69	1.23	**0.90**	**1.46***	**0.67**	0.83	**1.50***
PPP	**1.84***	0.85	**1.43***	**1.60***	1.15	**0.82**	**1.43***	**2.71***
MON	0.88	**1.04**	0.77	1.22	1.18	**1.69***	0.85	**1.52***
TR	**2.10***	1.30	1.09	0.76	1.05	0.82	**1.28**	**1.30**
RW	**1.73***	0.87	**1.46***	0.67	0.81	**1.65***	**1.54***	**2.34***
				h = 6				
YLDSPRD	1.40	1.53*	2.82*	0.94	1.83*	1.96*	1.18	1.33
IRD	**1.41***	1.11	2.49*	**0.96**	**1.86***	1.15	1.01	**1.94***
PPP	**3.06***	**1.55***	2.21*	**2.39***	**1.94***	1.19	**1.55***	**2.79***
MON	**2.47***	1.37	1.32	**1.84***	**2.10***	**2.14***	1.07	1.17
TR	**2.70***	**2.03***	2.09*	**1.85***	1.52*	1.32	**1.45***	1.25
RW	**1.55***	1.18	1.72*	0.63	1.06	1.46*	**1.79***	**2.53***
				h = 12				
YLDSPRD	3.46*	1.78*	4.09*	3.88*	2.29*	2.36*	2.37*	2.58*
IRD	3.23*	**2.48***	3.46*	2.94*	**2.43***	**2.67***	2.27*	2.48*
PPP	**4.82***	**3.65***	**4.68***	**4.44***	**3.46***	**2.68***	**3.46***	**4.55***
MON	**4.34***	**2.43***	2.15*	3.38*	**3.30***	**3.13***	2.21*	**2.59***
TR	**3.47***	**2.57***	2.27*	3.33*	**2.49***	**2.71***	**2.98***	**3.79***
RW	2.10*	**2.08***	2.99*	1.23	1.83*	2.10*	1.99*	**3.39***

Table 3. Rossi and Sekhposyan (2016) KS test statistics for a Kolmogorov-Smirnov type test of uniformity of density forecasts. We report KS test statistics for all considered currencies against the USD and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The first line reports the KS test statistic for the yield spread model. The results for the benchmark models are reported below. Test statistics larger than those of the yield spread model are **indicated in bold**. The larger the test statistic the stronger the evidence for misspecification of the density forecast. * indicates rejection of the null hypothesis of correct specification of the density forecasts at the 5% significance level. Critical values are taken from Rossi and Sekhposyan (2016). See Section 4.1 for a detailed description of all models.

cially over long horizons. It is not entirely surprising that the performance of the applied models deteriorates with the length of the forecasting horizon. Furthermore, our forecasting period encompasses the global financial crisis (GFC) which had significant impacts on foreign exchange markets (Guidolin and Tam, 2013). We suspect that this will also impact the forecasting un-

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	0.08	0.13	0.04	0.12	0.27	0.09	0.11	0.23
IRD	0.05	**0.16**	**0.06**	**0.13**	0.26	**0.31**	**0.21**	**0.44**
PPP	**0.20**	0.08	**0.17**	**0.30**	0.11	**0.14**	**0.88**	**1.25**
MON	**0.08**	0.05	**0.07**	0.08	0.11	**0.26**	**0.29**	**0.32**
TR	**0.44**	0.09	**0.11**	**0.15**	0.08	**0.19**	**0.26**	**0.21**
RW	**0.18**	**0.14**	**0.16**	0.08	0.06	**0.40**	**0.39**	**0.73**
				h = 3				
YLDSPRD	0.22	0.17	0.38	0.14	0.73	0.11	0.28	0.15
IRD	0.15	0.13	0.34	**0.18**	**0.81**	0.09	0.10	**0.58**
PPP	**1.26**	0.14	**0.88**	**0.86**	0.34	**0.13**	**0.69**	2.26*
MON	**0.25**	**0.24**	0.10	**0.40**	0.34	**0.53**	0.13	**0.54**
TR	**1.71***	**0.36**	0.28	0.10	0.26	**0.10**	0.35	**0.50**
RW	0.63	0.12	**0.59**	0.08	0.14	0.51	**0.64**	**1.70***
				h = 6				
YLDSPRD	0.45	0.55	2.51*	0.14	1.27	0.63	0.50	0.54
IRD	0.39	0.42	2.05*	**0.27**	1.11	0.28	0.07	**0.70**
PPP	**3.79***	**0.65**	2.50*	**2.04***	1.18	0.51	**0.95**	**3.34***
MON	**1.54***	0.30	0.42	**0.99**	1.15	**1.33**	0.22	0.34
TR	**2.90***	**1.11**	1.36	**0.86**	0.59	0.62	0.36	0.51
RW	**0.79**	0.34	1.41*	0.05	0.33	**0.75**	**1.03**	**2.39***
				h = 12				
YLDSPRD	3.91*	0.96	3.70*	4.91*	1.31	1.79*	1.81*	3.08*
IRD	3.11*	**1.57***	3.61*	2.97*	1.24	**1.86***	**2.27***	2.66*
PPP	**7.91***	**4.28***	**7.25***	**5.68***	**3.96***	**2.82***	**4.40***	**6.65***
MON	**4.55***	**1.48***	1.09	3.64*	**2.56***	**3.92***	1.10	1.72*
TR	**4.10***	**2.26***	2.13*	3.64*	**2.10***	**2.40***	**3.24***	**5.16***
RW	1.57*	**1.38**	**3.76***	0.35	1.17	1.66*	1.45*	**4.30***

