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Forecasts of Period-average Exchange Rates: Insights from Real-time Daily Data

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Abstract

Forecasting period-average exchange rates requires using high-frequency data to efficiently construct forecasts and to test the accuracy of these forecasts against the traditional random walk hypothesis. To achieve this, we construct the first *real-time* dataset of *daily* effective exchange rates for all available countries, both nominal and real. The real-time vintages account for the typical delay in the publication of trade weights and inflation. Our findings indicate that forecasts constructed with daily data can significantly improve accuracy, up to 40 per cent compared to using monthly averages. We also find that unlike bilateral exchange rates, daily effective exchange rates exhibit properties distinct from random walk processes. When applying efficient estimation and testing methods made possible for the first time by the daily data, we find new evidence of real-time predictability for effective exchange rates in up to fifty per cent of countries.

JEL Classification Numbers: C43, C5, F31, F37

Keywords: temporal aggregation, exchange rates, forecasting, forecast evaluation, high-frequency data

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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 – such as effective or bilateral rates expressed in real terms – which are constructed as the arithmetic average of daily closing exchange rates over a specified time interval, typically a month or a quarter. 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, revenue and costs, and broader economic conditions. For this reason, many policymakers, including international organisations 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)).

In this paper, we ask whether period-average exchange rates are forecastable in real time. The core contribution is a new real-time dataset of daily nominal and real effective exchange rates (EERs) for all countries, including the first daily real effective exchange rates (REERs). This dataset enables the first formal testing of real-time forecasts of period-average exchange rates against the traditional random walk benchmark. It also allows us to benefit from the efficiency gains from using high-frequency data to construct forecasts. With these data in hand, we revisit longstanding concerns in the literature that have not been possible to resolve until now due to data limitations.

Forecasting period-average exchange rates presents distinct challenges. One issue is that using period-average data when constructing forecasts can introduce information loss that diminishes forecasting accuracy (e.g. Wei 1978; Kohn 1982; Lütkepohl 1986). Since period-average exchange rates are constructed from daily point-sampled data, efficient forecasts require access to the underlying high-frequency observations. A second issue is the potential for spurious predictability due to time averaging (Working 1960; Marcellino 1999; Bork, Rovira Kaltwasser and Sercu 2022; Ellwanger and Snudden 2023). This explains why Meese and Rogoff (1983a) and much of the literature forecast end-of-period bilateral exchange rates instead. In contrast, forecasts of REERs have relied on period averages due to the historical absence of point-sampled or daily effective exchange rate data (Meese and Rogoff 1983a, p 9).

To navigate the body of existing work, we contribute a detailed survey of the temporal assumptions used in the exchange rate forecasting literature in Section 2. This survey identifies three gaps in the literature, which our paper aims to fill. First, the survey shows that the literature has yet to test the predictability of period-average exchange rates by comparing them with the traditional random walk benchmark. Second, it shows the literature forecasting period-average exchange rates uses models estimated on period-average inputs, suggesting the forecasts are potentially inefficient. Third, the survey shows that no paper has done a *real-time* evaluation of forecasts for period-average or point-sampled EERs, or for point-sampled bilateral real exchange rates (RERs).

To address these limitations, we construct a new exchange rate dataset. For all available countries, we construct *real-time* vintages at the daily frequency for the four types of daily exchange rate: nominal effective exchange rates (NEERs), REERs, bilateral nominal exchange rates (NERs) and bilateral RERs.

Using the new dataset, we evaluate how temporal aggregation affects the accuracy of real-time forecasts for period-average exchange rates. We assess both model-based and no-change forecasts, and test, for the first time, real-time out-of-sample forecasts of monthly averages against the traditional random walk benchmark.[1] The results reveal three key empirical findings that underscore 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 – for example, directional accuracy is improved by up to 40 per cent. This evidence for all exchange rates and almost all countries confirms the evidence for the USD/JPY bilateral rate by Ellwanger and Snudden (2023) and occurs because daily exchange rates are highly persistent. Our first finding suggests that the monthly average no-change benchmarks used for EERs since Meese and Rogoff (1983a) may provide too lenient a benchmark against which to assess forecast performance. However, importantly, we find that unlike bilateral exchange rates, the forecast precision gains from temporal disaggregation of daily EERs are far smaller. This is insightful, as it provides evidence that EERs exhibit properties distinct from random walk processes.

The second empirical finding is that both direct and recursive model-based forecasts estimated with daily or end-of-month inputs perform substantially and significantly better than forecasts estimated with month-average data. This is found to be robust across exchange rate measures and countries. Once again, this substantiates theoretical advantages regarding the gains in forecast accuracy when exchange rates are temporally disaggregated. These findings are encouraging; they show that one can substantially improve the accuracy of model forecasts for period-average exchange rates using real-time information from daily exchange rates. Interestingly, we also find evidence that end-of-period point-sampled exchange rate forecasts are useful for forecasts of period-average exchange rates. This implies that methods in existing studies examining forecasts of end-of-period exchange rates are potentially very useful for forecasts of period-average exchange rates.[2]

The third empirical finding is that when applying efficient estimation and testing methods, made possible for the first time by the daily data, we find new evidence of real-time predictability for period-average EERs in up to 50 per cent of countries. In contrast, for period-average bilateral exchange rates, there is substantial spurious predictability, in both directional accuracy and mean-squared precision, when temporally disaggregated model-based real-time forecasts are compared against period-average no-change forecasts.[3] This raises an important distinction between exchange rate measures as, for both real and effective measures of exchange rates, the use of high-frequency information substantially increases the likelihood of rejecting the random walk hypothesis. This suggests a refinement to the current consensus on the inability of exchange rates to outperform naive benchmarks. While bilateral NERs, derived from financial markets, behave like random walks, forecasts of bilateral RERs and EERs are more accurate when efficiently constructed using the real-time daily data.

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1 For forecasts of period averages, the traditional random walk no-change is given by the last observed end-of-period value (Ellwanger and Snudden 2023; McCarthy and Snudden forthcoming).

2 Zhang, Dufour and Galbraith (2016), Kohlscheen, Avalos and Schrimpf (2017) and Ca' Zorzi *et al* (2022) forecast point-sampled EERs. Froot and Ramadorai (2005) and Chen *et al* (2014), among other articles, forecast point-sampled bilateral RERs.

3 For example, forecasts of period-average bilateral NERs that rely on disaggregated data are found to outperform the month-average no-change forecast 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 forecast.

Our findings contribute to the broader understanding of temporal aggregation bias. We provide quantitative evidence to support theoretical claims that temporal averaging reduces forecast accuracy (Tiao 1972; Amemiya and Wu 1972; Kohn 1982; Lütkepohl 1986). Importantly, we show that the loss in accuracy from daily to monthly aggregation is considerably larger than what has been documented for aggregation from monthly to quarterly or quarterly to annual frequencies (e.g. Zellner and Montmarquette 1971; Lütkepohl 1986; Athanasopoulos *et al* 2011). This suggests that the gains from temporal aggregation should be understood to be of first order importance when the forecast target is a period average of daily data.

These results have broader implications for macroeconomic measurement. Although our focus is on month-average and end-of-month exchange rates, the informational loss from temporal aggregation is even more severe at quarterly frequencies. More generally, we recommend that end-of-period values for EERs be routinely reported, just as they are for bilateral exchange rates.

This paper serves as a guide to understanding temporal aggregation in exchange rate forecasting. The findings offer a framework for interpreting existing empirical results and for designing future forecast evaluations. By incorporating high-frequency data, we demonstrate that real-time forecasts of period-average exchange rates can be substantially improved, providing insights that are directly relevant for economic decision-making.

