Laurier Centre for Economic Research & Policy Analysis

LCERPA Working paper No. 2024-6

October 2024

Forecasts of Period-Average Exchange Rates: New Insights from Real-Time Daily Data

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October 16, 2024

Abstract

Forecasts of period-average exchange rates require the use of disaggregated data to both efficiently construct forecasts and test against the traditional random walk hypothesis. To achieve this, we construct real-time vintages of daily exchange rates for all countries, including real and nominal effective exchange rates. Our findings indicate that forecasts constructed with daily data can significantly improve accuracy compared to using monthly averages. We also find near universal spurious predictability when such forecasts are benchmarked against the period-average no-change. When applying efficient estimation and testing methods, we provide new evidence of real-time predictability for period-average real and effective exchange rates in up to fifty percent of countries.

JEL classification: C43, C5, F31, F37
Keywords: Temporal Aggregation, Exchange Rates, Forecasting, Forecast Evaluation

*The views expressed in this paper are those of the authors; no responsibility for them should be attributed to the Reserve Bank of Australia.

†We thank Reinhard Ellwanger, Massimiliano Marcellino, Vito Cormun and participants at the 43rd International Symposium on Forecasting, the Reserve Bank of Australia, the 58th Annual Meetings of the Canadian Economics Association, and the 9th Annual Conference of the Society for Economic Measurement (SEM) for their discussions, comments, and suggestions.

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1 Introduction

Exchange rate forecasting is crucial for guiding economic decisions in policymaking and investment strategies. Of particular interest in macroeconomic analysis are period-average exchange rates, both effective and bilateral, especially when expressed in real terms. Relative to exchange rates sampled at specific points in time ('point-sampled' rates), period-average exchange rates are more relevant to variables measured as flows over time, such as net exports, inflation, flow revenue and costs, and broader economic conditions. For this reason, many policymakers, including international organizations and central banks, make assumptions about period-average exchange rates as part of their routine forecasting processes (see, for instance Wieland and Wolters, 2013; Glas and Heinisch, 2023; International Monetary Fund, 2023).

However, two issues arise when forecasting period-average exchange rates. The first is that using period-average data when constructing forecasts can introduce information loss that diminishes forecasting accuracy (see, e.g., Wei, 1978; Kohn, 1982; Lütkepohl, 1986). Since period-average exchange rates, such as effective exchange rates, are constructed using the simple averages of daily point-sampled data, efficient forecasts require the underlying daily observations. The second is that period-average sampling introduces serial correlation (Working, 1960; Weiss, 1984; Marcellino, 1999), raising concerns over spurious predictability in forecasts (i.e. Bork et al., 2022). This is why Meese and Rogoff (1983) and much of the preceding literature chose instead to forecast point-sampled bilateral exchange rates (typically end of period). In contrast, forecasts for real effective exchange rates have always been constructed using period averages due to the absence of point-sampled data (Meese and Rogoff, 1983, pg. 9). Recent advances have since shown that it is possible to maintain the goal of forecasting the period average, as long as the last daily observation is available (Ellwanger and Snudden, 2023a; McCarthy and Snudden, 2024). In this paper, we address the critical data limitations that have barred efficient construction and testing of forecasts of period-average exchange rates.

For every country, we construct *real-time* vintages at the daily frequency for the four types of daily exchange rate: nominal effective exchange rates (NEERs), real effective exchange rates (REERs), bilateral nominal exchange rates (NERs) and bilateral real exchange rates (RERs). This is the first time that daily REERs have been constructed for any country. Moreover, this is the first real-time dataset for both effective exchange rates (EERs), which has thus far only been examined for nominal bilateral rates (i.e. Clarida and Taylor, 1997). In addition, while daily NEERs are already published by several national agencies and for a subset of countries by the Bank for International Settlements (BIS), we expand these measures to all countries. The daily effective exchange rates (EERs) are computed consistently across countries, and use the official

International Monetary Fund (IMF) weights.

We then quantify the real-time information gains from temporal disaggregation using the newly constructed daily measures of exchange rates. This includes an evaluation of the effects of temporal aggregation for model-based and no-change forecasts. The investigation also includes testing, for the first time, real-time out-of-sample forecasts of monthly average exchange rates against the traditional random walk no-change forecasts, which is given by the last observed end of month value. We find three empirical results regarding the quantification of the importance of temporal aggregation bias in exchange rate forecasting.

The first empirical finding is that, for all measures of exchange rates and for almost all countries, the month-average no-change benchmark is less accurate than the end-of-month no-change benchmark. The difference in performance is large, up to 40 percent for directional accuracy because daily exchange rates are highly persistent. This suggests that the no-change benchmarks used for effective exchange rates since Meese and Rogoff (1983) are much too lenient. This finding suggests that studies that found forecast improvements relative to the period-average no-change are unlikely to find that such gains translate when compared to the end-of-period no-change.

The second empirical finding is that both direct and recursive forecasts estimated with month-average data perform substantially worse than forecasts estimated with daily or end-of-month inputs. This is found to be very robust across exchange rate measures and for most countries. Once again, this substantiates theoretical concerns regarding the loss in forecast accuracy when exchange rates are temporally aggregated. These findings are also encouraging, as they show that substantial gains relative to current methods in model-based forecast accuracy of period average exchange rates can be achieved in real-time using information from daily exchange rates. Moreover, the results suggest that the point-sampled forecasts of EERs (Kohlscheen et al., 2017; Zhang et al., 2016; Ca'Zorzi et al., 2022) and bilateral RERs (e.g. Froot and Ramadorai, 2005; Chen et al., 2014) could be potentially quite informative on the desirable methods to forecast, and the general predictability, of period-averages exchange rates.

The third empirical finding is that there is substantial spurious predictability, in both directional accuracy and mean-squared precision, when model-based real-time forecasts are compared against period average no-change forecasts. For example, forecasts of period-average bilateral NERs are found to improve upon the monthly average no-change almost universally when end-of-month or daily inputs are used to construct forecasts. In contrast, we find little evidence that such forecasts can improve upon the traditional random walk no-change, which is the end-of-month no-change forecast. That said, we find evidence of real-time predictability for period average EERs and bilateral RERs for up to half of the countries. This finding illustrates that adoption of temporally disaggregated methods into exchange rate forecasting is highly desirable in real-world settings.

A detailed survey of the temporal assumptions in the exchange rate forecasting literature (provided in appendix A) shows that the use of daily real-time data advance our understanding in three main ways. For the first time, forecasts of period-average exchange rates are tested against the traditional random walk hypothesis (the end-of-period no-change forecast Ellwanger and Snudden, 2023a; McCarthy and Snudden, 2024). As such, we provide novel evidence of the predictability of period average exchange rates. The second contribution is to examine the forecast efficiency gains from temporal disaggregation of daily data. The third contribution is to examine real-time forecasts of EERs and period-average bilateral RERs. This contributes to several studies that have examined real-time forecasts of point-sampled bilateral ERs, (e.g. Clarida and Taylor, 1997; Clarida et al., 2003; Faust et al., 2003). Therefore, the substantial forecast gains documented using the new daily data can be operationalized in practice.

Our paper also contributes to the understanding of temporal aggregation bias more generally. The empirical findings provide quantitative evidence that supports the loss in forecast accuracy due to temporal aggregation in existing theoretic studies (Tiao, 1972; Amemiya and Wu, 1972; Kohn, 1982; Lütkepohl, 1986). Notably, the loss in forecast accuracy from daily to monthly aggregations is substantially larger than what has been found in existing quantitative studies which focused on monthly to quarterly data or quarterly to annual aggregation (see for example, Zellner and Montmarquette, 1971; Lütkepohl, 1986; Athanasopoulos et al., 2011, among others). Consequently, the loss in forecast accuracy is substantially larger than currently understood.

The results hold general lessons for temporal aggregation concerns in macroeconomic measurement. While our paper focuses on month-average and end-of-month exchange rates, the information loss caused by temporal aggregation is even greater for quarter-end and quarter-average exchange rates. This issue is especially relevant to countries whose official Consumer Price Index (CPI) data is only available quarterly (such as Australia and New Zealand), as exchange rate forecasts for these countries are often done with quarterly data. Moreover, reporting of end-of-period values for effective exchange rates should become common practice, for the same reasons that end-of-period bilateral exchange rates are reported.

Our paper serves as a guide to the topic of temporal aggregation in exchange rate forecasting. The implications of temporal aggregation bias offer researchers a roadmap to interpret existing findings and to inform future research. We illuminate the substantial gains of incorporating high-frequency information into real-time forecasts of period-average exchange rates, which will be of value for economic decision-making.

2 Data

We construct a comprehensive dataset of four types of exchange rate: bilateral NERs, bilateral RERs, NEERs and REERs.

For each type of exchange rate and country, we construct a sequence of real-time vintages of daily exchange rates, as explained in section 2.1. There is one vintage per month, which is intended to reflect all information that would have been available to a forecaster at the end of the month. Our decision to construct *real-time* vintages is not motivated by revisions, since NERs, CPIs and trade weights are rarely revised. Rather, our aim is to account for the typical delays in the publication of data the CPI and trade weights data.

For each monthly vintage, we also construct a vintage of month-average exchange rates and a vintage of end-of-month exchange rates. We do this using the corresponding vintage of daily exchange rates, as explained in 2.2.

Our dataset fills gaps left by official data sources. Firstly, while daily bilateral exchange rates are widely available, and the Bank for International Settlements publishes daily NEERs, we are the first to construct daily REERs. Secondly, while some authors have constructed real-time datasets of bilateral exchange rates, we are the first to construct a real-time dataset of EERs that accounts for the typical publication delay of weights.

2.1 Monthly Vintages of Daily Frequency Exchange Rates

Sections 2.1.1 describes the calculation of bilateral NERs and bilateral RERs respectively. Section 2.1.2 describes the calculation of NEERs and REERs. Detail on the inputs into these calculations (bilateral NERs, CPIs and trade weights) is provided in Appendix C.

2.1.1 Bilateral Exchange Rates

Constructing monthly vintages of bilateral NERs is straightforward. Bilateral NERs are available daily and observed in real time. As such, a bilateral NER vintage for a month is simply the daily NER on each day until the end of that month. For example, the March 2023 vintage of Canada's bilateral NER is simply its daily bilateral NER on each day up to 31 March 2023.

To construct monthly vintages of daily bilateral NERs we need data on both daily bilateral RERs and monthly CPI. To describe the calculations precisely, we introduce some notation. Let NER_t^i denote the bilateral NER of country i on day t. This is the value of the currency in terms of US dollars. Let CPI_m^i denote the CPI level in country i in month m. Finally, let RER_t^i denote the bilateral RER of country i on day t. This is the cost of goods and services in country i relative to the cost of goods and services in the United States.

The daily bilateral RER on day t of month m is the daily bilateral NER of that country multiplied by the ratio of country i's CPI level to the US CPI level.

$$RER_t^i \equiv NER_t^i \times \frac{CPI_m^i}{CPI_m^{\text{US}}} \tag{1}$$

An alternative approach would have been to combine the daily nominal price with daily CPI levels, where the daily CPI levels have been estimated by interpolating monthly levels. We chose the current approach because it is more transparent than the alternative, since it avoids needing to take a stand on how to perform the interpolation. The forecast results are qualitatively robust to alternative CPI assumptions, since fluctuations in CPI are typically dwarfed by movements in exchange rates.

A complication is that CPI data is published with a lag that differs by country. For example, as at the end of March 2023, the latest CPI data for the United States or Canada is for February 2023, which is a one-month lag. In contrast, some low or middle income countries may only publish their CPI two or three months later. When constructing a monthly vintage, we only use the monthly CPI data likely to have been known at the time. The CPI publications are from the World Bank dataset, see appendix C.2 for complete details. For consistency, we construct our own real-time vintages and nowcast the missing monthly CPI levels by assuming that CPI inflation remains constant at the latest rate known at the time.

2.1.2 Effective Exchange Rates

We also construct monthly vintages of daily EERs. This is more complex, both because a number of EER formulas are available, and because we only want each vintage to be constructed using CPI and trade weights data available at the time.

We compute daily EERs by adapting the formulas used for monthly EERs by the IMF. We use the IMF's method because we want our method to be consistent with our choice of weights, and we use the IMF weights because they are the most comprehensive in terms of countries and time periods. Other institutions use different formulas for computing EERs.[1]

To describe our method, we must define some terms. We use the term 'reporter' to refer to the country whose effective exchange rate we are computing, and we use the term 'partner' to refer to

[1]For REERs, the formulas differ in how they combine NERs and prices. For example, the Bank for International Settlements' approach is to aggregate the bilateral nominal exchange rates to obtain an NEER, separately aggregate the price levels, and then compute the REER by adjusting the NEER by aggregate price levels (Klau and Fung, 2006; Turner and Van 't dack, 1993). The IMF's previous approach was to directly aggregate the bilateral RERs (Bayoumi et al., 2006). In contrast, the IMF's current approach is to compute the REER as a ratio of products of bilateral NERs and CPIs. Moreover, for both NEERs and REERs, the formulas differ in how they aggregate across countries, which affects the properties of the series. For example, Vartia and Vartia (1984) show that the NEER used by the Bank of Finland at the time had an upward bias, unlike alternative index number formulas such as a Fisher index or Tornqvist index.

any other country included in the calculation. The 'weight reference period' is the period of a few years with which a set of weights is associated. For example, there is a set of weights based on the trade flows during the '2010 to 2012' weight reference period (see C.3 for details). Let $w^b_{r,j}$ denote the weight that reporter r puts on partner j in weight reference period b.

If we only have data for a single weight reference period, then we can compute the daily EER using a 'fixed weight' formula. Equation (2) is used to compute the daily REER of a reporter r on a day t in month m and weight reference period b. The numerator is the reporter's NER in US dollars multiplied by the reporter's price level. To compute the denominator, we multiply each partner's NER in US dollars with that partner's price level, and then aggregate across partners. To compute the NEER, simply set the CPI terms equal to 1.

$$REER^{r,b}_t = \frac{NER^r_t \times CPI^r_m}{exp\left(\sum_{j=1}^{J} w^{r,j}_b ln\left(NER^j_t \times CPI^j_m\right)\right)} \tag{2}$$

For each weight reference period, we only use partners whose exchange rates are available on all days in the period.[2] Additionally, if over half of partners by weight have missing exchange rates for a weight reference period, then we don't compute the REER for that period.

Typically, we want to compute the EER over a longer time period that spans multiple weight reference periods. In this case, we compute an EER by 'chaining' the fixed-weight indexes. The chained EER is set equal to 1 on the first day of our sample. For each subsequent day, the growth in the chained EER is set equal to the growth in the relevant fixed-weight EER. Formally:

$$\frac{EER^r_t}{EER^r_{t-1}} = \frac{EER^{r,b}_t}{EER^{r,b}_{t-1}}$$

where b is the weight reference period that contains day t.

This formula ensures that the numerator and denominator both use the same set of weights. For example, if we compute growth in the United Kingdom's chained-EER on 1 Jan 1996, which is the first day of the '1996 to 2003' weight reference period, we would compute:

$$\frac{EER^{\text{UK}}_{\text{1 Jan 1996}}}{EER^{\text{UK}}_{\text{31 Dec 1995}}} = \frac{EER^{\text{UK,1996 to 2003}}_{\text{1 Jan 1996}}}{EER^{\text{UK,1996 to 2003}}_{\text{31 Dec 1995}}}$$

To compute the chained REER on 31 Dec 1995, which the last day of the '1990 to 1995' weight

[2] An exception is that, when computing EERs over the 1990-1995 weight reference period, we compute EERs from 1990 to 1992 using partners whose exchange rates are available from 1990 to 1992, and then compute REERs from 1993 to 1995 using partners whose exchange rates are available from 1993 to 1995. This materially increases the number of partners included in the 1993 to 1995 calculations, because the number of countries with NER data increases materially from the start of the IMF NERs on 1 January 1993.

reference period, we would compute:

$$\frac{EER^{\text{UK}}_{\text{31 Dec 1995}}}{EER^{\text{UK}}_{\text{30 Dec 1995}}} = \frac{EER^{\text{UK,1990 to 1995}}_{\text{31 Dec 1995}}}{EER^{\text{UK,1990 to 1995}}_{\text{30 Dec 1995}}}$$

For each monthly vintage, we compute daily EERs by applying the above formulas to the data that a forecaster would have had access to as at the end of each month. This includes daily NERs that are published without delay, and the nowcasted vintage of monthly CPI. Trade weights are assumed to be unavailable for 5 years after the end of the period to which the weights relate. For example, the trade weights based on 2013-2015 trade flows are assumed to become available from the January 2021 vintage onwards. We assume a 5-year lag to emulate current practice at the IMF, since they are our source of trade weights.

