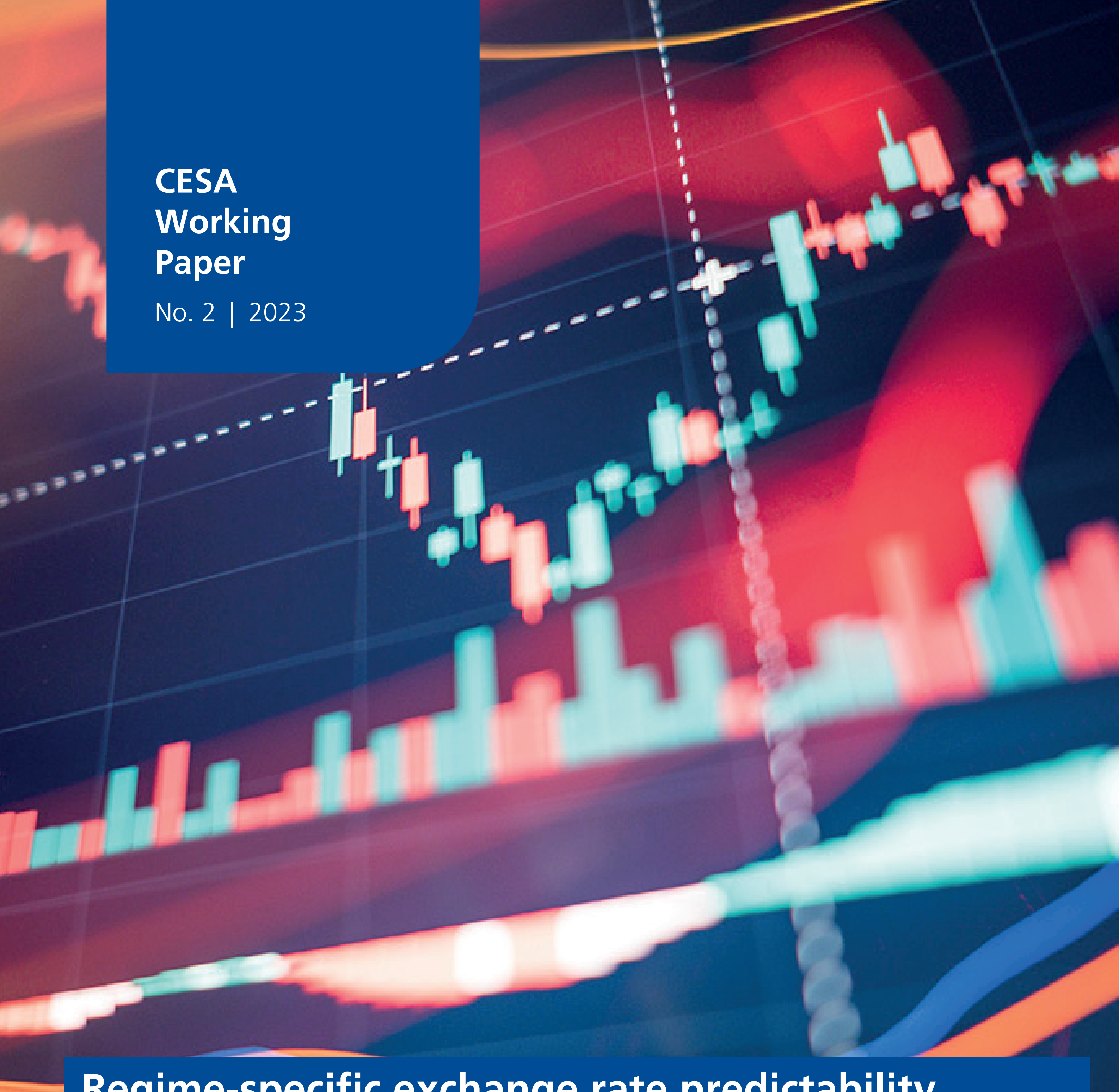


CESA
Working
Paper

No. 2 | 2023

Regime-specific exchange rate predictability

Joscha Beckmann[a,b], Marco Kerkemeier[a] and Robinson Kruse-Becher[a]

a University of Hagen (FernUniversität in Hagen)

b Kiel Institute for the World Economy

FernUniversität in Hagen

Regime-specific exchange rate predictability*

Joscha Beckmann[a], Marco Kerkemeier[b] and Robinson Kruse-Becher[c]

[a]University of Hagen[†] [b]University of Hagen[‡]
[c]University of Hagen[§]

October 25, 2023

Abstract

We study temporary phases of exchange rate predictability in a two-regime threshold predictive regression framework allowing for persistent predictors. Regime switches are triggered by an observable transition variable which relates to media news, expectations, uncertainty and global financial conditions. As predictors for G7 currencies and effective dollar exchange rates, we study various interest rate spreads, yield curve factors, uncertainty measures and deviations from fundamental exchange rate parities. Besides established uncertainty measures, we use a wide range of media sentiments and construct uncertainty measures from survey data as transition variables for the activation of the predictability regime. Our results emphasize that short recurring periods ('pockets') of significant predictability are characterized by nonlinear patterns. Pockets of predictability are triggered by increased media coverage and high uncertainty, illustrating that uncertainty plays a dual role in predictability, while media attention also affects the relevance of macroeconomic fundamentals and uncertainty as exchange rate predictors.

Keywords: Exchange rates, threshold predictive regression, interest rates, sentiments, uncertainty.

JEL classification: C32, C36, C52, C58, F31

*The authors would like to thank Matei Demetrescu, Eric Girardin, Anne Opschoor, Genaro Sucarrat, Dennis Umlandt, Pascal Goemans, Yuze Liu, Philip Letixerant and participants of the 7th International Workshop on Financial Markets and Nonlinear Dynamics (2023, Paris), 5th Quantitative Finance and Financial Econometrics Conference (2023, Marseille), 28th Forecasting Financial Markets Conference (2023, Rennes), 21st European Economics and Finance Society Conference (2023, Berlin), CESA Brown Bag Seminar (2023, Hagen) and Statistical Week (2023, Dortmund) for helpful comments and discussions. Jean-Yves Pitarakis kindly provided computer codes.

†**Corresponding author:** University of Hagen, Faculty of Business Administration and Economics and Center for Economic and Statistical Analysis (CESA), Universitätsstr. 41, 58097 Hagen, Germany, e-mail address: joscha.beckmann@fernuni-hagen.de and Kiel Institute for the World Economy, Germany.

‡University of Hagen, Faculty of Business Administration and Economics and Center for Economic and Statistical Analysis (CESA), Universitätsstr. 41, 58097 Hagen, Germany, e-mail address: marco.kerkemeier@fernuni-hagen.de.

§University of Hagen, Faculty of Business Administration and Economics and Center for Economic and Statistical Analysis (CESA), Universitätsstr. 41, 58097 Hagen, Germany, e-mail address: robinson.kruse-becher@fernuni-hagen.de

1 Introduction

The link between exchange rates and economic fundamentals has been elusive, and explaining exchange rate behaviour is a long-standing puzzle in international finance. The seminal study by Meese and Rogoff (1983) still represents a benchmark result in the exchange rate literature; exchange rate forecasts generated by structural models are unable to systematically outperform naive random walk forecasts (Reinhart and Rogoff, 2009; Rossi, 2013). The results are highly sensitive to the selection of currencies, sample periods and forecast horizons (Mark, 1995; Kilian, 1999; Faust, Rogers, and Wright, 2003; Cheung, Chinn, and Pascual, 2005). In a recent survey article, Rossi (2013) broadens the scope and provides a critical review of the recent literature on exchange rate forecasting and concludes that predictability depends on a number of choices such as predictors, forecast horizon, sample period, model, and the forecast evaluation method and that no clear pattern across different currencies emerges. Recently, a new strand of the literature has emphasized that the US-Dollar is strongly related to the global financial cycle and tends to appreciate in uncertain times. This has re-vitalized the literature on exchange rate predictability by proposing predictors which relate to the safe haven status of the US-Dollar and global financial conditions (Engel and Wu, 2023a; Engel and Wu, 2023b). Meanwhile, the literature on stock return prediction has introduced the idea of 'pockets of predictability' which reflect recurring short periods of predictability related to some state-dependent variable (Farmer, Schmidt, and Timmermann, 2023).

While several studies have focused on evaluating various exchange rate models and predictors, the literature is notably silent on potential determinants of exchange rate predictability. This paper aims to close this gap by systematically evaluating whether the predictability of exchange rate returns relates to observable variables, such as expectation, uncertainty or media news. We focus on these indicators as transition variables for several reasons. From a general point of view, various dimensions of expectation and uncertainty affect and reflect the state of the current economy, while the media sentiments we adopt provide a useful measure of the information available to market participants. From a theoretical point of view, discounted value approaches of exchange rate behaviour in the spirit of Engel and West (2005) postulate that the discounted value of future fundamentals as well as unobservable factors affect the (expected) link between exchange rates and macroeconomic fundamentals. The survey expectations we study constitute potential proxies for expectations and uncertainty regarding fundamentals. Moreover, other uncertainty measures and media news reflect proxies for unobservable factors and could also be responsible for fundamental variables becoming a scapegoat, an explanation for the time-varying relationship between exchange rate and fundamentals brought forward by Bacchetta and Van Wincoop (2013). Media information could also explain why agents in the foreign exchange rate market remain inattentive to specific kinds of news. Finally, there is empirical evidence that exchange rates are affected by expectations, uncertainty and media news. This holds both in the time series dimension for bilateral currencies as well as for portfolio returns in the cross-country dimension. Recent work by Ismailov and Rossi (2018) finds for example that uncertainty affects the validity of uncovered interest rate parity, while a rich literature has focused on safe haven currencies, in particular arguing that the US-Dollar appreciates in bad times. Recent studies have also shown that macroeconomic and financial risk factors as well as media sentiments affect market risk premia which essentially resemble deviations from uncovered interest rate parity (Filippou and Taylor, 2017).

Our empirical approach is based on a nonlinear threshold framework introduced by Gonzalo and Pitarakis (2012) and Gonzalo and Pitarakis (2017). It is able to disentangle two potentially different regimes in a predictive regression allowing for persistent predictors. It allows for robust inference on linearity and predictability. Here, the regime switch is characterized by an observable transition variable rather than some unobservable stochastic process. The data set we analyse takes the rich literature on exchange rate predictability into account. Our set of predictors includes conventional fundamental exchange rate models, the Taylor rule approach as well as yield curve and stock market dynamics. We take account for a rich set of uncertainty and media coverage measures as transition variables. We use newspaper-based uncertainty measures, volatility on foreign exchange rate markets, and macroeconomic and financial uncertainty. In addition, we consider various uncertainty measures based on survey data from Consensus Economics. We also include rich data on media news from MarketPsych which pays specific attention to news and media attention related to the foreign exchange rate market and has been adopted as a measure of public information in the foreign exchange market. Our data includes information related to both currency sentiment and the degree of media attention given to fundamentals and exchange rates. Finally, we include measures of global financial conditions. Given their dual role from a theoretical point of view, we consider uncertainty, sentiment and global financial condition measures as both transition variables and predictors. We assess this set of predictors for predictability of six bilateral dollar exchange rates and two measures which reflect the effective dollar exchange rate, allowing us to analyse regime-specific predictability from a general and currency-specific perspective.

Given the breadth and importance of the exchange rate literature, a number of questions fall beyond the scope of this analysis. In the present work, we are neither searching for the "best" model relative to the random walk nor are we interested in combining the explanatory power of different models in terms of real-time out of sample predictability.[1] Instead, we investigate the role of various transition variables offering different explanations and insights into the temporary predictability of exchange rates. For obvious reasons outlined above, we expect various predictors to fail in certain periods when compared with a prevailing mean prediction. However, this common result is a prerequisite for our investigation since we aim to explain why certain predictors perform well in some periods but fail in others.

While out-of-sample analyses may be useful for investigating historical predictive performance (see e.g. Diebold (2015), our aim is to understand the nonlinear mechanisms generating predictability from a more general viewpoint. Nonlinearity plays an important role in this argument as the out-of-sample evaluation hinges in particular on the data features, e.g. high media attention or high uncertainty. Besides the trickiness of picking a suitable out-of-sample period with representative features, the pertinent problem of low statistical power may easily arise due to small samples. In our analysis, we exploit the largest possible information given in full data set at hand. Inoue and Kilian (2005) convincingly argue that in-sample tests are typically more credible than those obtained by an out-of-sample analysis. It is also crucial to understand that not all predictors can actually be used for forecasting out-of sample in real time since some predictors, for example yield curve factors and output gap, are typically estimated over the full sample. Nonetheless, significant in-sample predictability might carry over to out-of-sample predictability. However, the latter is much more difficult to identify.

The remainder of this paper is organized as follows. Section 2 summarizes the existing literature on exchange rate predictors and the related literature. Section 3 provides our data set, while Section 4 introduces the threshold predictive regression approach. Section 5 presents and discusses our empirical results and findings, while Section 6 concludes.

[1]Recent studies have already accounted for model and parameter uncertainty issues by shifting the focus to combining models rather than relying on one single model. Recent results suggest that model combinations are also unable to provide significantly superior forecasts compared with the random walk (Beckmann and Schüssler, 2016).

2 Literature review

Our work relates to a rich literature dealing with exchange rate predictability. In the following, we summarize three strands of the literature which are most closely related to our aims and scopes and which deals with variables which we propose as potential drivers of exchange rate predictability. We start with the time-varying relationship between exchange rates and fundamentals which provides a starting point for our investigation before we turn to the literature which links uncertainty and global financial conditions to exchange rates. Finally, we discuss the link between media news and exchange rates.

We do not provide a detailed discussion of the conventional fundamental exchange rate models we use for the identification of relevant predictors. Instead, this information is provided in the data section and the Appendix. The predictors we analyse include various interest rate measures as well as information on money supply, inflation and industrial production. By including the interest rate differential as a predictor without any restriction on signs, we also include the possibility of profitable carry trade returns, that is, the possibility that currencies with higher interest rates appreciate, a result which contradicts uncovered interest rate parity.

2.1 The time-varying relationship between exchange rates and fundamentals

Given that the literature on exchange rate forecasting and the link between exchange rates and fundamentals is extremely voluminous, we focus on a selection of representative and influential papers. An early comprehensive overview is provided by Neely and Sarno (2002).

There is compelling general evidence that the relationship between exchange rates and fundamentals is subject to structural changes. This has been demonstrated by different studies that either allow for time-varying coefficients in the long-run exchange rate equation or instabilities with respect to the adjustment behaviour to disequilibrium. The most adequate set of fundamentals varies over time and does not show a recurring pattern (Meese, 1990; Beckmann, Belke, and Kühl, 2011). This is in line with different surveys which suggest that various fundamentals are important during different periods (Cheung and Chinn, 2001; Gehrig and Menkhoff, 2006). Theoretical models that explain such a pattern have been provided by Bacchetta and Van Wincoop (2004), Bacchetta and Van Wincoop (2006), Bacchetta and Van Wincoop (2013), Goldberg and Frydman (1996), and Frydman and Goldberg (2007). The main statement of both frameworks is that participants are not aware of the exact model coefficients. The empirical evidence regarding exchange rate predictability is nicely summarized in Rossi (2013). The bottom line is that different exchange rate models work at different points in time and that fundamental models are unable to consistently outperform simple benchmark models such as the random walk.[2]

Sarno and Valente (2009) identify a general caveat of exchange rate forecasting based on single models: The poor performance of traditional model criteria in the presence of frequent structural changes, not a lack of information embedded in fundamentals, is responsible for the poor forecasting performance. They identify the difficulty of selecting the best predictive model as a major caveat. From a general point of view, the main problem a researcher faces when trying to identify an adequate model is that in-sample explanation power does not necessarily translate into out-of sample predictability in the presence of parameter shifts (Rossi, 2006).