2. Literature Survey

This literature review offers a comprehensive survey of research forecasting effective and bilateral exchange rates. We complement other surveys in the exchange rate literature (Frankel and Rose 1995; Rogoff 1996; Engel *et al* 2007; Rossi 2013) by reporting 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 (e.g. Clarida and Taylor 1997). Specifically, if the exchange rates are expressed in real terms, 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 2.1) and bilateral exchange rates (Section 2.2). In cases where papers forecast multiple types of exchange rates, we include them in each section.

2.1 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 are important for understanding 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, Hjortsoe and Nenova 2018).

2.1.1 *Forecasts for period-average effective exchange rates*

We found 19 papers that examined forecasts of period-average EERs, as summarised in Table 1. 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 is a recent trend towards forecasting quarter-average EERs.

Table 1: 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
Amano and van Norden (1998a)	Return	M	Average	Average	Average	Real	N
Amano and van Norden (1998b)	Level	M	Average	Average	Average	Real	N
MacDonald (1998)	Level	Q	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, Etula and Shin (2010)	Return	M	Average	Average	Average	Nominal	N
Chen, Rogoff and Rossi (2010)	Return	Q	Average	Average	Average	Nominal	N
Chen *et al* (2014)	Level	A	Average	Average	Average	Nominal	N
Bańbura, Giannone and Lenza (2015)	Level	Q	Average	Average	Average	Nominal	N
Ca' Zorzi, Muck and Rubaszek (2016)	Level	M	Average	Average	Average	Real	N
Ca' Zorzi, Kolasa and Rubaszek (2017)	Level	Q	Average	Average	Average	Real	N
Hatzinikolaou and Polasek (2005)	Return	Q	Average	Average	Average	Nominal	N

Notes: 'Benchmark' refers to the no-change forecast that the forecast was compared against. 'Model estimation' refers to the data used in estimation.

We document three features of papers studying period-average EERs.

First, studies that compare the predictability of period-average EERs to that of a naive forecast have done so using the period-average no-change benchmark. This is potentially 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, including the special case of the random walk (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 2023) or directional accuracy (McCarthy and Snudden forthcoming). 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 per cent lower than the month-average no-change (Ellwanger and Snudden 2023). This calls into question the validity of the conclusions in studies whose naive no-change forecast used 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 periods aggregated over. Most of the information loss occurs when departing from 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 2023; Ellwanger, Snudden and Arango-Castillo 2023). In contrast, comparisons of already aggregated frequencies, such as monthly versus quarterly, have found that the effect is small or non-existent (e.g. Zellner and Montmarquette 1971; Lütkepohl 1986; Athanasopoulos *et al* 2011). Consequently, the loss in forecast accuracy may be substantial for period-average exchange rates, which are based on point-sampled daily prices. The degree of the information loss is an empirical question, quantified in Section 5.

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 3.

2.1.2 Forecasts for point-sampled effective exchange rates

Only three studies evaluate forecasts for end-of-period EERs, see Table 2. 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 REERs, which they construct for a basket of eight advanced economies. These studies compare forecasts against end-of-period no-change benchmarks and, hence, unlike the studies examining period-average exchange rates, correctly test against the null of no predictability.

Table 2: Papers Forecasting Point-sampled Effective Exchange Rates

Paper	Level or return	Frequency	Forecast target	Benchmark	Model estimation	Real or nominal	Real time
Zhang, Dufour and Galbraith (2016)	Return	D	EoP	EoP	EoP	Nominal	N
Kohlscheen, Avalos and Schrimpf (2017)	Return	D	EoP	EoP	EoP	Nominal	N
Ca' Zorzi *et al* (2022)	Level	Q	EoP	EoP	EoP	Real	N

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

The valid hypothesis testing in these papers is potentially informative on the predictability of period-average EERs. 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 *et al* 2023). 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 efficiency of point-sampled forecasts for period averages for all countries in Section 5.

2.2 Bilateral exchange rates

2.2.1 Forecasts for period-average bilateral exchange rates

We now survey 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 research on period-average bilateral exchange rates comprises eighteen papers (Table 3). Only three papers examine period-average bilateral RERs, and only one of those forecasts the level. In contrast to EERs, a few papers employ real-time methods for period-average bilateral exchange rates in nominal terms (Wright 2008; Molodtsova, Nikolsko-Rzhevskyy and Papell 2008; Carriero, Kapetanios and Marcellino 2009; Abbate and Marcellino 2018) and one in real terms (Kilian and Taylor 2003).

Table 3: 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 van Norden (1995)	Return	M	Average	Average	Average	Real	N
van Aarle, Boss and Hlouskova (2000)	Level	M	Average	Average	Average	Nominal	N
Fullerton, Hattori and Calderón (2001)	Return	A	Average	Average	Average	Nominal	N
Tawadros (2001)	Return	M	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, Lafrance and Murray (2008)	Return	Q	Average	Average	Average	Real	N
Molodtsova, Nikolsko-Rzhevskyy and Papell (2008)	Return	Q	Average	Average	Average	Nominal	Y
Wright (2008)	Return	M, Q	Average	Average	Average	Nominal	Y
Carriero, Kapetanios and Marcellino (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
Banerjee, Marcellino and Masten (2014)	Level	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, Johannsen and Rebelo (2021)	Return	Q	Average	Average	Average	Nominal	N

Notes: '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 summarised 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 effective exchange rates, 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 jeopardising forecast accuracy. In essence, our understanding of the predictability of period-average bilateral exchange rates remains limited.

2.2.2 Forecasts for point-sampled bilateral exchange rates

Lastly, we delve into the literature which has examined point-sampled bilateral exchange rates. Researchers may favour bilateral point-sampled exchange rates over bilateral period-average rates for some applications, 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 4. We also discuss papers that have examined point-sampled bilateral NERs, for which a summary table is reported in Appendix A.

Table 4: Papers Forecasting Point-sampled Effective Exchange Rates

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 Sweeney (1996)	Level	M	EoP	EoP	EoP	Real	N
Taylor, Peel and Sarno (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
Engel and West (2006)	Level	M	EoP	EoP	EoP	Real	N
Rapach and Wohar (2006)	Level	M	EoP*	EoP*	EoP*	Real	N
Chen and Chen (2007)	Level	M	EoP	EoP	EoP	Real	N
Clements and Fry (2008)	Return	Q	EoP	EoP	EoP	Real	N
Mumtaz and Sunder-Plassmann (2013)	Level	Q	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

Notes: 'Benchmark' refers to the no-change forecast that the forecast was compared against. 'Model estimation' refers to the data used in estimation. 'EoP' and 'MoP' refer to end-of-period and middle-of-period sampling, respectively. Authors were contacted for papers that did not provide information on temporal sampling; '*' denotes papers where the authors did not respond or responded and were unable to confirm so point-in-time sampling was assumed.

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 previous subsections. 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 5.

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), 14 out of 101 studies of point-sampled bilateral NERs have employed real-time forecasts.

2.3 Identified gaps in the literature

In summary, there are 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.

3. Data

The dataset includes real-time monthly vintages of daily bilateral and effective exchange rates, both nominal and real. While daily bilateral exchange rates are widely available, and the BIS publishes daily NEERs for a subset of countries, our dataset is the first to include daily REERs and to construct real-time vintages of EERs that account for the publication delays of trade weights. The daily EERs are computed consistently across countries using IMF trade weights and formulas.

For each type of exchange rate and country, we construct one real-time vintage of daily frequency per month, 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 data revisions, since NERs, CPIs, and trade weights are rarely revised. Rather, our aim is to reflect the typical delays in the publication of CPI and trade weight data.

From each vintage of daily data, we construct corresponding vintages of month-average and end-of-month exchange rates. These are derived directly from the daily observations available in each vintage.

3.1 Monthly vintages of daily frequency exchange rates

Section 3.1.1 describes the calculation of bilateral NERs and bilateral RERs. Section 3.1.2 describes the calculation of NEERs and REERs. Detail on the inputs into these calculations (bilateral NERs, CPIs and trade weights) is provided in Appendix B.