Table 4. Rossi and Sekhposyan (2016) CM test statistics for a Cramr-von-Mises type test of uniformity of density forecasts. We report CM test statistics for all considered currencies against the USD and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The first line reports the CM test statistic for the yield spread model. The results for the benchmark models are reported below. Test statistics larger than those of the yield spread model are **indicated in bold**. The larger the test statistic the stronger the evidence for misspecification of the density forecast. *,**,*** indicates rejection of the null hypothesis of correct specification of the density forecasts at the 10%,5%,1% significance level. Critical values are taken from Rossi and Sekhposyan (2016). See Section 4.1 for a detailed description of all models..

certainty as measured by tests of uniformity.[18]

[18] As a robustness test, we have re-calculated all statistical evaluation metrics excluding the crisis period. The results confirm that when the GFC is excluded, calculated KS and CV test statistics drop significantly and that the GFC thus, at least partly, contributes to the high uncertainty and poor performance of the exchange rate forecasts in our sample. RMSE and DA seem to be less affected. Detailed results for this analysis are not included here to save space but are available upon request to the authors.

6 Trading Strategy

6.1 Trading Rule Implementation

As suggested by Abhyankar et al. (2005); Corte et al. (2009); Moosa and Burns (2014), the ultimate test of the predictive power of an exchange rate model is the profitability of the forecasts. After all, statistical evidence of exchange rate predictability does not guarantee an investor to make profits with a strategy exploiting this predictive power.
To asses the profitability of the different models, we thus implement a simple trading strategy that utilizes the respective exchange rate forecasts $\widehat{\Delta s}^{M}_{t+h}$. Following Moosa and Burns (2014) we apply an intuitive approach that involves period-by-period trading based on the forecasted h-month horizon excess returns $\widehat{xs}^{M}_{t/t+h}$ predicted by model M:

$$\widehat{xs}^{M}_{t/t+h} = (i^{h}_{t} - i^{h,*}_{t}) - \widehat{\Delta s}^{M}_{t+h}. \tag{28}$$

Note that hereby the maturity of the interest rate differential $(i^{h}_{t} - i^{h,*}_{t})$ equals the forecasting horizon h.
The decision rule for trading is then based on whether the forecasted excess return $\widehat{xs}^{M}_{t/t+h}$ derived from the model forecast $\widehat{\Delta s}^{M}_{t+h}$ is positive or negative. A negative excess return, for example, indicates that the model forecasts an appreciation of the foreign currency which outweighs the interest rate differential[19] and thus suggests an investment in the foreign currency. The trading rule can therefore be defined as:[20]

$$\begin{aligned} &if \quad \widehat{xs}^{M}_{t/t+h} > 0 \quad \rightarrow \quad invest\; in\; home\; currency, \\ &if \quad \widehat{xs}^{M}_{t/t+h} < 0 \quad \rightarrow \quad invest\; in\; foreign\; currency. \end{aligned}$$

[19]Recall, that a rise in the nominal exchange rate s represents a depreciation of the home currency, while and a lower value represents an appreciation.

[20]Note that under the random walk without drift, the forecast change in the exchange rate is always zero. This means that the decision rule leads to going short on the low-interest currency and long on the high-interest currency which represents the common carry trade.

We then calculate the actual return xs^M_{t+h} for every trade based on the actual exchange rate changes over the corresponding horizon as:

$$xs^M_{t+h} = \begin{cases} (i^h_t - i^{h,*}_t) - \Delta s_{t+h} & for\ investments\ in\ home\ currency \\ (i^{h,*}_t - i^h_t) + \Delta s_{t+h} & for\ investments\ in\ foreign\ currency. \end{cases} \tag{29}$$

Note that we ignore transaction costs as the main purpose of our analysis is to compare the profitability of the considered models and the same number of trades are executed for all models.