2.2 Monthly Vintages of Monthly Exchange Rates

We derive month-average and end-of-month series from the daily series. For each vintage of daily exchange rates (of any type), we make a corresponding vintage of month-average exchange rates (by averaging the daily rates over each month) and a vintage of end-of-month exchange rates (by extracting the last daily rate of each month).

For bilateral RERs, an alternative would be to apply the bilateral RER formula to a month-average NER and a monthly CPI. However, this is exactly equivalent to our approach of computing an average of daily bilateral RERs.

$$RER^i_m \equiv \frac{1}{n}\sum_{t=1}^{n} RER^i_t = \frac{1}{n}\sum_{t=1}^{n} NER^i_t + \frac{CPI^i_m}{CPI^{\text{US}}_m}$$

Similarly, one could instead compute NEERs by applying the EER formula to month-average NERs, or compute REERs by applying the formula to month-average NERs and monthly CPI. This alternative approach gives EERs whose growth rates are very close to those from our chosen approach, except during periods of hyperinflation.

3 Method

3.1 Out-of-Sample Evaluation

We conduct an out-of-sample evaluation of forecasts of the month-average exchange rate. Although exchange rates are observed for all countries, our baseline sample uses 83 countries for which all types of exchange rates (bilateral NER, bilateral RER, NEER, REER) start no later than 1

January 1994. Using a common sample period and set of countries facilitates comparisons between the results for different types of exchange rates. For each of these countries, we produce real-time forecasts using each monthly vintage. To ensure that all forecasts are made with models estimated on at least 10 years of data, the forecast evaluation sample uses monthly vintages from January 2004 to September 2022.

When computing forecast errors for bilateral RERs, we target the actual outcome computed from the bilateral NERs and CPI data as at end June 2023. For EERs, we target the actual outcome computed with the bilateral NERs and CPI levels as at end June 2023, but with the weights known on the forecast date. In this case, the forecaster needs to predict the combined effect of changes in bilateral NERs and CPI levels, but not the weights. This approach best reflects the aims of policymakers, who typically do not try to predict the effect of future changes in weights, in part because new weights will typically not be released until after the end of the forecast horizon. This approach also ensures that the treatment of trade weights in the later forecast vintages are consistent with the earlier forecast vintages.

The sample of 83 countries includes those with various exchange arrangements (floating, fixed, other managed arrangements), including countries whose exchange arrangements changed part-way through the sample period (e.g. Lithuania, whose currency was pegged to the USD, then pegged to the euro, and then replaced by the euro). We include all countries in the forecast exercise and treat them equally. In doing so, we do not attempt to account for structural breaks such as changes in exchange rate regimes. We do this because we aim to quantify the effects of temporal aggregation generally rather than to take a stand on the best forecast practices for any specific country. Robustness in appendix E shows that the results are robust for a sample of countries that have maintained floating exchange rates regimes over the sample, as defined by Ilzetzki et al. (2019).

We employ two common real-time forecast evaluation criteria.

The first forecast evaluation criteria is the ratio of the root mean square forecast error (RMSFE) of a candidate model relative to the RMSFE of the benchmark. Specifically, the RMSFE ratio at horizon h, $RMSFE_h^{ratio}$, is computed as the quotient of the RMSFE of the model-based forecast and the RMSFE of the alternative forecast:

$$RMSFE_h^{ratio} = \sqrt{\frac{\frac{1}{M}\sum_{m=1}^{M}\left(A_{m+h} - \hat{A}_{m+h|m}^{candidate}\right)^2}{\frac{1}{M}\sum_{m=1}^{M}\left(A_{m+h} - \hat{A}_{m+h|m}^{bench}\right)^2}}, \tag{3}$$

where $\hat{A}_{m+h|m}^{candidate}$ represents the real-time candidate forecast for the h step ahead of forecast target A_{m+h}, and $\hat{A}_{m+h|m}^{bench}$ is the alternative benchmark forecast, for all periods of the evaluation sample, denoted as $m = 1, ..., M$. We also perform Diebold-Mariano tests (Diebold and Mariano, 1995) of the null that expected squared error loss is equal. To perform the test for a horizon h, we compute a loss differential for forecasts at that horizon (i.e. difference in squared errors). We then regress the loss differentials on an intercept, and use Newey and West (1987) standard errors. The two-sided test of the null that the intercept is zero uses standard normal critical values.

The second forecast criteria assesses directional accuracy and is computed using the success ratio (SR). The SR describes the fraction of times the forecasting model can correctly predict the change in direction of the series of interest, SR_h:

$$SR_k = \frac{1}{M} \sum_{m=1}^{M} \mathbb{1}[sgn(A_{m+h} - \hat{A}^{bench}_{m+h}) = sgn(\hat{A}^{candidate}_{m+h|m} - \hat{A}^{bench}_{m+h|m})], \tag{4}$$

where $sgn(.)$ is a sign function and $\mathbb{1}[.]$ is an indicator function taking the value of 1 if true and 0 otherwise. Note that, unlike the RMSFE ratios, the success ratios are not transitive across the comparison against the different no-change forecasts. That is, the forecast with the highest success ratio relative to the monthly average no-change is not necessarily the forecast with the highest success ratio relative to the end of month no-change. We also test the null of no directional accuracy by testing if the categorical random variables $sgn(A_{m+h} - \hat{A}^{bench}_{m+h})$ and $sgn(\hat{A}^{candidate}_{m+h|m} - \hat{A}^{bench}_{m+h|m})$ are independent of each other. The test statistic is calculated following Pesaran and Timmermann (2009).

3.2 Description of Forecasting Methods

This subsection describes the forecasting methods. These methods are in three broad categories: no change forecasts; recursive forecasts; and direct forecasts. We consider both recursive and direct forecasts for generality as both have advantages and disadvantages, so it is not obvious a priori which will perform better (see section 2.7.7 of Petropoulos et al. (2022)).

While our aim is to forecast the level of the exchange rates, we estimate the models using log levels. We take the natural log of the exchange rate, construct the no-change, autoregressive or direct forecast for the log of the period-average exchange rate, and the take the exponent of the forecast to convert back into the level of the period-average exchange rate. We do this because log variables are more likely to be closer to satisfying the assumptions of symmetric errors.[3]

We denote daily, month-average and end-of-month exchange rates by D_t, A_m and Z_m respectively. We now denote log levels by lower case letters: d_t, a_m and z_m. We continue to assume that

[3]For example, if we think it is equally likely that an exchange rate could appreciate by 1% or depreciate by 1%, then we should model the *log* exchange rate using a model with symmetric errors, rather than modelling the exchange rate itself as having symmetric errors.

there are n days in each month to simplify our notation. We let M denote the current month, which means the forecaster has access to data from months $m = 1, ..., M$ when making a real-time forecast for a future month $(M + h)$.

3.2.1 No Change Forecasts

We consider two types of no-change forecasts:

i) Month-average no-change. The forecast for the month-average in any future month $(M+h)$ is the last observed month-average:

$$\widehat{a}_{M+h|M} = a_M \quad \forall h$$

ii) End-of-month no-change. The forecast for the month-average in any future month $(M+h)$ is the current end-of-month level.

$$\widehat{a}_{M+h|m} = z_M \quad \forall h$$

Note that the 'daily no-change' forecast, where our forecast for the month-average level in any future month $M+h$ would be the latest daily level, d_{Mn}, is exactly equivalent to the end-of-month no-change forecast. This is because, in our forecast evaluation, the forecasts are always constructed at the end of last day of each month.

3.2.2 Recursive AR(1) Forecasts

We make recursive forecasts using autoregressive models of order 1, AR(1), estimated on exchange rate levels using OLS.[4] We consider the three ways to construct recursive forecasts of period averages:

i) Recursive Bottom-up. We estimate an AR(1) on daily exchange rates.

$$d_{t+1} = \alpha + \beta d_t + e_{t+1} \quad \forall t = 1, ..., Mn - 1 \tag{5}$$

We use this model to make recursive forecasts for the daily exchange rate for all future days. We then average those daily forecasts to obtain month-average forecasts (see i.e. Lütkepohl, 1986; Benmoussa et al., 2023).

$$\widehat{a}_{M+h|M} = \frac{1}{n} \sum_{t=1}^{n} \widehat{d}_{(M+h-1)n+t|M} \quad \forall h$$

[4] For a handful of countries, the estimated AR(1) model had a coefficient that was outside $(-1, 1)$, suggesting that exchange rates were non-stationary. Where this occurred, the country was excluded from our results.

ii) Recursive End-of-Period. We estimate an AR(1) model of end-of-month exchange rates.

$$z_{m+1} = \alpha + \beta z_m + e_{m+1} \quad \forall m = 1, ..., M-1 \tag{6}$$

The recursive forecasts for the end-of-month exchange rates are then used as forecasts for the monthly average. The forecast of the end-of-period EER can be equal to the period-average at short horizons when the underlying series is persistent and converges at longer horizons (Ellwanger and Snudden, 2023b). Importantly, this allows us to quantify whether existing point forecasts in the literature will be good forecasts for forecasts of period-average exchange rates.

iii) Recursive of month-average inputs. We estimate an AR(1) model of month-average exchange rates.

$$a_{m+1} = \alpha + \beta a_m + e_{m+1} \quad \forall m = 1, ..., M-1 \tag{7}$$

We then use this model to make recursive forecasts for all future horizons.

3.2.3 Direct Forecasts

We construct direct forecasts using linear regressions estimated on exchange rate levels. We consider the three ways to construct direct forecasts of period averages:

i) Direct UMIDAS. For each horizon h we estimate a regression of the month-average exchange rate in $(m+h)$ on the latest daily observation known on the forecast date. We estimate the parameters of the model with ordinary least squares without any restrictions. This is an example of an unrestricted Mixed Data Sampling (UMIDAS) model, as described in Foroni et al. (2015). Since the latest daily observation available on the forecast date is the current end-of-month exchange rate, z_m, this model can be written:

$$a_{m+h} = \alpha_h + \beta_h z_m + e_{m+h} \quad \forall m = 1, ..., M-h \tag{8}$$

We then use the estimated model to forecast the month-average exchange rate directly.

$$\widehat{a}_{M+h|M} = \widehat{\alpha}_h + \widehat{\beta}_h z_M$$

ii) Direct End-of-Period. For each horizon, we estimate a regression of the end-of-month exchange rate in $(m+h)$ on the end-of-month exchange rate in m.

$$z_{m+h} = \alpha_h + \beta_h z_m + e_{m+h} \quad \forall m = 1, ..., M-h \tag{9}$$

We then use this estimated model to produce an h-month-ahead forecast of the end-of-month exchange rate:

$$\widehat{z}_{M+h|M} = \widehat{\alpha}_h + \widehat{\beta}_h z_M$$

Again, the forecasts for the end-of-month exchange rates are then used as the forecasts for monthly average rates, $\hat{a}_{M+h} = \hat{z}_{M+h}$.

iii) Direct of month-average inputs. For each horizon in months, h, we estimate a regression of the month-average exchange rate in $(m+h)$ on the month-average exchange rate in month m.

$$a_{m+h} = \alpha_h + \beta_h a_m + e_{m+h} \quad \forall m = 1, ..., M-h \tag{10}$$

We then use the estimated model to directly forecast the month-average exchange rate in h months.

$$\widehat{a}_{M+h|M} = \widehat{\alpha}_h + \widehat{\beta}_h a_M$$

3.2.4 Robustness

In examining the robustness of the results, we consider and report alternative modelling assumptions. As a robustness check for the recursive forecasts, we considered pre-sample testing for order of integration and the number of autoregressive terms using information criteria, and then used resulting forecasts for returns to compute forecasts for levels. As another check, we also produced forecasts using the 'automatic ARIMA' procedure of Hyndman et al. (2022), which in each forecast period chooses the number of times to difference the series and selects the number of autoregressive and moving average terms. Similarly, for robustness of the direct forecasts, we considered pre-sample testing for the order of integration and estimating the direct forecast regressions using returns to compute forecasts for levels. We also explored pre-sample testing of the number of lagged terms on the right-hand of the direct forecasts, as well as expanding window estimates of restricted MIDAS parameter profiles (Ghysels et al., 2007).

The efficiency gains from temporal disaggregation are found to be a magnitude larger than other forecast assumptions, and the qualitative results are unchanged, see appendix F. While the differencing and parametrization assumptions can affect the estimates for specific countries, we find that alternative procedures gave qualitatively similar results for the forecast quantiles. Our goal is to understand the effects of temporal disaggregation in a univariate setting, not to take a stand on the best forecast model for any specific country. As such, our baseline model-based forecast assumptions are purposely kept simplistic and homogeneous across countries and exchange rates to highlight the general and mechanical loss of information using temporally aggregated data in forecasting. Evaluations of alternative exchange rate models, and questions for any given countries exchange rate, using the daily data provided presents an exciting avenue for future research.

4 Results

This section reports the quantitative results on the importance of temporal aggregation bias for exchange rate forecasts. All forecasts are constructed in real-time as described in section 3 using the data documented in section 2.

4.1 Comparison of No-Change Benchmarks

We begin by examining the extent to which the end-of-period no-change forecast outperforms the monthly average no-change forecast. We report results for the four types of exchange rates and, as a point of comparison, for a simulated random walk at the daily frequency aggregated to monthly data with $n = 21$.[5] Table 3 reports the median RMSFE ratios at various forecast horizons.

When the data follows a random walk, the end-of-month no-change forecast substantially outperforms the monthly average no-change forecast (Ellwanger and Snudden, 2023a; McCarthy and Snudden, 2024). The gains in the RMSFE are largest at the one-month ahead, showing a 17 percent reduction and, consistent with theory, the differences decline with the forecast horizon. These patterns are also present for directional accuracy. For 1-month-ahead forecasts, the median SR is 0.74, which means that the end-of-month no-change predicted the direction in which the month-average exchange rate moved 74% of the time. The SRs also decline at longer horizons, but remain above 0.5 up to 12 months ahead.

The pattern of the forecast gains observed for the simulated random walk are also observed for the alternative exchange rate measures. In particular, the median RMSFE ratios for NER are nearly identical to those obtained from a random walk. The results suggest that the NER exhibits properties most similar to a random walk followed by the RER, NEER, and REER. That said, even for NEER and REER, the end-of-month no-change forecast out-performs the monthly average no-change forecast at the one-month ahead by 7 and 3 percent, respectively. Moreover, the end-of-month no-change does at least as well as the monthly average up to 12 months ahead for all four exchange rate measures.

Regarding directional accuracy, the gains in the SR are also substantial but much more consistent across exchange rate measures. For all exchange rates, at one-month ahead, gains of around 20 percentage points are found relative to a coin flip. Moreover, even at the six-month ahead horizons,

[5]For the simulated random walk, we simulate 30 years worth of data in addition to burning the first 500 daily observations. We then apply our out-of-sample evaluation methodology to the simulated data, and iterate 5000 times.