3.1.1 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 RERs we need data on both daily bilateral NERs 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 constructed the daily bilateral RER using Equation (1) 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 data are from the World Bank dataset; see Appendix B.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.

3.1.2 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 weight 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.[4]

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

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4 For REERs, the formulas differ in how they combine NERs and prices. For example, the approach used by the BIS 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 (Turner and Van 't dack 1993; Klau and Fung 2006). The IMF's previous approach was to directly aggregate the bilateral RERs (Bayoumi, Lee and Jayanthi 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.

the '2010–2012' weight reference period (see Appendix B.3 for details). Let $w_{r,j}^{b}$ 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.

$$REER_t^{r,b} = \frac{NER_t^r \times CPI_m^r}{\exp\left(\sum_{j=1}^{J} w_b^{r,j} \ln\left(NER_t^j \times CPI_m^j\right)\right)} \tag{2}$$

For each weight reference period, we only use partners whose exchange rates are available on all days in the period.[5] 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 indices, as described in Appendix C.

3.2 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. To see this, let $t = 1, ..., n$ index the days in a month.

$$RER_m^i = \frac{1}{n}\sum_{t=1}^{n} RER_t^i = \frac{1}{n}\sum_{t=1}^{n}\left(NER_t^i \times \frac{CPI_m^i}{CPI_m^{\text{US}}}\right) = \left(\frac{1}{n}\sum_{t=1}^{n} NER_t^i\right) \times \frac{CPI_m^i}{CPI_m^{\text{US}}}$$

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.

5 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.

4. Method

4.1 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.

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 $m = 1, \ldots, M$. 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 relative to the benchmark:

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

where $\operatorname{sgn}(.)$ is a sign function and $\mathbb{1}[.]$ is an indicator function taking the value of one if true and zero otherwise. We also test the null of no directional accuracy by testing if the categorical random variables $\operatorname{sgn}(A_{m+h} - \hat{A}^{bench}_{m+h})$ and $\operatorname{sgn}(\hat{A}^{candidate}_{m+h|m} - \hat{A}^{bench}_{m+h|m})$ are independent of each other. The test statistic is calculated following Pesaran and Timmermann (2009).

4.2 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)). Model-based forecasts are re-estimated at each forecast step using expanding window estimation on the real-time data.

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 then 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.[6]

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 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 $M+h$.

4.2.1 No-change forecasts

We consider two types of no-change forecasts:
i) Month-average no-change. The forecast for the monthly average in any future month $M+h$ is the last observed monthly average:

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

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

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

6 For example, if we think it is equally likely that an exchange rate could appreciate by 1 per cent or depreciate by 1 per cent, 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.

This corresponds to the traditional assumption that the high-frequency series is a random walk. That is, if the daily exchange rate follows a random walk, then the expected period-average exchange rate in all future months equals the end-of-month no-change forecast (see Ellwanger and Snudden (2023); McCarthy and Snudden (forthcoming)). 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 each month.

4.2.2 Recursive AR(1) forecasts

We make recursive forecasts using autoregressive models of order 1 (AR(1)), estimated on exchange rate (log) levels using OLS.[7] 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.

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

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 Lütkepohl (1986); Benmoussa, Ellwanger and Snudden (forthcoming)).

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

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

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

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 *et al* 2023). 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.

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

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

4.2.3 Direct forecasts

We construct direct forecasts using linear regressions estimated on exchange rate (log) 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

7 For a handful of countries, the estimated AR(1) model has a coefficient that is outside $(-1,1)$, suggesting that exchange rates are non-stationary. Where this occurs, the country is excluded from our results.

of the model with OLS without any restrictions. This is the bottom-up direct forecast equivalent of Equation (5), see Lee and Snudden (2025), and unrestricted mixed data sampling (UMIDAS) (Foroni, Marcellino and Schumacher 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 directly forecast the month-average exchange rate.

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

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 month-average inputs. For each horizon 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.

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

5. Results

This section reports the quantitative results on the importance of temporal disaggregation for exchange rate forecasts. All forecasts are constructed in real time as described in Section 4 using the data documented in Section 3.

Subsection 5.1 compares the performance of the two no-change benchmarks. Subsection 5.2 compares the performance of the recursive and direct forecasting models to no-change benchmarks.

5.1 Comparison of no-change benchmarks

5.1.1 Median performance across countries

We begin by examining the extent to which the end-of-month no-change forecast outperforms the month-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 $n = 21$.[8] Table 5 reports the median RMSFE ratios at various forecast horizons.

8 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 5,000 times.

Table 5: Median Performance of End-of-month No-change Forecasts versus Month-average No-change Forecasts

	Horizon (months)					
	1	3	6	12	24	36
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	0.96	0.98	0.99	1.00	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	0.61	0.59	0.53	0.52	0.50
NEER	0.72	0.62	0.58	0.54	0.54	0.52
RER	0.69	0.59	0.56	0.52	0.51	0.49
REER	0.69	0.58	0.56	0.52	0.52	0.50

Notes: Forecast accuracy of end-of-month no-change forecast versus month-average no-change forecast. Reports the median across countries. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance. 'Random walk' is simulated using 5,000 iterations and 30 years of data.

When the simulated data follows a random walk, the end-of-month no-change forecast substantially outperforms the month-average no-change forecast (Ellwanger and Snudden 2023). The gains in the RMSFE are the largest one month ahead, showing a 17 per cent reduction and, consistent with theory, the differences decline with the forecast horizon. These patterns are also present for directional accuracy. For one-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 per cent of the time. The SRs also decline at longer horizons, but remain above 0.5 up to 12 months ahead.

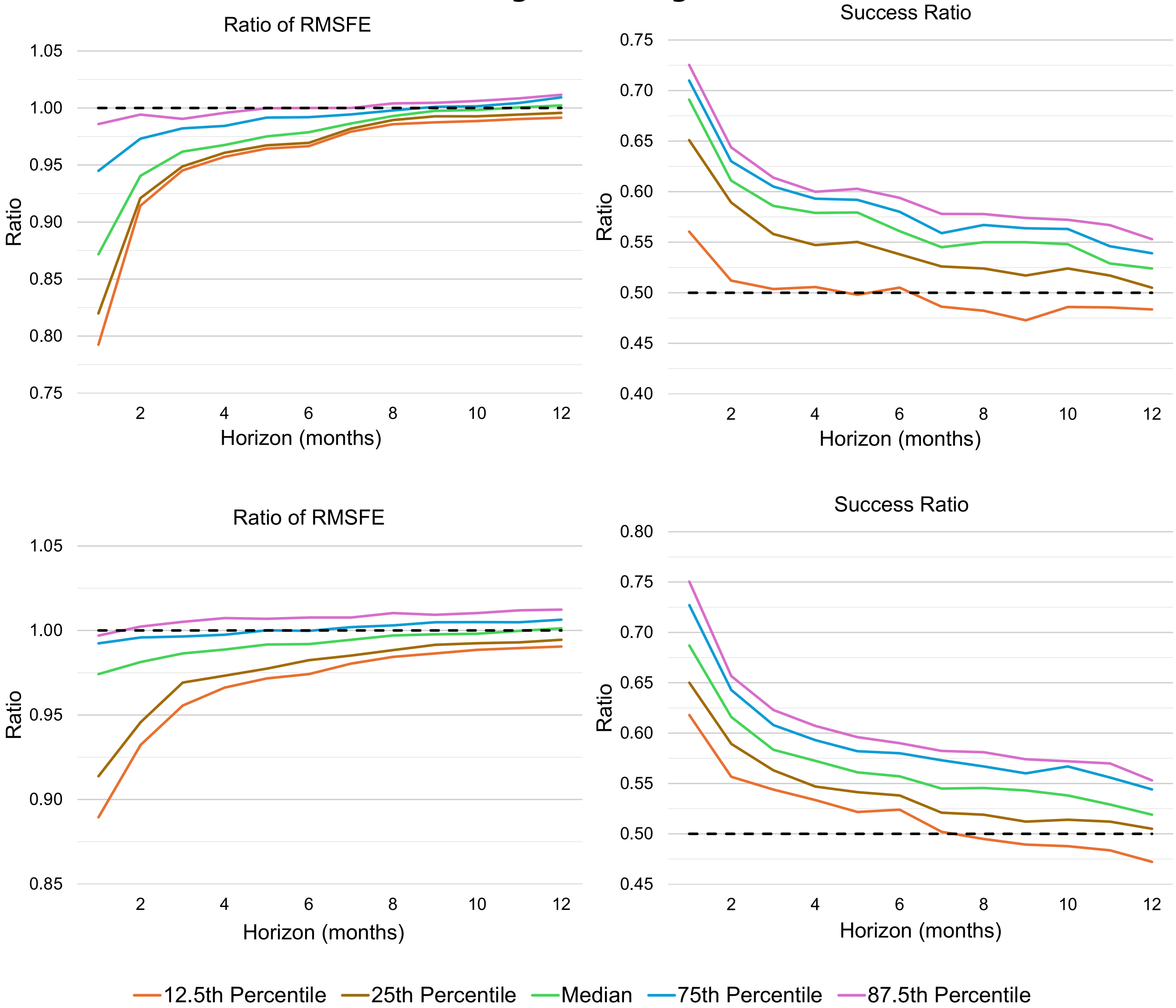
The pattern of the forecast gains observed for the simulated random walk are also observed for the alternative exchange rate measures. In particular, the median RMSFE ratios for NER are nearly identical to those obtained from a random walk. The results suggest that the NER exhibits properties most similar 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 outperforms the month-average no-change forecast one month ahead by 7 and 3 per cent, 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, we find gains of around 20 percentage points relative to a coin flip. Moreover, even at the six-month-ahead horizon, 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 month-average no-change.