We implement the trading strategy for every month of the forecasting period $P = T - R - h$ and summarize annualized mean returns $\overline{xs}^M$ across the entire forecasting period for each model. We further calculate the risk adjusted profitability xs^M_{ra} for every model M as a ratio of the mean return $\overline{xs}^M$ and the standard deviation σ^M_{xs} of the returns:

$$xs^M_{ra} = \frac{\overline{xs}^M}{\sigma^M_{xs}}. \tag{30}$$

We illustrated the applied trading strategy with a simple example. Let us assume that s is the log of the USD/CAD exchange rate and the $h = 6$ months interest rate differential $i^{h=6}_t - i^{h=6,*}_t$ between the US (home country) and Canada (foreign country) is $5\% - 2\% = 3\%$. Let us further assume that model M predicts a depreciation of the US dollar over the next $h = 6$ months period of $\widehat{\Delta s}^M_{t+6} = 4\%$.[21] The predicted negative semi-annual excess return $\widehat{xs}^M_{t/t+6}$ of $\frac{3\%}{2} - 4\% = -2.5\%$[22] would indicate an investment in the Canadian dollar as the predicted CAD appreciation outweighs the interest rate differential. Further assuming that the actual appreciation Δs_{t+6} of the Canadian dollar over the next 6-months horizon is only 1%, the investment in the Canadian dollar would yield a negative actual semi-annual return of $xs^M_{t/t+6} = \frac{3\%}{2} + 1\% = -0.5\%$ and thus an annualized return of $xs^M_{t/t+6,ann.} =$

[21] Again, recall that a rise in the nominal exchange rate s represents a depreciation of the home curreny (USD).

[22] Note, that the difference in annual interest rates has to be adjusted to match the semi-annual ($h = 6$-month) horizon of the exchange rate change.

$-0.5\% \cdot 2 = -1.0\%$. The strategy is implemented for every month of the forecasting period to obtain a time series of monthly annualized returns. If we assume that the mean return of all these trades is $\overline{xs}^M_{h=6} = 2.8\%$ with a standard deviation of $\sigma^M_{xs,h=6} = 14.6\%$ the annualized return-risk ratio or risk adjusted return is $xs^M_{h=6,ra} = \frac{2.8\%}{14.6\%} = 0.19$.

6.2 Trading Returns

We report annualized average monthly returns $\overline{xs}^M$ of the implemented trading strategy for all considered models including the random walk in Table 5. The first line reports the returns for the yield spread models. Returns smaller than those of the proposed yield spread model then indicate a superior performance of our model and are highlighted in bold.

Focusing on the results for the yield spread model first, we find positive returns for nearly all currencies and forecast horizons. The approach seems to work particularly well for the USD/CAD exchange rate where the simple strategy yields average monthly returns of up to 5.86%.

Overall, we also find promising results for our approach relative to the fundamental models and the random walk when the forecasting accuracy is assessed in terms of trading profitability. The suggested model predominantly generates higher returns than the traditional fundamental models.[23] This holds in particular for the USD/CAD and USD/JPY exchange rate. Note, that the random walk still does surprisingly well, which is further validation for the success of carry trade strategies. Nevertheless, the proposed yield spread model is able to beat the random walk for some of the currency/forecast horizon combinations.

In general, trading profitability also seems to be similarly currency specific as the previously applied statistical evaluation metrics. For some currencies, the suggested yield spread model works exceptionally well (e.g. the USD/CAD or CHF/GBP exchange rates) across all forecasting horizons, while for others currencies (in particular the JPY/CHF exchange rate) the profitability

[23]The relative performance of the models also does not change when the created returns are adjusted for risk. See Table A.5 in Appendix A.3.