Table 1: Median Performance of End-of-Month No-change Forecasts Versus Monthly Average No-Change Forecasts

Months Ahead	1	3	6	12	24	36
Measure			RMSFE Ratio			
Random-Walk	0.73	0.94	0.97	0.99	0.99	1.00
NER	0.76	0.93	0.97	1.00	1.00	1.00
NEER	0.93	0.97	0.98	0.99	1.00	1.00
RER	0.87	0.96	0.98	1.00	1.00	1.00
REER	0.97	0.99	0.99	1.00	1.00	1.00
			Success Ratio			
Random-Walk	0.74	0.61	0.58	0.55	0.54	0.53
NER	0.71	0.60	0.59	0.53	0.52	0.49
NEER	0.71	0.63	0.59	0.55	0.55	0.52
RER	0.68	0.59	0.56	0.52	0.51	0.49
REER	0.69	0.59	0.56	0.52	0.52	0.50

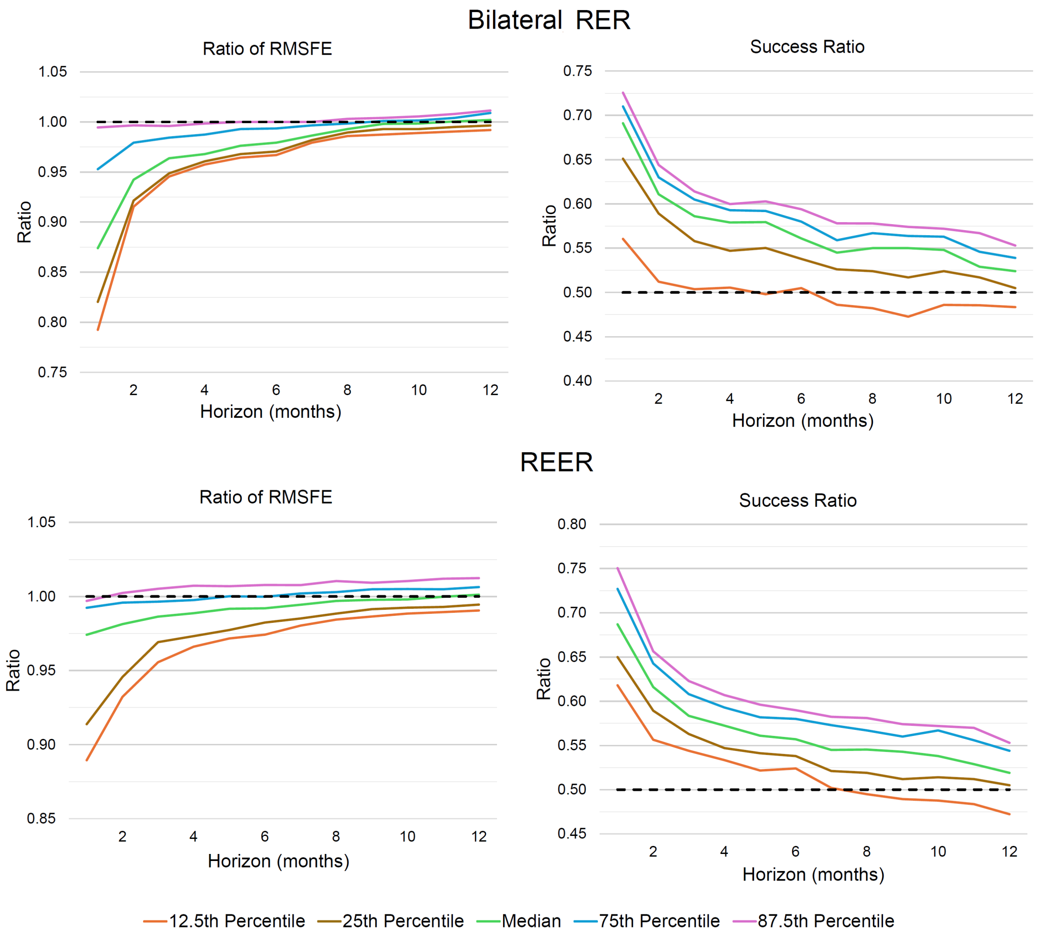
Note: Forecast accuracy of end-of-month no-change forecast versus monthly average no-change forecast. Reports the median across countries. "Random Walk" is simulated using 5000 iterations and 30 years of data. Values of the RMSFE ratio less than one improve upon the monthly average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance.

gains of 6 to 9 percentage points are found for all exchange rates. The results clearly indicate that the end-of-month no-change is a more accurate naive forecast than the monthly average no-change.

Now we explore how robust these forecast gains are across countries. Figure 1 reports the quantiles of the RMSFE and SRs for the end-of-month no-change forecast relative to the monthly average no-change forecast at horizons of 1 to 12 months for the RER and REER. The gains in forecast performance are found at almost every horizon for every exchange rate measure for both directional accuracy and mean-squared precision. At the 1-month horizon in particular, gains are present for all quantiles shown, which means they were present for at least 87.5% of countries. The forecast gains are even larger and more robust for the NER and NEER, as is reported in Figure D1 in the appendix. This indicates that the differences between the end-of-month no-change and the monthly average no-change in our sample is near universal, in addition to being substantial.

The results suggest that the loss in forecast from temporal aggregation of daily exchange rates to the monthly frequency is sizable. This is due to the high persistence of daily exchange rates and the large degree of aggregation (Zellner and Montmarquette, 1971; Tiao, 1972; Amemiya and Wu, 1972), and is consistent with the evidence of daily data observed for other aggregated macroeconomic variables (Ellwanger and Snudden, 2023b,a). The substantial and consistent differences in forecast accuracy show the importance of using the correct no-change benchmark in practice. This calls into question the validity of conclusions in the existing literature derived from testing against the period-average no-change benchmark.

Figure 1: Distribution of Forecast Performance of End-of-Month Versus Monthly Average Forecasts



Note: Plot shows quantiles for 83 countries. Forecasts are compared relative to the period-average no-change forecast. Values of the RMSFE ratio less than one improve upon the monthly average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance.

4.2 Real-time Model-Based Forecast Accuracy

We now quantify the information gains from temporally disaggregation when constructing real-time model-based forecasts of monthly average exchange rates. We evaluate forecasts from the three recursive models and the three direct models described in section 3. To be consistent with the last section, and the existing literature for EERs, we begin by comparing the forecasts to the monthly average no-change forecast.

The median forecast performance of model-based forecasts of the bilateral RERs is reported in Table 2. When recursive and direct forecasts are estimated with monthly average data, the forecasts do worse than the monthly average no-change forecast in terms of median RMSFE at all horizons and in terms of median SR at horizons up to one year. These results illustrate that, even though the monthly average no-change is an inefficient naive forecast, the inefficiency of forecasts estimated with period-averages can give the perception that it is difficult to beat. When estimated with monthly average data, the recursive and direct forecasts are almost indistinguishable from each other in terms of RMSFE up to a 2-year horizon, and in terms of SR at all horizons.

Table 2: Median Performance of Forecasts for Monthly Average Bilateral RER

Forecast	Model Inputs	1	3	6	12	24	36
				RMSFE Ratio			
Recursive	Month-Average	1.00	1.01	1.01	1.02	1.04	1.06
Recursive	End-of-Month	0.88	0.97	0.99	1.01	1.03	1.04
Recursive	Bottom-up	0.88	0.97	0.99	1.02	1.05	1.05
Direct	Month-Average	1.00	1.01	1.01	1.01	1.07	1.24
Direct	End-of-Month	0.88	0.96	0.98	1.00	1.07	1.24
Direct	UMIDAS	0.87	0.96	0.98	1.00	1.05	1.23
				Success Ratio			
Recursive	Month-Average	0.49	0.48	0.47	0.48	0.55	0.54
Recursive	End-of-Month	0.68	0.57	0.54	0.51	0.57	0.56
Recursive	Bottom-up	0.68	0.57	0.53	0.52	0.58	0.57
Direct	Month-Average	0.49	0.49	0.49	0.49	0.55	0.54
Direct	End-of-Month	0.68	0.57	0.53	0.52	0.56	0.54
Direct	UMIDAS	0.68	0.58	0.54	0.51	0.56	0.54

Note: Reports the median result across countries relative to the monthly average no-change forecast. Note, "End-of-Month" uses the end-of-month forecast as the forecast of the monthly average. "Recursive bottom-up" ex-post averages daily forecasts. Direct UMIDAS forecasts restrict to the end-of-month observation. Values of the RMSFE ratio less than one improve upon the monthly average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance.

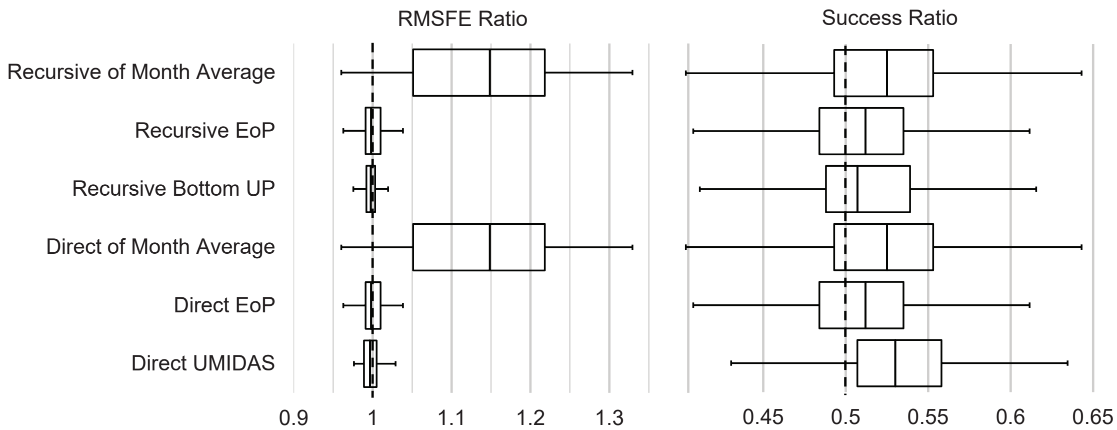
For both recursive and direct forecasts, using end-of-period or bottom-up methods result in substantially better real-time forecast performance than month-average inputs. The gains are very similar to what was observed from the end-of-month no-change forecast at the one-month ahead, with 12 percent improvements in RMSFE and 36 percent improvement in the SR. These findings reinforce that the loss of forecast accuracy is substantial when model-based forecasts use aggregated daily data. For both disaggregated forecast methods, we again find that the median performance of the recursive and direct forecasts are almost indistinguishable from each other in terms of directional accuracy, and for the RMSFE up to a 2-year horizon.

Interestingly, the results indicate that the forecasts constructed using end-of-month levels does about as well as the bottom-up forecasts constructed using daily data for real-time forecasts of the monthly average level. This evidence regarding the usefulness of end-of-period forecasts as a forecast of the period average suggests that studies which have shown promise at end-of-period forecasts should be considered as candidates for period average forecasts.

We now examine the model-based forecast performance relative to the end-of-month no-change forecast. The distribution of RMSFEs and SRs from the different model-based forecasts at the

1-month-ahead for bilateral RERs are reported in Figure 2. For the RMSFE, the results reinforce the conclusions drawn from the exchange rate of the median country. Specifically, model-based forecasts using disaggregated methods have much lower RMSFE ratios compared to models estimated with month-average inputs. In fact, the forecasts constructed using month-average inputs are so poor that the entire interquartile range (IQR) of RSMFE ratios (indicated by the box) is above the country with the highest ratio constructed using end-of-month or daily inputs. These results show that, like the gains for no-change forecasts, the differences between the disaggregated model-based forecasts and the models estimated with monthly average data are substantial and near universal.

Figure 2: Accuracy of 1-month-ahead Forecasts for Bilateral RER relative to End-of-month No-change Benchmark



Note: Note, "EoP" uses the end-of-month forecast as the forecast of the monthly average. "Recursive bottom-up" ex-post averages daily forecasts. Direct UMIDAS forecasts restricts to the end-of-month observation. Outliers have been omitted. Values of the RMSFE ratio less than one improve upon the monthly average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance.

In contrast to the RMSFE, the SR is non-transitive, meaning that the best forecast relative to the monthly average no-change is not guaranteed to be the best forecast relative to the end-of-period no-change. This can be seen in the results for the SRs in Figure 2. In particular, even though we still observe substantial deterioration in RMSFEs for model-based forecasts estimated with monthly average data, they perform similarly to the disaggregated approaches in directional accuracy. This can be seen in the overlap in the IQRs of the SRs for the three types of inputs. However, direct forecasts using daily inputs exhibit some of the largest and most robust forecast gains, with the lower bound of the IQR above 0.5. This suggests that mixed-frequency direct forecasts may have some advantages in forecasting directional accuracy, at least at short horizons.

Qualitatively, the results are very similar for the other exchange rates and are reported in appendix D. Substantial RMSFE gains are found for all exchange rates and are robust across countries when disaggregated model-based forecasts are employed. These results are all indicative that time-averaging introduces a loss of information for model-based forecasts of monthly average exchange rates. Integrating information from daily or end-of-month inputs into model-based forecasts can substantially enhance forecast accuracy compared to specifications with month-average inputs.

4.3 Evidence of Real-time Predictability

We now formally test the real-time predictability of period average exchange rates. Specifically, we report the share of countries for which we find significant outperformance of the model-based forecasts against both no-change benchmarks in terms of mean-square accuracy and directional accuracy, see Table 3.

Table 3: Percent of Countries with Significant One-Month Ahead Exchange Rate Forecasts

		Versus End-of-Month No-change				Versus Monthly Average No-change			
Forecast	Model-Inputs	REER	RER	NEER	NER	REER	RER	NEER	NER
		Mean-Square Accuracy							
Recursive	Month-Average	10%	5%	6%	1%	43%	10%	27%	3%
Recursive	End-of-Month	46%	19%	28%	3%	55%	79%	49%	74%
Recursive	Bottom-up	56%	31%	37%	3%	65%	81%	54%	74%
Direct	Month-Average	10%	5%	6%	1%	43%	10%	19%	3%
Direct	End-of-Month	46%	19%	28%	3%	55%	80%	49%	75%
Direct	UMIDAS	41%	19%	30%	4%	52%	77%	53%	80%
		Directional Accuracy							
Recursive	Month-Average	14%	13%	13%	10%	16%	6%	8%	7%
Recursive	End-of-Month	30%	6%	13%	5%	98%	91%	100%	93%
Recursive	Bottom-up	28%	10%	33%	12%	99%	87%	97%	95%
Direct	Month-Average	14%	13%	13%	9%	15%	6%	8%	7%
Direct	End-of-Month	30%	6%	29%	5%	98%	91%	97%	93%
Direct	UMIDAS	26%	15%	16%	18%	100%	88%	99%	94%

Note: Reports the share of countries where the forecast model is significant at the five percent level by the end of the forecast evaluation sample. Note, "end-of-month" inputs in model estimation use the end-of-month point forecast as the forecast of the monthly average. Recursive and daily uses the bottom-up approach. Direct forecasts use UMIDAS restricted to the end-of-month observation.

Immediately notable is that comparisons to the monthly average no-change result in significant forecasts in the majority of cases when disaggregated methods are employed. For example, for forecasts of the monthly average NER, the disaggregated model-based forecasts significantly outperform the monthly average no-change up to 80 and 95 percent for mean-square accuracy and directional accuracy, respectively. However, this is a perfect example of spurious predictability. There is little evidence of short-term predictability of bilateral NERs when comparisons are correctly made against the random walk hypothesis, i.e. the end-of-month no-change forecast. For NERs, not even for five percent of countries do any of the forecasts exhibit significant predictability in RMSFE terms. This is substantial evidence that when forecasting a period-average, comparisons relative to the period-average no-change benchmark can lead to sizable type-I error.

Interestingly, evidence of real-time predictability is present for the forecasts of the other exchange rates. For bilateral RERs, significant RMSFE gains relative to the end-of-month no-change forecast are found for up to 31 percent of countries, and up to 15 percent of countries for the SR. These are slightly better for NEERs, with significant RMSFE gains relative to the end-of-month no-change forecast found for up to 37 percent of countries, and up to 33 percent of countries for the SR. By far, the most predictable exchange rate is the REERs, with up to 56 percent of countries exhibiting significant predictability and up to 30 percent for the SR. These findings of significant predictability are the first time that forecasts of period-average exchange rates have been compared against the traditional random-walk hypothesis no-change forecast.

5 Conclusion

Our findings from the novel real-time daily data have three implications. First, they show the importance of comparing forecasts for period-averages against the end-of-month no-change benchmark to avoid spurious predictability. The substantial differences in the forecast performance of the end-of-month versus the monthly average no-change forecast call into question previous empirical results on forecasts for period average exchange rates. Secondly, our findings show that incorporating information from daily or end of month exchange rates results in substantial gains in real-time forecast accuracy. This holds promising potential to improve current forecasting practices, and the decisions that are reliant on these forecasts. It also shows the need to begin calculating and reporting end-of-month and daily measures of effective exchange rates in official data sources. Finally, the evidence indicates that the period average EERs and bilateral RERs of many countries are forecastable in real-time. Exploring techniques that use daily inputs to forecast period-average exchange rates offers a promising avenue for future research.

References

Abbate, A. and Marcellino, M. (2018). Point, interval and density forecasts of exchange rates with time varying parameter models. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 181(1):155–179.

Amemiya, T. and Wu, R. Y. (1972). The effect of aggregation on prediction in the autoregressive model. *Journal of the American Statistical Association*, 67(339):628–632.

Athanasopoulos, G., Hyndman, R. J., Song, H., and Wu, D. C. (2011). The tourism forecasting competition. *International Journal of Forecasting*, 27(3):822–844.

Bayoumi, T., Lee, J., and Jayanthi, S. (2006). New Rates from New Weights. *IMF Staff Papers*, 53(2):1–4.

Benmoussa, A. A., Ellwanger, R., and Snudden, S. (2023). Carpe diem: Can daily oil prices improve model-based forecasts of the real price of crude oil? *LCEPRA Working Papers, 2023-5*.

Bork, L., Kaltwasser, P. R., and Sercu, P. (2022). Aggregation bias in tests of the commodity currency hypothesis. *Journal of Banking & Finance*, 135:106392.

Brewer, K. R. (1973). Some consequences of temporal aggregation and systematic sampling for arma and armax models. *Journal of Econometrics*, 1(2):133–154.

Carriero, A., Kapetanios, G., and Marcellino, M. (2009). Forecasting exchange rates with a large bayesian var. *International Journal of Forecasting*, 25(2):400–417.

Ca'Zorzi, M., Cap, A., Mijakovic, A., and Rubaszek, M. (2022). The reliability of equilibrium exchange rate models: A forecasting perspective. *International Journal of Central Banking*, 18(3):229–280.