Several studies have adopted non-linear threshold models for the ex-post link between exchange rates and fundamentals.[3] Sarno, Valente, and Leon (2006) find non-linearities in the spot-forward exchange relationship which are compatible with theories concerning transaction costs and limits to speculation based on exponential smooth transition models. Baillie and Kilic (2006) apply logistic smooth transition models for spot returns and find evidence of an outer regime that is consistent with uncovered interest parity. Taylor, Peel, and Sarno (2001) illustrate that large deviations from purchasing power parity result in quicker adjustment of the nominal exchange rate towards long-run equilibrium.

2.2 Uncertainty, global financial conditions and exchange rates

There are different starting points for analysing the time-varying forecasting ability of exchange rate models in the context of uncertainty. First, there is strong evidence that some currencies, such as the US-Dollar or the Japanese Yen, tend to appreciate in times of high uncertainty. According to the definition of Habib and Stracca (2012), safe haven currencies provide a hedge for portfolios in case of shocks to global risk aversion. Safe asset properties are also reflected in low pecuniary

[2] Some studies identify periods in which selected models outperform random walk forecasts. While the results of Cheung, Chinn, and Pascual (2005) do suggest that exchange rate models do not outperform the random walk at any time horizon, Molodtsova and Papell (2009) find predictability at the one month horizon for the Taylor Rule exchange rate model. Relying on a related framework, Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2011) find predictability for the Mark/US-Dollar (respectively EUR/USD) exchange rate for one quarter for real-time, but not revised, data.

[3] Other studies have applied Markov-Switching models where the regime is determined by an unobservable stochastic process (Engel, 1994; Frömmel, MacDonald, and Menkhoff, 2005a; Frömmel, MacDonald, and Menkhoff, 2005b; Sarno and Valente, 2006).

returns of assets which result from their liquidity and safety, the so-called convenience yield (Engel and Wu, 2023a). Furthermore, it has been argued that tighter global financial conditions coincide with a stronger US-Dollar. Against this background, changes in the liquidity or convenience yield on government bonds and global financial conditions have been proposed as exchange rate predictors (Engel and Wu, 2023b).

The existing empirical literature has also provided some evidence that uncertainty affects exchange rate predictability. Various measures of uncertainty and yield curve factors have become particularly popular in this regard (Rossi, 2013). Ismailov and Rossi (2018) find that uncovered interest rate parity does hold in five industrialized countries vis-a'-vis the US-Dollar at times when uncertainty is not exceptionally high, and breaks down during periods of high uncertainty. Common macro factors (Filippou and Taylor, 2017) and macroeconomic risk and uncertainty measures have also been identified as potential drivers of excess returns in the cross-section (Cochrane, 2017). Sarno and Schmeling (2014) analyse cross-sections of excess returns based on currency portfolios and find that macro fundamentals have substantial economic information content for the future behavior of exchange rates and future currency excess returns in a way that is consistent with a risk-based approach to foreign exchange (FX) markets. According to their results, the joint cross-sections of excess returns to currency portfolios is largely driven by common exposure to dynamic business cycle risks.

Some theoretical models also offer an alternative starting point from a theoretical perspective. Bacchetta and Van Wincoop (2013) follow the view of Engel and West (2005) that exchange rates can be defined as a discounted value of future fundamentals as a starting point. They argue that large and frequent variations in the relationship between the exchange rate and macro fundamentals naturally evolve when structural parameters in the economy are unknown and subject to changes. In such cases, market participants give 'excessive' weight to some (macroeconomic) fundamentals during specific periods, i.e. the so-called 'scapegoats'. The larger the deviations from its mean, the more likely it is that a specific variable becomes the scapegoat. Possible proxies for such scapegoat effects include uncertainty, media attention and global financial condition measures. We argue that many of these measures are both transition variables and predictors and our empirical approach accommodates both possibilities. As outlined above, they can directly affect the role of the US-Dollar, for example in terms of an appreciation in times of uncertainty. At the same time, exchange rate predictability based on fundamental models could depend on uncertainty, media coverage or global financial conditions, for example as a result of scapegoat effects. We consider various proxies for risk, uncertainty and expected fundamentals which should reflect both the current set of available information and potentially unexpected macroeconomic news, an issue discussed in the next section.

2.3 Media news and exchange rates

The importance of news has been recognized in the exchange rate literature for a long time. The conventional news approach postulates that unexpected news drive a wedge between expected and unexpected exchange rates (Froot and Frankel, 1989). While identifying adequate proxies for news remains an issue, the emergence of text-based indicators has greatly extended the possibilities for researchers. Early evidence has shown that non-fundamental news captured via market surprises have an effect on the exchange rate which goes beyond conventional fundamentals and order flow (Dominguez and Panthaki, 2006). Filippou, Nguyen, and Taylor (2023) construct news sentiment for the foreign exchange market and find that an investment strategy that buys (sells) currencies with low (high) media sentiment generates significant returns which are associated with an overreaction of traders. Their work is closely related to the rich literature which deals with the predictive power of sentiments on the stock market, a literature inspired by Baker and Wurgler (2007) who adopt survey-based indicators and which has recently turned to analysing the relevance of news-based sentiment indicators.

However, conclusive evidence that exchange rates are affected by news over lower frequencies has not been established yet and we argue that newspaper information has the potential to affect the relevance of fundamentals as a transition variable. Such an argument can be derived from the scapegoat approach outlined above and behavioural exchange rate models which emphasize that market participants attach different weights to fundamentals over time. Media coverage could also affect or incorporate safe haven aspects and coverage of the global financial cycle. The data we use also reflects the degree of media attention attached to fundamentals or the exchange rate (rather than sentiment). We use such a variable as a potential transition variable, allowing, for example, for stronger effects of fundamentals in case of high news coverage.

3 Data

Our main dataset runs from 1999:01 until 2017:12 and includes the G7 currencies based on a monthly frequency.[4]

In line with the literature, we apply a variety of predictors. These include purchasing power parity (PPP), interest rate differentials, both symmetric and asymmetric Taylor rules, monetary fundamentals, yield curve factors, interest rate spreads, WTI oil price and MSCI stock market spreads. Data on stock prices, industrial production, money supply and interest rates is taken from Refinitiv Datastream and the IMF.

Survey data on exchange rate expectations is obtained from Consensus Economics. Bacchetta and Van Wincoop (2006) and Cavusoglu and Neveu (2015) rely on the same data set as an approximation of expectations. Data on expected macroeconomic fundamentals is obtained from Consensus Economics. We focus on expectations regarding GDP, industrial production, inflation, and 3 months and 10 years interest rates. For inflation and GDP, we transform fixed event into fixed horizon forecasts following the averaging procedure adopted by Dovern, Fritsche, and Slacalek (2012). The data from Consensus Economics are widely used given their coverage and the information about individual participants. Our data set enables us to include both country-specific and global disagreement regarding the future path of various macroeconomic fundamentals. To account for news-based uncertainty, we include the Economic Policy Uncertainty Index (EPU) from Baker, Bloom, and Davis (2016). We also consider macroeconomic and financial uncertainty measures which are provided by Jurado, Ludvigson, and Ng (2015) and reflect common unexpected variations in a large number of economic indicators. We also include bond factors introduced by Ludvigson and Ng (2009). To account for global risk, we rely on the CBOE VIX S&P 500 implied volatility index (Lustig, Roussanov, and Verdelhan, 2011). Currency volatility is approximated via the G10 currency option volatility index of JP Morgan (VXY). As a measure of global financial conditions, we use the measure of Miranda-Agrippino and Rey (2015). Data on convenience yields is taken from Engel and Wu (2023b).

While the Economic Policy Uncertainty Index (EPU) is a broad measure of newspaper coverage, we also use several additional text-based indicators which are directly related to currencies and macroeconomic fundamentals. We use MarketPsych (see `https://www.marketpsych.com/`) for data

[4] These currencies are Australian Dollar (AUD), Canadian Dollar (CAD), Euro (EUR), Japanese Yen (JPY), Swiss Franc (CHF), Pound Sterling (GBP) and US-Dollar (USD).

on sentiment and media coverage in this context. The corresponding data set is based on a broad set of media coverage which is filtered via natural language processing in the first step. Reuters news and additional sources are included over the sample period and both newspaper and social media coverage are included. Sentiments are provided for country, country markets and currencies and are scaled between -1 and $+1$. We also rely on Buzz which reflects how popular a specific topic has been over a given time period. The term ratesBuzz reflects content regarding the 'central bank', 'debt default', 'interest rates', 'interest rates forecast', and 'monetary policy loose vs. tight'. We also include stockmarketbuzz which reflects news coverage about the stock market. Overall, this data set constitutes a granular perspective on both news related to exchange rates and macroeconomic fundamentals.

Further information on data and transformations can be found in the data Appendix.

4 Methodology

In our analysis, we consider threshold predictive regressions for the log returns of nominal exchange rates. Gonzalo and Pitarakis (2012) introduce important instrumental variable-based tests for linearity and predictability. The instrument is self-generated within the system from the persistent and endogenous predictor (IVX). This section is organized as follows: We first take a closer look at the linear predictive regression setting, illustrate its shortcomings and explain why we use a threshold regression specification instead. After that, we review threshold predictive regressions and discuss how valid inference can be conducted using the IVX approach.

4.1 Problems with linear predictive regressions

An ordinary linear predictive regression stated, for example, by Jansson and Moreira (2006) and Campbell and Yogo (2006) uses a highly persistent variable (x_t) to predict a dependent variable (y_{t+1}) like asset returns, which is typically serially uncorrelated:

$$y_{t+1} = \alpha + \beta x_t + u_{t+1} \quad t = 1, \ldots, T. \tag{1}$$

Clearly, such a setup might easily lead to an unbalanced regression. The literature on inference within such predictive regressions has rapidly developed over the past few years with contributions by, inter alia, Magdalinos and Phillips (2009), Breitung and Demetrescu (2015), Kostakis, Magdalinos, and Stamatogiannis (2015), Demetrescu and Hillmann (2022), and Farmer, Schmidt, and Timmermann (2023).

Since the literature has clearly demonstrated that there might be time-varying predictability in returns of assets, especially stock market returns, (Pesaran and Timmermann, 2002; Paye and Timmermann, 2006; Rapach and Wohar, 2006; Timmermann, 2008; Henkel, Martin, and Nardari, 2011; Dangl and Halling, 2012; Gonzalo and Pitarakis, 2012; Farmer, Schmidt, and Timmermann, 2023), it is reasonable to take a closer look at threshold predictive regressions. This is worthwhile because in the case the underlying data-generating process contains threshold effects, the linear predictive regression model is mis-specified.[5] This could lead to the wrong conclusion of no predictability while there might be one regime where predictability emerges and another one with hardly any signs of predictability. Because the non-linearity in the predictability of (nominal) exchange rate returns is mostly neglected, we take a closer look at the asset class of currencies.

The main advantage of predictive regressions is that R^2 measures obtained from them are straight forward to interpret and provide useful information regarding the amount of predictability. Typically, the empirical R^2 for return predictive regressions takes on very low values up to 1% which reflects hardly any signs of predictability, see e.g., Goyal and Welch (2003) and Welch and Goyal (2008). Within a threshold predictive regression, there might be one regime with predictability and a corresponding R^2 of more than just 1% and a no-predictability regime with an R^2 close to 0. Another related concept applied during the analysis is the 'joint' R^2 which is just a weighted average of regime-specific R^2s based on the number of observations within the regimes.

4.2 Threshold predictive regressions

Instead of considering the well-known predictive regression setting in which a persistent predictor enters the system only in a linear way, we consider a generalized version which allows for certain forms of nonlinearity. The applied framework consists of two different regimes, namely one which

[5]It can be shown that the OLS estimator for β is inconsistent under threshold effects as introduced below.

is associated with predictability and the other one shows signs of low or even no predictability:[6]

$$y_{t+1} = \begin{cases} \alpha_1 + \beta_1 x_t + u_{t+1} & \text{if } q_t \leq \gamma \\ \alpha_2 + \beta_2 x_t + u_{t+1} & \text{if } q_t > \gamma \end{cases} \tag{2}$$

with x_t being a highly persistent predictor which is treated as a nearly integrated process $x_t = \rho_T x_{t-1} + v_t$ with $\rho_T = 1 - c/T$ and $c > 0$. q_t is the stationary threshold variable given as $q_t = \mu_q + u_{qt}$. The stationarity assumption of q_t is generally made, and we study the case of persistent transition variables as many meaningful transition variables are stationary, but strongly persistent. At the end of this section, we provide a new set of finite-sample critical values and size experiments for such situations. The threshold parameter γ is unknown and estimated via OLS. In case of linearity, i.e., $\alpha_1 = \alpha_2 \equiv \alpha; \beta_1 = \beta_2 \equiv \beta$, the threshold predictive regression model becomes a linear predictive regression model, as specified in Eq. (1).

Before digging deeper into the assumptions underlying the model framework of Gonzalo and Pitarakis (2012), we take a broader perspective on threshold models. The great advantage of threshold models is their ability to directly relate regime switches to transition variables which are observable. In our context, the magnitude of the transition variable may enforce a regime shift and thereby a different strength of predictability. A working hypothesis applied is that there are 'pockets of predictability' (Farmer, Schmidt, and Timmermann, 2023) which means that there is a predictability and a no-predictability regime. Due to the empirical finding that predictability regimes can occur very quickly over time, a threshold approach is often favoured over a logistic smooth transition version, see Kilic (2018). Note that the threshold case can be interpreted as a special case of the smooth logistic case in which the transition speed parameter approaches infinity. Moreover, a piecewise linear structure can be seen as an approximation to a much wider family of nonlinear regime-switching behaviour. In our case, we apply uncertainty and sentiment measures (typical ones like VIX and Refinitiv MarketPsych sentiments) as transition variables. Thus, we can test if there are different regimes of predictability related to uncertainty and sentiment measures, or in other words, we investigate the question 'Does uncertainty and sentiment have an effect on the predictability of logarithmic nominal exchange rate returns?'.

[6] A situation in which both regimes are characterized by predictability is also possible, but is rarely observed for financial data. An example can be that a predictor has a positive influence in times when the transition variable is larger than a specific threshold and a negative effect in times when the transition variable is equal to or below its threshold.

4.3 Testing and interpretation issues

Besides testing the linearity hypothesis $H_0^L : \alpha_1 = \alpha_2,\ \beta_1 = \beta_2$ within the threshold predictive regression, we are also interested in testing the null of no predictability (under the maintained hypothesis H_0^L) $H_0^P : \alpha_1 = \alpha_2,\ \beta_1 = \beta_2 = 0$. As the predictor x_t is typically highly persistent (local-to-unity autoregressive parameter), standard inference techniques cannot be applied, while the parameters can be estimated via OLS. Due to the potential correlation of the innovation term of the predictor with the error term in the predictive regression equation, an IV-type estimator is applied. When interpreting rejections of H_0^P the issue arises that a rejection could be caused solely by a switching intercept (i.e. $\alpha_1 \neq \alpha_2$) while $\beta_1 = \beta_2 = 0$. This well-known issue can be tackled by different approaches. These approaches include (but are not limited to) applying the IVX-adjusted statistic for $H_0^P : \beta_1 = \beta_2 = 0$ without maintaining hypothesis H_0^L (Gonzalo and Pitarakis, 2017). A second approach relies on the empirical descriptive comparison of R^2 measures in both regimes. Dissimilarity between both R^2s suggests nonlinearities. The third approach would be to test for a threshold effect in $y_{t+1} = \alpha_1 \mathbf{1}(q_t \leq \gamma) + \alpha_2 \mathbf{1}(q_t > \gamma) + u_{t+1}$ via $H_0 : \alpha_1 = \alpha_2$ by maintaining the no-predictability restriction. We choose the second way because it is both reliable and easy to communicate and interpret. A threshold predictive regression with switching intercepts only and no predictability leads to an R^2 of zero in both regimes. More details are provided in the empirical analysis in Section 5.

4.4 Threshold parameter and Wald statistics

The threshold parameter is stated as: $\gamma \in \Gamma = [\gamma_1, \gamma_2]$ with $P(q_t \leq \gamma_1) = \pi_1 > 0$ and $P(q_t \leq \gamma_2) = \pi_2 < 1$ as also done by Caner and Hansen (2001). Hence, the threshold parameter γ can take values within a certain interval which is trimmed. Rewriting the threshold predictive regression model (Eq. (2)) in matrix notation yields: $y = Z\theta + u$ with $Z = (X_1\ X_2), \theta = (\theta_1\ \theta_2)$ and $\theta_i = (\alpha_i, \beta_i)'$ for $i = 1, 2$.