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	2.76	3.94	1.83	4.35	-0.01	1.92	-0.48	-5.28
IRD	**1.63**	**2.30**	**-0.60**	**2.00**	1.26	**-0.23**	0.79	-2.41
PPP	**1.85**	**3.01**	**-0.63**	**2.29**	**-2.52**	3.64	3.49	-3.46
MON	**1.00**	**1.37**	**-1.68**	**0.26**	1.00	2.93	1.06	-0.76
TR	**2.37**	**1.10**	4.40	**3.78**	2.14	**1.23**	2.30	-1.48
RW	**-1.10**	**1.57**	4.10	**1.48**	0.94	5.61	2.12	-1.76
				h = 3				
YLDSPRD	1.73	5.86	0.84	3.67	-2.03	1.41	-0.18	-1.70
IRD	**1.43**	**1.81**	1.59	**1.06**	2.38	2.49	**-0.44**	-1.10
PPP	**-0.11**	**-0.19**	**-0.65**	**2.01**	**-2.68**	1.56	**-1.90**	-1.48
MON	**-0.69**	**0.10**	**0.26**	**-1.52**	0.57	2.79	**-0.46**	**-2.22**
TR	1.74	**4.48**	**0.35**	**0.97**	-1.49	2.42	**-1.67**	**-3.73**
RW	**-0.61**	**1.44**	4.96	**3.31**	1.44	5.63	2.31	1.60
				h = 6				
YLDSPRD	0.56	4.34	1.54	5.31	-1.09	1.68	3.00	0.14
IRD	3.07	**-0.15**	1.92	**2.20**	1.14	2.20	**0.85**	**-0.08**
PPP	1.20	**-1.07**	1.69	**1.03**	0.49	1.71	**-0.68**	**-1.94**
MON	**-1.36**	**-0.56**	2.43	**-1.84**	1.18	2.39	**-0.75**	**-2.40**
TR	**-1.50**	**2.86**	**0.00**	**-0.61**	**-2.10**	**0.52**	**-0.20**	**-2.10**
RW	**-1.76**	**1.76**	5.35	**2.51**	1.32	5.69	**2.43**	1.12
				h = 12				
YLDSPRD	-1.37	2.90	-0.58	1.60	0.76	1.27	0.82	2.81
IRD	1.11	**1.10**	0.98	**1.08**	**-0.42**	**0.76**	**-2.92**	**0.49**
PPP	-0.25	**-0.06**	0.36	**1.06**	1.34	2.19	**-4.90**	**-1.90**
MON	0.12	**-0.33**	1.75	**-1.50**	1.28	2.82	**-4.27**	**-2.58**
TR	-0.01	**-0.31**	0.56	**-1.83**	**-1.53**	**-0.97**	**-5.03**	**-2.78**
RW	**-2.08**	**1.05**	5.45	2.11	1.38	5.77	2.49	**0.73**

Table 5. Annualized average monthly returns $\overline{xs}^M$ (in %) of a trading strategy based on the model's forecasts for the time period from 1995:01 – 2014:12 and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The higher the average return the more successful is trading based on the model's forecasts. Average returns's smaller than the yield spread (YLDSPRD) model indicate a superior risk-return relationship of the yield spread model, and are **reported in bold**. See Section 4.1 for a detailed description of the models and Section 6.1 for a description of the trading strategy.

is somewhat disappointing.
It is also important to note, that simply trading based on exchange rate forecasts without additional discretionary trading rules or the creation of portfolios does not generally produce impressive returns. The majority of annualized returns is not very high and several trading strategies based on forecasts even yield negative average returns. Taking into account reasonable transaction costs would probably see more of the remaining profits diminish. Nonetheless, we find that also for the applied trading strategy our proposed approach typically yields better results than traditional fundamentals-based exchange rate models.

7 Conclusion

This paper proposes using the level and slope of the yield spread curve between two economies for the prediction of exchange rates. We apply these two variables as proxies reflecting the market's unobservable expectations of current and future macroeconomic fundamentals and investigate their forecasting accuracy in an extensive out-of-sample forecasting exercise against traditional models based on interest rate, price, monetary and Taylor rule fundamentals as well as the random walk.
We find that the proposed approach is able to beat traditional fundamental exchange rate models in terms of all considered forecasting evaluation metrics. While we find currency specific results for the RMSE, the yield spread model consistently outperforms the benchmark models in terms of direction accuracy and density forecasts. Although our model fails to beat the random walk in terms of the RMSE – which should hardly be surprising based on previous findings in the literature – it is also superior to a random walk in forecasting the direction of exchange rate changes and produces better specified density forecasts for some currencies. Our investigation of major cross rates confirms that these results are not only restricted to exchange rates against the USD but also hold for other currencies.
We also assess the profitability of our approach by implementing a period-

by-period trading strategy and find that trading based on the implemented yield spread level and spread slope model consistently generates higher risk-adjusted returns compared to traditional fundamental models and is also able to beat the random walk for several currencies considered in this study.

The difference in conclusions depending on the choice of currency or statistical and economic forecasting metrics highlights the importance of applying a variety of measures to provide a conclusive assessment of a model's forecasting ability. Simply minimizing the mean squared error is not always adequate from an economic standpoint and may miss out on important aspects of exchange rate forecasts such as the direction of change and profitability. Depending on the purpose of the forecast, e.g. hedging, trading or macroeconomic modeling, different models may be more appealing to market participants.

Overall, our promising results provide further evidence that there is an important place for models based on financial variables in exchange rate forecasting. Evans and Lyons (2007), Guo and Savickas (2008) and Rime et al. (2010) have previously shown that financial variables related to stock returns and order flow have the ability to improve exchange rate forecasts. Recently, Chen and Tsang (2013) and Bui and Fisher (2016) also found predictive power of cross-country Nelson-Siegel factors for exchange rates conducting an in-sample analysis. These factors are closely associated with the empirical spread level and slope suggested in this study. We complement their findings and show that the empirical yield spread level and slope also have the potential to successfully forecast exchange rates in an out-of-sample setting.