Chen, S.-L., Jackson, J. D., Kim, H., and Resiandini, P. (2014). What drives commodity prices? *American Journal of Agricultural Economics*, 96(5):1455–1468.

Clarida, R. H., Sarno, L., Taylor, M. P., and Valente, G. (2003). The out-of-sample success of term structure models as exchange rate predictors: a step beyond. *Journal of International Economics*, 60(1):61–83.

Clarida, R. H. and Taylor, M. P. (1997). The term structure of forward exchange premiums and the forecastability of spot exchange rates: correcting the errors. *Review of Economics and Statistics*, 79(3):353–361.

Diebold, F. X. and Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3):253–263.

Dornbusch, R. (1987). Exchange rates and prices. *American Economic Review*, 77(1):93–106.

Ellwanger, R. and Snudden, S. (2023a). Forecasts of the real price of oil revisited: Do they beat the random walk? *Journal of Banking and Finance*, 154(106962):1–8.

Ellwanger, R. and Snudden, S. (2023b). Seize the last day: Period-end-price sampling for forecasts of temporally aggregated data. *LCERPA Working Papers, 2023-6*.

Engel, C., Mark, N. C., West, K. D., Rogoff, K., and Rossi, B. (2007). Exchange rate models are not as bad as you think [with comments and discussion]. *NBER Macroeconomics Annual*, 22:381–473.

Faust, J., Rogers, J. H., and Wright, J. H. (2003). Exchange rate forecasting: the errors we've really made. *Journal of International Economics*, 60(1):35–59.

Forbes, K., Hjortsoe, I., and Nenova, T. (2018). The shocks matter: improving our estimates of exchange rate pass-through. *Journal of International Economics*, 114:255–275.

Foroni, C., Marcellino, M., and Schumacher, C. (2015). Unrestricted mixed data sampling (midas): Midas regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 178(1):57–82.

Frankel, J. A. and Rose, A. K. (1995). Empirical research on nominal exchange rates. *Handbook of International Economics*, 3:1689–1729.

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

Ghysels, E., Sinko, A., and Valkanov, R. (2007). Midas regressions: Further results and new directions. *Econometric reviews*, 26(1):53–90.

Glas, A. and Heinisch, K. (2023). Conditional macroeconomic survey forecasts: Revisions and errors. *Journal of International Money and Finance*, 138:102927.

Goldberg, P. and Knetter, M. M. (1997). Goods prices and exchange rates: What have we learned? *Journal of Economic Literature*, 35(3):1243–1272.

Ha, J., Kose, A., and Ohnsorge, F. L. (2021). One-Stop Source : A Global Database of Inflation. Policy Research Working Paper Series 9737, The World Bank.

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E., and Yasmeen, F. (2022). *forecast: Forecasting functions for time series and linear models*. R package version 8.19.

Ilzetzki, E., Reinhart, C. M., and Rogoff, K. S. (2019). Exchange arrangements entering the twenty-first century: Which anchor will hold? *The Quarterly Journal of Economics*, 134(2):599–646.

International Monetary Fund (2023). *Assumptions and Conventions*. International Monetary Fund.

Kilian, L. and Taylor, M. P. (2003). Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics*, 60(1):85–107.

Klau, M. and Fung, S. S. (2006). The new BIS effective exchange rate indices. *BIS Quarterly Review*, 2006(March):51–65.

Kohlscheen, E., Avalos, F. H., and Schrimpf, A. (2017). When the walk is not random: commodity prices and exchange rates. *International Journal of Central Banking*, 13(2):121–158.

Kohn, R. (1982). When is an aggregate of a time series efficiently forecast by its past? *Journal of Econometrics*, 18(3):337–349.

Lütkepohl, H. (1986). Forecasting temporally aggregated vector ARMA processes. *Journal of Forecasting*, 5(2):85–95.

Marcellino, M. (1999). Some consequences of temporal aggregation in empirical analysis. *Journal of Business & Economic Statistics*, 17(1):129–136.

McCarthy, M. and Snudden, S. (2024). Predictable by construction: Assessing forecast directional accuracy of temporal aggregates. *LCERPA Working Papers, 2024-5*.

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

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. *Journal of Monetary Economics*, 55:S63–S79.

Newey, W. K. and West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, pages 777–787.

Pesaran, M. H. and Timmermann, A. (2009). Testing dependence among serially correlated multicategory variables. *Journal of the American Statistical Association*, 104(485):325–337.

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., and Boylan, J. (2022). Forecasting: theory and practice. *International Journal of Forecasting*, 38(3):705–871.

Rogoff, K. (1996). The purchasing power parity puzzle. *Journal of Economic Literature*, 34(2):647–668.

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

Shambaugh, J. (2008). A new look at pass-through. *Journal of International Money and Finance*, 27(4):560–591.

Telser, L. G. (1967). Discrete samples and moving sums in stationary stochastic processes. *Journal of the American Statistical Association*, 62(318):484–499.

Tiao, G. C. (1972). Asymptotic behaviour of temporal aggregates of time series. *Biometrika*, 59(3):525–531.

Turner, P. and Van 't dack, J. (1993). Measuring international price and cost competitiveness. BIS Economic Papers 39, Bank for International Settlements.

Vartia, Y. and Vartia, P. (1984). Descriptive index number theory and the Bank of Finland currency index. *The Scandinavian Journal of Economics*, 86(3):352–364.

Wei, W. W. (1978). Some consequences of temporal aggregation in seasonal time series models. In *Seasonal analysis of economic time series*, pages 433–448. NBER.

Weiss, A. A. (1984). Systematic sampling and temporal aggregation in time series models. *Journal of Econometrics*, 26(3):271–281.

Wieland, V. and Wolters, M. (2013). Chapter 5 - forecasting and policy making. In Elliott, G. and Timmermann, A., editors, *Handbook of Economic Forecasting*, volume 2 of *Handbook of Economic Forecasting*, pages 239–325. Elsevier.

Working, H. (1960). Note on the correlation of first differences of averages in a random chain. *Econometrica*, 28(4):916–918.

Wright, J. H. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics*, 146(2):329–341.

Zellner, A. and Montmarquette, C. (1971). A study of some aspects of temporal aggregation problems in econometric analyses. *The Review of Economics and Statistics*, 53(4):335–342.

Zhang, H. J., Dufour, J.-M., and Galbraith, J. W. (2016). Exchange rates and commodity prices: Measuring causality at multiple horizons. *Journal of Empirical Finance*, 36:100–120.

A Literature Survey

This literature review offers a comprehensive analysis of research on forecasting effective exchange rates (EERs) and bilateral exchange rates. Our analysis compliments other surveys in the exchange rate literature (Frankel and Rose, 1995; Rogoff, 1996; Engel et al., 2007; Rossi, 2013) by reporting and discussing the validity of the temporal assumptions used in each study. We report the frequency and temporal sampling of the data of the forecast target, in estimation, and the benchmark against which forecasts are evaluated. For each paper, we assess the type of exchange rate targeted, including if real or nominal and if in levels or returns. We confine our examination to papers published or accepted for publication as of 2023. We also record if forecast analysis was conducted in 'real-time', defined as forecasts made with models estimated only on data available at the time of the forecast (see for example Clarida and Taylor (1997)). Specifically, if the exchange rates are expressed in real terms, then this requires that they are computed using CPI observations that account for the lag in publication. For EERs, this requires real-time treatment of the trade weights.

As the main focus of the survey is the temporal methods used for the forecasts, our survey separately documents forecasts of point-sampled and period average exchange rates. We also delineate studies into those that examine EERs, section A.1, and bilateral exchange rates, section A.2. In cases where papers forecast multiple types of exchange rates, we include them in each section.

A.1 Effective Exchange Rates

Our initial focus is on forecasts of EERs, which are prominent in macroeconomics. REERs are important because they reveal relative price levels between a nation and its trade partners, which influences trade flows. NEERs are useful summaries of a country's nominal exchange rate with its trading partners. Among other things, they can be used to forecast the extent to which nominal exchange rate movements will contribute to domestic inflation (Dornbusch, 1987; Goldberg and Knetter, 1997; Shambaugh, 2008; Forbes et al., 2018).

A.1.1 Forecasts for Period-Average Effective Exchange Rates

We found 18 papers that examined forecasts of period-average EERs, as summarized in Table A1. Around half of these papers concentrate on forecasts of the level of EERs rather than returns in EERs, with the focus on real versus nominal EERs also approximately split. Most studies forecast month-average EERs, although there's a recent trend towards forecasting quarter-average EERs.

We document three findings for period-average EERs.

First, studies that compare the predictability of period-average EERs to that of a naive forecast

Table A1: Papers Forecasting Period-Average Effective Exchange Rates

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Hooper and Morton (1982)	Level	M, Q	Average	Average	Average	Both	N
Meese and Rogoff (1983a)	Level	M	Average	Average	Average	Nominal	N
Meese and Rogoff (1983b)	Level	M	Average	Average	Average	Real	N
Boughton (1987)	Both	M	Average	Average	Average	Both	N
Throop (1993)	Return	Q	Average	Average	Average	Real	N
MacDonald (1997)	Level	Q	Average	Average	Average	Real	N
Amano and Norden (1998a)	Return	M	Average	Average	Average	Real	N
Amano and Norden (1998b)	Level	M	Average	Average	Average	Real	N
Siddique and Sweeney (1998)	Level	M	Average	Average	Average	Real	N
Sarantis (1999)	Level	M	Average	Average	Average	Real	N
Bergin (2003)	Return	Q	Average	Average	Average	Both	N
Gourinchas and Rey (2007)	Return	Q	Average	Average	Average	Nominal	N
Adrian et al. (2009)	Return	M	Average	Average	Average	Nominal	N
Chen et al. (2010)	Return	Q	Average	Average	Average	Nominal	N
Chen et al (2014)	Level	A	Average	Average	Average	Nominal	N
Ca'Zorz et al. (2016)	Level	M	Average	Average	Average	Real	N
Ca'Zorz et al. (2017)	Level	Q	Average	Average	Average	Real	N
Hatzinikolaou and Polasek (2019)	Return	Q	Average	Average	Average	Nominal	N

Note: "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation.

have done so using the period-average no-change benchmark. This is problematic as forecast improvements relative to the period-average no-change forecast are theoretically expected for all autoregressive integrated moving average representations of the levels of daily data (Telser, 1967; Brewer, 1973; Weiss, 1984; Marcellino, 1999). This parallels concerns over spurious predictability for returns: Working (1960) shows that aggregation converts the growth rate of a random walk–an entirely unpredictable process–into a cumulative moving average process that is predictable based on past returns. Hence, forecasts of a period-average, whether expressed in levels or returns, are expected to outperform a period-average no change benchmark even if the underlying exchange rate is a random walk (and hence unpredictable, by definition). Since this predictability arises by construction, it has been typically referred to as 'spurious predictability'. To avoid such spurious predictability, forecasts of period-averages need to be compared against the end-of-period no-change forecast. This is because only the end-of-period no-change reflects the null hypothesis that all future exchange rates, averaged or not, are conditionally unpredictable. This is true whether one is assessing mean-square forecast accuracy (Ellwanger and Snudden, 2023a) or directional accuracy (McCarthy and Snudden, 2024). Moreover, the differences in the two no-change forecasts are substantial; if the daily series is a random walk, the end-of-month no-change will have mean-square accuracy 44% lower than the monthly average no-change (Ellwanger and Snudden, 2023a). This calls into question the validity of the conclusions in the existing literature pertaining to period average exchange rates.

Second, the literature on period-average EERs has always used models estimated with period-average data. However, this is expected to compromise forecast accuracy due to information loss from temporal aggregation (Zellner and Montmarquette, 1971; Tiao, 1972; Amemiya and Wu, 1972; Wei, 1978; Kohn, 1982; Lütkepohl, 1986). The information loss is expected to be large for daily to monthly data aggregation, given the high persistence of daily exchange rates and the large number of temporal periods aggregated over. Most of the information loss occurs from departures of no aggregation, and occurs over the first few observations (Tiao, 1972). Substantial gains in forecast accuracy have been documented in practice for daily to monthly aggregations (Ellwanger and Snudden, 2023b,a). In contrast, comparisons of already aggregated frequencies have found that the effect is small or non-existent (see for example, Zellner and Montmarquette, 1971; Lütkepohl, 1986; Athanasopoulos et al., 2011, among others). Consequently, the loss in forecast accuracy, may be substantially larger than currently understood for period-average exchange rates. The degree of the information loss is an empirical question, quantified in section 4.

Finally, we find that no study has conducted a real-time forecast evaluation for any period-average EERs. Hence, it remains unclear if the methods proposed in existing studies would be useful in practical applications if adopted by policymakers or other forecasters. The lack of real-time forecast evaluations may reflect the absence of real-time EER data vintages that account for the delay in the publication of trade weights, a gap that we remedy with our dataset in section 2.

A.1.2 Forecasts for Point-Sampled Effective Exchange Rates

Only three studies evaluate forecasts for end-of-period EERs, see Table A2. As was the case for period-average EERs, none of the studies use real-time methods. Forecasts for end-of-period NEERs were examined by Kohlscheen et al. (2017) and Zhang et al. (2016). Zhang et al. (2016) specifically discuss the information loss from temporal aggregation in their motivation of daily forecasts of NEERs. Additionally, Ca'Zorzi et al. (2022) stand alone in examining forecasts of end-of-period real EERs, which they construct for a basket of eight advanced economies. These studies compared forecasts against end-of-period no-change benchmarks and, hence, unlike the studies examining period average exchange rates, correctly tested against the null of no predictability.

The valid hypothesis testing in these papers is potentially informative on the predictability of period-average EERs exchange rates. This is because, under certain conditions, a forecast for the end-of-period EER can be an excellent forecast of the period-average at long horizons and at short horizons when the underlying series is persistent (Ellwanger and Snudden, 2023b). However, the applicability to exchange rates is a question that can only be answered quantitatively. Due to the interest in the forecastability of period-average EERs in macroeconomics, we examine the

Table A2: Papers Forecasting Point-sampled Effective Exchange Rates

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Kohlscheen et al. (2016)	Return	D	EoP	EoP	EoP	Nominal	N
Zhang et al. (2016)	Return	D	EoP	EoP	EoP	Nominal	N
Ca'Zorzi et al. (2022)	Level	Q	EoP	EoP	EoP	Real	N

Note: "Benchmark" refers to the no-change forecast that the forecast was compared against. "EoP" refers to end-of-period sampling. "Model Estimation" refers to the data used in estimation.

efficiency of point-sampled forecasts for period averages for all countries in section 4.

A.2 Bilateral Exchange Rates

A.2.1 Forecasts for Period-Average Bilateral Exchange Rates

We now examine the literature on forecasting period-average bilateral exchange rates. Bilateral exchange rates provide insights into relative price levels between a pair of countries and are therefore relevant to flows between them. The body of research on period-average bilateral exchange rates is less extensive than that on EERs, with only seventeen papers, see Table A3. Moreover, only three papers examine period-average bilateral RERs, and only one of those forecast the level. In contrast to EERs, a few papers employ real-time methods for period-average bilateral exchange rates in nominal terms (Wright, 2008; Carriero et al., 2009; Molodtsova et al., 2008; Abbate and Marcellino, 2018) and one in real terms (Kilian and Taylor, 2003).

Table A3: Papers Forecasting Period-Average Bilateral Exchange Rates

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Backus (1984)	Level	Q	Average	Average	Average	Nominal	N
Amano and Norden (1995)	Return	M	Average	Average	Average	Real	N
Aarle et al. (2000)	Level	M	Average	Average	Average	Nominal	N
Fullerton et al. (2001)	Return	Y	Average	Average	Average	Nominal	N
Kilian and Taylor (2003)	Level	Q	Average	Average	Average	Real	Y
Harvey (2005)	Return	A	Average	Average	Average	Nominal	N
Islam and Hasan (2006)	Level	Q	Average	Average	Average	Nominal	N
Issa et al. (2008)	Return	Q	Average	Average	Average	Real	N
Molodtsova et al. (2008)	Return	Q	Average	Average	Average	Nominal	Y
Wright (2008)	Return	M, Q	Average	Average	Average	Nominal	Y
Carrieroa et al. (2009)	Level	M	Average	Average	Average	Nominal	Y
Molodtsova and Papell (2009)	Return	M	Average	Average	Average	Nominal	N
Giacomini and Rossi (2010)	Return	M	Average	Average	Average	Nominal	N
Tawadros (2010)	Return	M	Average	Average	Average	Nominal	N
Fratzscher et al. (2015)	Return	M	Average	Average	Average	Nominal	N
Abbate and Marcellino (2018)	Level	M	Average	Average	Average	Nominal	Y
Eichenbaum et al. (2021)	Return	Q	Average	Average	Average	Nominal	N

Note: "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation.