The Wald statistic for testing a general restriction on θ is then given by

$$\begin{aligned} W_T(\lambda) =& \frac{\hat{\theta}' R' [R(Z'Z)^{-1} R']^{-1} R\hat{\theta}}{\hat{\sigma}_u^2} \\ & \hat{\theta} = (Z'Z)^{-1} Z'y \\ & \hat{\sigma}_u^2 = T^{-1} \left(y'y - \sum_{i=1}^{2} y' X_i (X_i' X_i)^{-1} X_i' y \right). \end{aligned} \tag{3}$$

Under H_0 the threshold parameter γ is unidentified, thus the inference is conducted based on the supremum Wald statistic $\sup_{\lambda \in [\pi_1, \pi_2]} W_T(\lambda)$ with $\pi_1 = F(\gamma_1)$ and $\pi_2 = F(\gamma_2)$. The advantage of using a representation based on λ instead of γ is that the interpretation is simplified. While a specific threshold value for γ might be hard to interpret, probabilities π_1 and π_2 are scale-invariant and much easier to handle. The null hypotheses are given as:

$$H_0^L : \alpha_1 = \alpha_2, \beta_1 = \beta_2$$
$$H_0^P : \alpha_1 = \alpha_2, \beta_1 = \beta_2 = 0.$$

Under the validity of H_0^L, the resulting predictive regression reads $y_{t+1} = \alpha + \beta x_t + u_{t+1}$, while $y_{t+1} = \alpha + u_{t+1}$ results under the validity of H_0^P.

To obtain the limiting distributions of the linearity and the predictability test statistics, a few assumptions have to be made. The innovation term v_t of the predictor is given by $v_t = \Psi(L)e_t$ with $\Psi(L) = \sum_{J=0}^{\infty} \psi_j L^j$. Furthermore, $\sum_{j=0}^{\infty} j|\psi_j| < \infty, \Psi(1) \neq 0$ and u_t is a martingale difference sequence (m.d.s.). Hence, it might follow, for instance, a stationary and invertible ARMA process. Let $\tilde{\omega}_t = (u_t, e_t)', \mathcal{F}_t^{\tilde{\omega}q} = \{\tilde{\omega}_s, u_{qs} | s \leq t\}$. It is further assumed that $E(\tilde{\omega}_t | \mathcal{F}_{t-1}^{\tilde{\omega}q}) = 0, E(\tilde{\omega}_t \tilde{\omega}_t' | \mathcal{F}_{t-1}^{\tilde{\omega}q}) = \tilde{\Sigma} > 0, \sup_t E\tilde{\omega}_{it}^4 < \infty$. The predictive regression residual u_t and the noise term e_t of the innovations to the predictor have zero-mean, a constant positive definite covariance matrix and finite fourth-order moments. Regarding the transition variable, it is assumed that $q_t = \mu_q + u_{qt}$ has a distribution $F(.)$ which is both continuous and strictly increasing. Additionally, u_{qt} is strictly stationary, ergodic and strongly mixing. Lagged values of q_t are uncorrelated with the predictive regression disturbance, but q_t might be contemporaneously correlated with it and also with v_t.

4.5 Limiting distributions of test statistics and IVX estimators

Under the given assumptions and $T \to \infty$, the sup Wald statistic for linearity has the following limit distribution:

$$\sup_{\lambda} W_T^L(\lambda) \Rightarrow \sup_{\lambda} \frac{BB(\lambda)' BB(\lambda)}{\lambda(1-\lambda)} \tag{4}$$

with $BB(\lambda)$ being a bivariate Brownian bridge and $\lambda \in [\pi_1, \pi_2]$ with $\pi_1 = F(\gamma_1)$ and $\pi_2 = F(\gamma_2)$. This distribution does not depend on any kind of nuisance parameter and also not on the local-to-unity parameter c. p-values can be obtained by the approximation procedure of Hansen (1997).

For the predictability test statistic the following limit distribution is obtained under the assumption of exogeneity, i.e. $\omega_{uv} = 0$:

$$\sup_{\lambda} W_T^P(\lambda) \Rightarrow W(1)^2 + \sup_{\lambda} \frac{BB(\lambda)'BB(\lambda)}{\lambda(1-\lambda)}, \tag{5}$$

where $W(r)$ is a standard Wiener process leading to the first term being distributed as a χ_1^2-random variable. Importantly, an IVX estimator is applied next to obtain a valid inference procedure under endogeneity, i.e. $\omega_{uv} \neq 0$.

In line with Phillips and Magdalinos (2009), Gonzalo and Pitarakis (2012) implement an instrumental variable estimator to obtain the same limit distribution for $\sup_\lambda W_T^P(\lambda)$ under both circumstances - exogeneity ($\omega_{uv} = 0$) and endogeneity ($\omega_{uv} \neq 0$), because up to now, the limiting distribution of $\sup_\lambda W_T^P(\lambda)$ has been obtained under the assumption of exogeneity. This is of course problematic, because the relevant case for empirical exchange rate applications is endogeneity.

To be able to construct the IVX estimator, some pre-work needs to be done. $W_T^P(\lambda)$ can be written as: $W_T^P(\lambda) \equiv \frac{\hat{\sigma}_{lin}^2}{\hat{\sigma}_u^2} W_T(\beta = 0) + W_T^L(\lambda)$ with $W_T(\beta = 0) = \frac{1}{\hat{\sigma}_{lin}^2} \frac{(\sum x_{t-1}y_t - T\bar{x}\bar{y})^2}{\sum x_{t-1}^2 - T\bar{x}^2}, \hat{\sigma}_{lin}^2 = T^{-1}[y'y - y'X(X'X)^{-1}X'y]$. Here, $W_T(\beta = 0)$ is the Wald statistic for the hypothesis $H_0 : \beta = 0$ in the linear predictive regression $y_{t+1} = \alpha + \beta x_t + u_{t+1}$. The $W_T(\beta = 0)$ term is replaced with an IVX-version, so that it does not depend on the parameter c anymore. In line with Phillips and Magdalinos (2009) the IVX estimator for β is then defined as

$$\tilde{\beta}^{IVX} = \frac{\sum y_t^* \tilde{z}_{t-1}^*}{\sum x_{t-1}^* \tilde{z}_{t-1}^*} \tag{6}$$

with $\tilde{z}_t = R_T \tilde{z}_{t-1} + \Delta x_t$. Here, R_T is an artificial slope coefficient $R_T = 1 - \frac{c_z}{T^\delta}, c_z > 0, \delta < 1$. Importantly, the self-generated instrument from the predictor x_t (hence, IVX) is somewhat less persistent than the original predictor in order to mitigate the endogeneity problem, but still persistent enough to serve as a relevant instrument.

Furthermore, $y_t^*, x_t^*, \tilde{z}_t^*$ are demeaned versions of y_t, x_t, z_t. The IVX-based Wald statistic is then:

$$W_T^{IVX}(\beta = 0) = \frac{(\tilde{\beta}^{IVX})^2 (\sum x_{t-1}^* \tilde{z}_{t-1}^*)^2}{\tilde{\sigma}_u^2 \sum (\tilde{z}_{t-1}^*)^2} \tag{7}$$

with $\tilde{\sigma}_u^2 = T^{-1}(\sum y_t^* - \tilde{\beta}^{IVX} x_{t-1}^*)^2$. Thus, the modified Wald statistic is stated as

$$W_T^{P,IVX}(\lambda) = W_T^{IVX}(\beta = 0) + W_T^L(\lambda). \tag{8}$$

The resulting limit distribution for $\delta \in (2/3, 1)$ is

$$\sup_\lambda W_T^{P,IVX}(\lambda) \Rightarrow W(1)^2 + \sup_\lambda \frac{BB(\lambda)' BB(\lambda)}{\lambda(1-\lambda)}. \tag{9}$$

Hence, exactly the same limiting distribution is restored even under endogeneity when applying the IVX estimator.

The estimation of the threshold parameter λ is then done based on least squares

$$\hat{\lambda} = \arg\min_\lambda S_T(\lambda) \tag{10}$$

with $S_T(\lambda)$ being the concentrated sum of squared error function.

4.6 Monte Carlo simulations, finite-sample critical values and size experiments

We simulate finite-sample critical values for the supremum linearity and the predictability tests. We generate a persistent predictor with autoregressive local-to-unity parameter with first-order-autoregressive innovations, and a persistent transition variable. Such a setup leads to critical values which account for the typical properties of our data set used in the empirical analysis which are more persistent than those considered in Gonzalo and Pitarakis (2012). The basic setup follows the specifications in Gonzalo and Pitarakis (2012). The authors consider a mildly persistent transition variable. In order to account for the features of our data set, we impose the setting: $\alpha = 0.01$, $\beta = \{0, 0.1\}$, $T = 250$, $c = 2.5$, $\rho = 0.2$, $\phi = 0.98$, $\sigma_{ue} = \{0, -0.1\}$, $\sigma_{uu_q} = 0.3$ and $\sigma_{eu_q} = 0.4$. For the tests we set $\delta = 0.8$ and $\pi_1 = 1 - \pi_2 = 0.1$, as in our empirical analysis and as recommended by Gonzalo and Pitarakis (2012). In our Monte Carlo simulations, we use 10,000 replications for the critical values and 2,000 replications for the subsequent size experiments.

The finite-sample critical values for the linearity test statistic are 16.116 and 17.822 for the nominal significance levels of 1% and 0.5%, respectively. For the predictability test, we obtain 17.864 and 19.350, respectively. The size experiments yield empirical rejection rates of 1.05% and 0.5% for the linearity test, and 0.95% and 0.45% for the predictability test. Overall, the finite-sample critical values yield an accurate empirical size of the tests. When comparing the newly obtained finite-sample critical values to the ones reported in Gonzalo and Pitarakis (2012), we see that they are slightly larger which reflects the increased persistence in the transition variable.

5 Empirical results

5.1 Overview

In our broad empirical analysis we consider six exchange rate pairs from G7 currencies against the US-Dollar (USD), i.e., AUD, CAD, EUR, JPY, CHF and GBP. We thus take y_{t+1} to be the first-differenced log exchange rate between the US and another country. Regarding the potential predictors x_t, we consider 26 possible candidate variables per exchange rate pair. These are level, slope and curvature yield curve factors from the US and the respective country. Similarly, we consider term spreads and deviations from a(n) (a)symmetric Taylor rule in both countries, the purchasing power parity and a monetary exchange rate . We also include the interest rate differential which reflects both uncovered interest rate parity and the possibility of profitable carry trades. Both the stock market performance and liquidity measure by Engel and Wu (2023b) also include both countries. In addition, we include the global factor of risky asset prices, the WTI oil price and the JP Morgan exchange rate implied volatility VXY and the stock market implied volatility VIX as global predictors.

Regarding the transition variables q_t, we have 70 candidates at our disposal. Among these are, similar to the predictors, country-specific and global variables, but not variables which cover contributions from both countries by construction. For the country-specific variables, we have the economic policy uncertainty index, forecast uncertainty (as measured by the standard deviation of the distribution of 1-step ahead forecasts) for GDP growth, industrial production growth, CPI inflation, three-month and ten-year interest rates obtained from Consensus Economics, and media coverage which includes buzz and sentiment on a range of economic variables like exchange rates, interest rates, inflation and stock markets.[7] Uncertainty measures for the US include the VIX and

[7]As a large fraction of our transition variables are country-specific, we also consider equally weighted transition variables from the two countries under study to account for potential contributions from both countries to the uncertainty in a specific variable. As an example, we consider weighted buzz values on interest rates in the US and Europe as an alternative transition variable to the pure buzz values on interest rates in the US or Europe. As it turns out, these weighted transition variables only play a minor role in comparison to their pure versions putting full weight on one country and zero weight on the other country. Therefore, we do not report these additional results here.

macro, financial and economic uncertainty indexes as well as bond factors. Further global variables, which also act as predictors, include the VXY and global factor of risky assets.[8] In total, we have $6 \times 26 = 156$ pairs of exchange rates and predictors. For each predictor, one transition variable is selected according to the largest value of the linearity test statistic, see e.g. Teräsvirta, Tjostheim, and Granger (2010).

Out of the 156 cases, we find 83 rejections of linearity and 78 rejections of no predictability.[9] Joint rejections are found in 74 cases which corresponds to 47 percent. This result clearly points towards the relevance of non-linear predictability patterns in the investigated data set. It shows that predictability occurs quite frequently and does not reflect exceptional cases. More importantly, it shows that the transition variables we consider are useful for identifying predictability regimes.

In the following, we provide a couple of summary statistics on the 74 cases (see Tables 4 to 6). They are distributed across the six different G7 currency pairs as follows (ordered by magnitude): AUD (23), GBP (17), EUR (17), CHF (8), JPY (5) and CAD (4). We observe a striking, but potentially not too surprising, heterogeneity across the different exchange rates under consideration (Table 1).

Table 1: Number of non-linearity and predictability cases per currency

Currency	Non-linearity and predictability
AUD	23
GBP	17
EUR	17
CHF	8
JPY	5
CAD	4

Predictor variables are interest rate differentials (18) at different horizons for all exchange rates except the CAD; term spreads (8) with different maturities for the AUD, EUR and GBP; level (3), slope (4) and curvature (4) Nelson-Siegel factors for all currencies except the JPY; (a)symmetric Taylor rule deviations (9 symmetric and 5 asymmetric) for all currencies except the JPY; VIX and VXY (4 and 4) for AUD, EUR, CHF and GBP; deviations from PPP (3) for AUD, CHF and GBP; liquidity measure by Engel and Wu (2023b) (2) for EUR and GBP; global factor of risky assets by Miranda-Agrippino and Rey (2015) (2) for AUD and EUR; deviations from monetary

[8] As the framework does not cover self-exciting threshold predictive regressions, we do not study the cases in which the predictor is the same as the transition variable, i.e. for the VIX, VXY and the global factor of risky assets by Miranda-Agrippino and Rey (2015).

[9] We operate with a nominal significance level of 0.5 percent, a trimming value of ten percent, i.e. $\pi_1 = 0.1$ and $\pi_2 = 0.9$, and set $\delta = 4/5$ for the artificial autoregressive parameter in the IVX testing strategy as recommended in Gonzalo and Pitarakis (2012). We use finite-sample critical values which are obtained by Monte Carlo simulation, see Section 4.

fundamentals (2) for AUD and GBP; oil price (2) for AUD and JPY; and stock market index and growth differentials (2 and 2) for AUD and EUR and EUR and GBP, respectively (Table 2).

Table 2: Predictors

Predictor	Number of cases
Interest rate differentials	18
Term spreads	8
Nelson-Siegel: level factor	3
Nelson-Siegel: slope factor	4
Nelson-Siegel: curvature factor	4
Symmetric Taylor rule	9
Asymmetric Taylor rule	5
VIX	4
VXY	4
Purchasing power parity	3
Liquidity measure of Engel and Wu (2023b)	2
Global factor of Miranda-Agrippino and Rey (2015)	2
Monetary fundamentals	2
WTI oil price	2
Stock market index	2
Stock market growth differentials	2

Such strong evidence for the predictive power of interest rates and yield curve factors is in line with existing evidence which has illustrated that interest rates display strong ties to exchange rates. This result is also intuitive given that exchange rate changes display much stronger variations compared with other macroeconomic fundamentals, such as money supply or consumer prices. The Taylor rule has been widely proposed as a competitive fundamental exchange rate model based on the way central banks set interest rates. It is therefore not surprising that using interest rates directly or adopting yield curve factors (which also reflect risk premia and expectations) also provides interesting predictability results.

Overall, our findings do not exclude the possibility that macro fundamentals exhibit predictive power for exchange rates in a different framework which for example allows for time-variation in coefficients, different model sets over time or simply another forecasting horizon (Sarno, 2005). However, our main aim is not to identify the best combination of fundamentals or a comparison of estimates over different samples. We are rather interested in identifying channels which are able to generate predictability and therefore stick with the simple representation of fundamentals.