There are several possible explanations why the yield spread level and slope work relatiely well in forecasting exchange rates. When the exchange rate is understood as an asset price and determined by the sum of expected future fundamentals these indicators act as natural proxies whose forward-looking character summarizes market expectations for these fundamentals. Further, because sovereign yield spreads and foreign exchanges are susceptible to the same macroeconomic risk the expected risk premia that investors require for holding these assets might closely relate to each other.

From an empirical forecasting perspective it is also favorable to focus on a small number of variables which reflect a broad range of unobservable macroeconomic information and business conditions. First, this allows for parsimonious modeling and previous research has shown, that simple specifications often deliver accurate forecasts, see, for example, Clark and McCracken (2013). Second, our approach is more flexible to changes in business conditions over time and less vulnerable to the omitted variables bias than traditional models based on selected observable fundamentals.

It is important to note that exchange rates are notoriously difficult to predict empirically and the forecasting success often depends on the choice of currency, forecast horizon, in-sample window length, sample period and evaluation method. We also find that our approach works better for some currencies and horizons than for others. But considering all applied evaluation metrics as well as the trading profitability, we provide a promising, multifaceted picture of the forecast performance of the proposed yield spread models. In addition, our approach is parsimonious and based on readily available, market-driven data, which makes it straightforward to being applied in practice.

We thus hope that our study contributes to a renewed interest in the empirical assessment of exchange rate forecasting models based on financial variables, as they are an intuitive and promising resolution, in particular when exchange rates are understood as an asset price. Further research is required, for instance, to fully understand the dynamics of the term structure of yield spreads and its relation to macroeconomic fundamentals and exchange rates. It may also be worthwhile to combine our approach with other financial variables, e.g. stock returns, or factors derived from a range of financial variables which may reflect other aspects of the business cycle and exchange rate determination, to further increase the forecasting accuracy.

Appendix

A.1 Descriptive Statistics

Currency	Mean	Std	Min	Max	Skewness	Kurtosis
			h = 1			
USD/AUD	0.000	0.035	-0.18	0.09	-0.73	5.92
USD/CAD	0.001	0.024	-0.14	0.09	-0.64	7.94
USD/CHF	0.001	0.031	-0.12	0.13	0.15	4.38
USD/JPY	-0.001	0.032	-0.10	0.16	0.52	5.78
USD/GBP	0.000	0.024	-0.10	0.09	-0.34	4.59
CHF/GBP	-0.001	0.027	-0.18	0.08	-1.10	10.27
GBP/JPY	-0.001	0.037	-0.09	0.18	1.08	6.61
JPY/CHF	0.002	0.035	-0.14	0.11	-0.68	4.59
			h = 3			
USD/AUD	0.002	0.064	-0.36	0.22	-1.07	8.24
USD/CAD	0.003	0.040	-0.17	0.15	-0.19	6.01
USD/CHF	0.003	0.051	-0.12	0.13	0.05	2.64
USD/JPY	-0.003	0.058	-0.16	0.22	0.47	4.06
USD/GBP	0.000	0.043	-0.20	0.14	-0.83	7.70
CHF/GBP	-0.003	0.047	-0.25	0.16	-0.59	6.46
GBP/JPY	-0.003	0.069	-0.15	0.35	1.54	8.34
JPY/CHF	0.006	0.060	-0.23	0.16	-0.47	4.36
			h = 6			
USD/AUD	0.005	0.095	-0.39	0.27	-0.77	6.05
USD/CAD	0.005	0.059	-0.22	0.16	-0.32	5.10
USD/CHF	0.006	0.072	-0.20	0.18	-0.10	2.69
USD/JPY	-0.006	0.082	-0.20	0.22	0.04	2.99
USD/GBP	0.000	0.065	-0.32	0.16	-1.46	8.48
CHF/GBP	-0.005	0.067	-0.26	0.25	-0.20	5.17
GBP/JPY	-0.006	0.101	-0.19	0.49	1.53	7.84
JPY/CHF	0.011	0.085	-0.29	0.23	-0.49	3.91
			h = 12			
USD/AUD	0.010	0.133	-0.38	0.33	-0.14	3.05
USD/CAD	0.011	0.080	-0.26	0.22	-0.22	3.96
USD/CHF	0.013	0.100	-0.23	0.30	0.05	2.92
USD/JPY	-0.007	0.111	-0.26	0.25	-0.18	2.27
USD/GBP	0.002	0.087	-0.33	0.17	-1.29	5.96
CHF/GBP	-0.011	0.100	-0.36	0.29	0.07	4.14
GBP/JPY	-0.009	0.144	-0.27	0.51	0.97	4.12
JPY/CHF	0.019	0.118	-0.33	0.28	-0.54	3.20

Table A.1. Descriptive statistics for h=1, h=3, h=6 and h=12 months nominal exchange rate changes (home currency price per unit of foreign currency) for the time period from 1995:01 – 2014:12. Source: Bloomberg.