Unfortunately, like for EERs, all papers summarized are found to compare forecasts to the period-average no-change benchmark, and never to the end-of-period no-change benchmark. As with the EER literature, forecasts are expected to outperform the period-average no-change benchmark by construction, even if the daily series is a random walk and hence unpredictable by definition. This reveals that for both bilateral and EERs, there is a critical gap in the understanding of the forecastability of period-average exchange rates. Moreover, like EERs, these studies universally use period-average inputs in estimation, potentially jeopardizing forecast accuracy. In essence, our understanding of the predictability of period-average bilateral exchange rates remains limited.

A.2.2 Forecasts for Point-Sampled Bilateral Exchange Rates

Lastly, we delve into the literature which has examined point-sampled bilateral exchange rates. Researchers may favor bilateral point-sampled exchange rates over bilateral period-average rates when precision is paramount, such as in asset valuation or trade settlements at specific time intervals. Our survey documents 14 studies examining real rates and 101 studies examining nominal rates. The literature examining point-sampled bilateral RERs is presented in Table A4. We also discuss papers that have examined point-sampled bilateral NERs, for which summary tables are reported in appendix B.

Table A4: Papers Forecasting Point-Sampled Bilateral RERs

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Boughton (1987)	Both	M	EoP*	EoP*	EoP*	Real	N
Meese and Rogoff (1988)	Level	M	EoP	EoP	EoP	Real	N
Throop (1993)	Return	Q	EoP*	EoP*	EoP*	Real	N
Jorion and Sweeny (1996)	Level	M	EoP	EoP	EoP	Real	N
Taylor et al. (2001)	Level	M	EoP	EoP	EoP	Real	N
Chen and Rogoff (2003)	Level	Q	EoP	EoP	EoP	Real	N
Froot and Ramadorai (2005)	Return	D	MoP	MoP	MoP	Real	N
Rapach and Wohar (2006)	Level	M	EoP*	EoP*	EoP*	Real	N
Engel and West (2006)	Level	M	EoP	EoP	EoP	Real	N
Clements and Fry (2008)	Return	Q	EoP	EoP	EoP	Real	N
Mumtaz et al. (2012)	Level	Q	EoP*	EoP*	EoP*	Real	N
Chen and Chen (2014)	Level	M	EoP	EoP	EoP	Real	N
Ca'Zorzi and Rubaszek (2020)	Return	M	EoP	EoP	EoP	Real	N
Liu and Shaliastovich (2022)	Return	M	EoP	EoP	EoP	Real	N

Note: "*" is used in cases where the paper did not provide information whether exchange rates are average or point sampled, and so point-in-time sampling was assumed. "EoP" and "MoP" refer to end-of-period and middle-of-period sampling, respectively. "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation.

In all cases, papers are found to construct forecasts using point-sampled data and compare them to point-sampled no-change forecasts. This suggests that conclusions derived from hypothesis testing in these papers are valid, and do not suffer from the concerns of spurious predictability discussed in the last sections. Again, the valid hypothesis testing for RERs is potentially quite informative on the predictability of period-average bilateral exchange rates and will be quantified in section 4.

Finally, no paper has investigated real-time forecasts of point-sampled bilateral RERs. This disparity suggests a knowledge gap regarding real-time forecasts for bilateral RERs. In contrast, since Clarida and Taylor (1997), 16 out of 101 studies of point-sampled bilateral NERs have employed real-time forecasts.

A.3 Identified Gaps in the Literature

In summary, we make three key findings from the survey . First, we found that the literature has yet to test the predictability of period-average exchange rates by comparing them with the no-change benchmark that reflects the random walk hypothesis. This raises questions, not only regarding the validity of the conclusions in these studies, but also on the predictability of these rates more generally. Second, we found that the literature forecasting period-average exchange rates uses models estimated on period-average inputs rather than end-of-period or daily inputs. This questions the efficiency of the forecasts. Finally, we found that no paper has conducted a real-time evaluation of forecasts for period-average or point-sampled EERs, or for point-sampled bilateral RERs. This calls into question the usefulness of proposed forecasts in practice. Taken together, our findings suggest that researchers know little about the predictability of period-average exchange rates. Our paper aims to fill these gaps.

B Point-in-Time Sampled Nominal Bilateral Exchange Rates

Table B1: Summary of Literature Focusing on Point-in-Time Sampled Nominal Bilateral Exchange Rates, part 1/3

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Edwards (1983)	Level	M	EoP	EoP	EoP	Nominal	N
Meese and Rogoff (1983a)	Level	M	EoP	EoP	EoP	Nominal	N
Meese and Rogoff (1983b)	Level	M	EoP	EoP	EoP	Nominal	N
Fama (1984)	Return	M	EoP	EoP	EoP	Nominal	N
Somanath (1986)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Boothe and Glassmna (1987)	Level	M	EoP	EoP	EoP	Nominal	N
Boughton (1987)	Both	M	EoP*	EoP*	EoP*	Nominal	N
Schinasi and Swamy (1987)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Wolff (1987)	Level	M	EoP	EoP	EoP	Nominal	N
Hodrick (1989)	Return	M	EoP	EoP	EoP	Nominal	N
Diebold and Nason (1990)	Return	W	MoP	MoP	MoP	Nominal	N
Engel and Hamilton (1990)	Return	Q	EoP	EoP	EoP	Nominal	N
Chinn (1991)	Level	Q	EoP	EoP	EoP	Nominal	N
Meese and Rose (1991)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Mizrach (1992)	Return	D	EoP	EoP	EoP	Nominal	N
Canova (1993)	Level	W	MoP	MoP	MoP	Nominal	N
Krager and Kruger (1993)	Return	W	EoP	EoP	EoP	Nominal	N
Macdonald and Taylor (1993)	Level	M	EoP	EoP	EoP	Nominal	N
Throop (1993)	Return	Q	EoP*	EoP*	EoP*	Nominal	N
Diebold et al. (1994)	Return	D	SoP	SoP	SoP	Nominal	N
Engel (1994)	Return	Q	EoP	EoP	EoP	Nominal	N
MacDonald and Taylor (1994)	Level	M	EoP	EoP	EoP	Nominal	N
Chinn and Meese (1995)	Level	M	EoP	EoP	EoP	Nominal	N
Diebold and Mariano (1995)	Return	M	EoP	EoP	EoP	Nominal	Y
Mark (1995)	Return	Q	EoP	EoP	EoP	Nominal	N
Clarida and Taylor (1997)	Both	W	EoP	EoP	EoP	Nominal	Y
Groen (1999)	Return	M	EoP	EoP	EoP	Nominal	N
Kilian (1999)	Return	Q	EoP*	EoP*	EoP*	Nominal	N
Berkowitz and Giogianni (2001)	Return	Q	EoP	EoP	EoP	Nominal	N
Clements and Smith (2001)	Level	W	EoP	EoP	EoP	Nominal	N
Hwang (2001)	Return	M	EoP*	EoP*	EoP*	Nominal	N
Mark and Sul (2001)	Return	Q	EoP	EoP	EoP	Nominal	N
Rapach and Wohar (2002)	Level	A	EoP*	EoP*	EoP*	Nominal	N
Clarida et al. (2003)	Return	W	EoP*	EoP*	EoP*	Nominal	Y

Note: Papers whose "Forecast Target" are point-in-time sampled nominal bilateral exchange rates. "*" is used in cases where the paper did not provide information whether exchange rates are average or point sampled, and so point-in-time sampling was assumed. "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation. "EoP", "MoP", and "SoP" refer to end-, middle-, and start-of-period sampling, respectively.

Table B2: Summary of Literature Focusing on Point in Time Sampled Nominal Bilateral Exchange Rates, part 2/3

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Faust et al. (2003)	Return	Q	EoP	EoP	EoP	Nominal	Y
Qi and Wu (2003)	Level	M	EoP	EoP	EoP	Nominal	N
Rapach and Wohar (2004)	Both	Q	EoP*	EoP*	EoP*	Nominal	N
Abhyankar et al. (2005)	Return	M	EoP	EoP	EoP	Nominal	N
Cheung et al. (2005)	Both	Q	EoP	EoP	EoP	Nominal	N
Engel and West (2005)	Level	Q	EoP	EoP	EoP	Nominal	N
Evans and Lyons (2005)	Return	D	EoP	EoP	EoP	Nominal	N
Groen (2005)	Level	Q	EoP	EoP	EoP	Nominal	N
Rossi (2005)	Level	Q	EoP*	EoP*	EoP*	Nominal	N
Clark and West (2006)	Return	M	EoP	EoP	EoP	Nominal	N
Rossi (2006)	Return	M	EoP	EoP	EoP	Nominal	N
Moosa (2007)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Alquist and Chinn (2008)	Level	Q	EoP	EoP	EoP	Nominal	N
Engel et al. (2008)	Return	Q	EoP	EoP	EoP	Nominal	N
Adrian et al. (2009)	Return	M	EoP	EoP	EoP	Nominal	N
Della Corte et al. (2009)	Return	M	EoP*	EoP*	EoP*	Nominal	N
Sarno and Valente (2009)	Return	Q	EoP*	EoP*	EoP*	Nominal	Y
Wang and Wu (2009)	Return	M	EoP	EoP	EoP	Nominal	N
Altavilla and De Frauwe (2010)	Both	Q	EoP*	EoP*	EoP*	Nominal	N
Bacchetta et al. (2010)	Return	M	EoP	EoP	EoP	Nominal	N
Cerra and Saxena (2010)	Level	A	EoP	EoP	EoP	Nominal	N
Chen et al. (2010)	Return	Q	EoP	EoP	EoP	Nominal	N
Rime et al. (2010)	Return	D	EoP	EoP	EoP	Nominal	N
Li (2011)	Return	M	EoP	EoP	EoP	Nominal	N
Lopez-Suarez & Rodriguez-Lopez	Return	Q	EoP	EoP	EoP	Nominal	N
Molodtsova et al. (2011)	Return	Q	MoP	MoP	MoP	Nominal	Y
Pacelli et al. (2011)	Level	D	EoP*	EoP*	EoP*	Nominal	N
Rossi and Sekhposyan (2011)	Return	M	EoP	EoP	EoP	Nominal	N
Bianco et al. (2012)	Return	W	EoP	EoP	EoP	Nominal	N
Chinn and Moore (2012)	Return	M	EoP	EoP	EoP	Nominal	N
Della Corte et al. (2012)	Return	Q	EoP*	EoP*	EoP*	Nominal	Y
Molotsova and Papell (2012)	Return	Q	EoP	EoP	EoP	Nominal	Y
Rossi and Inoue (2012)	Level	M	EoP*	EoP*	EoP*	Nominal	N

Note: Papers whose "Forecast Target" are point-in-time sampled nominal bilateral exchange rates. "*" is used in cases where the paper did not provide information whether exchange rates are average or point sampled, and so point-in-time sampling was assumed. "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation. "EoP", "MoP", and "SoP" refer to end-, middle-, and start-of-period sampling, respectively.

Table B3: Summary of Literature Focusing on Point in Time Sampled Nominal Bilateral Exchange Rates, part 3/3

Paper	Level or Return	Frequency	Forecast Target	Benchmark	Model Estimation	Real or Nominal	Real-time
Wang and Wu (2012)	Return	M	EoP	EoP	EoP	Nominal	N
Bashar and Kabir (2013)	Level	Q	EoP*	EoP*	EoP*	Nominal	N
Chen and Tsang (2013)	Return	M	EoP	EoP	EoP	Nominal	N
Moosa and Burns (2013)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Morales-Arias and Moura (2013)	Return	M	EoP*	EoP*	EoP*	Nominal	N
Park and Park (2013)	Both	Q	EoP*	EoP*	EoP*	Nominal	N
Rossi (2013)	Both	M, Q	EoP*	EoP*	EoP*	Nominal	N
Berge (2014)	Return	M	EoP	EoP	EoP	Nominal	N
Garratt Mise (2014)	Return	Q	EoP	EoP	EoP	Nominal	N
Ince (2014)	Return	Q	EoP	EoP	EoP	Nominal	Y
Moosa and Burns (2014a)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Moosa and Burns (2014b)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Moosa and Burns (2014c)	Level	M	EoP*	EoP*	EoP*	Nominal	N
Engel et al. (2015)	Return	Q	EoP	EoP	EoP	Nominal	N
Ferraro et al. (2015)	Return	D	EoP	EoP	EoP	Nominal	Y
Ferraro et al. (2015)	Return	M	SoP	SoP	SoP	Nominal	Y
Ferraro et al. (2015)	Return	Q	MoP	MoP	MoP	Nominal	Y
Li et al. (2015)	Return	M	EoP	EoP	EoP	Nominal	N
Beckman and Schussler (2016)	Return	M	EoP	EoP	EoP	Nominal	Y
Byrne et al. (2016)	Return	Q	EoP	EoP	EoP	Nominal	N
Kohlscheen et al. (2016)	Return	D	EoP*	EoP*	EoP*	Nominal	Y
Zhang et al. (2016)	Return	D	EoP*	EoP*	EoP*	Nominal	N
Bryne et al. (2017)	Return	M	EoP	EoP	EoP	Nominal	N
Kouwenberg et al (2017)	Return	Q	EoP*	EoP*	EoP*	Nominal	Y
Cheung el al. (2018)	Both	Q	EoP	EoP	EoP	Nominal	N
Engel et al. (2019)	Return	M	EoP	EoP	EoP	Nominal	N
Kremens and Martins (2019)	Return	M	MoP	MoP	MoP	Nominal	N
Beckmann et al. (2020)	Return	M	EoP	EoP	EoP	Nominal	Y
Ca'Zorzi and Rubaszek (2020)	Return	M	EoP	EoP	EoP	Nominal	N
Bork et al. (2022)	Return	M	EoP	EoP	EoP	Nominal	N
Lilley et al. (2022)	Return	M	EoP*	EoP*	EoP*	Nominal	N
Liu and Shaliastovich (2022)	Return	M	EoP	EoP	EoP	Nominal	N
Engel and Wu (2023a)	Return	M	EoP	EoP	EoP	Nominal	N
Engel and Wu (2023b)	Return	M	EoP	EoP	EoP	Nominal	N

Note: Papers whose "Forecast Target" are point-in-time sampled nominal bilateral exchange rates. "*" is used in cases where the paper did not provide information whether exchange rates are average or point sampled, and so point-in-time sampling was assumed. "Benchmark" refers to the no-change forecast that the forecast was compared against. "Model Estimation" refers to the data used in estimation. "EoP", "MoP", and "SoP" refer to end-, middle-, and start-of-period sampling, respectively.

C Inputs into Bilateral RER and REER Calculations

Section 2 describes how we constructed real-time vintages of bilateral RERs and REERs. This appendix provides detail on each of the inputs into these calculations. I.e. Daily nominal exchange rates (NERs); daily consumer price index (CPI) levels; and trade weights.

C.1 Daily Nominal Exchange Rates

C.1.1 IMF Nominal Exchange Rates

We extracted daily NERs from an the IMF database 'Global Data Source'.[6] We extracted all of the series from the 'live' versions of IMF databases in October 2022. Earlier vintages were not available.

Table C1: IMF Data used as Inputs into EER Calculations

Indicator code	Indicator name	Units	Frequency	Earliest period	Latest period	Countries available
EDNA	Exchange rate for EER, period average	USD per national currency	Daily	1 Jan 1993	21 Oct 2022	165
Weights	Weights	Percent	Ocassional	1990-1995	2016-Latest	193

The EDNA data provides a single time series for each country. Where a country has adopted a new currency during the sample period, the exchange rates of the two currencies are spliced together so that EDNA does not contain a level shift when the new currency is adopted.[7]

C.1.2 Splicing on Eikon Nominal Exchange Rates

The IMF NERs start on 1 January 1993 for some countries, and later for others. For many countries, Eikon NERs are available from an earlier date. For many countries, we splice the Eikon NERs onto the IMF NERs, resulting in a longer time series of NERs, and increasing the estimation sample for our models.

We perform the splicing in stages.

1. For each country with an IMF NER, we guess the currency they used before the start of the IMF NERs. This is needed because each Eikon NER series refers to a currency, while each

[6] The Global Data Source database contains two similar series: EDNA and EDNA_EER. For some countries, EDNA_EER only reports exchange rates on trading days, and reports N/A on other days. EDNA reports rates on all days, because on weekends and public holidays it carries forward the observation from the last trading day. The two series are otherwise identical. We use EDNA_EER, but since we carry forward the observation from the last trading day this is equivalent to using EDNA.

[7] For example, the EDNA data contains a single series for Austria from 1 January 1993 onwards, even though Austria switched from the Austrian Schilling to the Euro on 1 January 1999. For days before the adoption of a new currency, EDNA reports the Schilling/USD exchange rate. From 1 January 1999, EDNA starts at the Schilling/USD rate and is then grown based on the euro/USD exchange rate. Splicing exchange rates in this way avoids a jump in EDNA, which avoids a jump in RERs or REERs.