5.1.2 Performance and hypothesis tests for all countries

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 month-average no-change forecast at horizons of 1 to 12 months for the RER and REER. The gains across quantiles indicates that the differences between the end-of-month no-change and the month-average no-change in our sample is widespread, in addition to being substantial.[9]

Figure 1: **Distribution of Forecast Performance of End-of-month No-change versus Month-average No-change Forecasts**



Notes: Plot shows quantiles for 83 countries. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund; World Bank.

Improvements in the forecasts are statistically significant for a large fraction of countries, for both mean squared and directional accuracy (Table 6).

The results suggest that the loss in forecast accuracy from temporal aggregation of daily exchange rates to the monthly frequency is sizable. This is due to the high persistence of daily exchange rates (Zellner and Montmarquette 1971; Amemiya and Wu 1972; Tiao 1972), and is consistent with the evidence on other aggregated macroeconomic variables (Ellwanger and Snudden 2023; Ellwanger *et al* 2023). The substantial and consistent differences in forecast accuracy indicate the importance of using the correct no-change benchmark in practice.

9 The forecast gains are even larger and more robust for the NER and NEER, as is reported in Figure D1.

Table 6: **Share of Countries with Significant Improvement in Forecast Performance – End-of-month No-change versus Month-average No-change**

	Horizon (months)					
	1	3	6	12	24	36
Mean square accuracy (%)						
REER	46	24	14	3	3	3
RER	79	33	13	8	14	14
NEER	59	35	33	9	10	14
NER	96	81	62	14	14	9
Directional accuracy (%)						
REER	100	84	54	15	6	8
RER	91	69	31	31	47	32
NEER	100	96	78	22	22	10
NER	100	95	89	23	15	4

Note: Reports the per cent of countries where the end-of-month no-change improved upon the month-average no-change at the 5 per cent level of significance by the end of the forecast evaluation sample.

5.2 Comparison of model-based to no-change forecasts

We now quantify the information gains from temporal disaggregation when constructing real-time model-based forecasts of monthly average exchange rates using the three recursive and the three direct methods as described in Section 4. We report on the distribution of RMSFE ratios and SRs over our sample period, and then turn to hypothesis tests.

5.2.1 Performance over the sample period

To be consistent with Subsection 5.1, and the existing literature for EERs, we begin by comparing the forecasts to the month-average no-change forecast.

The median forecast performance of model-based forecasts of the bilateral RERs is reported in Table 7. When recursive and direct forecasts are estimated with monthly average data, the forecasts do worse than the month-average no-change forecast in terms of median RMSFE at all horizons and in terms of median SR at horizons up to one year. The month-average no-change forecast can seem hard to beat even though it is an inefficient naive forecast because model-based forecasts with period-average inputs are also inefficient. When estimated with monthly average data, the recursive and direct forecasts are almost indistinguishable from each other in terms of RMSFE up to a two-year horizon, and in terms of SR at all horizons.

In contrast, for both recursive and direct forecasts, the use of high-frequency data in end-of-month or bottom-up methods results in substantially better real-time forecast performance than using month-average inputs. The gains are very similar to what was observed from the end-of-month no-change forecast one month ahead, with a 12 percentage point improvement in RMSFE and an 18 percentage point improvement in the SR. These findings reinforce that the gains in forecast accuracy are substantial when model-based forecasts use disaggregated daily data.

Table 7: Median Performance of Forecasts for Month-average Bilateral RER

Forecast	Model inputs	Horizon (months) 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

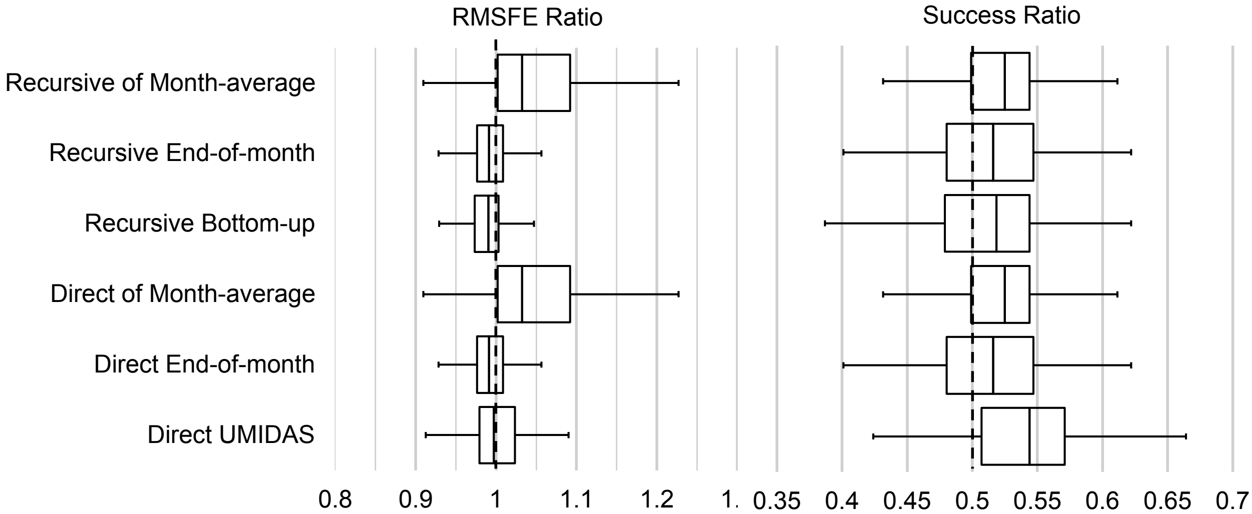
Notes: Reports the median result across countries relative to the month-average no-change forecast. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance.

Interestingly, the results indicate that end-of-month forecasts do about as well as the bottom-up forecasts constructed using daily data for real-time forecasts of the monthly average level. This evidence suggests that methods that have been shown to perform well when forecasting end-of-period exchange rates may perform well for period-average exchange rates.