Country	Mean	Std	Min	Max	Skewness	Kurtosis
			log(p)			
US	4.478	0.140	4.23	4.69	-0.08	1.68
AU	4.449	0.160	4.19	4.71	0.03	1.66
CA	4.501	0.115	4.31	4.68	-0.09	1.68
CH	4.553	0.044	4.47	4.62	-0.20	1.57
JP	4.618	0.013	4.60	4.65	0.62	2.33
UK	4.493	0.122	4.30	4.72	0.47	1.96
			π			
US	0.023	0.011	-0.02	0.05	-0.67	5.04
AU	0.027	0.013	0.00	0.06	0.26	3.64
CA	0.019	0.009	-0.01	0.05	-0.04	3.89
CH	0.007	0.008	-0.01	0.03	0.30	3.14
JP	0.001	0.011	-0.03	0.04	1.04	4.60
UK	0.021	0.010	0.01	0.05	0.86	3.55
			log(m1)			
US	7.272	0.294	6.97	7.97	1.00	2.80
AU	5.123	0.399	4.32	5.74	-0.34	2.00
CA	5.812	0.478	5.02	6.62	0.09	1.83
CH	5.631	0.402	4.93	6.36	0.31	2.03
JP	5.871	0.456	4.95	6.41	-0.61	1.77
UK	6.453	0.532	5.40	7.22	-0.34	1.84
			i			
US	2.854	2.350	0.07	6.54	0.06	1.30
AU	5.054	1.361	2.50	7.52	-0.06	2.54
CA	3.017	1.843	0.24	8.06	0.34	2.38
CH	0.967	1.055	-2.00	3.50	0.56	2.66
JP	0.217	0.329	0.00	2.25	3.51	19.76
UK	3.818	2.396	0.40	7.50	-0.39	1.67
			log(y)			
US	4.601	0.095	4.36	4.77	-0.90	3.39
AU	4.531	0.098	4.32	4.73	-0.31	2.57
CA	4.490	0.148	4.21	4.71	-0.49	2.07
CH	4.638	0.155	4.36	4.86	-0.07	1.60
JP	4.623	0.069	4.34	4.76	-0.70	5.18
UK	4.657	0.053	4.55	4.73	-0.68	1.96
			y^{gap}			
US	-0.048	0.062	-0.21	0.06	-0.33	2.79
AU	-0.011	0.032	-0.08	0.07	0.07	2.35
CA	-0.018	0.036	-0.09	0.07	-0.09	2.08
CH	0.020	0.047	-0.07	0.15	0.70	2.89
JP	0.005	0.067	-0.28	0.11	-1.33	5.90
UK	-0.043	0.040	-0.14	0.03	-0.23	2.51

Table A.2. Descriptive statistics of the macroeconomic time series for the US, Australia, Canada, Switzerland, Japan and the United Kingdom for the time period from 1995:01 – 2014:12. Sources: IMF's International Financial Statistics, Datastream. See Section 4.3 for a detailed description of the variables.