IMF NER series refers to a country.

2. Check if Eikon has data on the currency of interest. This is not the case for some discontinued currencies.

3. Check if the Eikon NERs start earlier than the IMF NERs. This is not the case for currencies introduced relatively recently.

4. Check that the Eikon and IMF NERs are the same during any period when both series are available. If this were not the case, it would suggest that we have guessed the currency incorrectly, or that the Eikon and IMF NERs are not comparable for some other reason.

5. Splice the series if the previous checks are met. We use the IMF series on each day it is available, and the Eikon series otherwise.

Using the above process, we are able to splice Eikon and IMF NERs for 62 countries (Table C2).

Table C2: Countries where Splicing was Possible

Situation	Number.of.Countries
No splice as pre-1993 currency not guessed	55
No splice as Eikon lacks data on pre-1993 currency	13
No splice as Eikon NERs start no earlier than IMF NERs	35
No splice as Eikon and IMF differ on overlapping days	11
Splice made	51

To determine which exchange rate each country used before the start of the IMF data, we rely on the IMF exchange arrangements and exchange restrictions dataset. This dataset lists the currency that each currency used in each year as early as 1999. We assume that a country did not introduce a new currency before 1999 if it did not withdraw a currency before 2004. We allow for this 5-year gap between introducing and withdrawing a currency because countries sometimes introduce a new currency and withdraw the old one a few years later.[8] We determine if the country withdrew a currency before 2002 using the list of discontinued currencies that accompanies the ISO-4217 standard for currency codes.[9]

There are 11 countries where splicing was not possible because the Eikon and IMF NERs differ during an overlapping period. This check could, in principle, detect cases where the country's

[8]For example, the IMF exchange arrangements dataset lists France as using the euro in all years from 1999 onwards. If a gap was not allowed, one would erroneously conclude that France had not introduced any new currency before the end of 1999, and hence that before 1999 it had always used the currency the IMF lists it as using in 1999, which was the euro. Similarly, in 1998 Russia replaced the old Russian Ruble (ISO code RUR) with the new Russian Ruble (ISO code RUB), but the old Russian Ruble is listed as being withdrawn in 2004.

[9]`https://www.six-group.com/en/products-services/financial-information/data-standards.html`

currency has been guessed incorrectly. However, the series tend to be broadly similar, suggesting that the currency has been guessed correctly, but Eikon and IMF providing different exchange rates for the same currency, such as a black market rate versus an official rate.

C.2 Monthly Consumer Price Index Levels

C.2.1 World Bank Dataset of Monthly CPI Levels

The World Bank CPI dataset provides a variety of inflation measures for a large set of countries since 1970. We use the monthly headline CPI indexes. These are available for 171 countries in total, though individual countries drop in and out of the sample. The dataset is described in Ha et al. (2021). As the authors do not specify whether the data is seasonally adjusted, we assume that it is non-seasonally adjusted. As such, any seasonal pattern in the CPI index levels will translate into a seasonal pattern in the RERs. Our main estimates rely on these non-seasonally adjusted CPIs.

By restricting ourselves to the monthly dataset, we exclude countries for which only quarterly indexes are available. However, these tend to be the countries that also have shorter histories of nominal exchange rates, with the notable exceptions of Australia and New Zealand.

C.2.2 Constructing Real-time Vintages of Monthly CPIs

To determine the latest CPI outcomes known to forecasters at the time of their forecast. To determine this, we need to know the 'publication lag', which is the number of months it takes for the statistical agency to publish a country's CPI after the relevant month.

We estimate the publication lag using the World Bank dataset. Typically, the World Bank dataset reports the latest CPI outcome available when they compiled the dataset. We know the dataset was compiled in January 2023.[10] The latest month for which data is available varies by country (Table C3). For many countries, the latest observation is December 2022, so the publication lag is estimated to be 1 month. Similarly, for countries where the latest observation is November 2022, October 2022 or September 2022, we estimate the publication lag to be 2, 3 or 4 months respectively.

There are some countries where the latest observation is even earlier than September 2022. Taken at face value, this suggest a publication lag of 5 months or more, which seems implausible. In some of these countries, such as Ghana, the latest observation in the World Bank dataset is not actually the latest outcome published by the statistical agency. In other countries, such as

[10] We use the January 2023 vintage of the dataset. The webpage for the dataset says it was last updated on 2 February 2023. Either the dataset was made available on this date, or it was made available slightly earlier than the webpage was updated in some other way on 2 February 2023.

Afghanistan, the statistical agency has suspended its CPI. This means the latest observation is far in the past, but prior to the suspension of the CPI series, the publication lag may have been much shorter. We take the pragmatic approach of setting the publication lag to 4 months wherever the latest observation was before September 2022.

Table C3: World Bank Monthly CPI Dataset

Latest Observation	Number of Countries	Apparent Publication Lag
Dec 2022	60	1
Nov 2022	36	2
Oct 2022	13	3
Sep 2022	18	4
Earlier	44	5

To construct the real-time CPI vintages for a country, we extract subsets of the latest vintage of CPI outcomes using our estimated publication lag. Each CPI vintage is intended to contain the data available at the end of a specified month. For example, the July 2020 vintage of Belarusian CPI is intended to contain Belarusian CPI available at the end of July 2020. Since Belarus's publication lag is 2 months, we make this vintage by extracting Belarusian CPI levels up to May 2020.

Instead of constructing our own real-time vintages from World Bank data, we could have used the real-time vintages of the OECD's Main Economic Indicators, both those provided on the OECD website and those compiled by the Dallas Fed. This would avoid the need to estimate the publication lags, removing one source of error in our estimates. We decided against this for two reasons. Firstly, some vintages are missing.[11] Second, the OECD vintages are only available for 35 countries, most of which use the Euro or have a floating exchange rate, limiting our ability to evaluate forecasts for real exchange rates governed by other exchange rate regimes.

C.2.3 Extrapolating Monthly CPI Levels

The CPI vintage for a particular month contains the data available at the end of that month. We will use that CPI vintage to compute an RER up to the end of the month. Hence, we need to extrapolate the CPI data from the latest observation to the end of the specified month. For example, given the July 2020 Belarusian vintage, we need to extrapolate from the latest observation of May 2020 to the end of July 2020. The number of months by which we need to extrapolate the series is the publication lag, so it varies from 1 to 4 months depending on the country.

[11] The Dallas Fed provides vintages up to Q4 1998, while the OECD website provides vintages from January 2000 onwards, so neither provides vintages for 1999. Additionally, the vintages that the OECD website lists as relating to April 2021, January 2020 and August 2017 are actually duplicates of the vintages for other months.

Our approach is to use linear extrapolation. i.e. We compute the rate of change for the log CPI from the second-latest month to the latest month, and then extrapolate that forward as far as needed. Since this interpolation does not affect the actual outcomes, just the inputs we provide to our forecasting methods, the quality of our approach to extrapolation should ultimately be judged by the performance of the forecasts.

C.3 Trade Weights

An effective exchange rate of a country aggregates together information about that country's trading partners. To do this, we need weights that each country places on its trading partners. We use the trade weights produced by the IMF.[12] The IMF has published eight sets of weights, each referring to a different time period, ranging from 1979-1989 to 2016-2018 (Table C4). The weights are available for almost all countries. For a given reporting country (i.e. the country whose EER is being calculated), the number of partners with weights varies. For example, in 1979-1989, China has weights for 20 partners, while Iraq only has weights for 11 partners. We use the IMF weights because they cover a longer time period and a larger number of countries than alterantive sources of weights, such as those published by the BIS. The IMF's method for computing these weights is described in Bayoumi et al. (2006).

Table C4: Descriptive Statistics for IMF Weights

Period	Number of reporting countries	Average number of partner countries
1979-1989	155	18
1990-1995	187	17
1996-2003	187	20
2004-2006	190	30
2007-2009	191	31
2010-2012	192	24
2013-2015	192	27
2016-2018	192	29

When constructing real-time vintages of REERs, we assume that the set of trade weights for a period only become available with a 5 year delay. Historically, the delay between the end of a weight reference period and the IMF publishing new weights has varied over time. We assume a 5 year delay to approximate the IMF's current practice. For example, the January 2000 vintage is the first to have access to the 1990-1995 weights.[13] As the weights are published with a lag, the

[12] These weights are contained in two internal databases: the information notice system (INS) and global data source (GDS).

[13] The aim of our paper is to provide evidence on how useful different methods of temporal aggregation would be if adopted today. For that purpose it is better to provide the forecasting models with data that mimics the delays

REERs for the latest days must be calculated with the weights for an earlier period. For example, in the January 2022 vintage, the daily REERs from 1 January 2019 to 31 January 2022 must be computed with the 2016-2018 weights, as these are the latest available at the time.[14]

Ideally, our real-time vintages of REERs would not only account for the fact that each set of weights to be published with a lag, but would also account for the fact that a given set of weights are revised over time. For example, in March 2019 the IMF revised the weights for 2004-2006, which had been published some time ago.[15]. Unfortunately, previous vintages of weights are not available, so it is not possible to account for this.

Although our real-time vintages of REERs take into account the tendency of the IMF to publish weights with a lag, they don't take into account the tendency of the IMF to revise the weights over time.

we expect to see in the future, which is achieved by choosing a 5 year delay. If we instead constructed the vintages using the longer delays that were used historically, our results would be less informative to forecasters choosing a temporal aggregation method today.

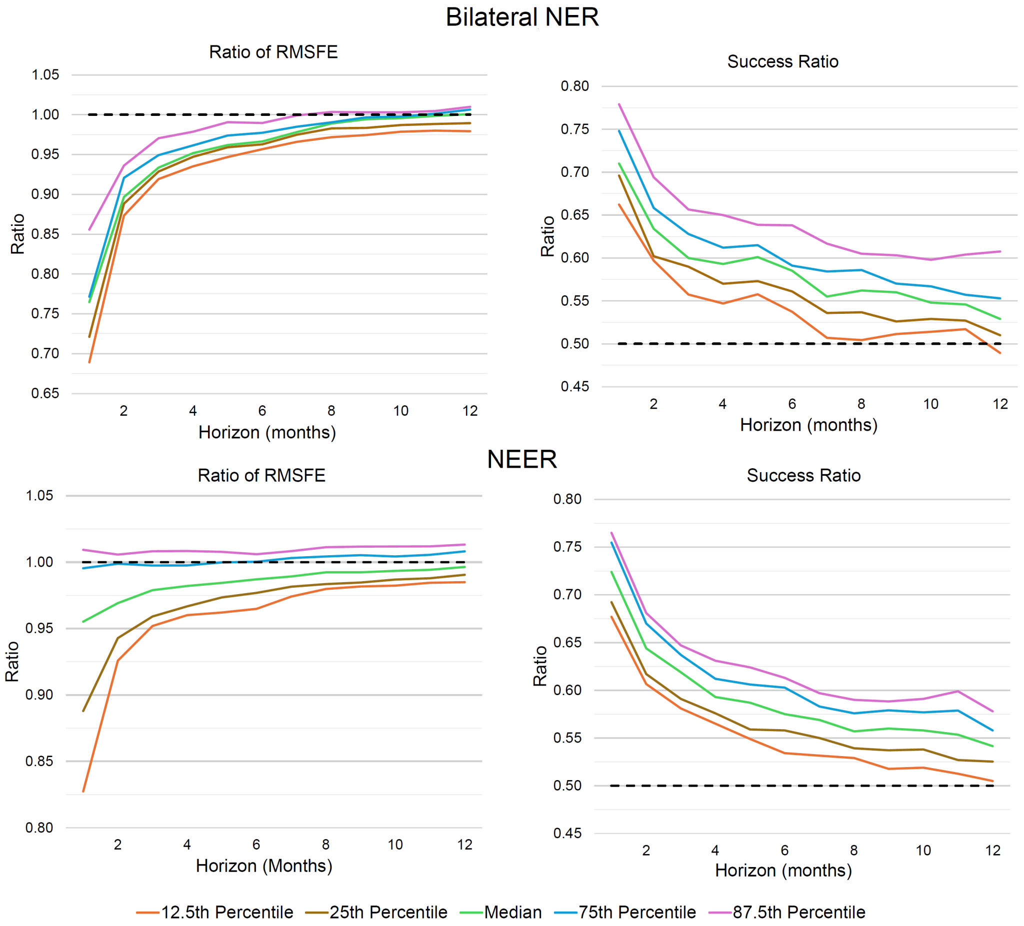
[14]The IMF follows the same practice. For this reason, they refer to the '2016-2018' weights as the '2016-Latest' weights. We use the term '2016-2018' weights to emphasise that these weights are based only on trade data for these three years, and will eventually be followed by weights for later periods, such as '2019-2021'.

[15]https://www.imf.org/en/News/Articles/2019/03/26/pr1993-the-imf-updates-the-effective-exchange-rates-indices

D Real-time Forecast Accuracy for Other Exchange Rates

D.1 No-Change Forecasts

Figure D1: Distribution of Forecast Performance of End-of-Month Versus Monthly Average Forecasts



Note: Plot shows quantiles for 83 countries. Relative to period average no-change forecast.

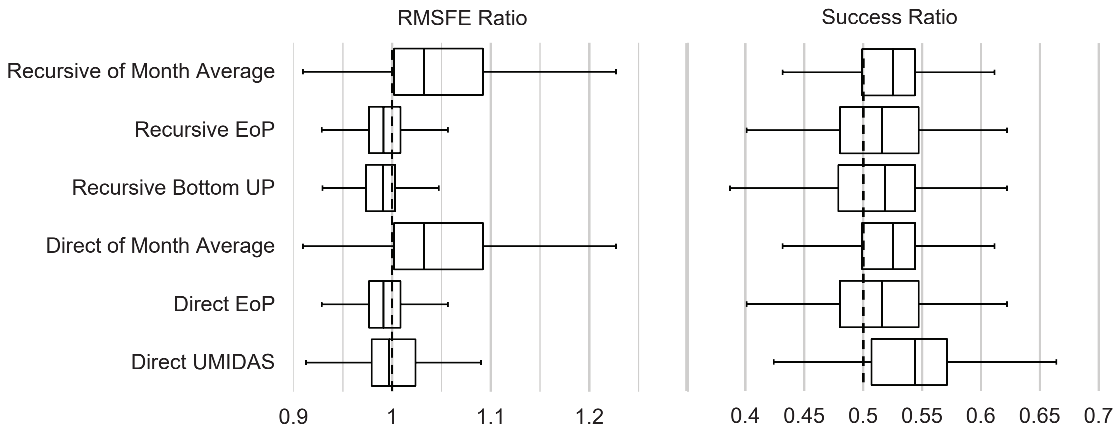
D.2 Model-Based Forecasts

Table D1: Median Monthly Average Real Effective Exchange Rate Forecasts

Forecast	Model Inputs	1	3	6	12	24	36
				RMSFE Ratio			
Recursive	Month-Average	1.00	0.99	0.99	1.00	1.01	1.02
Recursive	End-of-Month	0.96	0.98	0.98	1.01	1.02	1.01
Recursive	Bottom-up	0.95	0.97	0.99	1.03	1.04	1.04
Direct	Month-Average	1.00	0.98	0.99	0.99	1.03	1.09
Direct	End-of-Month	0.96	0.97	0.98	0.99	1.04	1.10
Direct	UMIDAS	0.97	0.97	0.98	0.99	1.03	1.09
				Success Ratio			
Recursive	Month-Average	0.51	0.51	0.51	0.53	0.56	0.54
Recursive	End-of-Month	0.68	0.57	0.54	0.54	0.57	0.55
Recursive	Bottom-up	0.67	0.57	0.53	0.52	0.56	0.53
Direct	Month-Average	0.51	0.51	0.52	0.53	0.56	0.54
Direct	End-of-Month	0.68	0.57	0.54	0.53	0.56	0.53
Direct	UMIDAS	0.69	0.58	0.54	0.54	0.56	0.53

Note: Reports the median across relative to the monthly average no-change forecast. Note, "end-of-period" inputs in model estimation and uses the end-of-month point forecast as the forecast of the monthly average. Recursive and daily is an example of the bottom-up approach. Direct forecasts use UMIDAS restricted to the end-of-month observation.