5.2 Drivers and characteristics of predictability

While the result of temporary predictability is not new itself, we now turn to the key question of whether predictability is driven by observable factors in greater detail based on the transition variables we consider. This question is new and sheds light on the mechanisms behind time-varying predictability. The selected transition variables mainly belong to the group of sentiments. In 38 cases (around 51.35%), transition variables constructed from sentiment data are selected. Exchange rate, interest rate and stock market buzz are selected in 20 cases (10 for EUR, 6 for AUD, 3 for CAD and 1 for CHF). In 18 cases, sentiment variables are selected with a focus on economic variables like economic growth, debt default, trade balance and budget deficit. These are majorly selected for the AUD, and especially debt default sentiment. The remaining selected transition variables are mostly forecast uncertainty measures from Consensus Economics (15) (on various economic variables) and uncertainty measures by Jurado, Ludvigson, and Ng (2015) (14) covering various aspects of economic and financial uncertainty at different horizons based on data from the US economy (Table 3). It is important to keep in mind that the sentiment data is based on newspaper coverage and is available in real-time, while the uncertainty measure of Jurado, Ludvigson, and Ng (2015) reflects common uncertainty based on model-based forecast errors. Overall, these results suggest that media coverage and uncertainty are of key relevance for predictability via macroeconomic fundamentals and global variables related to uncertainty and financial conditions. We discuss the resulting interactions in greater detail below.

Table 3: Chosen transition variables

Transition variable category	Times chosen
Buzz variables	20
Sentiment	18
Forecast uncertainty	15
Uncertainty (Jurado, Ludvigson, and Ng, 2015)	14
Global factor (Miranda-Agrippino and Rey, 2015)	5
VIX	1
Macro bond factor (Ludvigson and Ng, 2009)	1

After having provided summary information on the currencies, predictors and transition variables, we now take a closer look at the strength of predictability as measured by the predictive regression coefficient of determination. Here, we distinguish between regime-specific and joint (regime-weighted) predictability in comparison with the benchmark of a linear predictive regression.

First, we note that we typically find a relatively small fraction of observations in the predictability regime, while the majority of observations belong to the regime of no predictability. This is reflected in the relatively high (in some cases per construction low, e.g. some sentiment variables) threshold values expressed as quantiles of the transition variables. The average number of observations in the predictability regime is 44 months (around 20% of the total sample). This result resembles the existing evidence that predictability reflects rather rule than exception, while also showing that the number of observations is not negligible.

If we would ignore non-linear features in the predictability, we would opt for the linear predictive regression framework which would be misleading under existing non-linearity. We test for remaining autocorrelation in the linear predictive regression residuals via the Ljung-Box test with one lag and find no significant evidence against the null hypothesis. Furthermore, we test for heteroskedasticity by applying the CUSUM of squares-based test by Deng and Perron (2008) and obtain no rejections.[10] These results verify the assumptions in the underlying inferential tool. Robust HAC-based inference leads to the conclusion of insignificant intercept and slope coefficients, but these should be taken with a pinch of salt. Clearly, the linear predictive regression is misspecified from the angle of neglected non-linearity. This becomes evident when considering the results for the estimated threshold predictive regression.

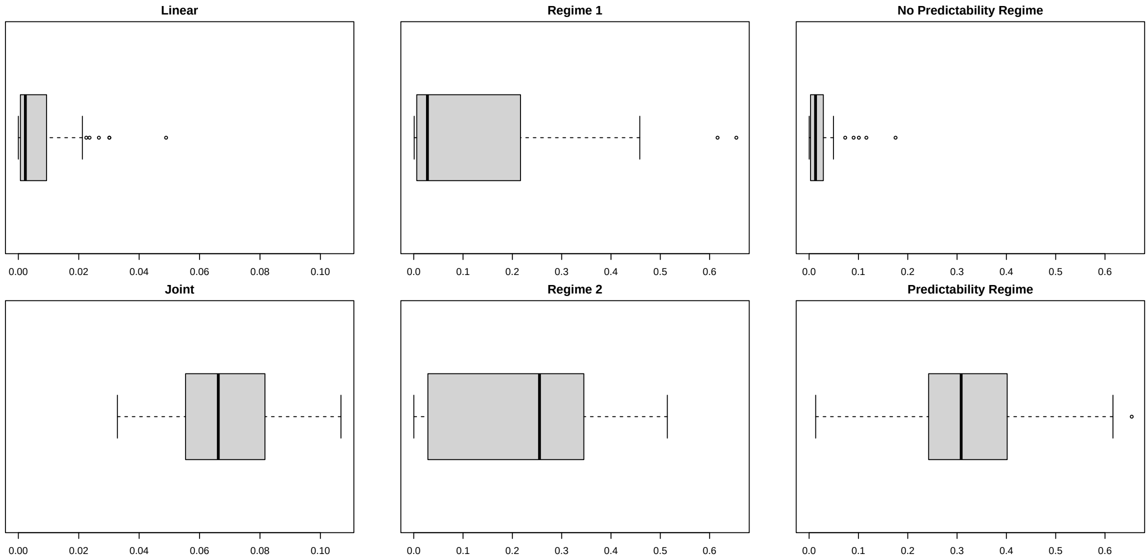
In the linear framework, the R^2 takes an average value of 0.61%. This pretty low number is comparable to the literature on equity premium prediction, see e.g. Welch and Goyal (2008). It also reflects the existing evidence on exchange rate returns. Turning to regime-specific predictability, we find clear increases in the overall predictability. The average of the R^2 values increases to 31.78%. On the contrary, the second regime is characterized by no predictability which is reflected in an average value of the R^2 of 1.87%. Now, turning to the regime-weighted R^2 which can be compared with the linear case, we find 6.79%. Hence, there is a strong non-linear pattern in predictability. When accounting for different regimes over time as triggered by some transition variable, we can not only detect regime-specific predictability patterns, but also the general level of predictability is found to be more than ten times higher as in the linear case.[11]

Fig. 1 displays the boxplots for the linear case, the joint regime-dependent case and the two individual regimes. Clearly, the predictability regime can be either regime 1 (where the transition variable falls below a certain threshold) or regime 2 (vice versa). In order to get a clearer distinction, we sort the regimes according to the quantile corresponding to the threshold value and set a cut-off at the

[10] This holds for all other cases, too.

[11] We do not find any case in which predictability is rather low in both regimes even though the test for predictability has led to a rejection. We therefore conclude that the rejections are not driven by solely switching intercepts.

Figure 1: Box plots of predictability



median. The resulting boxplots clearly demonstrate the general distinction between predictability and no predictability.

Table 4: IVX test results in threshold predictive regressions (AUD and CAD)

q_t	x_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
Rey_Global	LL_AUS	21.11	21.27	0.18	12.67	1.83	*6.05	89	138	0.21	0.39
ERU_h1	SS_AUS	34.61	37.96	1.71	0.09	*50.02	*5.18	204	23	0.68	0.90
Rey_Global	CC_AUS	26.81	27.57	0.38	7.02	9.02	*8.17	97	130	0.25	0.43
STO_buzz_AUS	SS_USA	24.17	25.71	0.62	2.67	26.59	*5.95	196	31	335.12	0.86
Rey_Global	CC_USA	19.54	22.13	0.66	14.17	1.34	*6.05	84	143	0.18	0.37
EG_AUS	SPR_AUS_10Y_TB	50.31	54.94	2.36	*65.42	0.07	*8.16	28	199	0.00	0.12
STO_buzz_AUS	SPR_USA_10Y_TB	27.52	28.94	0.47	2.62	30.25	*6.41	196	31	335.12	0.86
EG_AUS	SPR_AUS_5Y_TB	45.34	50.77	2.67	*61.61	0.02	*7.65	28	199	0.00	0.12
STO_buzz_AUS	SPR_USA_5Y_TB	21.81	22.46	0.31	2.03	24.23	*5.07	196	31	335.12	0.86
ERU_h1	IRD_AUS_USA_1M	36.42	36.93	0.04	1.27	44.35	*5.65	204	23	0.68	0.90
DD_AUS	IRD_AUS_USA_3M	35.81	36.27	0.03	3.04	32.91	*8.46	185	42	0.22	0.81
DD_AUS	IRD_AUS_USA_6M	38.41	38.83	0.02	3.00	35.57	*8.91	185	42	0.22	0.81
DD_AUS	IRD_AUS_USA_12M	37.62	38.18	0.04	3.17	34.49	*8.85	185	42	0.22	0.81
DD_AUS	AUD_USD_PPP	18.54	19.38	1.17	0.29	22.95	4.40	185	42	0.22	0.81
DD_AUS	MON_AUD_USD	23.72	23.75	0.27	0.51	25.81	*5.21	184	43	0.22	0.81
IR_buzz_USA	VIX	33.65	34.79	0.76	4.52	40.90	*9.35	197	30	3246.68	0.87
Rey_Global	VXY	23.99	24.12	0.13	11.15	4.93	*7.22	84	143	0.18	0.37
EFU_h1	Rey_Global	31.34	33.99	1.52	0.43	33.95	*5.77	191	36	1.11	0.84
ERU_h1	log_WTI	21.81	22.72	1.02	0.15	32.36	3.57	203	24	0.68	0.89
IR_buzz_USA	STR_AUS	27.52	31.03	1.42	0.61	47.00	*6.77	197	30	3246.68	0.87
USA_IP_FC_SD	STR_USA	26.61	38.30	4.89	0.14	43.21	*6.81	192	35	0.97	0.85
IR_buzz_USA	ATR_AUS	27.28	30.84	1.46	0.63	46.75	*6.75	197	30	3246.68	0.87
DD_AUS	STO_AUS	26.04	27.08	0.00	1.47	25.77	*5.87	185	42	0.22	0.81
DD_USA	CC_CAN	20.60	20.81	0.00	0.75	26.22	3.91	199	28	0.53	0.88
IR_buzz_USA	STR_CAN	21.42	21.63	0.14	0.12	38.49	*5.21	197	30	3246.68	0.87
IR_buzz_USA	STR_USA.1	24.36	26.39	0.99	0.35	46.40	*6.46	197	30	3246.68	0.87
IR_buzz_USA	ATR_CAN	21.45	21.66	0.15	0.12	38.59	*5.22	197	30	3246.68	0.87

In the first column are the chosen transition variables while in the second are the predictors. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates a value larger than 5%.

Table 5: IVX test results in threshold predictive regressions (EUR and JPY)

q_t	x_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
buzz_EUR	ETA_EUR	22.18	24.66	0.86	11.61	7.68	*9.83	125	102	6425.96	0.55
MB_F1	CC_DEU	28.47	29.54	0.24	0.55	40.74	*5.71	198	29	0.39	0.87
buzz_EUR	SS_USA	24.05	24.35	0.10	31.87	2.87	*10.18	57	170	3007.96	0.25
buzz_EUR	SPR_USA_10Y_TB	25.50	25.74	0.05	32.94	3.17	*10.68	57	170	3007.96	0.25
buzz_EUR	SPR_USA_5Y_TB	22.59	22.64	0.02	26.78	3.66	*9.49	57	170	3007.96	0.25
buzz_EUR	IRD_EUA_USA_1M	23.73	24.04	0.11	26.33	4.45	*10.26	60	167	3169.23	0.26
buzz_EUR	IRD_EUA_USA_3M	21.85	22.26	0.13	25.88	3.70	*9.59	60	167	3169.23	0.26
buzz_EUR	IRD_EUA_USA_6M	22.40	22.65	0.07	25.74	3.94	*9.73	60	167	3169.23	0.26
buzz_EUR	IRD_EUA_USA_12M	21.81	22.08	0.07	26.25	3.49	*9.53	60	167	3169.23	0.26
IR_buzz_USA	VIX	28.66	28.77	0.05	2.10	*50.27	*8.50	197	30	3246.68	0.87
buzz_EUR	VXY	21.54	22.25	0.35	35.52	0.07	*9.95	63	164	3244.37	0.28
USA_IP_FC_SD	Rey_Global	23.90	24.12	0.22	4.44	10.09	*7.69	97	130	0.25	0.43
USA_IP_FC_SD	STR_EUA	22.04	22.13	0.07	2.92	18.93	*5.54	190	37	0.94	0.84
USA_IP_FC_SD	STR_USA	20.55	26.08	2.25	0.21	30.83	4.95	192	35	0.97	0.85
USA_IP_FC_SD	ATR_EUA	22.12	22.20	0.07	2.88	19.08	*5.53	190	37	0.94	0.84
TB_EUA	STO_EUA	19.39	19.95	0.80	35.75	0.08	*5.13	33	194	0.00	0.15
Rey_Global	STG_EUA	20.60	20.67	0.00	4.57	7.32	*6.15	97	130	0.25	0.43
TMU_h3	IRD_JPN_USA_1M	21.00	21.21	0.04	22.23	2.26	*7.56	61	166	0.73	0.27
TMU_h3	IRD_JPN_USA_3M	20.48	20.66	0.05	21.65	2.21	*7.37	61	166	0.73	0.27
TMU_h3	IRD_JPN_USA_6M	20.36	20.51	0.06	21.61	2.17	*7.33	61	166	0.73	0.27
TMU_h3	IRD_JPN_USA_12M	20.26	20.40	0.06	21.28	2.25	*7.30	61	166	0.73	0.27
EFU_h3	log_WTI	20.12	20.24	0.15	3.89	22.05	*7.43	183	44	1.10	0.81

In the first column are the chosen transition variables while in the second are the predictors. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates a value larger than 5%.

Table 6: IVX test results in threshold predictive regressions (CHF and GBP)

q_t	x_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
EFU_h3	LL_CHE	18.85	19.55	0.40	2.67	20.42	*6.28	181	46	1.09	0.80
USA_3MIR_FC_SD	IRD_CHE_USA_6M	19.64	20.85	0.37	0.76	40.16	4.95	203	24	0.58	0.89
USA_3MIR_FC_SD	IRD_CHE_USA_12M	20.06	21.34	0.44	0.88	40.77	*5.12	203	24	0.58	0.89
STO_buzz_USA	CHF_USD_PPP	19.65	20.63	0.40	0.16	27.27	*7.72	164	63	8075.24	0.72
INF_FC_CHE	VIX	28.39	28.63	0.12	43.42	2.04	*6.25	23	204	0.00	0.10
INF_FC_CHE	VXY	24.12	24.16	0.02	35.05	2.43	*5.75	23	204	0.00	0.10
INF_FC_CHE	STR_CHE	26.91	27.21	0.02	45.34	0.59	*5.54	25	202	0.00	0.11
INF_FC_CHE	ATR_CHE	27.28	27.59	0.02	45.84	0.61	*5.62	25	202	0.00	0.11
SNT_USD	ETA_GBR	22.75	30.22	2.12	43.65	0.06	*7.39	38	189	-0.10	0.17
EMU_h1	LL_GBR	23.61	23.62	0.01	1.03	31.44	4.25	203	24	0.74	0.89
ERU_h1	SS_GBR	21.51	23.55	0.46	0.25	29.99	3.28	204	23	0.68	0.90
ERU_h1	SPR_GBR_10Y_TB	22.01	24.92	0.58	0.32	30.84	3.43	204	23	0.68	0.90
ERU_h1	SPR_GBR_5Y_TB	21.33	25.17	1.22	1.00	30.32	3.99	204	23	0.68	0.90
GBR_CPI_FC_SD	IRD_GBR_USA_1M	28.30	28.67	0.14	0.83	26.45	*6.95	173	54	0.39	0.76
GBR_CPI_FC_SD	IRD_GBR_USA_3M	30.09	30.28	0.09	1.05	27.54	*7.38	173	54	0.39	0.76
GBR_CPI_FC_SD	IRD_GBR_USA_6M	34.45	34.63	0.10	1.22	30.93	*8.32	173	54	0.39	0.76
GBR_CPI_FC_SD	IRD_GBR_USA_12M	31.20	31.29	0.08	1.40	27.97	*7.75	173	54	0.39	0.76
VIX	GBP_USD_PPP	31.94	32.34	0.65	0.14	*50.10	*5.23	204	23	29.15	0.90
STO_USA	MON_GBP_USD	21.07	21.07	0.22	37.77	0.02	4.03	24	203	-0.17	0.11
USA_3MIR_FC_SD	VIX	23.15	28.26	1.26	3.88	17.79	*9.30	139	88	0.42	0.61
POS_USD	VXY	18.13	22.33	1.13	19.93	1.27	*7.30	73	154	0.17	0.32
USA_3MIR_FC_SD	STR_GBR	32.64	32.65	0.04	2.60	35.57	*9.60	179	48	0.51	0.79
USA_IP_FC_SD	STR_USA.5	26.70	33.21	3.01	0.11	37.67	*5.93	192	35	0.97	0.85
USA_IP_FC_SD	ATR_GBR	26.76	33.26	3.01	0.11	37.74	*5.94	192	35	0.97	0.85
BD_GBR	STG_GBR	24.99	25.66	0.14	1.65	*51.42	*6.71	204	23	0.00	0.90

In the first column are the chosen transition variables while in the second are the predictors. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates an R^2 of more than 5%.

