Fundamentals and exchange rate forecastability with machine learning methods

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FUNDAMENTALS AND EXCHANGE RATE FORECASTABILITY WITH MACHINE LEARNING METHODS*

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Abstract

Using methods from machine learning – sequential ridge regression and the exponentially weighted average strategy both with discount factors – that do not estimate a model but directly output forecasts we show that fundamentals from simple exchange rate models (PPP, UIRP and monetary models) consistently allow to improve exchange rate forecasts for major currencies over the floating period era 1973–2014 at a 1 month forecast and allow to beat the no-change forecast. "Classic" fundamentals hence contain useful information about exchange rates even for short forecasting horizons. Such conclusions cannot be obtained when using rolling or recursive OLS regressions as in the literature.

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1. Introduction

In this work we document the usefulness of prediction techniques borrowed from machine learning – sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors – as we reconsider the ability of simple models based on "classic" fundamentals to forecast short-term changes in exchange rates. We study "traditional" fundamentals from the purchasing power parity models (PPP), uncovered interest rate parity (UIRP) and a standard monetary model that the traditional exchange rate forecasting literature (based on OLS methods) failed to find effective (see Rossi [2013] for a recent comprehensive review). We show that with our methods we are able broadly to improve forecasting forward the 1–month exchange rate for the floating rate period 1973–2014 using the standardly employed root mean square error (RMSE) criterion. We obtain similar success with predicting the direction of change of the exchange rates and conducting several robustness checks. Our conclusion is therefore that "classic" fundamentals contain useful information about exchange rates even at short forecasting horizons[1] when proper machine-learning tools (directly geared towards maximizing the quality of predictions) are used. These findings are contrary to the consensus findings in the literature started by the famous Meese and Rogoff [1983] result of the inability of short-term forecasts based on fundamentals to outperform the most demanding no-change / random walk prediction[2]. This has important implications both for economic theory (see for example Alvarez et al. [2007]) and policy. Our success with this difficult forecasting problem shows that these methods could be used in many other relevant economic applications.

Machine learning methods at hand. The common feature for the methods we use is the following. They do not aim to estimate the coefficients of some model but rather treat the coefficients as numbers to be picked over time in order to form good predictions. Indeed, these methods do not rely on some stochastic modeling of the exchange rates (e.g., in terms of a linear combination of the fundamentals plus some stochastic errors). We describe in Section 3.3 the theoretical guarantees that can be proven instead for these methods: that their RMSEs converge, as the number of instances to be predicted increases, to the RMSE of the best fixed linear model (which is in

[1] Forecastability of the exchange rates over longer time periods, such as 2-year forward forecasts and beyond was established in the literature, see Section 1.1.

[2] The rare exceptions are that of Clark and West [2006] that demonstrate the predictability of a UIRP-based model or Wright [2008] that uses Bayesian Model Averaging methods. See a longer discussion below.

particular weakly smaller than the RMSE of the no-change / random walk prediction). One can also show that no such guarantee can be achieved for conventional (rolling) OLS. Note finally that our methods are general forecasting methods that were not specifically designed for exchange rate forecasting. They proved to work well in other problems (forecasting of air quality, electricity consumption or the production of oil reservoirs; see Cesa-Bianchi and Lugosi [2006] as well as the papers Mauricette et al. [2009] and Stoltz [2010]).

More precisely, our first method – the exponentially weighted average strategy with discount factors – allows to weigh fundamentals by their past performance: the coefficients picked over time reflect the relative average past performance of each fundamental. They vary over time as the performance of each fundamental evolves: this is a reactive method (while not being too reactive: it does not overfit data). If some fundamentals always perform poorly they are discarded[3] but in general, many coefficients are non-zero.

Our second method – sequential ridge regression with discount factors – resembles OLS regressions, but it prevents the in-sample-overfitting issue they encounter by including a regularization term in an otherwise standard ordinary least squares (OLS). This leads to better and more stable performance out-of-sample.

For both methods, we consider variants of the basic machine-learning formulations that include discount factors so that most recent forecasting errors matter more than older ones. This allows for our variants to accommodate structural breaks that might be present in the data (such as changes in the conduct of monetary policy, crisis times etc.) better than the original formulations; this is also true for any accommodating behavior of market participants[4]. It is to be stressed that both the discount factors and the parameters of the methods described above (a learning rate for the exponentially weighted average strategy with discount factors, a regularization factor for sequential ridge regression with discount factors) are computed from the data up to the period for which the forecast is given rather than exogenously imposed[5]. Our methodology is hence entirely data-driven and does not rely on some educated guesses about important parameters as for example in Wright [2008] for Bayesian model averaging methods.

[3]This could potentially help to identify the "most fashionable" fundamentals considered by traders as in the scapegoat model of exchange rates of Bacchetta and Wincoop [2004].

[4]Consider the comparison of forecasts in the time period around the Plaza agreement shown in Table 9 and discussed in Appendix C.

[5]Unsurprisingly, models that we call "oracles" – acting as if these optimal parameters were known beforehand – perform better.

Main results put in perspective. What we show is that the basic fundamentals considered in the literature have predictive power even at short horizons which was deemed a lost cause in international economics and may be useful for conducting policy- or market-oriented exchange rate forecasts. The improvements in the forecasts using fundamentals we document (up to 7 $\%$ in terms of RMSE) are not large; the fundamentals we consider do not help to add a lot of predictive content relative to the one of "no change" from the previous observed exchange rate. The observations of Engel and West [2005] may well be valid: current and past fundamentals may have low correlations with future exchange rate realizations. Fundamentals may have little predictive power against an exchange rate that can be approximated by a random walk although they may add *some* useful information.