Figure D2: Accuracy of 1-month-ahead Forecasts for REER relative to End-of-month No-change Benchmark



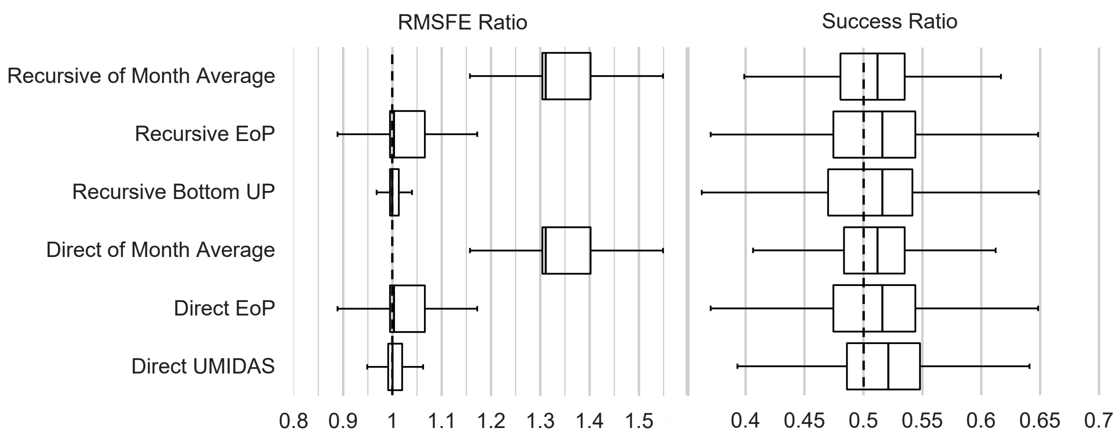
Note: Outliers have been omitted.

Table D2: Median Monthly Average Nominal Bilateral Exchange Rate Forecasts

Forecast	Model Inputs	1	3	6	12	24	36
				RMSFE Ratio			
Recursive	Month-Average	1.00	1.01	1.01	1.02	1.05	1.07
Recursive	End-of-Month	0.77	0.95	0.99	1.02	1.03	1.07
Recursive	Bottom-up	0.76	0.95	0.98	1.01	1.02	1.06
Direct	Month-Average	1.00	1.01	1.01	1.02	1.08	1.32
Direct	End-of-Month	0.77	0.95	0.98	1.00	1.07	1.31
Direct	UMIDAS	0.76	0.95	0.98	1.00	1.07	1.31
				Success Ratio			
Recursive	Month-Average	0.51	0.45	0.47	0.50	0.57	0.57
Recursive	End-of-Month	0.70	0.56	0.53	0.51	0.56	0.58
Recursive	Bottom-up	0.69	0.57	0.52	0.51	0.52	0.55
Direct	Month-Average	0.51	0.45	0.48	0.51	0.57	0.56
Direct	End-of-Month	0.69	0.57	0.52	0.53	0.57	0.57
Direct	UMIDAS	0.69	0.58	0.53	0.53	0.58	0.57

Note: Reports the median across relative to the monthly average no-change forecast. Note, "end-of-period" inputs in model estimation and uses the end-of-month point forecast as the forecast of the monthly average. Recursive and daily is an example of the bottom-up approach. Direct forecasts use UMIDAS restricted to the end-of-month observation.

Figure D3: Accuracy of 1-month-ahead Forecasts for Bilateral NER relative to End-of-month No-change Benchmark



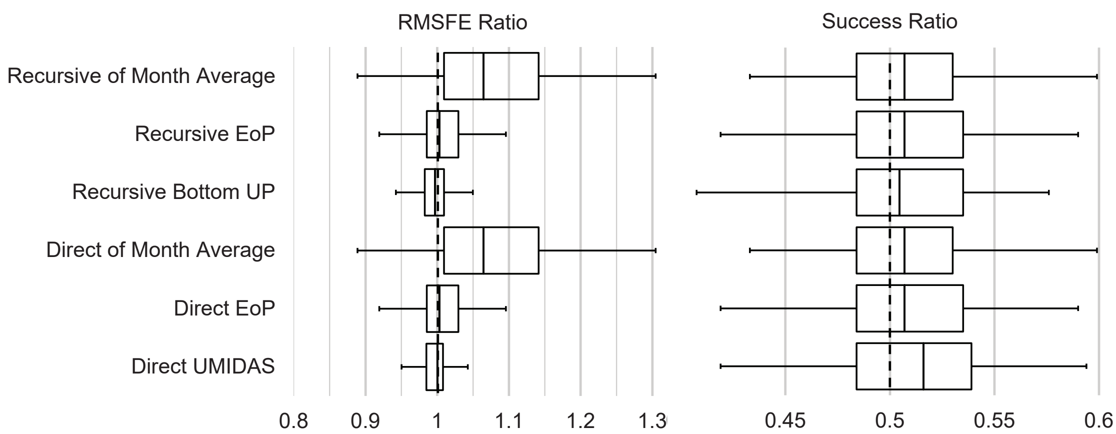
Note: Outliers have been omitted.

Table D3: Median Monthly Average Nominal Effective Exchange Rate Forecasts

Forecast	Model Inputs	1	3	6	12	24	36
				RMSFE Ratio			
Recursive	Month-Average	1.00	1.01	1.02	1.05	1.12	1.15
Recursive	End-of-Month	0.95	0.99	1.01	1.04	1.10	1.11
Recursive	Bottom-up	0.95	0.99	1.04	1.07	1.13	1.14
Direct	Month-Average	1.00	1.01	1.03	1.06	1.14	1.20
Direct	End-of-Month	0.95	0.99	1.01	1.06	1.14	1.21
Direct	UMIDAS	0.95	0.98	1.01	1.06	1.14	1.19
				Success Ratio			
Recursive	Month-Average	0.50	0.49	0.49	0.50	0.51	0.49
Recursive	End-of-Month	0.69	0.57	0.53	0.53	0.51	0.48
Recursive	Bottom-up	0.70	0.56	0.52	0.52	0.50	0.48
Direct	Month-Average	0.50	0.50	0.50	0.52	0.51	0.47
Direct	End-of-Month	0.69	0.57	0.53	0.52	0.51	0.47
Direct	UMIDAS	0.71	0.57	0.53	0.52	0.51	0.48

Note: Reports the median across relative to the monthly average no-change forecast. Note, "end-of-period" inputs in model estimation and uses the end-of-month point forecast as the forecast of the monthly average. Recursive and daily is an example of the bottom-up approach. Direct forecasts use UMIDAS restricted to the end-of-month observation.

Figure D4: Accuracy of 1-month-ahead Forecasts for NEER relative to End-of-month No-change Benchmark



Note: Outliers have been omitted.

E Robustness: Countries with Flexible Exchange Rates

Table E4: Median Performance of End-of-Month No-change Forecasts Versus Monthly Average No-Change Forecasts, Countries with Flexible Exchange Rates

Months Ahead	1	3	6	12	24	36
Measure			RMSFE Ratio			
Random-Walk	0.73	0.94	0.97	0.99	0.99	1.00
NER	0.76	0.93	0.97	1.00	1.00	1.00
NEER	0.93	0.98	0.98	0.99	0.99	1.00
RER	0.83	0.95	0.97	1.00	1.00	1.00
REER	0.94	0.97	0.99	1.00	1.00	1.00
			Success Ratio			
Random-Walk	0.74	0.61	0.58	0.55	0.54	0.53
NER	0.72	0.60	0.59	0.53	0.54	0.50
NEER	0.72	0.60	0.57	0.55	0.55	0.51
RER	0.71	0.60	0.57	0.54	0.52	0.49
REER	0.71	0.59	0.54	0.54	0.54	0.53

Note: Forecast accuracy of end-of-month no-change forecast versus monthly average no-change forecast. Countries with floating exchange rates are defined following Ilzetzki et al. (2019). Reports the median across countries. "Random Walk" is simulated using 5000 iterations and 30 years of data. Values of the RMSFE ratio less than one improve upon the monthly average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance.

Table E5: Percent of Flexible Exchange Rate Countries with Significant One-Month Ahead Exchange Rate Forecasts

		Versus End-of-Month No-change				Versus Monthly Average No-change			
Forecast	Model-Inputs	REER	RER	NEER	NER	REER	RER	NEER	NER
					Mean-Square Accuracy				
Recursive	Month-Average	0%	0%	0%	0%	33%	0%	22%	0%
Recursive	End-of-Month	44%	25%	22%	0%	56%	100%	78%	100%
Recursive	Bottom-up	33%	38%	22%	0%	67%	100%	78%	100%
Direct	Month-Average	0%	0%	0%	0%	33%	0%	22%	0%
Direct	End-of-Month	44%	25%	22%	0%	56%	100%	67%	100%
Direct	UMIDAS	33%	13%	22%	0%	78%	100%	67%	100%
					Directional Accuracy				
Recursive	Month-Average	22%	38%	22%	0%	22%	13%	25%	0%
Recursive	End-of-Month	22%	25%	33%	14%	100%	100%	100%	100%
Recursive	Bottom-up	11%	25%	33%	0%	100%	100%	100%	100%
Direct	Month-Average	22%	38%	0%	0%	22%	13%	25%	0%
Direct	End-of-Month	22%	25%	33%	14%	100%	100%	78%	100%
Direct	UMIDAS	25%	17%	11%	33%	100%	100%	100%	100%

Note: Reports the share of countries where the forecast model is significant at the five percent level by the end of the forecast evaluation sample. Countries with floating exchange rates are defined following Ilzetzki et al. (2019). Note, "end-of-month" inputs in model estimation use the end-of-month point forecast as the forecast of the monthly average. Recursive and daily uses the bottom-up approach. Direct forecasts use UMIDAS restricted to the end-of-month observation.

F Robustness: Model-Based Forecast Assumptions[16]

Table F6: Median Monthly Average Real Bilateral ER Forecasts, Alternative Model Assumptions

Forecast	Model Inputs	1	3	6	12	24	36
				RMSFE Ratio			
Recursive	Month-Average	1.01	1.01	1.02	1.03	1.06	1.08
Recursive	End-of-Month	0.89	0.97	0.99	1.02	1.04	1.07
Recursive	Bottom-up	0.88	0.96	0.99	1.01	1.01	1.03
Direct	Month-Average	1.02	1.01	1.01	1.03	1.07	1.24
Direct	End-of-Month	0.88	0.97	0.99	1.01	1.07	1.24
Direct	UMIDAS	0.88	0.96	0.99	1.01	1.07	1.24
				Success Ratio			
Recursive	Month-Average	0.56	0.52	0.51	0.49	0.54	0.52
Recursive	End-of-Month	0.68	0.59	0.54	0.52	0.57	0.54
Recursive	Bottom-up	0.68	0.57	0.54	0.52	0.59	0.57
Direct	Month-Average	0.56	0.51	0.51	0.50	0.55	0.54
Direct	End-of-Month	0.68	0.57	0.53	0.52	0.56	0.54
Direct	UMIDAS	0.68	0.57	0.54	0.52	0.56	0.54

Note: Reports the median across relative to the monthly average no-change forecast. Note, "end-of-period" inputs in model estimation and uses the end-of-month point forecast as the forecast of the monthly average. Direct forecasts use UMIDAS. Recursive and daily is an example of the bottom-up approach.

Table F7: Percent of Flexible Exchange Rate Countries with Significant One-Month Ahead Exchange Rate Forecasts, Alternative Model Assumptions

		Versus End-of-Month No-change				Versus Monthly Average No-change			
Forecast	Model-Inputs	REER	RER	NEER	NER	REER	RER	NEER	NER
					Mean-Square Accuracy				
Recursive	Month-Average	9%	3%	9%	3%	18%	6%	25%	26%
Recursive	End-of-Month	45%	15%	26%	1%	58%	73%	54%	87%
Recursive	Bottom-up	59%	32%	43%	4%	68%	82%	63%	96%
Direct	Month-Average	8%	0%	8%	0%	14%	4%	19%	20%
Direct	End-of-Month	44%	9%	24%	0%	55%	73%	46%	75%
Direct	UMIDAS	38%	8%	24%	0%	51%	76%	55%	84%
					Directional Accuracy				
Recursive	Month-Average	14%	14%	11%	14%	48%	62%	51%	69%
Recursive	End-of-Month	15%	10%	19%	10%	98%	89%	100%	100%
Recursive	Bottom-up	28%	20%	34%	32%	99%	89%	100%	100%
Direct	Month-Average	14%	13%	10%	11%	41%	51%	43%	58%
Direct	End-of-Month	18%	6%	16%	8%	98%	87%	99%	95%
Direct	UMIDAS	38%	14%	16%	12%	100%	88%	99%	95%

Note: Reports the share of countries where the forecast model is significant at the five percent level by the end of the forecast evaluation sample. Note, "end-of-month" inputs in model estimation use the end-of-month point forecast as the forecast of the monthly average. Direct forecasts use UMIDAS. Recursive and daily uses the bottom-up approach.

[16]Both the maximum likelihood used in the automatic ARIMA procedure of Hyndman et al. (2022), and non-linear least squared used for the restricted MIDAS functions (Ghysels et al., 2007) exhibited convergence failure rates that differed by exchange rate measure and forecast method. To show consistent forecast samples, we report the pre-sample testing for order of integration and the number of lagged terms on the right-hand side of equations 5–10. Additional estimates can be made available upon request.

G Papers Surveyed

Abbate, A. and Marcellino, M. (2018). Point, interval and density forecasts of exchange rates with time varying parameter models. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 181(1):155–179.

Abhyankar, A., Sarno, L., and Valente, G. (2005). Exchange rates and fundamentals: evidence on the economic value of predictability. *Journal of International Economics*, 66(2):325–348.

Adrian, T., Etula, E., and Shin, H. S. (2010). Risk appetite and exchange rates. *FRB of New York Staff Report*, (361).

Alquist, R. and Chinn, M. D. (2008). Conventional and unconventional approaches to exchange rate modelling and assessment. *International Journal of Finance & Economics*, 13(1):2–13.

Altavilla, C. and De Grauwe, P. (2010). Forecasting and combining competing models of exchange rate determination. *Applied Economics*, 42(27):3455–3480.

Amano, R. A. and Van Norden, S. (1995). Terms of trade and real exchange rates: the Canadian evidence. *Journal of International Money and Finance*, 14(1):83–104.

Amano, R. A. and Van Norden, S. (1998a). Exchange rates and oil prices. *Review of International Economics*, 6(4):683–694.

Amano, R. A. and Van Norden, S. (1998b). Oil prices and the rise and fall of the US real exchange rate. *Journal of International Money and Finance*, 17(2):299–316.

Bacchetta, P., Van Wincoop, E., and Beutler, T. (2010). Can parameter instability explain the Meese-Rogoff puzzle? In *NBER International Seminar on Macroeconomics*, volume 6, pages 125–173. The University of Chicago Press Chicago, IL.

Backus, D. (1984). Empirical models of the exchange rate: separating the wheat from the chaff. *Canadian Journal of Economics*, 17(4):824–846.

Bashar, O. and Kabir, S. H. (2013). Relationship between commodity prices and exchange rate in light of global financial crisis: evidence from Australia. *International Journal of Trade, Economics and Finance*, 4(5):265–269.

Beckmann, J., Koop, G., Korobilis, D., and Schüssler, R. A. (2020). Exchange rate predictability and dynamic Bayesian learning. *Journal of Applied Econometrics*, 35(4):410–421.

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

Berge, T. J. (2014). Forecasting disconnected exchange rates. *Journal of Applied Econometrics*, 29(5):713–735.

Bergin, P. R. (2003). Putting the 'new open economy macroeconomics' to a test. *Journal of International Economics*, 60(1):3–34.

Berkowitz, J. and Giorgianni, L. (2001). Long-horizon exchange rate predictability? *Review of Economics and Statistics*, 83(1):81–91.

Bianco, Dal, M., Camacho, M., and Quiros, G. P. (2012). Short-run forecasting of the euro-dollar exchange rate with economic fundamentals. *Journal of International Money and Finance*, 31(2):377–396.

Boothe, P. and Glassman, D. (1987). Comparing exchange rate forecasting models: Accuracy versus profitability. *International Journal of forecasting*, 3(1):65–79.

Bork, L., Kaltwasser, P. R., and Sercu, P. (2022). Aggregation bias in tests of the commodity currency hypothesis. *Journal of Banking & Finance*, 135:106392.

Boughton, J. M. (1987). Tests of the performance of reduced-form exchange rate models. *Journal of International Economics*, 23(1-2):41–56.

Byrne, J. P., Korobilis, D., and Ribeiro, P. J. (2016). Exchange rate predictability in a changing world. *Journal of International Money and Finance*, 62:1–24.

Byrne, J. P., Korobilis, D., and Ribeiro, P. J. (2018). On the sources of uncertainty in exchange rate predictability. *International Economic Review*, 59(1):329–357.

Canova, F. (1993). Modelling and forecasting exchange rates with a Bayesian time-varying coefficient model. *Journal of Economic Dynamics and Control*, 17(1-2):233–261.

Carriero, A., Kapetanios, G., and Marcellino, M. (2009). Forecasting exchange rates with a large Bayesian VAR. *International Journal of Forecasting*, 25(2):400–417.