We now examine the model-based forecast performance relative to the end-of-month no-change forecast, that is, the naive forecast that represents the random walk hypothesis. The distribution of RMSFEs and SRs from the different model-based forecasts at the one-month-ahead horizon for REERs are reported in Figure 2. Model-based forecasts using disaggregated methods have much lower RMSFE ratios compared to models estimated with month-average inputs. The forecasts made with month-average inputs are so poor that the entire interquartile range (IQR) of RMSFE ratios is above the median RMSFE 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.

Even though we observe substantial deterioration in RMSFEs for model-based forecasts estimated with monthly average data, the pattern is less clear for directional accuracy, as shown in Figure 2. This can be seen in the overlap in the IQRs of the SRs for the month-average, end-of-month and daily inputs. However, the UMIDAS forecasts exhibit some of the largest and most robust forecast directional accuracy gains, with the lower bound of the IQR above 0.5. This suggests that mixed-frequency direct forecasts may have notable advantages in forecasting directional accuracy, at least at short horizons.

Figure 2: **Accuracy of One-month-ahead Forecasts for REER Relative to End-of-month No-change Benchmark**



Notes: The box and whisker plots show the distribution of RMSFE ratios and SRs across countries. '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 use the end-of-month observation only. Outliers have been omitted. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund; World Bank.

Qualitatively, the results are very similar for the other exchange rates and are reported in Appendix F. 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.

5.3 Hypothesis tests

We now formally test the real-time predictability of month-average exchange rates against the naive forecast that reflects the random walk hypothesis. Previous tests of predictability in the literature tested against the month-average no-change benchmark, which does not reflect the random walk hypothesis (see Section 2). Table 8 reports the share of countries for which we find significant outperformance of the model-based forecasts against both the end-of-month and the month-average no-change benchmarks in terms of mean square accuracy and directional accuracy.

Immediately notable is that comparisons to the month-average no-change result in substantially more statistically significant forecasts when disaggregated methods are employed. For example, for forecasts of the monthly average NER, the disaggregated model-based forecasts significantly outperform the month-average no-change for up to 80 and 95 per cent of countries in terms of 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 the exact same model-based forecasts are tested against the random walk hypothesis, that it, the end-of-month no-change forecast. For NERs, less than 5 per cent of countries 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 a sizable type-I error rate.

Table 8: **Share of Countries with Significant Improvement in Forecast Performance – Model-based versus Benchmarks**

Forecast	Model inputs	versus end-of-month no-change				versus month-average no-change			
		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 per cent of countries for which the model-based forecast one-month-ahead significantly outperforms the benchmark at a five per cent level of significance.

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 per cent of countries, and up to 15 per cent 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 per cent of countries, and up to 33 per cent of countries for the SR. By far, the most predictable exchange rate is the REER, with up to 56 per cent of countries exhibiting significant predictability based on RMSFE and up to 30 per cent based on the SR. We emphasise that this is the first time that forecasts of period-average exchange rates have been compared against the traditional random walk hypothesis. Hence, the finding of statistically significant predictability of period-average exchange rates, relative to the traditional random walk benchmark, is new to the literature.

5.4 Robustness

The use of the same univariate models for all countries in the baseline analysis is intentional. This approach allows us to isolate the informational loss due to temporal aggregation, rather than to make model-specific recommendations for individual countries. Nonetheless, the main results are robust to alternative model specifications and to using a subset of countries.

Appendix E presents forecasts based on pre-sample testing for the order of integration and lag length using the Akaike information criterion (AIC). These tests are applied to the daily ARIMA specification, and the resulting lag structure is imposed on the recursive and direct forecast models in Equations (5) to (10). Forecast performance remains qualitatively unchanged.

We also assess model selection using the automatic ARIMA procedure of Hyndman *et al* (2022), estimated by maximum likelihood, as well as restricted MIDAS regressions estimated via nonlinear least squares (Ghysels, Sinko and Valkanov 2007). Although these methods produce broadly similar forecasts, they exhibit convergence failure rates that vary by the exchange rate series and forecast method. For this reason, their results are omitted to maintain consistent samples across specifications.

Further, Appendix F confirms that the core findings hold for the subset of countries that maintained flexible exchange rate regimes over the sample period, as defined by Ilzetzki, Reinhart and Rogoff (2019). Forecast performance and significance patterns for these countries closely mirror those of the full sample.

Together, these robustness checks demonstrate that the paper's main conclusions are not sensitive to the precise model parameterisation or country sample. While model assumptions can matter for individual countries, the median forecast performance and the share of countries with significant gains remain stable. Across all specifications, the forecast gains from using disaggregated inputs dominate those from changing other model assumptions, underscoring the first-order importance of temporal aggregation in forecasting period-average exchange rates.

6. Conclusion

We construct a novel real-time dataset of daily bilateral and effective exchange rates, both nominal and real, for a broad set of countries. These data enable the first real-time evaluation of forecasts for period-average exchange rates and allow us to assess the effects of temporal aggregation. Our analysis yields three main findings.

First, the month-average no-change forecast benchmark substantially underperforms the end-of-month no-change benchmark for EERs. This questions the empirical results of the surveyed papers examining period-average exchange rates.

Second, incorporating information from daily or end-of-month exchange rates substantially improves the accuracy of real-time forecasts. This points to the potential for improving current forecasting practices, leading to better decision-making. It also highlights the need for official data providers to begin publishing end-of-month and daily measures of EERs, rather than the current practice of only reporting period-average EERs.

Third, we find that period-average EERs and bilateral real exchange rates are forecastable in real time for many countries. These findings motivate further exploration of temporally disaggregated methods and a reassessment of the predictability of EERs.

More broadly, the daily real-time dataset introduced in this paper creates the possibility for a wide range of applications, including the identification of high-frequency shocks, the analysis of dynamic responses, and the evaluation of economic theory and policy. Both the survey and daily data offer a foundation for new empirical work in macroeconomics.

Appendix A: Point-in-time Sampled Nominal Bilateral Exchange Rates

Table A1: **Summary of Literature Focusing on Point-in-time Sampled Nominal Bilateral Exchange Rates**

(*continued next page*)

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 Glassman (1987)	Level	M	EoP	EoP	EoP	Nominal	N
Boughton (1987)	Both	M	EoP*	EoP*	EoP*	Nominal	N
Wolff (1987)	Level	M	EoP	EoP	EoP	Nominal	N
Hodrick (1989)	Return	M	EoP	EoP	EoP	Nominal	N
Schinasi and Swamy (1989)	Level	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
Kräger and Kugler (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, Gardeazabal and Yilmaz (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 Giorgianni (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
Faust, Rogers and Wright (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

Table A1: **Summary of Literature Focusing on Point-in-time Sampled Nominal Bilateral Exchange Rates**
(*continued next page*)