Apparently, the next questions concern some specific cases (i) in which the strongest predictability are found and (ii) general evolution of predictability over time. First, we give a couple of example cases and then provide a general and detailed perspective on the timing of predictability in exchange rates triggered by transition variables. There are six cases in which the regime-specific predictability exceeds 50 percent. These are marked in Tables 4 to 6 with a star in the columns $R^2_{(1)}$ (regime 1 for which predictability is triggered by values of the transition variable being lower than the threshold) or $R^2_{(2)}$ (regime 2, vice versa). These occur only for AUD (3), GBP (2) and EUR (1). In these six cases, predictor variables are related to interest rates, stock market volatility, PPP deviations and stock market growth differentials. There is quite some heterogeneity regarding the nature of the transition variable, but mostly driven by sentiment-related variables and either stock market volatility or model-based forecast uncertainty. The largest degree of regime-specific predictability (65.42%) is found for the AUD with a term spread predictor and economic growth sentiment as the transition variable. The largest joint R^2 (10.68%) is obtained for EUR with a term spread predictor and the euro area buzz as the transition variable. Overall, there are 64 cases in which the joint R^2 exceeds five percent - these are marked by a star in column $R^2_{(1,2)}$. We find the following distribution across currencies: AUD (21), EUR (16), GBP (12), CHF (7), JPY (5) and CAD (3). Again, the majority of cases (44/64) are characterized by interest rate related as predictors, mostly in the form of interest rate differentials and yield curve factors with some degree of heterogeneity regarding the transition variables.

We identify several cases where higher media attention related to interest rates and stock prices in the US triggers substantial predictability based on interest rate differentials and yield curve factors in the second regime, for example for AUD and EUR. These results are intuitive since higher uncertainty or higher media attention increase predictability. Interestingly, we find that buzz related to the EUR has a different effect in the sense that lower buzz coincides with stronger predictability. This points to periods of high buzz which align with news or developments which are interpreted differently by market participants, leading to less relevance of our predictors for the path of the exchange rate. On the opposite periods of low buzz can reflect a consensus that specific factors drive exchange rates.

In case of buzz, the number of observations in the predictability regime is comparably higher. This result is also intuitive since higher media coverage of an exchange rate can also reflect unexpected exchange rate movements which make the exchange rate harder to predict. Exchange rate buzz also does not provide any direct link to the predictors we adopt. On the contrary, higher buzz related to fundamentals directly reflects information about the news coverage related to macroeconomic fundamentals which is likely to increase the attention attached to these fundamentals.

Having established evidence for regime-specific predictability for bilateral US-Dollar exchange rates, we now extend our analysis by analyzing effective US-Dollar exchange rates. The literature on the global financial cycle and the global role of the US-Dollar has also focused on the path of the US-Dollar against emerging markets, illustrating for example that global financial conditions or uncertainty is strongly correlated with movements of the effective US-Dollar exchange rate (Obstfeld and Zhou, 2023). We use data on the broad effective US exchange rate from the Federal Reserve and the Bank for International Settlements. We only select predictors and transition variables which reflect US or global dynamics, implying that we exclude measures which solely reflect information about countries other than the US. As the descriptive statistics indicate, the effective exchange returns (BIS and FED) are serially correlated.[12] This empirical observation is in contrast to the individual G7 currencies investigated above. The serial correlation might be explained by sticky trade weights which drive the effective exchange rates. Such an empirical feature of the return data is not innocuous, as demonstrated in Yang, Long, Peng, and Cai (2020). In particular, predictive regression residuals need to be serially uncorrelated by assumption which is endangered by the significant autocorrelation in the effective exchange rate returns. As a consequence, the standard IVX approach by Kostakis, Magdalinos, and Stamatogiannis (2015) can be severely size-distorted. To this end, an IVX-AR approach has been proposed. In simple terms, a Cochrane-Orcutt transformation is applied to the predictive regression to account for the serial correlation. This approach has been shown to work well in practice. Here, we adopt the IVX-AR approach to the threshold predictive regression case as the proposed solution in Yang, Long, Peng, and Cai (2020) is originally designed for the linear case.

The results for effective exchange rates confirm the importance of media attention as a determinant of exchange rate predictability. For the measure provided by the Federal Reserve, buzz is identified as the transition variable in nine out of eleven cases (Table 7). It is also selected in one out of three cases for the measure provided by the BIS (Table 8). In the following, we briefly discuss the three cases identified for both effective exchange rate measures. Two of these reflect predictability of exchange rates via symmetric Taylor rules which positively depend on the degree of uncertainty with higher uncertainty, either captured by disagreement regarding US industrial production or financial uncertainty. The other case illustrates the predictive power of the VIX in case of high

[12] A Ljung-Box test confirms the significance of the first-order autocorrelation coefficient.

media attention for the USD with buzz acting as a transition variable. In all three cases (for the BIS effective exchange rate), the R-squared is substantially higher in case of the second regime (24.25 vs. 0.91 for buzz as transition variable, 52.03 vs. 0.22 for industrial production disagreement and 27.72 vs. 6.70 for financial uncertainty). The predictability regime includes 62 observations for buzz as a transition variable, 77 for financial uncertainty and 35 for industrial production disagreement, confirming the previous result that predictability occurs frequently throughout the sample period. These results are important since they illustrate that the key dynamics we have identified for bilateral exchange rates continue to hold with regard to the overall path of the US-Dollar. Uncertainty plays a dual role in exchange rate predictability, acting both as a predictor and transition variable, while the degree of media attention is of key importance for predictability, for example in the sense that uncertainty has stronger predictive power in case of high media coverage. This illustrates that the media narrative matters for safe haven properties of the US-Dollar.

We also run the IVX-AR procedure on the individual G7 currencies which are almost serially uncorrelated. In this case, the Cochrane-Orcutt transformation is not needed, but applied as a sanity check. We find almost the same results as with the standard IVX approach and decide not to report these results here in order to save space.

Table 7: IVX-AR test results for effective exchange rates (of FED)

q_t	x_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
TFU_h1	STR_USA	23.41	28.00	1.87	6.73	27.59	*13.84	150	77	1.00	0.66
buzz_USD	LL_USA	22.35	22.36	0.60	0.84	15.95	4.98	165	62	18399.97	0.73
buzz_USD	SS_USA	22.73	22.73	0.01	1.96	15.50	*5.68	165	62	18399.97	0.73
buzz_USD	CC_USA	23.28	24.77	0.28	3.05	13.67	*5.96	165	62	18399.97	0.73
buzz_USD	VIX	25.54	30.45	1.77	1.27	28.22	*8.66	165	62	18399.97	0.73
buzz_USD	VXY	18.91	21.70	1.86	1.32	17.68	*5.81	165	62	18399.97	0.73
buzz_USD	Rey_Global	18.86	20.52	0.81	1.85	12.76	4.84	165	62	18399.97	0.73
buzz_USD	log_WTI	23.15	23.89	0.07	2.40	15.56	*6.01	165	62	18399.97	0.73
USA_IP_FC_SD	STR_USA	27.88	31.96	1.62	1.20	44.21	*7.86	192	35	0.97	0.85
buzz_USD	SPR_USA_10Y_TB	25.38	25.38	0.00	2.26	17.55	*6.45	165	62	18399.97	0.73
buzz_USD	SPR_USA_5Y_TB	23.93	24.31	0.06	1.67	19.10	*6.45	165	62	18399.97	0.73

In the first column are the chosen transition variables while in the second are the predictors. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates an R^2 of more than 5%.

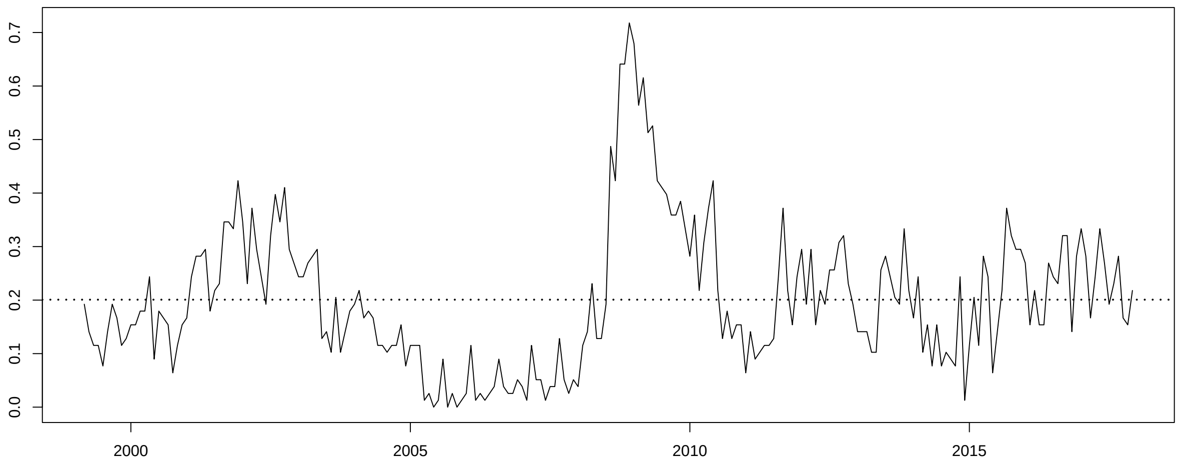
Table 8: IVX-AR test results for effective exchange rates (of BIS)

q_t	x_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
TFU_h1	STR_USA	23.29	27.88	1.86	6.70	27.72	*13.86	150	77	1.00	0.66
buzz_USD	VIX	19.48	20.73	0.37	0.91	24.25	*7.31	165	62	18399.97	0.73
USA_IP_FC_SD	STR_USA	27.65	34.73	3.38	0.22	*52.03	*8.25	192	35	0.97	0.85

In the first column are the chosen transition variables while in the second are the predictors. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates an R^2 of more than 5%.

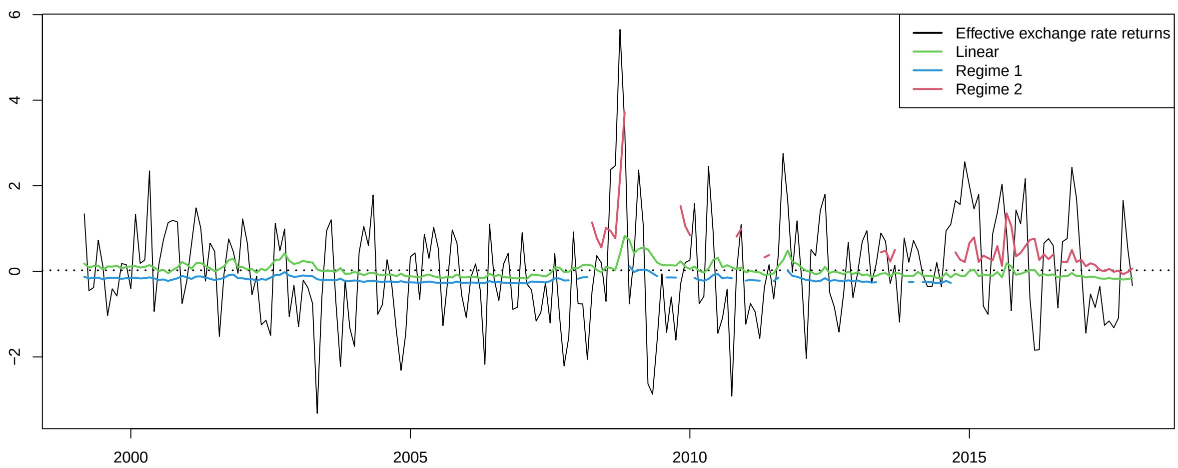
In order to provide an overview of the timing of predictability, we show in Fig. 2 the average number of cases over time in which the predictability regime is active. Strikingly, there is a cluster of strong predictability in the second half of 2008 and also partly in 2009. The maximum is 71.8% which is located in December, 2008. This gives clear evidence that predictability sharply increased during the Great Financial Crisis. After the peak, there is a gradual mean-reversion to the overall average of 20.1%. Predictability arises from forward-looking interest rate fundamentals and is triggered by high levels of uncertainty as captured by our transition variables during the Great Financial Crisis. A persistent predictability regime across the financial crisis is also plausible given the increase in uncertainty in this period and the established fact that some currencies, like the USD and the JPY, appreciate in times of uncertainty. This pattern is in line with the findings of Fratzscher (2009) which suggest that several currencies, in particular those in which US investors held relatively large portfolio investments, experienced significantly larger depreciations against the US-Dollar. However, our findings are not restricted to the period around 2009 and show that predictability is not restricted to one specific period and occurs permanently over time.

Figure 2: Fraction of active predictability regime (averages over time)



To shed further light on the timing of predictability, we also consider the case of the effective dollar exchange rate (of FED) with VIX as a predictor and buzz as a transition variable in some more detail. The estimated threshold value for the activation of the predictability regime is relatively high (73% expressed as quantile λ) supporting the notion that in times of high uncertainty, interest rate predictors become important. As previously discussed, the no-predictability regime is characterized by a low R^2 value while the picture is reversed for the second regime of predictability. The joint R^2 (as weighted by the regimes with 165 observations for the no-predictability and 62 observations for the predictability regime) results in 8.66%. Fig. 3 illustrates the fitted values from the estimated linear and two-regime threshold predictive regressions, respectively. The graph illustrates recurring periods of predictability not only during the Great Financial Crisis, but also afterwards. This confirms that predictability follows a pattern over time and is not a singular event but consists of several brief periods, a pattern which is perfectly in line with the result by Farmer, Schmidt, and Timmermann (2023) that 'pockets', that is short periods of significant predictability, can be identified for the stock market.

Figure 3: Timing of predictability for effective dollar exchange rate with VIX as predictor and buzz as transition variable



Overall, our results provide important insights into exchange rate dynamics. Higher media coverage related to interest rates which is reflected in the second regime coincides with stronger predictability of interest rates and yield curve factors. The importance of sentiment and media attention is also interesting from a behavioural perspective. The classical distinction between chartists and fundamentalists as market participants argues that only some market participants pay attention to macroeconomic fundamentals. Intuitively, higher media coverage is likely to increase the weight participants attach to the corresponding fundamentals when making their forecast. An interesting question is why buzz, that is media attention per se, turns out to be more important compared with sentiment indicators which also reflect the content of news, such as positive vs. negative news coverage. This can be explained by the fact that sentiments can take positive and negative values which opens the possibility of multiple combinations with the predictors, such as the interest differential, in an environment of positive and negative sentiment. On the other hand, the interpretation of buzz is more straightforward since it corresponds to high or low coverage. Our results suggest that higher coverage of the exchange rate often occurs in times of uncertainty about the future path of the exchange rate, resulting in lower predictability while higher coverage of interest rates tends to increase the predictive power of predictors related to interest rates.

Our results also link to the scapegoat approach which has addressed the exchange rate disconnect puzzle from a theoretical point of view. The underlying idea is that a fundamental becomes a scapegoat for unexpected exchange rate changes if it deviates from its long-term trend. Our results offer a different perspective in the sense that fundamentals become more important as predictors if they receive high media attention. Both explanations are complementary since unexpected changes are likely to coincide with higher media attention. The fact that our results show substantial predictably after the 2008 financial crisis when monetary policy entered a new era aligns with this line of reasoning. It is of course important to keep in mind, that we analyze exchange rate returns and not expected exchange rate returns with often substantial forecast errors driving a potential wedge between both.