Ca'Zorzi, M., Cap, A., Mijakovic, A., and Rubaszek, M. (2022). The reliability of equilibrium exchange rate models: A forecasting perspective. *International Journal of Central Banking*, 18(3):229–280.

Ca'Zorzi, M., Kolasa, M., and Rubaszek, M. (2017). Exchange rate forecasting with DSGE models. *Journal of International Economics*, 107:127–146.

Ca'Zorzi, M., Muck, J., and Rubaszek, M. (2016). Real exchange rate forecasting and PPP: This time the random walk loses. *Open Economies Review*, 27:585–609.

Ca'Zorzi, M. and Rubaszek, M. (2020). Exchange rate forecasting on a napkin. *Journal of International Money and Finance*, 104:102168.

Cerra, V. and Saxena, S. C. (2010). The monetary model strikes back: Evidence from the world. *Journal of International Economics*, 81(2):184–196.

Chen, S. and Chen, H. (2007). Oil prices and real exchange rates. *Energy Economics*, 29(3):390–404.

Chen, S., Jackson, J. D., Kim, H., and Resiandini, P. (2014). What drives commodity prices? *American Journal of Agricultural Economics*, 96(5):1455–1468.

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

Chen, Y., Rogoff, K. S., and Rossi, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics*, 125(3):1145–1194.

Chen, Y. and Tsang, K. P. (2013). What does the yield curve tell us about exchange rate predictability? *Review of Economics and Statistics*, 95(1):185–205.

Cheung, Y., Chinn, M. D., and Pascual, A. G. (2005). Empirical exchange rate models of the nineties: Are any fit to survive? *Journal of International Money and Finance*, 24(7):1150–1175.

Cheung, Y., Chinn, M. D., Pascual, A. G., and Zhang, Y. (2019). Exchange rate prediction redux: New models, new data, new currencies. *Journal of International Money and Finance*, 95:332–362.

Chinn, M. D. (1991). Some linear and nonlinear thoughts on exchange rates. *Journal of International Money and Finance*, 10(2):214–230.

Chinn, M. D. and Meese, R. A. (1995). Banking on currency forecasts: how predictable is change in money? *Journal of International Economics*, 38(1-2):161–178.

Chinn, M. D. and Moore, M. J. (2011). Order flow and the monetary model of exchange rates: Evidence from a novel data set. *Journal of Money, Credit and Banking*, 43(8):1599–1624.

Clarida, R. H., Sarno, L., Taylor, M. P., and Valente, G. (2003). The out-of-sample success of term structure models as exchange rate predictors: a step beyond. *Journal of International Economics*, 60(1):61–83.

Clarida, R. H. and Taylor, M. P. (1997). The term structure of forward exchange premiums and the forecastability of spot exchange rates: correcting the errors. *Review of Economics and Statistics*, 79(3):353–361.

Clark, T. E. and West, K. D. (2006). Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. *Journal of Econometrics*, 135(1-2):155–186.

Clements, K. W. and Fry, R. (2008). Commodity currencies and currency commodities. *Resources Policy*, 33(2):55–73.

Clements, M. P. and Smith, J. (2001). Evaluating forecasts from setar models of exchange rates. *Journal of International Money and Finance*, 20(1):133–148.

Della Corte, P., Sarno, L., and Sestieri, G. (2012). The predictive information content of external imbalances for exchange rate returns: How much is it worth? *Review of Economics and Statistics*, 94(1):100–115.

Della Corte, P., Sarno, L., and Tsiakas, I. (2009). An economic evaluation of empirical exchange rate models. *The Review of Financial Studies*, 22(9):3491–3530.

Diebold, F. X., Gardeazabal, J., and Yilmaz, K. (1994). On cointegration and exchange rate dynamics. *The Journal of Finance*, 49(2):727–735.

Diebold, F. X. and Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3):253–263.

Diebold, F. X. and Nason, J. A. (1990). Nonparametric exchange rate prediction? *Journal of International Economics*, 28(3-4):315–332.

Edwards, S. (1983). Floating exchange rates, expectations and new information. *Journal of Monetary Economics*, 11(3):321–336.

Eichenbaum, M. S., Johannsen, B. K., and Rebelo, S. T. (2021). Monetary policy and the predictability of nominal exchange rates. *The Review of Economic Studies*, 88(1):192–228.

Engel, C. (1994). Can the markov switching model forecast exchange rates? *Journal of International Economics*, 36(1-2):151–165.

Engel, C., Lee, D., Liu, C., Liu, C., and Wu, S. P. Y. (2019). The uncovered interest parity puzzle, exchange rate forecasting, and taylor rules. *Journal of International Money and Finance*, 95:317–331.

Engel, C., Mark, N. C., and West, K. D. (2007). Exchange rate models are not as bad as you think. *NBER Macroeconomics Annual*, 22:381–473.

Engel, C., Mark, N. C., and West, K. D. (2015). Factor model forecasts of exchange rates. *Econometric Reviews*, 34(1-2):32–55.

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

Engel, C. and West, K. D. (2006). Taylor rules and the Deutschmark: Dollar real exchange rate. *Journal of Money, Credit and Banking*, 38(5):1175–1194.

Engel, C. and Wu, S. P. Y. (2023). Liquidity and exchange rates: An empirical investigation. *The Review of Economic Studies*, 90(5):2395–2438.

Engle, C. and Hamilton, J. D. (1990). Long swings in the dollar: Are they in the data and do markets know it? *American Economic Review*, 80(4):689–713.

Evans, M. D. D. and Lyons, R. K. (2005). Meese-rogoff redux: Micro-based exchange-rate forecasting. *American Economic Review*, 95(2):405–414.

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

Faust, J., Rogers, J. H., and Wright, J. H. (2003). Exchange rate forecasting: the errors we've really made. *Journal of International Economics*, 60(1):35–59.

Ferraro, D., Rogoff, K., and Rossi, B. (2015). Can oil prices forecast exchange rates? an empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance*, 54:116–141.

Fratzscher, M., Rime, D., Sarno, L., and Zinna, G. (2015). The scapegoat theory of exchange rates: the first tests. *Journal of Monetary Economics*, 70:1–21.

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

Fullerton, T. M., Hattori, M., and Calderón, C. (2001). Error correction exchange rate modeling: evidence for Mexico. *Journal of Economics and Finance*, 25(3):358–368.

Garratt, A. and Mise, E. (2014). Forecasting exchange rates using panel model and model averaging. *Economic Modelling*, 37:32–40.

Giacomini, R. and Rossi, B. (2010). Forecast comparisons in unstable environments. *Journal of Applied Econometrics*, 25(4):595–620.

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

Groen, J. J. (1999). Long horizon predictability of exchange rates: Is it for real? *Empirical Economics*, 24:451–469.

Groen, J. J. (2005). Exchange rate predictability and monetary fundamentals in a small multi-country panel. *Journal of Money, Credit and Banking*, pages 495–516.

Harvey, J. T. (2005). Post keynesian versus neoclassical explanations of exchange rate movements: a short look at the long run. *Journal of Post Keynesian Economics*, 28(2):161–179.

Hatzinikolaou, D. and Polasek, M. (2005). The commodity-currency view of the australian dollar: a multivariate cointegration approach. *Journal of Applied Economics*, 8(1):81–99.

Hodrick, R. J. (1989). Risk, uncertainty, and exchange rates. *Journal of Monetary Economics*, 23(3):433–459.

Hooper, P. and Morton, J. (1982). Fluctuations in the dollar: A model of nominal and real exchange rate determination. *Journal of International Money and Finance*, 1:39–56.

Hwang, J.-K. (2001). Dynamic forecasting of monetary exchange rate models: evidence from cointegration. *International Advances in Economic Research*, 7(1):51–64.

Ince, O. (2014). Forecasting exchange rates out-of-sample with panel methods and real-time data. *Journal of International Money and Finance*, 43:1–18.

Islam, M. F. and Hasan, M. S. (2006). The monetary model of the dollar-yen exchange rate determination: A cointegration approach. *International Journal of Business and Economics*, 5(2):129.

Issa, R., Lafrance, R., and Murray, J. (2008). The turning black tide: energy prices and the canadian dollar. *Canadian Journal of Economics*, 41(3):737–759.

Jorion, P. and Sweeney, R. J. (1996). Mean reversion in real exchange rates: evidence and implications for forecasting. *Journal of International Money and Finance*, 15(4):535–550.

Kilian, L. (1999). Exchange rates and monetary fundamentals: what do we learn from long-horizon regressions? *Journal of Applied Econometrics*, 14(5):491–510.

Kilian, L. and Taylor, M. P. (2003). Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics*, 60(1):85–107.

Kohlscheen, E., Avalos, F. H., and Schrimpf, A. (2017). When the walk is not random: commodity prices and exchange rates. *International Journal of Central Banking*, 13(2):121–158.

Kouwenberg, R., Markiewicz, A., Verhoeks, R., and Zwinkels, R. C. (2017). Model uncertainty and exchange rate forecasting. *Journal of Financial and Quantitative Analysis*, 52(1):341–363.

Kräger, H. and Kugler, P. (1993). Non-linearities in foreign exchange markets: a different perspective. *Journal of International Money and Finance*, 12(2):195–208.

Kremens, L. and Martin, I. (2019). The quanto theory of exchange rates. *American Economic Review*, 109(3):810–843.

Li, J., Tsiakas, I., and Wang, W. (2015). Predicting exchange rates out of sample: Can economic fundamentals beat the random walk? *Journal of Financial Econometrics*, 13(2):293–341.

Lilley, A., Maggiori, M., Neiman, B., and Schreger, J. (2022). Exchange rate reconnect. *Review of Economics and Statistics*, 104(4):845–855.

Liu, Y. and Shaliastovich, I. (2022). Government policy approval and exchange rates. *Journal of Financial Economics*, 143(1):303–331.

Lopez-Suarez, C. F. and Rodriguez-Lopez, J. A. (2011). Nonlinear exchange rate predictability. *Journal of International Money and Finance*, 30(5):877–895.

MacDonald, R. (1998). What determines real exchange rates?: The long and the short of it. *Journal of International Financial Markets, Institutions and Money*, 8(2):117–153.

MacDonald, R. and Taylor, M. P. (1993). The monetary approach to the exchange rate: rational expectations, long-run equilibrium, and forecasting. *Staff Papers*, 40(1):89–107.

MacDonald, R. and Taylor, M. P. (1994). The monetary model of the exchange rate: long-run relationships, short-run dynamics and how to beat a random walk. *Journal of international money and finance*, 13(3):276–290.

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

Mark, N. C. and Sul, D. (2001). Nominal exchange rates and monetary fundamentals: evidence from a small post-bretton woods panel. *Journal of International Economics*, 53(1):29–52.

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

Meese, R. A. and Rogoff, K. (1983b). The out-of-sample failure of empirical exchange rate models: sampling error or misspecification? In *Exchange rates and international macroeconomics*, pages 67–112. University of Chicago Press.

Meese, R. A. and Rogoff, K. (1988). Was it real? the exchange rate-interest differential relation over the modern floating-rate period. *Journal of Finance*, 43(4):933–948.

Meese, R. A. and Rose, A. K. (1991). An empirical assessment of non-linearities in models of exchange rate determination. *The Review of Economic Studies*, 58(3):603–619.

Mizrach, B. (1992). Multivariate nearest-neighbour forecasts of EMS exchange rates. *Journal of Applied Econometrics*, 7(S1):S151–S163.

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. *Journal of Monetary Economics*, 55:S63–S79.

Molodtsova, T., Nikolsko-Rzhevskyy, A., and Papell, D. H. (2011). Taylor rules and the euro. *Journal of Money, Credit and Banking*, 43(2-3):535–552.

Molodtsova, T. and Papell, D. H. (2013). Taylor rule exchange rate forecasting during the financial crisis. In *NBER International Seminar on Macroeconomics*, volume 9, pages 55–97. University of Chicago Press Chicago, IL.

Moosa, I. and Burns, K. (2013). The monetary model of exchange rates is better than the random walk in out-of-sample forecasting. *Applied Economics Letters*, 20(14):1293–1297.

Moosa, I. and Burns, K. (2014a). A reappraisal of the Meese–Rogoff puzzle. *Applied Economics*, 46(1):30–40.

Moosa, I. and Burns, K. (2014b). The unbeatable random walk in exchange rate forecasting: Reality or myth? *Journal of Macroeconomics*, 40:69–81.

Moosa, I. A. (2007). Neoclassical versus Post Keynesian models of exchange rate determination: a comparison based on nonnested model selection tests and predictive accuracy. *Journal of Post Keynesian Economics*, 30(2):169–185.

Morales-Arias, L. and Moura, G. V. (2013). Adaptive forecasting of exchange rates with panel data. *International Journal of Forecasting*, 29(3):493–509.

Mumtaz, H. and Sunder-Plassmann, L. (2013). Time-varying dynamics of the real exchange rate: An empirical analysis. *Journal of Applied Econometrics*, 28(3):498–525.

Pacelli, V., Bevilacqua, V., and Azzollini, M. (2011). An artificial neural network model to forecast exchange rates. *Journal of Intelligent Learning Systems and Applications*, 3(02):57–69.

Park, C. and Park, S. (2013). Exchange rate predictability and a monetary model with time-varying cointegration coefficients. *Journal of International Money and Finance*, 37:394–410.

Qi, M. and Wu, Y. (2003). Nonlinear prediction of exchange rates with monetary fundamentals. *Journal of Empirical Finance*, 10(5):623–640.

Rapach, D. E. and Wohar, M. E. (2002). Testing the monetary model of exchange rate determination: new evidence from a century of data. *Journal of International Economics*, 58(2):359–385.

Rapach, D. E. and Wohar, M. E. (2004). Testing the monetary model of exchange rate determination: a closer look at panels. *Journal of International Money and Finance*, 23(6):867–895.

Rapach, D. E. and Wohar, M. E. (2006). The out-of-sample forecasting performance of nonlinear models of real exchange rate behavior. *International Journal of Forecasting*, 22(2):341–361.

Rime, D., Sarno, L., and Sojli, E. (2010). Exchange rate forecasting, order flow and macroeconomic information. *Journal of International Economics*, 80(1):72–88.

Rogoff, K. S. and Stavrakeva, V. (2008). The continuing puzzle of short horizon exchange rate forecasting. Technical report, National Bureau of Economic Research.

Rossi, B. (2005). Testing long-horizon predictive ability with high persistence, and the meese–rogoff puzzle. *International Economic Review*, 46(1):61–92.

Rossi, B. (2006). Are exchange rates really random walks? some evidence robust to parameter instability. *Macroeconomic Dynamics*, 10(1):20–38.

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

Rossi, B. and Inoue, A. (2012). Out-of-sample forecast tests robust to the choice of window size. *Journal of Business & Economic Statistics*, 30(3):432–453.

Rossi, B. and Sekhposyan, T. (2011). Understanding models' forecasting performance. *Journal of econometrics*, 164(1):158–172.

Sarantis, N. (1999). Modeling non-linearities in real effective exchange rates. *Journal of International Money and Finance*, 18(1):27–45.

Sarno, L. and Valente, G. (2009). Exchange rates and fundamentals: Footloose or evolving relationship? *Journal of the European Economic Association*, 7(4):786–830.

Schinasi, G. J. and Swamy, P. A. V. B. (1989). The out-of-sample forecasting performance of exchange rate models when coefficients are allowed to change. *Journal of International Money and Finance*, 8(3):375–390.

Siddique, A. and Sweeney, R. J. (1998). Forecasting real exchange rates. *Journal of International Money and Finance*, 17(1):63–70.

Somanath, V. S. (1986). Efficient exchange rate forecasts: Lagged models better than the random walk. *Journal of international Money and Finance*, 5(2):195–220.

Tawadros, G. B. (2001). The predictive power of the monetary model of exchange rate determination. *Applied Financial Economics*, 11(3):279–286.

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 puzzles. *International Economic Review*, 42(4):1015–1042.

Throop, A. W. (1993). A generalized uncovered interest parity model of exchange rates. *Economic Review-Federal Reserve Bank of San Francisco*, (2):3.

Van Aarle, B., Boss, M., and Hlouskova, J. (2000). Forecasting the euro exchange rate using vector error correction models. *Review of World Economics*, 136:232–258.

Wang, J. and Wu, J. J. (2012). The taylor rule and forecast intervals for exchange rates. *Journal of Money, Credit and Banking*, 44(1):103–144.

Wolff, C. C. (1987). Time-varying parameters and the out-of-sample forecasting performance of structural exchange rate models. *Journal of Business & Economic Statistics*, 5(1):87–97.

Wright, J. H. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics*, 146(2):329–341.

Zhang, H. J., Dufour, J.-M., and Galbraith, J. W. (2016). Exchange rates and commodity prices: Measuring causality at multiple horizons. *Journal of Empirical Finance*, 36:100–120.