Paper	Level or return	Frequency	Forecast target	Benchmark	Model estimation	Real or nominal	Real time
Abhyankar, Sarno and Valente (2005)	Return	M	EoP	EoP	EoP	Nominal	N
Cheung, Chinn and Garcia Pascual (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
Engel *et al* (2007)	Return	Q	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
Della Corte, Sarno and Tsiakas (2009)	Return	M	EoP†	EoP†	EoP†	Nominal	N
Sarno and Valente (2009)	Return	Q	EoP†	EoP†	EoP†	Nominal	Y
Adrian, Etula and Shin (2010)	Return	M	EoP	EoP	EoP	Nominal	N
Altavilla and De Grauwe (2010)	Both	Q	EoP*	EoP*	EoP*	Nominal	N
Bacchetta, van Wincoop and Beutler (2010)	Return	M	EoP	EoP	EoP	Nominal	N
Cerra and Saxena (2010)	Level	A	EoP	EoP	EoP	Nominal	N
Chen, Rogoff and Rossi (2010)	Return	Q	EoP	EoP	EoP	Nominal	N
Rime, Sarno and Sojli (2010)	Return	D	EoP	EoP	EoP	Nominal	N
Chinn and Moore (2011)	Return	M	EoP	EoP	EoP	Nominal	N
Li (2011)	Return	M	EoP	EoP	EoP	Nominal	N
López-Suárez and Rodríguez-López (2011)	Return	Q	EoP	EoP	EoP	Nominal	N
Molodtsova, Nikolsko-Rzhevskyy and Papell (2011)	Return	Q	MoP	MoP	MoP	Nominal	Y
Pacelli, Bevilacqua and Azzollini (2011)	Level	D	EoP*	EoP*	EoP*	Nominal	N
Rossi and Sekhposyan (2011)	Return	M	EoP	EoP	EoP	Nominal	N
Dal Bianco, Camacho and Pérez-Quirós (2012)	Return	W	EoP	EoP	EoP	Nominal	N
Della Corte, Sarno and Sestieri (2012)	Return	Q	EoP†	EoP†	EoP†	Nominal	Y
Rossi and Inoue (2012)	Level	M	EoP†	EoP†	EoP†	Nominal	N
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
Galimberti and Moura (2013)	Both	M	EoP	EoP	EoP	Nominal	N
Molodtsova and Papell (2013)	Return	Q	EoP	EoP	EoP	Nominal	Y
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 and 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

Table A1: **Summary of Literature Focusing on Point-in-time Sampled Nominal Bilateral Exchange Rates**

(*continued*)

Paper	Level or return	Frequency	Forecast target	Benchmark	Model estimation	Real or nominal	Real time
Burns and Moosa (2015)	Return	M	EoP*	EoP*	EoP*	Nominal	N
Engel, Mark and West (2015)	Return	Q	EoP	EoP	EoP	Nominal	N
Ferraro, Rogoff and Rossi (2015)	Return	D	EoP	EoP	EoP	Nominal	Y
Ferraro, Rogoff and Rossi (2015)	Return	M	SoP	SoP	SoP	Nominal	Y
Ferraro, Rogoff and Rossi (2015)	Return	Q	MoP	MoP	MoP	Nominal	Y
Li, Tsiakas and Wang (2015)	Return	M	EoP	EoP	EoP	Nominal	N
Beckmann and Schüssler (2016)	Return	M	EoP	EoP	EoP	Nominal	Y
Byrne, Korobilis and Ribeiro (2016)	Return	Q	EoP	EoP	EoP	Nominal	N
Zhang, Dufour and Galbraith (2016)	Return	D	EoP*	EoP*	EoP*	Nominal	N
Kohlscheen, Avalos and Schrimpf (2017)	Return	D	EoP*	EoP*	EoP*	Nominal	Y
Kouwenberg *et al* (2017)	Return	Q	EoP*	EoP*	EoP*	Nominal	Y
Byrne, Korobilis and Ribeiro (2018)	Return	M	EoP	EoP	EoP	Nominal	N
Christou *et al* (2018)	Return	M, Q	EoP*	EoP*	EoP*	Nominal	N
Cheung *et al* (2019)	Both	Q	EoP	EoP	EoP	Nominal	N
Engel *et al* (2019)	Return	M	EoP	EoP	EoP	Nominal	N
Kremens and Martin (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, Rovira Kaltwasser and Sercu (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

Notes: Papers whose 'Forecast target' are point-in-time sampled nominal bilateral exchange rates. Authors were contacted for papers that did not provide information on temporal sampling; * denotes papers where the authors did not respond or responded and were unable to confirm so point-in-time sampling was assumed, whereas † denotes papers where the authors responded and confirmed point-in-time sampling. '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.

Appendix B: Inputs into Bilateral RER and EER Calculations

Section 3 describes how we constructed real-time vintages of bilateral RERs and REERs. This appendix provides detail on each of the inputs into these calculations: daily NERs; daily CPI levels; and trade weights.

B.1 Daily nominal exchange rates

B.1.1 IMF nominal exchange rates

We use daily NERs from an internal IMF database called 'Global Data Source'. They are expressed in 'USD per units of national currency', and were available for 165 countries. The earliest observation was 1 January 1993 and the latest was 21 October 2022.[10] These data provide 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.[11]

B.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 identify 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 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 they are not the same, it would suggest that we have identified 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.

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10 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.

11 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/US dollar exchange rate. From 1 January 1999, EDNA starts at the schilling/US dollar rate and is then grown based on the euro/US dollar exchange rate. Splicing exchange rates in this way avoids a jump in EDNA, which avoids a jump in RERs or REERs.

Using the above process, we are able to splice Eikon and IMF NERs for 51 countries (Table B1).

Table B1: 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

Sources: Authors' calculations; Eikon; International Monetary Fund.

To determine which exchange rate each country used before the start of the IMF data, we rely on the IMF annual reports on exchange arrangements and exchange restrictions (AREAER). This dataset lists the currency that each country 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 five-year gap between introducing and withdrawing a currency because countries sometimes introduce a new currency and withdraw the old one a few years later.[12] 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.[13]

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

B.2 Monthly consumer price index levels

B.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 indices. These are available for 171 countries in total, though individual countries drop in and out of the sample. The dataset is described in Ha, Kose and Ohnsorge (2021). As the authors do not specify whether the dataset is seasonally adjusted, we assume that it is not 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 not seasonally adjusted CPIs.

By restricting ourselves to the monthly dataset, we exclude countries for which only quarterly indices were available at the time of our analysis. 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.

12 For example, the IMF AREAER 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.

13 Available at <https://www.six-group.com/en/products-services/financial-information/data-standards.html>.

B.2.2 Constructing real-time vintages of monthly CPIs

To construct real-time vintages of monthly CPIs, we need 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.[14] The latest month for which data are available varies by country (Table B2). For many countries, the latest observation is December 2022, so the publication lag is estimated to be one month. Similarly, for countries where the latest observation is November 2022, October 2022 or September 2022, we estimate the publication lag to be two, three or four months respectively.

Table B2: World Bank Monthly CPI Dataset

Latest observation	Number of countries	Apparent publication lag
December 2022	60	1
November 2022	36	2
October 2022	13	3
September 2022	18	4
Earlier	44	5

There are some countries where the latest observation is even earlier than September 2022. Taken at face value, this suggest a publication lag of five 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 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 four months wherever the latest observation was before September 2022.

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 CPI available at the end of July 2020. Since Belarus's publication lag is two 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 data from 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

14 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.

reasons. Firstly, some vintages are missing.[15] 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.

B.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 one to four months depending on the country.

Our approach is to use linear extrapolation. That is, 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.

B.3 Trade weights

An effective exchange rate of a country aggregates together information about that country's trading partners. To do this, we need the weights that each country places on its trading partners. We use the trade weights produced by the IMF. The IMF has produced eight sets of weights, each referring to a different time period, ranging from 1979–1989 to 2016–2018 (Table B3). The weights are available for almost all countries, and are available on request to the IMF. 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 alternative 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 B3: 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 five-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 five-year

15 The Dallas Fed provides vintages up to 1998:Q4, 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.

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.[16] As the weights are published with a lag, the 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.[17]

Ideally, our real-time vintages of REERs would not only account for the fact that each set of weights is 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 (International Monetary Fund 2019). 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.

16 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 we expect to see in the future, which is achieved by choosing a five-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.

17 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'.