Spread	Mean	Std	Min	Max	Skewness	Kurtosis
			US - AU			
3m	-2.180	1.619	-5.50	0.94	0.14	2.06
60m	-1.864	1.314	-4.89	0.72	0.05	2.16
120m	-1.313	0.705	-3.20	0.14	-0.41	2.71
Spread Level	-1.786	1.146	-4.11	0.45	0.19	2.10
Spread Slope	0.867	1.269	-1.51	3.13	-0.09	1.85
			US - CA			
3m	-0.273	0.965	-2.59	2.32	0.56	3.21
60m	-0.352	0.721	-2.14	1.30	0.20	2.42
120m	-0.189	0.578	-2.02	0.66	-1.12	3.86
Spread Level	-0.271	0.667	-1.88	1.20	0.07	2.72
Spread Slope	0.084	0.895	-2.65	1.44	-0.76	3.33
			US - CH			
3m	1.560	1.586	-1.09	4.52	0.27	1.46
60m	1.712	1.271	-0.61	4.56	0.37	1.88
120m	1.859	0.562	0.15	3.37	0.20	2.83
Spread Level	1.710	1.100	-0.22	4.01	0.30	1.68
Spread Slope	0.299	1.205	-2.08	2.32	-0.21	1.62
			US - JP			
3m	2.502	2.181	-0.46	6.28	0.10	1.36
60m	2.868	1.824	0.09	6.23	-0.04	1.60
120m	2.874	0.896	0.76	4.79	-0.35	2.65
Spread Level	2.748	1.582	0.32	5.62	-0.02	1.59
Spread Slope	0.372	1.568	-2.61	2.84	-0.14	1.49
			US - UK			
3m	-0.987	1.048	-3.40	0.89	-0.68	2.28
60m	-0.759	0.745	-2.59	0.56	-0.40	2.27
120m	-0.271	0.656	-2.39	1.39	-0.52	4.17
Spread Level	-0.672	0.700	-2.25	0.65	-0.21	2.16
Spread Slope	0.716	1.049	-1.56	3.08	0.18	2.15
			CH - UK			
3m	-2.547	1.738	-6.16	-0.07	0.03	1.88
60m	-2.471	1.324	-5.24	-0.11	-0.03	2.12
120m	-2.130	0.753	-4.29	-0.99	-1.25	3.85
Spread Level	-2.383	1.176	-4.94	-0.44	-0.14	1.98
Spread Slope	0.417	1.474	-2.11	3.90	-0.02	1.93
			UK - JP			
3m	3.489	2.285	0.01	6.99	-0.46	1.67
60m	3.627	1.935	0.01	6.80	-0.49	1.89
120m	3.144	1.024	0.83	5.75	0.02	2.83
Spread Level	3.420	1.685	0.29	5.96	-0.45	1.84
Spread Slope	-0.345	1.620	-3.51	2.75	0.30	1.87
			JP - CH			
3m	-0.942	0.974	-3.36	0.26	-0.76	2.64
60m	-1.156	0.897	-3.28	0.21	-0.33	2.40
120m	-1.014	0.650	-2.35	0.29	0.08	2.21
Spread Level	-1.037	0.793	-2.96	0.18	-0.42	2.50
Spread Slope	-0.072	0.684	-1.78	1.52	0.00	2.40

Table A.3. Descriptive statistics of sovereign yield spreads for 3-months, 36-months and 120-months maturity and the empirical yield spread level $L_t^{\Delta sy}$ and spread slope $S_t^{\Delta sy}$ for the time period from 1995:01 – 2014:12. Source: Bloomberg. See Section 4.2 for the calculation of the sovereign yield spreads and the spread level and slope.

A.2 Statistical Significance of Direction Accuracy

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
IRD	**0.30**	-0.15	**0.60**	**1.34**	-1.05	**0.90**	0.15	0.75
PPP	**1.34**	**0.75**	**1.04**	**1.64**	**2.11***	-0.30	**3.15***	1.05
MON	**0.60**	-1.50	**0.89**	**1.64**	0.45	0.00	**2.39***	0.30
TR	**1.34**	**0.45**	-0.45	**1.05**	-0.75	**1.66**	**0.30**	**0.15**
RW	**1.49**	0.00	**0.75**	**1.79**	0.30	-0.45	**1.64**	-0.30
				h = 3				
IRD	**0.76**	1.95	**0.00**	**0.15**	-1.96”	**-0.90**	1.05	-0.45
PPP	**4.08***	**4.54***	**2.85***	**-0.15**	**1.52**	-0.75	**4.78***	1.82
MON	**1.05**	2.25*	**1.80**	**3.98***	0.30	-2.71”	**1.80**	-1.20
TR	**2.25***	**0.61**	1.95	**1.35**	-1.20	**-1.65**	**0.75**	**0.00**
RW	**2.40***	2.70*	**1.95**	**1.20**	-0.45	-1.35	**1.50**	-0.45
				h = 6				
IRD	**1.07**	3.78*	**-0.77**	**0.78**	-2.28”	**0.46**	1.98*	0.91
PPP	**4.71***	**5.79***	**0.00**	**3.18***	**0.61**	-1.06	**5.03***	5.12*
MON	**3.63***	1.99*	**-0.92**	**6.64***	0.30	-2.72”	**3.78***	0.76
TR	**3.48***	**2.74***	2.27*	**4.23***	-2.90”	**0.15**	**3.02***	**1.97***
RW	**3.25***	4.16*	**1.29**	**3.86***	-1.13	-2.19”	**3.40***	2.04*
				h = 12				
IRD	-0.31	**3.88***	-0.31	**0.32**	**1.08**	**1.08**	**1.54**	**1.26**
PPP	**5.14***	**5.69***	**0.77**	**2.47***	**1.85**	-0.15	**7.96***	**6.76***
MON	**2.32***	**4.33***	-2.34”	**8.41***	**3.10***	-2.33”	**3.24***	**3.54***
TR	**0.92**	**6.16***	**1.08**	**4.01***	**0.92**	**2.85***	**3.71***	**4.31***
RW	**1.15**	**5.62***	-0.08	**3.15***	**1.46**	-0.38	**2.54***	**3.92***