From a more general perspective our results point towards a new transmission channel with regard to monetary policy effects on the exchange rate since higher coverage of interest rates is often strongly related to monetary policy announcements or communication. These results align with the results by Mueller, Tahbaz-Salehi, and Vedolin (2017) who analyses currency portfolios and finds that investment strategies involving short positions in USD and long positions in foreign currencies exhibit distinct price patterns around scheduled FOMC meetings which reflect periods of more media attention.

5.3 Robustness tests and extensions

We conduct various robustness tests and extensions. On the one hand, we analyse whether the strong evidence for the importance of media coverage only reflects a slightly better performance compared with the second best choice for the different predictors. To tackle this issue, we exclude media coverage from our set of transition variables and re-run our analysis. In one specification, we do not include any buzz variable in the underlying data set but allowed for sentiment. In a second specification, we exclude both buzz and sentiment.

In our original set up, buzz or sentiment is selected in 38 cases as a driver of predictability. If we exclude buzz, only 10 of those cases are identified as cases of predictability. If both sentiment and buzz are excluded, only 11 cases survive. These results show that the evidence for regime-specific predictability drops significantly, implying that media attention is a particularly strong driver of predictability.

Given the step-by-step approach for a set of potentially correlated predictors, we ask whether adopting a dynamic factor model approach provides comparable or even superior results given that some studies have shown that factor models are potentially useful for analysing and forecasting exchange rates (Greenaway-McGrevy, Mark, Sul, and Wu, 2018). Against this background, we include several measures of uncertainty, sentiment and interest rates, allowing for the possibility that using combined information of several predictors leads to better results. In order to cope with the multiple predictor case, we use the dynamic factor model in state-space form by Doz, Giannone, and Reichlin (2012). Estimation is carried out via the EM algorithm. We apply the dynamic factor model currency-wise. The potential predictors are differenced once as stationarity is required for this part of the analysis. After the factor estimation and extraction, the resulting component is re-integrated by taking cumulative sums. The lag length in the underlying VAR model is selected via the BIC and equals one for all six currencies. In accordance with our framework, we are interested in the first factor. For the AUD, CAD, EUR, CHF and the GBP, we find that the factor is most heavily driven by the yield curve slope and the term spread (10-years minus the 3-month Treasury bill rate) with individual R^2 values above 90%. For the JPY, level and slope of the yield curve matter most. More generally, we find interest rates to dominate the factor in all cases. Essentially, the factors are all majorly driven by interest rates rather than stock markets, oil prices, PPP deviations or deviations from a monetary model. Notably, Taylor rule deviations are not driving the factors, but rather yield curve components, term spreads and the interest rate differential (ordered by importance). The picture looks different if we use only pre-selected predictors (according to our predictability test results) as input variables to the dynamic factor model. Here, interest rates still dominate, but the factors are most strongly driven by the interest rate differential, except for CAD and CHF, where deviations from the Taylor rule drive the factor. The test results are reported in Table 9 in which we distinguish whether all potential predictors are considered (upper panel) or whether they are pre-selected (lower panel).

Table 9: Results of dynamic factor model analysis

ALL	q_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
AUD	STO_buzz_AUS	25.85	27.27	0.61	2.73	28.45	*6.26	196	31	335.12	0.86
CAD	BR_USA	14.25	14.27	0.00	20.63	0.52	2.75	25	202	-0.21	0.11
EUR	buzz_EUR	24.30	24.59	0.09	31.90	2.97	*10.27	57	170	3007.96	0.25
JPY	BR_buzz_USA	22.95	25.32	0.72	0.37	32.99	*8.31	172	55	4227.24	0.76
CHF	INF_FC_CHE	10.70	12.75	0.89	23.27	0.22	2.57	23	204	0.00	0.10
GBP	STO_buzz_GBR	17.59	17.92	0.13	0.90	35.95	4.46	204	23	877.93	0.90

PRESELECT	q_t	$\sup W_T^L$	$\sup W_T^P$	R^2	$R^2_{(1)}$	$R^2_{(2)}$	$R^2_{(1,2)}$	T_1	T_2	γ	λ
AUD	DD_AUS	38.33	38.75	0.03	3.26	34.99	*9.02	185	42	0.22	0.81
CAD	IR_buzz_USA	25.78	27.48	0.67	0.25	47.83	*6.56	197	30	3246.68	0.87
EUR	buzz_EUR	22.44	22.71	0.07	25.84	3.94	*9.75	60	167	3169.23	0.26
JPY	EMU_h3	15.07	15.31	0.00	13.30	1.87	*5.46	72	155	0.74	0.32
CHF	INF_FC_CHE	24.14	24.45	0.01	41.30	0.48	5.00	25	202	0.00	0.11
GBP	GBR_CPI_FC_SD	36.15	36.41	0.33	0.63	34.81	*8.49	175	52	0.41	0.77

In the first column are the currencies while in the second are the transition variables. The sup Wald statistics for the null of linearity ($\sup W_T^L$) and no predictability ($\sup W_T^P$) are stated in columns three and four. After that, the coefficient of determination for the linear predictive regression model (R^2) and for both regimes ($R^2_{(1)}, R^2_{(2)}$) as well as the joint coefficient of determination ($R^2_{(1,2)}$) are provided. T_1 and T_2 show the number of observations in regime 1, respectively regime 2. In the last two columns are the threshold parameter γ and the quantile λ. ALL indicates that all predictors are included while PRESELECT illustrate that only predictors identified by the predictability test are considered. A $*$ in the columns for $R^2_{(1)}$ and $R^2_{(2)}$ illustrates regimes with an R^2 of more than 50%, while a $*$ in the column $R^2_{(1,2)}$ indicates an R^2 of more than 5%.

Let us first study the results in the upper panel. First of all, we only find three (out of six) rejections of the no-predictability hypothesis (for AUD, EUR and JPY). For these currencies, we also obtain a rejection of the linearity hypothesis. The overall predictability by using the first factor extracted from the dynamic factor model is comparable to the previous results. When turning to the case of pre-selected predictors, we find in some cases slightly stronger predictability, in some slightly less. Only for JPY, no rejection of the no-predictability hypothesis is found. In all other five cases, also the linearity hypothesis is rejected. While for the GBP, the factor with pre-selected variables increases predictability remarkably (joint $R^2 = 8.49\%$), there are also some losses in predictability, e.g., for JPY (joint $R^2 = 5.46\%$). Overall, we do not find factors to have stronger predictability than individual variables. Moreover, the usage of individual predictors eases the economic interpretation as opposed to factors.

6 Conclusion

Although the time-varying performance of fundamental exchange rate models is already well-established, we provide a new perspective on the nature of predictability based on a comprehensive data set of exchange rate models and several potential drivers of predictability embedded in those models. Our results resemble findings for the stock market by Farmer, Schmidt, and Timmermann (2023) that short periods with significant predictability ('pockets') are accompanied by prolonged periods of no predictability. However, we do not only confirm that predictability comes and goes and is a periodic event, but we also provide significant evidence for non-linear patterns in exchange rate predictability. We illustrate that predictability periods are mainly driven by media attention and uncertainty as observable variables for both bilateral and the effective dollar exchange rate.

Our results are important for the theoretical underpinning of the exchange rate disconnect puzzle. While the role of uncertainty has been widely discussed in the context of exchange rates, for example in the context of safe haven currencies, we show that the degree of uncertainty plays a dual role in predictability, also affecting the usefulness of other exchange rate predictors. The role of media attention and sentiments has been less explored and our findings suggest that the predictive power of interest rates and yield curve factors depend on the extent of media coverage in the sense that more attention paid to interest rates tends to indicate stronger predictability, while high coverage of the exchange rate itself has the potential to result in lower exchange rate predictability. Our results also show that uncertainty is a useful predictor for the effective US-Dollar exchange rate in times of high media coverage.

To the best of our knowledge, such an attention channel has not been explored and could act as a useful extension of theoretical models which explain the time-varying importance of fundamentals such as the scapegoat approach and research on expectations and behaviour of market participants. Given that monetary policy decisions and communication affect media coverage related to interest rates and exchange rates, our results can also be extended in order to evaluate whether and how monetary policy announcements affect exchange rate predictability, a result which has also been brought forward by Mueller, Tahbaz-Salehi, and Vedolin (2017) in the context of currency portfolios.

From an empirical point of view, our findings point to the possibility of incorporating media attention and ex-ante uncertainty when predicting exchange rates in real-time, an exercise which is beyond the scope of this paper. The non-linear predictability we have identified based on the full sample does not necessarily translate into real-time out-of sample predictability. One useful way forward would be to include media coverage or uncertainty measures in the pool of potential predictors when predicting exchange rates based on empirical approaches which allow for time-varying inclusion of predictors and/or changes in the underlying coefficients.

References

Bacchetta, P. and Van Wincoop, E. (2004). "A scapegoat model of exchange-rate fluctuations". In: *American Economic Review* 94.2, pages 114–118.

Bacchetta, P. and Van Wincoop, E. (2006). "Can information heterogeneity explain the exchange rate determination puzzle?" In: *American Economic Review* 96.3, pages 552–576.

Bacchetta, P. and Van Wincoop, E. (2013). "On the unstable relationship between exchange rates and macroeconomic fundamentals". In: *Journal of International Economics* 91.1, pages 18–26.

Baillie, R. T. and Kilic, R. (2006). "Do asymmetric and nonlinear adjustments explain the forward premium anomaly?" In: *Journal of International Money and Finance* 25.1, pages 22–47.

Baker, M. and Wurgler, J. (2007). "Investor sentiment in the stock market". In: *Journal of Economic Perspectives* 21.2, pages 129–152.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). "Measuring economic policy uncertainty". In: *The Quarterly Journal of Economics* 131.4, pages 1593–1636.

Beckmann, J., Belke, A., and Kühl, M. (2011). “The dollar-euro exchange rate and macroeconomic fundamentals: A time-varying coefficient approach”. In: *Review of World Economics* 147.1, pages 11–40.

Beckmann, J. and Schüssler, R. (2016). “Forecasting exchange rates under parameter and model uncertainty”. In: *Journal of International Money and Finance* 60, pages 267–288.

Breitung, J. and Demetrescu, M. (2015). “Instrumental variable and variable addition based inference in predictive regressions”. In: *Journal of Econometrics* 187.1, pages 358–375.

Campbell, J. Y. and Yogo, M. (2006). “Efficient tests of stock return predictability”. In: *Journal of Financial Economics* 81.1, pages 27–60.

Caner, M. and Hansen, B. E. (2001). “Threshold autoregression with a unit root”. In: *Econometrica* 69.6, pages 1555–1596.

Cavusoglu, N. and Neveu, A. R. (2015). “The predictive power of survey-based exchange rate forecasts: Is there a role for dispersion?” In: *Journal of Forecasting* 34.5, pages 337–353.

Cheung, Y.-W. and Chinn, M. D. (2001). “Currency traders and exchange rate dynamics: A survey of the US market”. In: *Journal of International Money and Finance* 20.4, pages 439–471.

Cheung, Y.-W., Chinn, M. D., and Pascual, A. G. (2005). “Empirical exchange rate models of the nineties: Are any fit to survive?” In: *Journal of International Money and Finance* 24.7, pages 1150–1175.

Cochrane, J. H. (2017). “Macro-Finance”. In: *Review of Finance* 21.3, pages 945–985.

Dangl, T. and Halling, M. (2012). “Predictive regressions with time-varying coefficients”. In: *Journal of Financial Economics* 106.1, pages 157–181.

Della Corte, P. and Tsiakas, I. (2012). “Statistical and economic methods for evaluating exchange rate predictability”. In: *Handbook of Exchange Rates, edited by James, J., Marsh, I. W., and Sarno, L., Wiley*, pages 221–263.

Demetrescu, M. and Hillmann, B. (2022). “Nonlinear predictability of stock returns? Parametric versus nonparametric inference in predictive regressions”. In: *Journal of Business & Economic Statistics* 40.1, pages 382–397.

Deng, A. and Perron, P. (2008). “The limit distribution of the CUSUM of squares test under general mixing conditions”. In: *Econometric Theory* 24.3, pages 809–822.

Dibiasi, A. and Iselin, D. (2021). “Measuring knightian uncertainty”. In: *Empirical Economics* 61, pages 2113–2141.

Diebold, F. X. (2015). "Comparing predictive accuracy, twenty years later: A personal perspective on the use and abuse of Diebold-Mariano tests". In: *Journal of Business & Economic Statistics* 33.1, pages 1–9.

Dominguez, K. M. E. and Panthaki, F. (2006). "What defines 'news' in foreign exchange markets?" In: *Journal of International Money and Finance* 25.1, pages 168–198.

Dovern, J., Fritsche, U., and Slacalek, J. (2012). "Disagreement among forecasters in G7 countries". In: *The Review of Economics and Statistics* 94.4, pages 1081–1096.

Doz, C., Giannone, D., and Reichlin, L. (2012). "A quasi-maximum likelihood approach for large, approximate dynamic factor models". In: *The Review of Economics and Statistics* 94.4, pages 1014–1024.

Engel, C. (1994). "Can the Markov switching model forecast exchange rates?" In: *Journal of International Economics* 36.1-2, pages 151–165.

Engel, C. and West, K. D. (2005). "Exchange rates and fundamentals". In: *Journal of Political Economy* 113.3, pages 485–517.

Engel, C. and Wu, S. P. Y. (2023a). "Forecasting the U.S. Dollar in the 21st century". In: *Journal of International Economics* 141.103715.

Engel, C. and Wu, S. P. Y. (2023b). "Liquidity and exchange rates: An empirical investigation". In: *Review of Economic Studies* forthcoming.

Farmer, L. E., Schmidt, L., and Timmermann, A. (2023). "Pockets of predictability". In: *The Journal of Finance* 78.3, pages 1279–1341.

Faust, J., Rogers, J. H., and Wright, J. H. (2003). "Exchange rate forecasting: The errors we've really made". In: *Journal of International Economics* 60.1, pages 35–59.

Filippou, I., Nguyen, M. T., and Taylor, M. P. (2023). "Investor attention to news on financial integration and currency returns". In: *Working Paper*.

Fratzscher, M. (2009). "What explains global exchange rate movements during the financial crisis?" In: *Journal of International Money and Finance* 28.8, pages 1390–1407.

Frömmel, M., MacDonald, R., and Menkhoff, L. (2005a). "Do fundamentals matter for the D-Mark/Euro-Dollar? A regime switching approach". In: *Global Finance Journal* 15.3, pages 321–335.

Frömmel, M., MacDonald, R., and Menkhoff, L. (2005b). "Markov switching regimes in a monetary exchange rate model". In: *Economic Modelling* 22.3, pages 485–502.

Froot, K. A. and Frankel, J. A. (1989). “Forward discount bias: Is it an exchange risk premium?” In: *The Quarterly Journal of Economics* 104.1, pages 139–161.

Frydman, R. and Goldberg, M. D. (2007). *Imperfect knowledge economics: Exchange rates and risk.* Princeton University Press.

Gehrig, T. and Menkhoff, L. (2006). “Extended evidence on the use of technical analysis in foreign exchange”. In: *International Journal of Finance & Economics* 11.4, pages 327–338.

Goldberg, M. D. and Frydman, R. (1996). “Imperfect knowledge and behaviour in the foreign exchange market”. In: *The Economic Journal* 106.437, pages 869–893.

Gonzalo, J. and Pitarakis, J.-Y. (2012). “Regime-specific predictability in predictive regressions”. In: *Journal of Business & Economic Statistics* 30.2, pages 229–241.

Gonzalo, J. and Pitarakis, J.-Y. (2017). “Inferring the predictability induced by a persistent regressor in a predictive threshold model”. In: *Journal of Business & Economic Statistics* 35.2, pages 202–217.

Goyal, A. and Welch, I. (2003). “Predicting the equity premium with dividend ratios”. In: *Management Science* 49.5, pages 639–654.