Appendix C: Calculation of Chained EER

Section 3.1.2 explains how we calculate an EER for a period with a single weight reference period. However, typically, we want to compute the EER over multiple weight reference periods. In this case, we compute an EER by 'chaining' the fixed-weight indices. 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:

$$\frac{EER_t^r}{EER_{t-1}^r} = \frac{EER_t^{r,b}}{EER_{t-1}^{r,b}}$$

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 January 1996, which is the first day of the '1996–2003' weight reference period, we would compute:

$$\frac{EER_{\text{1 Jan 1996}}^{\text{UK}}}{EER_{\text{31 Dec 1995}}^{\text{UK}}} = \frac{EER_{\text{1 Jan 1996}}^{\text{UK,1996–2003}}}{EER_{\text{31 Dec 1995}}^{\text{UK,1996–2003}}}$$

To compute the chained REER on 31 December 1995, which the last day of the '1990–1995' weight reference period, we would compute:

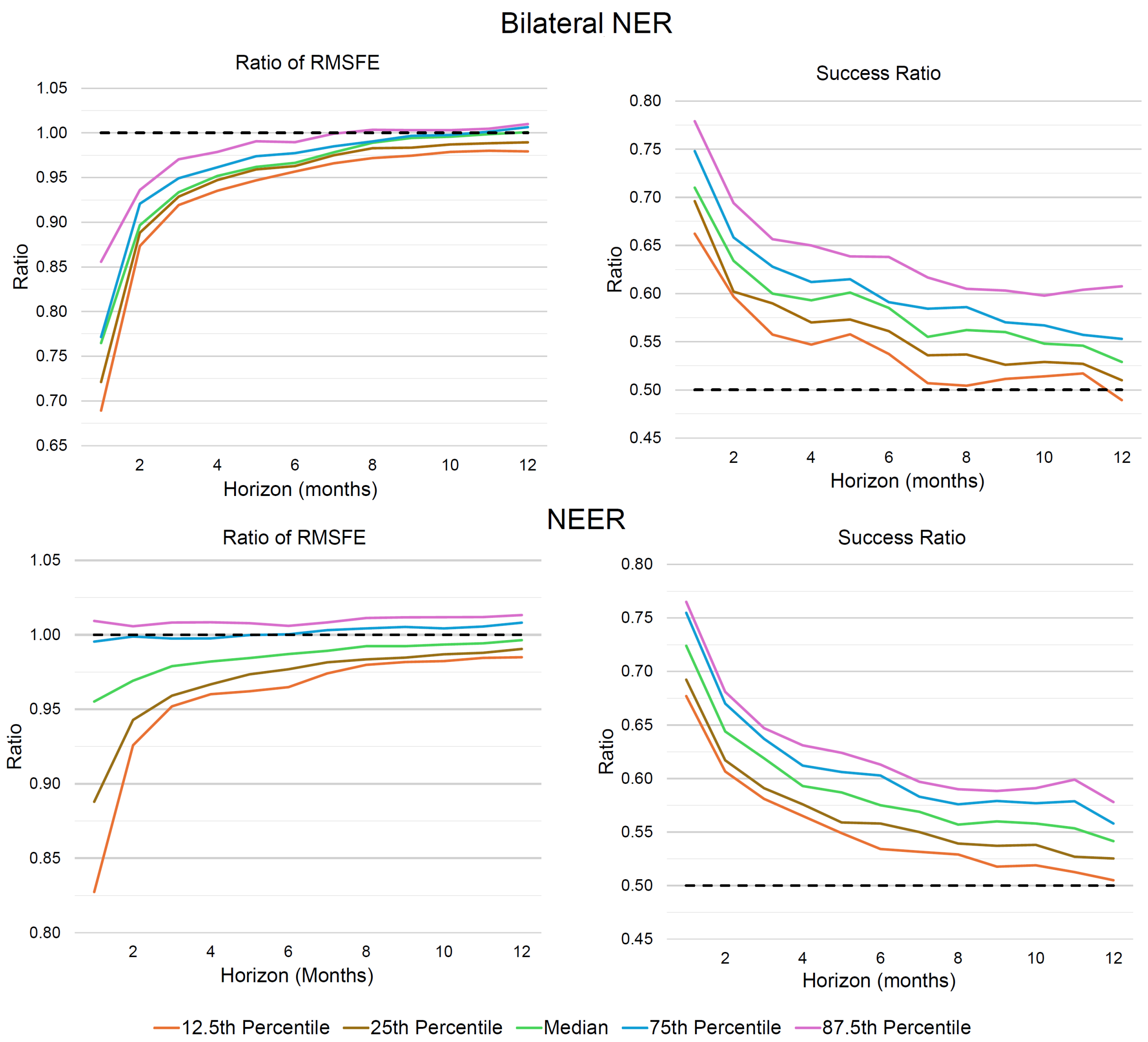
$$\frac{EER_{\text{31 Dec 1995}}^{\text{UK}}}{EER_{\text{30 Dec 1995}}^{\text{UK}}} = \frac{EER_{\text{31 Dec 1995}}^{\text{UK,1990–1995}}}{EER_{\text{30 Dec 1995}}^{\text{UK,1990–1995}}}$$

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 five years after the end of the period to which the weights relate (see Appendix B.3). 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 five-year lag to emulate current practice at the IMF, since they are our source of trade weights.

Appendix D: Real-time Forecast Accuracy for Other Exchange Rates

D.1 No-change forecasts

Figure D1: Distribution of Forecast Performance of End-of-month No-change versus Month-average No-change Forecasts



Notes: Plot shows quantiles for 83 countries. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund.

D.2 Model-based forecasts

Table D1: Median Performance of Forecasts for Month-average REER

Forecast	Model inputs	Horizon (months) 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

Notes: Reports the median result across countries relative to the month-average no-change forecast. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance.

Table D2: Median Performance of Forecasts for Month-average Bilateral NER

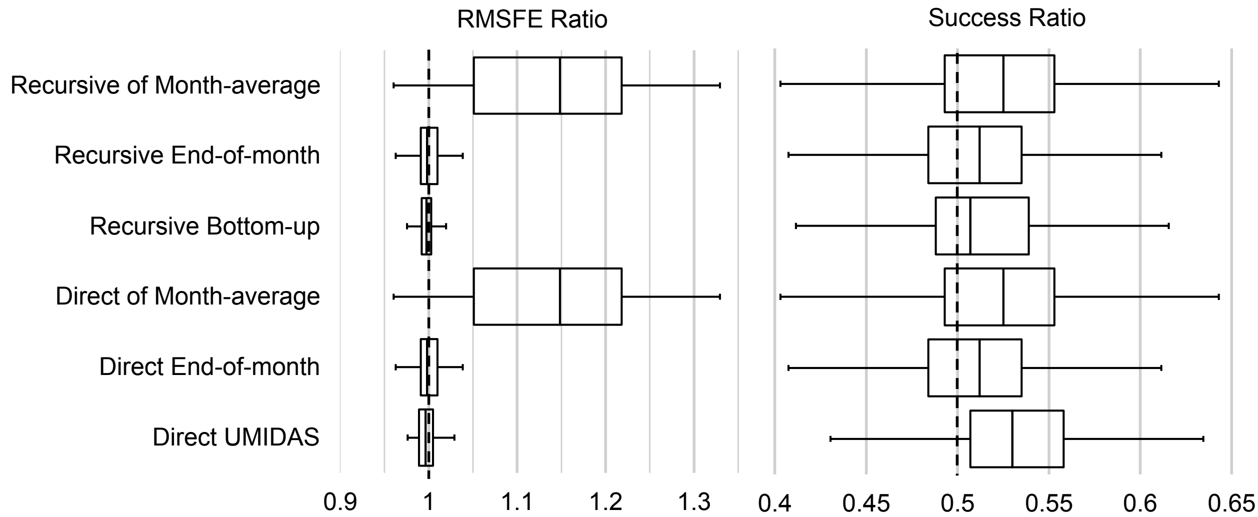
Forecast	Model inputs	Horizon (months) 1	3	6	12	24	36
RMSFE ratio							
Recursive	Month-average	1.00	1.01	1.01	1.02	1.05	1.07
Recursive	End-of-month	0.77	0.95	0.99	1.02	1.03	1.07
Recursive	Bottom-up	0.76	0.95	0.98	1.01	1.02	1.06
Direct	Month-average	1.00	1.01	1.01	1.02	1.08	1.32
Direct	End-of-month	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

Notes: Reports the median result across countries relative to the month-average no-change forecast. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance.