Table A.4. Z-scores of a conventional test of the significance of proportions for the direction accuracy (DA) of the yield spread model (YLDSPRD) against the benchmark models for the time period from 1995:01 – 2014:12 and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The DA statistic reported in the corresponding Table 2 denote the proportion of forecasts that correctly predict the direction of the exchange rate movement over horizon *h*. Positive z-scores (**highlighted in bold**) in this table indicate a higher direction accuracy of the yield spread model. Negative z-scores indicate a lower direction accuracy. Z-scores above/below 1.96/-1.96 (indicated with */”) imply statistical significance of the results on a 5% or lower level. See section 4.1 for a detailed description of the models.

A.3 Risk adjusted trading returns

	USD/ AUD	USD/ CAD	USD/ CHF	USD/ JPY	USD/ GBP	CHF/ GBP	GBP/ JPY	JPY/ CHF
				h = 1				
YLDSPRD	0.06	0.13	0.05	0.13	0.00	0.06	-0.01	-0.13
IRD	**0.04**	**0.07**	**-0.02**	**0.06**	0.04	**-0.01**	0.02	-0.06
PPP	**0.04**	**0.10**	**-0.02**	**0.07**	**-0.08**	0.11	0.08	-0.08
MON	**0.02**	**0.04**	**-0.04**	**0.01**	0.03	0.09	0.02	-0.02
TR	**0.05**	**0.04**	0.12	**0.11**	0.07	**0.04**	0.05	-0.04
RW	**-0.02**	**0.05**	0.11	**0.04**	0.03	0.17	0.05	-0.04
				h = 3				
YLDSPRD	0.06	0.35	0.04	0.18	-0.11	0.08	-0.01	-0.08
IRD	**0.05**	**0.10**	0.08	**0.05**	0.13	0.14	**-0.02**	-0.05
PPP	**0.00**	**-0.01**	**-0.03**	**0.10**	**-0.14**	0.08	**-0.07**	-0.07
MON	**-0.02**	**0.01**	**0.01**	**-0.08**	0.03	0.15	**-0.02**	**-0.10**
TR	0.06	**0.26**	**0.02**	**0.05**	-0.08	0.13	**-0.06**	**-0.17**
RW	**-0.02**	**0.08**	0.25	**0.17**	0.08	0.32	0.09	0.07
				h = 6				
YLDSPRD	0.03	0.35	0.10	0.39	-0.07	0.13	0.15	0.01
IRD	0.15	**-0.01**	0.13	**0.15**	0.08	0.16	**0.04**	**0.00**
PPP	0.06	**-0.08**	0.12	**0.07**	0.03	0.13	**-0.03**	**-0.13**
MON	**-0.07**	**-0.04**	0.17	**-0.13**	0.08	0.18	**-0.04**	**-0.16**
TR	**-0.07**	**0.22**	**0.00**	**-0.04**	**-0.14**	**0.04**	**-0.01**	**-0.14**
RW	**-0.09**	**0.13**	0.39	**0.17**	0.09	0.46	**0.12**	0.07
				h = 12				
YLDSPRD	-0.10	0.34	-0.06	0.16	0.08	0.12	0.06	0.28
IRD	0.08	**0.12**	0.09	**0.10**	**-0.04**	**0.07**	**-0.20**	**0.05**
PPP	-0.02	**-0.01**	0.03	**0.10**	0.14	0.21	**-0.36**	**-0.19**
MON	0.01	**-0.04**	0.17	**-0.15**	0.13	0.28	**-0.31**	**-0.26**
TR	0.00	**-0.03**	0.05	**-0.18**	**-0.16**	**-0.09**	**-0.37**	**-0.28**
RW	**-0.15**	**0.12**	0.61	0.21	0.14	0.66	0.17	**0.07**

Table A.5. Annualized risk adjusted returns xs_{ra}^{M} of a monthly trading strategy based on the model's forecasts for the time period from 1995:01 – 2014:12 and h=1, h=3, h=6 and h=12 months-ahead forecasting horizons. The risk adjusted returns are calculated as the ratio of the monthly mean return $\overline{xs}^{M}$ and the standard deviation σ_{xs}^{M} of the monthly returns. The higher the risk adjusted return the better is the risk-return relation of the model's forecasts. Risk adjusted returns's smaller than the yield spread (YLDSPRD) model indicate a superior risk-return relationship of the yield spread model, and are **reported in bold**. See Section 4.1 for a detailed description of the models and Section 6.1 for a description of the trading strategy.

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