Greenaway-McGrevy, R., Mark, N. C., Sul, D., and Wu, J.-L. (2018). “Identifying exchange rate common factors”. In: *International Economic Review* 59.4, pages 2193–2218.

Habib, M. M. and Stracca, L. (2012). “Getting beyond carry trade: What makes a safe haven currency?” In: *Journal of International Economics* 87.1, pages 50–64.

Hansen, B. E. (1997). “Approximate asymptotic p values for structural change tests”. In: *Journal of Business & Economic Statistics* 15.1, pages 60–67.

Henkel, S. J., Martin, J. S., and Nardari, F. (2011). “Time-varying short-horizon predictability”. In: *Journal of Empirical Economics* 99.3, pages 560–580.

Inoue, A. and Kilian, L. (2005). “In-smple or out-of-sample tests of predictability: Which one should we use?” In: *Econometric Reviews* 23.4, pages 371–402.

Ismailov, A. and Rossi, B. (2018). “Uncertainty and deviations from uncovered interest rate parity”. In: *Journal of International Money and Finance* 88, pages 242–259.

Jansson, M. and Moreira, M. J. (2006). “Optimal inference in regression models with nearly integrated regressors”. In: *Econometrica* 74.3, pages 681–714.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). “Measuring uncertainty”. In: *American Economic Review* 105.3, pages 1177–1216.

Kilian, L. (1999). “Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions?” In: *Journal of Applied Econometrics* 14.5, pages 491–510.

Kilic, R. (2018). “Robust inference for predictability in smooth transition predictive regressions”. In: *Econometric Reviews* 37.10, pages 1067–1094.

Kostakis, A., Magdalinos, T., and Stamatogiannis, M. P. (2015). “Robust econometric inference for stock return predictability”. In: *The Review of Financial Studies* 28.5, pages 1506–1553.

Ludvigson, S. C. and Ng, S. (2009). “Macro factors in bond risk premia”. In: *The Review of Financial Studies* 22.12, pages 5027–5067.

Lustig, H., Roussanov, N., and Verdelhan, A. (2011). “Common risk factors in currency markets”. In: *The Review of Financial Studies* 24.11, pages 3731–3777.

Magdalinos, T. and Phillips, P. C. B. (2009). “Limit theory for cointegrated systems with moderately integrated and moderately explosive regressors”. In: *Econometric Theory* 25.2, pages 482–526.

Mark, N. C. (1995). “Exchange rates and fundamentals: Evidence on long-horizon predictability”. In: *The American Economic Review* 85.1, pages 201–218.

Meese, R. A. (1990). “Currency fluctuations in the post-Bretton Woods era”. In: *Journal of Economic Perspective* 4.1, pages 117–134.

Meese, R. A. and Rogoff, K. S. (1983). “Empirical exchange rate models of the seventies”. In: *Journal of International Economics* 14.1-2, pages 3–24.

Miranda-Agrippino, S. and Rey, H. (2015). “World asset markets and the global financial cycle”. In: *NBER Working Paper Series.*

Molodtsova, T., Nikolsko-Rzhevskyy, A., and Papell, D. H. (2008). “Taylor rules with real-time data: A tale of two countries and one exchange rate”. In: *Journal of Monetary Economics* 55, pages 63–79.

Molodtsova, T., Nikolsko-Rzhevskyy, A., and Papell, D. H. (2011). “Taylor rules and the Euro”. In: *Journal of Money, Credit and Banking* 43.2-3, pages 535–552.

Molodtsova, T. and Papell, D. H. (2009). “Out-of-sample exchange rate predictability with Taylor rule fundamentals”. In: *Journal of International Economics* 77.2, pages 167–180.

Mueller, P., Tahbaz-Salehi, A., and Vedolin, A. (2017). “Exchange rates and monetary policy uncertainty”. In: *The Journal of Finance* 72.3, pages 1213–1252.

Neely, C. J. and Sarno, L. (2002). “How well do monetary fundamentals forecast exchange rates?” In: *The Federal Reserve Bank of St. Louis Working Paper Series.*

Obstfeld, M. and Zhou, H. (2023). “The global dollar cycle”. In: *NBER Working Paper Series* 31004.

Patton, A. J. and Timmermann, A. (2010). “Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion”. In: *Journal of Monetary Economics* 57.7, pages 803–820.

Paye, B. S. and Timmermann, A. (2006). “Instability of return prediction models”. In: *Journal of Empirical Finance* 13.3, pages 274–315.

Pesaran, M. H. and Timmermann, A. (2002). “Market timing and return prediction under model instability”. In: *Journal of Empirical Finance* 9.5, pages 495–510.

Phillips, P. C. B. and Magdalinos, T. (2009). “Econometric inference in the vicinity of unity”. In: *Working Paper*.

Rapach, D. E. and Wohar, M. E. (2006). “Structural breaks and predictive regression models of aggregate U.S. stock returns”. In: *Journal of Financial Econometrics* 4.2, pages 238–274.

Reinhart, C. M. and Rogoff, K. S. (2009). *This time is different - eight centuries of financial folly*. Princeton University Press.

Rossi, B. (2006). “Are exchange rates really random walks? Some evidence robust to parameter instability”. In: *Macroeconomic Dynamics* 10.1, pages 20–38.

Rossi, B. (2013). “Exchange rate predictability”. In: *Journal of Economic Literature* 51.4, pages 1063–1119.

Sarno, L. (2005). “Viewpoint: Towards a solution to the puzzles in exchange rate economics: Where do we stand?” In: *The Canadian Journal of Economics* 38.3, pages 673–708.

Sarno, L. and Schmeling, M. (2014). “Which fundamentals drive exchange rates? A cross-sectional perspective”. In: *Journal of Money, Credit and Banking* 46.2-3, pages 267–292.

Sarno, L. and Valente, G. (2006). “Deviations from purchasing power parity under different exchange rate regimes: Do they revert and, if so, how?” In: *Journal of Banking & Finance* 30.11, pages 3147–3169.

Sarno, L. and Valente, G. (2009). “Exchange rates and fundamentals: Footloose or evolving relationship?” In: *Journal of the European Economic Association* 7.4, pages 786–830.

Sarno, L., Valente, G., and Leon, H. (2006). “Nonlinearity in deviations from uncovered interest parity: An explanation of the forward bias puzzle”. In: *Review of Finance* 10.3, pages 443–482.

Taylor, M. P., Peel, D. A., and Sarno, L. (2001). “Nonlinear mean-reversion in real exchange rates: Toward a solution to the purchasing power parity puzzle”. In: *International Economic Review* 42.4, pages 1015–1042.

Teräsvirta, T., Tjostheim, D., and Granger, C. W. J. (2010). *Modelling nonlinear economic time series*. Oxford University Press.

Timmermann, A. (2008). “Elusive return predictability”. In: *International Journal of Forecasting* 24.1, pages 1–18.

Welch, I. and Goyal, A. (2008). “A comprehensive look at the empirical performance of equity premium prediction”. In: *The Review of Financial Studies* 21.4, pages 1455–1508.

Wright, J. H. (2011). “Term premia and inflation uncertainty: Empirical evidence from an international panel dataset”. In: *American Economic Review* 101.4, pages 1514–1534.

Yang, B., Long, W., Peng, L., and Cai, Z. (2020). “Testing the predictability of U.S. housing price index returns based on an IVX-AR model”. In: *Journal of the American Statistical Association* 115.532, pages 1598–1619.

Appendix

A List of abbreviations

The following abbreviations are used for the predictors which are applied in the 74 cases where linearity and no predictability are rejected:

Table 10: Predictor abbreviations part I

Abbreviation	Explanation
ATR_AUS	Asymmetric Taylor rule deviations Australia
ATR_CAD	Asymmetric Taylor rule deviations Canada
ATR_CHE	Asymmetric Taylor rule deviations Switzerland
ATR_EUA	Asymmetric Taylor rule deviations Euro Area
ATR_GBR	Asymmetric Taylor rule deviations UK
AUD_USD_PPP	Deviations from purchasing power parity Australia USA
CC_AUS	Yield curve curvature factor Australia
CC_CAN	Yield curve curvature factor Canada
CC_DEU	Yield curve curvature factor Germany
CC_USA	Yield curve curvature factor USA
CHF_USD_PPP	Deviations from purchasing power parity Switzerland USA
ETA_EUR	Engel and Wu (2023b) liquidity measure Euro
ETA_GBR	Engel and Wu (2023b) liquidity measure UK
GBP_USD_PPP	Deviations from purchasing power parity UK USA
IRD_AUS_USA_1M	Interest rate differential Australia USA 1 month
IRD_AUS_USA_3M	Interest rate differential Australia USA 3 months
IRD_AUS_USA_6M	Interest rate differential Australia USA 6 months
IRD_AUS_USA_12M	Interest rate differential Australia USA 12 months
IRD_CHE_USA_6M	Interest rate differential Switzerland USA 6 months
IRD_CHE_USA_12M	Interest rate differential Switzerland USA 12 months
IRD_EUA_USA_1M	Interest rate differential Euro Area USA 1 month
IRD_EUA_USA_3M	Interest rate differential Euro Area USA 3 months
IRD_EUA_USA_6M	Interest rate differential Euro Area USA 6 months
IRD_EUA_USA_12M	Interest rate differential Euro Area USA 12 months
IRD_GBR_USA_1M	Interest rate differential UK USA 1 month
IRD_GBR_USA_3M	Interest rate differential UK USA 3 months
IRD_GBR_USA_6M	Interest rate differential UK USA 6 months
IRD_GBR_USA_12M	Interest rate differential UK USA 12 months
IRD_JPN_USA_1M	Interest rate differential Japan USA 1 month
IRD_JPN_USA_3M	Interest rate differential Japan USA 3 months
IRD_JPN_USA_6M	Interest rate differential Japan USA 6 months
IRD_JPN_USA_12M	Interest rate differential Japan USA 12 months
LL_AUS	Yield curve level factor Australia
LL_CHE	Yield curve level factor Switzerland
LL_GBR	Yield curve level factor UK
MON_AUD_USD	Deviations of monetary fundamentals for AUD-USD
MON_GBP_USD	Deviations of monetary fundamentals for GBP-USD
log_WTI	Logarithm of the WTI oil price
Rey_Global	Global factor of risky assets of Miranda-Agrippino and Rey (2015)

Table 11: Predictor abbreviations part II

Abbreviation	Explanation
SPR_AUS_5Y_TB	Spread between 5 years government bonds and treasury bills Australia
SPR_AUS_10Y_TB	Spread between 10 years government bonds and treasury bills Australia
SPR_GBR_5Y_TB	Spread between 5 years government bonds and treasury bills UK
SPR_GBR_10Y_TB	Spread between 10 years government bonds and treasury bills UK
SPR_USA_5Y_TB	Spread between 5 years government bonds and treasury bills USA
SPR_USA_10Y_TB	Spread between 10 years government bonds and treasury bills USA
SS_AUS	Yield curve slope factor Australia
SS_GBR	Yield curve slope factor UK
SS_USA	Yield curve slope factor USA
STG_EUA	Stock market growth differential Euro Area
STG_GBR	Stock market growth differential UK
STO_AUS	Stock market index Australia
STO_EUA	Stock market index Euro Area
STR_AUS	Symmetric Taylor rule deviations Australia
STR_CAD	Symmetric Taylor rule deviations Canada
STR_CHE	Symmetric Taylor rule deviations Switzerland
STR_EUA	Symmetric Taylor rule deviations European Area
STR_GBR	Symmetric Taylor rule deviations UK
STR_USA	Symmetric Taylor rule deviations USA
VIX	CBOE S&P 500 volatility index
VXY	G10 currency volatility index

The following abbreviations are used for transition variables:

Table 12: Transition variable abbreviations part I

Abbreviation	Explanation
BD_GBR	Budget deficit sentiment UK
buzz_EUR	Buzz value for Euro
DD_AUS	Debt default sentiment Australia
DD_USA	Debt default sentiment USA
EFU_h1	Economic financial uncertainty measure of Jurado, Ludvigson, and Ng (2015) for 1 month
EFU_h3	Economic financial uncertainty measure of Jurado, Ludvigson, and Ng (2015) for 3 months
EG_AUS	Economic growth sentiment Australia
EMU_h1	Economic macro uncertainty measure of Jurado, Ludvigson, and Ng (2015) for 1 month
ERU_h1	Economic real uncertainty measure of Jurado, Ludvigson, and Ng (2015) for 1 month
GBR_CPI_FC_SD	Consumer price index forecast disagreement UK
INF_FC_CHE	Inflation forecast sentiment Switzerland
IR_buzz_USA	Interest rate buzz USA
MB_F1	Macro bond factor of Ludvigson and Ng (2009)
POS_USD	Positive sentiment USD
Rey_Global	Global factor of risky assets of Miranda-Agrippino and Rey (2015)

Table 13: Transition variable abbreviations part II

Abbreviation	Explanation
SNT_USD	Sentiment USD
STO_buzz_AUS	Stock market buzz Australia
STO_buzz_USA	Stock market buzz USA
STO_USA	Stock market sentiment USA
TB_EUA	Trade balance deficit sentiment Euro Area
TMU_h3	Total macro uncertainty measure of Jurado, Ludvigson, and Ng (2015) for 3 months
USA_IP_FC_SD	Industrial production forecast disagreement USA
USA_3MIR_FC_SD	3 month interest rate forecast disagreement USA
VIX	CBOE S&P 500 volatility index

B Dependent variable - exchange rates

The variable of interest/target during the analysis are the log returns of the following six currencies with respect to the US-Dollar (USD) at the end of each month: Australian Dollar (AUD), Canadian Dollar (CAD), Euro (EUR), Japanese Yen (JPY), Swiss Franc (CHF), and Pound Sterling (GBP).[13] These six exchange rates are the focus of our analysis due to the availability of data and their great economic influence (e.g., measured based on trading volume). The exchange rates are expressed in USD. That means, it is shown how much USD one obtains for one unit of currency $A \in \{$AUD, CAD, EUR, JPY, CHF, GBP$\}$. Full names and data stream codes are given below:

Table 14: Dependent variables - exchange rates

ISO 4217	Datastream code	Full name
AUD_USD	AUOCC016	AU EXCHANGE RATE END PERIOD NADJ
CAD_USD	CNOCC016	CN EXCHANGE RATE END PERIOD NADJ
EUR_USD	EKOCC016	EK EXCHANGE RATE END PERIOD NADJ
JPY_USD	JPOOC016	JP EXCHANGE RATE END PERIOD NADJ
CHF_USD	SWOCC016	SW EXCHANGE RATE END PERIOD NADJ
GBP_USD	UKOCC016	UK EXCHANGE RATE END PERIOD NADJ

Additionally, to provide some information about the linear dependence between the currency returns, we also calculate the cross-correlations for our investigated time horizon:

[13]To be consistent and have some structure, the sorting is done based on the country names, so Australia, Canada, Eurozone/Germany, Japan, Switzerland, UK, USA. Therefore, the currency ISO codes are not sorted in order!

Table 15: Cross-correlations of exchange rate returns

	AUD	CAD	EUR	JPY	CHF	GBP
AUD	1					
CAD	0.686	1				
EUR	0.663	0.485	1			
JPY	0.136	0.069	0.189	1		
CHF	0.550	0.323	0.821	0.308	1	
GBP	0.549	0.433	0.640	0.048	0.521	1

On top of this, having a closer look at the mean, standard deviation and partial correlation of first order for each currency is meaningful:

Table 16: Descriptive statistics of exchange rate returns

	AUD	CAD	EUR	JPY	CHF	GBP
Mean	-0.095	-0.082	-0.023	-0.015	-0.165	0.087
Std. Dev.	3.525	2.642	2.916	2.717	2.961	2.481
PACF(1)	0.087	-0.068	0.027	0.077	-0.072	0.051

As an add on, we consider effective exchange rate measures provided by the BIS and the Federal Reserve.

C Predictors

C.1 Interest rate spreads

We use three different kinds of interest rates spreads. First, we consider the difference between the yields of 10 year government bonds and 3 month treasury bills. Second, we consider the difference between the yields of 5 year government bonds and 3 month treasury bills.