Table D3: Median Performance of Forecasts for Month-average NEER							
Forecast	Model inputs	Horizon (months)					
		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

Notes: Reports the median result across countries relative to the month-average no-change forecast. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance.

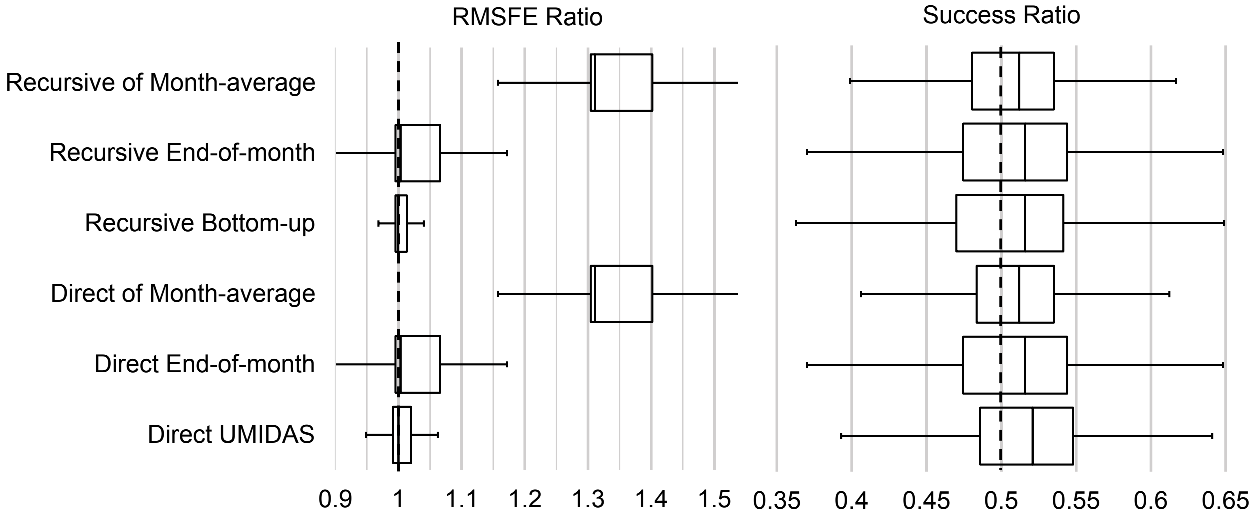
Figure D2: **Accuracy of One-month-ahead Forecasts for Bilateral RER Relative to End-of-month No-change Benchmark**



Notes: The box and whisker plots show the distribution of RMSFE ratios and SRs across countries. '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 use the end-of-month observation only. Outliers have been omitted. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund; World Bank.

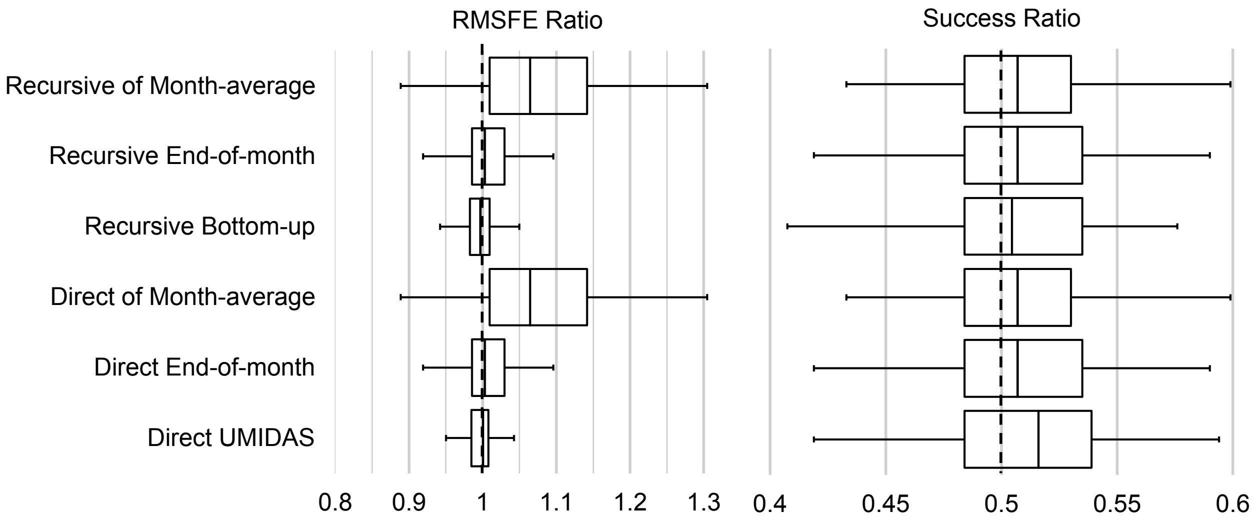
Figure D3: **Accuracy of One-month-ahead Forecasts for Bilateral NER Relative to End-of-month No-change Benchmark**



Notes: The box and whisker plots show the distribution of RMSFE ratios and SRs across countries. '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 use the end-of-month observation only. Outliers have been omitted. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund.

Figure D4: **Accuracy of One-month-ahead Forecasts for NEER Relative to End-of-month No-change Benchmark**



Notes: The box and whisker plots show the distribution of RMSFE ratios and SRs across countries. '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 use the end-of-month observation only. Outliers have been omitted. RMSFE ratios less than 1 (indicated by the dashed line) improve upon the month-average no-change. Success ratios greater than 0.5 (indicated by the dashed line) are improvements upon random chance.

Sources: Authors' calculations; Eikon; International Monetary Fund.

Appendix E: Robustness – Model-based Forecast Assumptions

This appendix presents forecasts that use pre-sample testing for order of integration and the number of autoregressive terms using AIC. These tests were applied to the daily ARIMA specification, and the equivalent lag structure was imposed on Equations (5) to (10).

Table E1: **Median Performance of Forecasts for Month-average Bilateral RER – Alternative Model Assumptions**

Forecast	Model inputs	Horizon (months) 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

Notes: Reports the median result across countries relative to the month-average no-change forecast. RMSFE ratios less than 1 improve upon the month-average no-change. Success ratios greater than 0.5 are improvements upon random chance.

Table E2: **Share of Countries with Significant One-month-ahead Exchange Rate Forecasts – Alternative Model Assumptions**

Forecast	Model inputs	versus end-of-month no-change REER	RER	NEER	NER	versus month-average no-change 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

Notes: Reports the per cent of countries for which the model-based forecast one-month-ahead significantly outperforms the benchmark at a five per cent level of significance.

Appendix F: Robustness – Countries with Flexible Exchange Rates

Table F1: **Median Performance of End-of-month No-change Forecasts versus Month-average No-change Forecasts – Countries with Flexible Exchange Rates**

	Horizon (months)					
	1	3	6	12	24	36
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

Notes: Forecast accuracy of end-of-month no-change forecast versus month-average no-change forecast. Reports the median across countries. Values of the RMSFE ratio less than 1 improve upon the month-average no-change. Values of the success ratio greater than 0.5 are improvements upon random chance. 'Random walk' is simulated using 5,000 iterations and 30 years of data.

Table F2: **Share of Flexible Exchange Rate Countries with Significant One-month-ahead Exchange Rate Forecasts**

Forecast	Model inputs	versus end-of-month no-change				versus month-average no-change			
		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

Notes: Reports the per cent of countries for which the model-based forecast one-month-ahead significantly outperforms the benchmark at a five per cent level of significance. Countries with floating exchange rates are defined following Ilzetzki *et al* (2019).

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