Full names and datastream codes are given below:

Table 17: Interest rates

Country	Datastream code	Full name
Australia	GSAUD3M	AUSTRALIAN DOLLAR 3M DEPOSIT (RFV) - MIDDLE RATE
Australia	TRAU5YT	RF AUSTRALIA GVT BMK BID YLD 5Y - RED. YIELD
Australia	TRAU10T	RF AUSTRALIA GVT BMK BID YLD 10Y - RED. YIELD
Canada	TRCN3MT	RF CANADA GVT BMK BID YLD 3M - RED. YIELD
Canada	TRCN5YT	RF CANADA GVT BMK BID YLD 5Y - RED. YIELD
Canada	TRCN10T	RF CANADA GVT BMK BID YLD 10Y - RED. YIELD
Germany	TRBD3MT	RF GERMANY GVT BMK BID YLD 3M - RED. YIELD
Germany	TRBD5YT	RF GERMANY GVT BMK BID YLD 5Y - RED. YIELD
Germany	TRBD10T	RF GERMANY GVT BMK BID YLD 10Y - RED. YIELD
Japan	TRJP3MT	RF JAPAN GVT BMK BID YLD 3M - RED. YIELD
Japan	TRJP5YT	RF JAPAN GVT BMK BID YLD 5Y - RED. YIELD
Japan	TRJP10T	RF JAPAN GVT BMK BID YLD 10Y - RED. YIELD
Switzerland	TRSW3MT	RF SWITZERLAND GVT BMK BID YLD 3M - RED. YIELD
Switzerland	TRSW5YT	RF SWITZERLAND GVT BMK BID YLD 5Y - RED. YIELD
Switzerland	TRSW10T	RF SWITZERLAND GVT BMK BID YLD 10Y - RED. YIELD
UK	TRUK3MT	RF UK GVT BMK BID YLD 3M - RED. YIELD
UK	TRUK5YT	RF UK GVT BMK BID YLD 5Y - RED. YIELD
UK	TRUK10T	RF UK GVT BMK BID YLD 10Y - RED. YIELD
USA	TRUS3MT	RF US GVT BMK BID YLD 3M - RED. YIELD
USA	TRUS5YT	RF US GVT BMK BID YLD 5Y - RED. YIELD
USA	TRUS10T	RF US GVT BMK BID YLD 10Y - RED. YIELD

Because Australia does not provide such a treasury bill rate like the other six countries, a 3 month deposit rate is used as a proxy.

C.2 Yield curve factors

The yield curve factors level, slope and curvature are used. They are calculated based on the method proposed by Wright (2011).

C.3 Taylor Rule (STR)

We rely on Della Corte and Tsiakas (2012), who use a simple version of the original model of Taylor (1993) for the nominal fed funds rate (x_t). We define the symmetric Taylor rule as the difference of inflation rate (π_t) and its equilibrium value (π_t^*) multiplied by 1.5 and add the output gap ($y_t^g - y_t^{*g}$) multiplied by 0.1:

$$x_t = 1.5(\pi_t - \pi_t^*) + 0.1(y_t^g - y_t^{*g}).$$

We use industrial production as a proxy for the national income which is in line with the literature. Since there are data availability issues for IP, the interpolated GDP is used as a proxy for Australia and Switzerland. The output gap is then calculated based on a Hodrick-Prescott filter with the smoothing parameter chosen as $\lambda = 14,400$.

Besides a simple version of the original model of Taylor (1993), we also adopt an asymmetric Taylor rule, see Della Corte and Tsiakas (2012). Central banks might also account for real exchange rate movements:

$$x_t = 1.5(\pi_t - \pi_t^*) + 0.1(y_t^g - y_t^{*g}) + 0.1(s_t + p_t^* - p_t).$$

C.4 WTI oil price

Because it is the most important type of oil, the logarithmic WTI oil price is considered.

C.5 Interest rate differentials (IRD)

The IRD (x_t) is calculated based on Della Corte and Tsiakas (2012). It is simply the difference between the interest rate in the domestic (i_t) and the foreign currency/country (i_t^*, in our case USD):

$$x_t = i_t - i_t^*.$$

The full names and data stream codes are given below:

Table 18: Short-term interest rates

Country	Datastream code	Full name
Australia	BBAUD1M	AUSTRALIA INTERBANK 1 MTH (LDN DISC - OFFERED RATE
Australia	BBAUD3M	AUSTRALIA INTERBANK 3 MTH (LDN DISC - OFFERED RATE
Australia	BBAUD6M	AUSTRALIA INTERBANK 6 MTH (LDN DISC - OFFERED RATE
Australia	BBAUD12	AUSTRALIA INTERBANK 12 MTH (LD DISC - OFFERED RATE
Canada	BBCAD1M	CANADA INTERBANK 1 MTH (LDN DISC - OFFERED RATE
Canada	BBCAD3M	CANADA INTERBANK 3 MTH (LDN DISC - OFFERED RATE
Canada	BBCAD6M	CANADA INTERBANK 6 MTH (LDN DISC - OFFERED RATE
Canada	BBCAD12	CANADA INTERBANK 12 MTH (LD DISC - OFFERED RATE
Euro Area	EIBOR1M	EBF EURIBOR 1M DELAYED - OFFERED RATE
Euro Area	EIBOR3M	EBF EURIBOR 3M DELAYED - OFFERED RATE
Euro Area	EIBOR6M	EBF EURIBOR 6M DELAYED - OFFERED RATE
Euro Area	EIBOR1Y	EBF EURIBOR 12M DELAYED - OFFERED RATE
Japan	BBJPY1M	IBA JPY IBK. LIBOR 1M DELAYED - OFFERED RATE
Japan	BBJPY3M	IBA JPY IBK. LIBOR 3M DELAYED - OFFERED RATE
Japan	BBJPY6M	IBA JPY IBK. LIBOR 6M DELAYED - OFFERED RATE
Japan	BBJPY12	IBA JPY IBK. LIBOR 12M DELAYED - OFFERED RATE
Switzerland	BBCHF1M	IBA CHF IBK. LIBOR 1M DELAYED DISC - OFFERED RATE
Switzerland	BBCHF3M	IBA CHF IBK. LIBOR 3M DELAYED - OFFERED RATE
Switzerland	BBCHF6M	IBA CHF IBK. LIBOR 6M DELAYED - OFFERED RATE
Switzerland	BBCHF12	IBA CHF IBK. LIBOR 12M DELAYED - OFFERED RATE
UK	BBGBP1M	IBA GBP IBK. LIBOR 1M DELAYED - OFFERED RATE
UK	BBGBP3M	IBA GBP IBK. LIBOR 3M DELAYED - OFFERED RATE
UK	BBGBP6M	IBA GBP IBK. LIBOR 6M DELAYED - OFFERED RATE
UK	BBGBP12	IBA GBP IBK. LIBOR 12M DELAYED - OFFERED RATE
USA	BBUSD1M	IBA USD IBK. LIBOR 1M DELAYED - OFFERED RATE
USA	BBUSD3M	IBA USD IBK. LIBOR 3M DELAYED - OFFERED RATE
USA	BBUSD6M	IBA USD IBK. LIBOR 6M DELAYED - OFFERED RATE
USA	BBUSD12	IBA USD IBK. LIBOR 12M DELAYED - OFFERED RATE

Like it should be obvious from the table, the interest rates for each country are given for 1, 3, 6, and 12 months. Thus, the uncovered interest rate parity is calculated for each of these four time horizons.

C.6 Purchasing Power Parity (PPP)

Relying on Della Corte and Tsiakas (2012), we define PPP deviations (x_t) as the difference of the logarithmic domestic price level (p_t), the logarithmic foreign price level (p_t^*, here: USA) and the logarithmic nominal exchange rate (s_t) as:

$$x_t = p_t - p_t^* - s_t.$$

We use the logarithmic CPI values of the different countries:

Table 19: Consumer price indices (CPI)

Country	Datastream code	Full name
Australia	AUCCPI..F	AU CPI (STANDARDIZED) NADJ
Canada	CNCONPRCF	CN CPI NADJ
Euro Area	EMCPHARMF	EM HICP - ALL ITEMS NADJ
Japan	JPCONPRCF	JP CPI: NATIONAL MEASURE NADJ
Switzerland	SWCONPRCF	SW CPI (2020M12=100) NADJ
UK	UKCPHMT1F	UK CPI INDEX 00 : ALL ITEMS- ESTIMATED PRE-97 2015=100 NADJ
USA	USCONPRCF	US CPI - ALL URBAN SAMPLE: ALL ITEMS NADJ

We directly reset the base in datastream to January 2015, so that all CPIs have the same base. Because they are not seasonally adjusted, we have done so in R via the 'seasonal' package which implements the X-13ARIMA-SEATS seasonal adjustment which is extensively used by the US Census Bureau.

C.7 Monetary fundamentals

Della Corte and Tsiakas (2012) define the deviation (x_t) of the logarithmic nominal exchange rate (s_t) from its fundamentals logarithmic domestic money supply (m_t), logarithmic foreign money supply (m_t^*), logarithmic domestic national income (y_t) and logarithmic foreign national income (y_t^*) as:

$$x_t = (m_t - m_t^*) - (y_t - y_t^*) - s_t.$$

We use the M3 aggregate as the money supply and the industrial production as a proxy for national income. But because for Australia and Switzerland there is no monthly industrial production data available for the complete horizon, we use their GDP instead. So, to calculate $(y_t - y_t^*)$, we use the US GDP for y_t^*.

C.8 MSCI stock market spreads

To account for the development of the stock markets in the countries under investigation, we calculate two different kinds of predictors. The first one is the difference between the logarithmic price of the MSCI stock market index of country A, with A $\in$ {Australia, Canada, Euro Area, Japan, Switzerland, UK} and the logarithmic price of the MSCI stock market index of the USA. The second factor is the difference between the 12 months log return of country A's MSCI stock market index and the 12 months log return of the US MSCI stock market index.

The MSCI data have the following datastream codes and names:

Table 20: Stock market indices

Country	Datastream code	Full name
Australia	MSAUST$(RI)	MSCI AUSTRALIA U$ - TOT RETURN IND
Canada	MSCNDA$(RI)	MSCI CANADA U$ - TOT RETURN IND
Germany	MSGERM$(RI)	MSCI GERMANY U$ - TOT RETURN IND
Japan	MSJPAN$(RI)	MSCI JAPAN U$ - TOT RETURN IND
Switzerland	MSSWIT$(RI)	MSCI SWITZERLAND U$ - TOT RETURN IND
UK	MSUTDK$(RI)	MSCI UK U$ - TOT RETURN IND
USA	MSUSAM$(RI)	MSCI USA U$ - TOT RETURN IND

D Transition variables

D.1 Uncertainty measures

The VIX is used as a measure for implied volatility on the stock market while the JP Morgan's VXY index represents a measure of implied volatility for the G10 currencies. Both measures are used in logs.

We obtain economic policy uncertainty measures developed by Baker, Bloom and Davis (2016) from `https://www.policyuncertainty.com/` for Australia, Canada, Europe, Japan, UK and USA. Because there are no data available for Switzerland, we use daily data from `https://kof.ethz.ch/prognosen-indikatoren/indikatoren/kof-unsicherheitsindikator.html` and preprocessed them to monthly data by using the average daily value for each month as in Dibiasi and Iselin (2021).

We also use the macro and financial uncertainty measure by Jurado, Ludvigson, and Ng (2015) available at `https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes` and the Macro bond factors of Ludvigson and Ng (2009) which include nine different macro bond factors. All these factors are calculated based on a large monthly panel data set consisting of over 130 economic activity measures using principal component analysis.

We also adopt data from Consensus Economics which reflect the disagreement of analysts about GDP, industrial production, CPI, 3 month interest rate and 10 year government bond yield. These are measured by the standard deviation of the different forecasts. For interest rates, the disagreement corresponds to the next 3 or 12 months while disagreement regarding GDP is provided for the current and the next year. We therefore adopt the following simple weighting introduced by Patton and Timmermann (2010) to transform these fixed event forecasts into fixed horizon forecast over the next 12 months.

$$\hat{g}_{t,t-12} = w\hat{g}_{1,0} + (1-w)\hat{g}_{2,1},$$

where $\hat{g}_{t,t-12}$ represents the approximated fixed horizon growth rate forecast while $\hat{g}_{1,0}$ and $\hat{g}_{2,1}$ give the fixed event forecasts for the current and the next year and w denotes the ad hoc weight $(24-t)/12$.

Additionally, we use a global factor of risky asset prices of Miranda-Agrippino and Rey (2015) and a liquidity factor of Engel and Wu (2023b).

D.2 Sentiments

Refinitiv MarketPsych Analytics provides sentiment data with regard to currencies and countries. The idea is to apply textual data analysis on media coverage. The corresponding data is provided for different content sets: news, social media, and combined measures. We adopt the combined measure with alternative estimates available upon request. Exclusively English-language text is used until February 2020. Since that point in time, Arabic, Chinese, Japanese, Dutch, French, German, Indonesian, Italian, Korean, Russian, Spanish and Portuguese language news sources were included.

Reuters news is present in the entire historical news dataset. Additional mainstream news sources are also collected by MarketPsych. The social media collection process which starts in 1998 covers internet forum and message board content. LexisNexis social media content was added in 2008 and tweets were included in 2009. The algorithm which is used to filter the underlying information is based on supervised machine learning and is also trained to avoid misinterpretation.

Sentiments are provided for various terms and are usually scaled between -1 and $+1$. Buzz indicates how popular a specific topic is. The term ratesBuzz includes coverage related to the 'central bank', 'debt default', 'interest rates', 'interest rates forecast', and 'monetary policy loose vs. tight'.

We rely on ratesBuzz as a proxy to measure how the public perceives monetary policy uncertainty based on media appearances of interest rate discussions and buzz related to exchange rates which reflects the extent of media coverage related to the exchange rate.

We adopt the following currency sentiments:

- **Buzz** $\in [0, \infty)$
- **Sentiment** $\in [-1, 1]$. It is positive references net of negative references
- **Positive** $\in [0, 1]$. Overall positive references
- **Negative** $\in [0, 1]$. Overall negative references

We also use the following 14 different sentiment measures for each country:

- **Buzz** $\in [0, \infty)$.
- **Inflation sentiment** $\in [-1, 1]$; consumer price increases, net of references to consumer price decreases
- **Inflation forecasts sentiment** $\in [-1, 1]$; forecasts of consumer price increases, net of forecasts of consumer price decreases (deflation)
- **Trade balance sentiment** $\in [-1, 1]$; exports, net of references to imports
- **Budget deficit sentiment** $\in [-1, 1]$; a budget deficit, net of references to a surplus
- **Debt default sentiment** $\in [0, 1]$; debt defaults and bankruptcies in a country
- **Monetary policy sentiment** $\in [-1, 1]$; monetary policy being loose, net of references to monetary policy being tight
- **Economic growth sentiment** $\in [-1, 1]$; increased business activity, net of references to decreased business activity
- **Interest rates sentiment** $\in [-1, 1]$; interest rates rising, net of references to rates falling
- **Interest rates buzz** $\in [0, \infty)$; sum of all references underlying the centralBank, debtDefault, interestRates, interestRatesForecast, and monetaryPolicyLooseVsTight
- **Bond rate sentiment** $\in [-1, 1]$; overall positive references, net of negative references
- **Bond rate buzz** $\in [0, \infty)$; sum of all references to the country's bonds and debt (excluding corporate debt) in that country
- **Stock index sentiment** $\in [-1, 1]$; overall positive references, net of negative references
- **Stock index buzz** $\in [0, \infty)$; sum of all relevant references toward stock markets

CESA Working Paper

Series

CESA Working Paper No. 1 | 2023
Andreas Hauptmann, Benjamin Schwanebeck and Hans-Jörg Schmerer
Plant-level adjustments to imports and exports at the extensive margin

CESA Working Paper No. 2 | 2023
Joscha Beckmann, Marco Kerkemeier and Robinson Kruse-Becher
Regime-specific exchange rate predictability

FernUniversität in Hagen