In our study, apart from the particular machine-learning methods, we used data and forecast evaluation methods that are standard in the literature as discussed in Rossi [2013]. We use lagged fundamentals and do not detrend, filter or seasonally adjust the data in any way. We use single-equation methods and our benchmark for comparison is the no change in the exchange rate prediction. We study the most important floating currency pairs for the entire period 1973–2014 since the breakup of the Bretton Woods fixed exchange rate system. We use two samples as encountered in the literature: the end-of-month exchange rate sample (with one reading of the exchange rate at the end of the month) and a sample with average monthly exchange rates as used by for example Molodtsova and Papell [2009] to allow for comparability with the Taylor-rule models they suggest.

We conduct several robustness checks – such as trying out different (sub)samples, variations on the exact form of the fundamentals included, etc., and our results are upheld. Furthermore, investigation of statistical properties of the errors shows that our improvement is uniform rather than driven by a few well predicted instances. There are several themes discussed by Rossi [2013] that also hold in our study. Traditional linear estimation methods (rolling or recursive OLS) with our fundamentals fail to forecast exchange rates better than the no change in exchange rates prediction. With the addition of several fundamentals (aggregating information) we do not get gains in the precision of predictions – that is, parsimonious models work best. Fundamentals contemporaneous with the forecast period (actually realized values, as used in Meese and Rogoff [1983]) perform poorly.

Our study is not comprehensive nor exhaustive in nature. Our goal is not to provide the best forecasts of exchange rates possible by finding fundamentals from a wide menu that was considered in the vast literature that have the strongest predictive power (or aggregating the information contained therein) but rather to show the usefulness of methods of machine learning in application to well-known and hard to crack economic problems. A valid question is whether the gains from prediction could significantly improve the utility for investors using portfolio investment strategies following our forecasts – akin to the exercise undertaken by Corte et al. [2012] for the Gourinchas and Rey [2007] model. Such an exercise is beyond the scope of this study, however, as we concentrate solely on the forecast performance of our machine-learning methods for single-equation methods.

1.1. Related literature

Exchange rate forecasting literature. Rossi [2013] provides a comprehensive recent review of the exchange-rate forecasting literature so we keep ours at a bare minimum. There were different ways in which researchers tried to cope with the negative result of Meese and Rogoff [1983] that showed that the simple exchange rate models from the 1970s (i.e., that proposed the fundamentals we study here) did poorly in comparison to a random walk without drift (a no-change prediction) in forecasting the exchange rates in the floating period after 1973 for short forecast horizons. One way, that we pursue here, was to use better econometric tools to extract information from the data. Some of the solutions proposed involved for example cointegration techniques as in Mark [1995] combined with the usage of panel data such as in Mark and Sul [2001], long samples in panels as in Rapach and Wohar [2002] and including a large set of countries as in Cerra and Saxena [2010]. These techniques typically are used for longer-horizon (above 1 year) forecasts when it is believed that the long-run relationship as modeled by the cointegrating equations kicks in. The cited studies obtain some success in demonstrating predictability and/or forecastability at longer horizons (typically longer than 2 years). We focus on short-term forecasts and use single-equation methods – a setup in which forecastability was not ascertained largely till today. For the short-run, Greenaway-Mcgrevy et al. [2012] obtain considerable success in outpredicting the no-change prediction using factor analysis extracting the factors from the exchange rates themselves (but not the economic fundamentals)[6]. Bianco et al. [2012] obtain forecastability for the Euro/U.S. dollar rate at weekly to monthly horizons using a stylized econometric model that mixes information

[6]The problem is that factor analysis comes with no theoretical guarantees. Moreover, there is no theoretical reason (as opposed to regular economic models) why such relationships should hold.

from different fundamentals arriving at different frequencies. Our method is more general, directly geared for prediction, and importantly comes with some theoretical guarantees on the convergence of the RMSEs (see Section 3.3).

Sequential combination of fundamentals. The methodology used for forecasting in this paper consists of sequentially combining (aggregating) fundamentals. The distinguishing feature of our methodology is that it is sequential in nature: in contrast, all other approaches we know of in the forecasting of exchange rates use batch estimation or learning methods that need to be run in an incremental way (which usually leads to the loss of the theoretical guarantees associated with the batch case). These approaches can be divided into two groups: estimation methods of the statistics literature and the learning methods of the machine-learning literature.

The second group contains, for instance, the studies of Wright [2008] for exchange rates or Bajari et al. [2015] for demand estimation. The first reference is perhaps the closest effort to ours insofar as the idea of extracting information from fundamentals to forecast exchange rates is concerned. The method at hand is called Bayesian model averaging. The building blocks for prediction therein are a great number of predictors, many of which do not come from the standard models considered in this paper (not only classic fundamentals are used). The approach of Wright [2008] does not improve the forecasts upon a no-change prediction in a statistically significant way in most cases he considers. Moreover, it is not clear how to properly choose the “shrinkage” parameter that guards the informativeness of priors not knowing the properties of the data ex ante. Our methods, in contrast, are entirely data driven.

As for estimation methods, two approaches related to ours are estimations of nonlinear models and models with time-varying parameters. Rossi [2013] discusses that different nonlinear methods were not particularly successful in forecasting exchange rates while Rossi [2006] questions the robustness of the time-varying parameter models. Bacchetta et al. [2010] argue that the gain from using such an approach would be practically minimal. These authors find on simulated data that the benefits from using such models in terms of greater explanatory power are in practice outweighed by additional estimation errors of the time-varying parameters. Schinasi and Swamy [1989] reassess the study of Meese and Rogoff [1983] using various nonlinear methods, including an early version of a ridge regression. Engel [1994] documents a failure of a Markov-switching model to beat the no-change prediction in forecasting.

Other issues considered in exchange rate forecasting. Another way that researchers tried to improve the ability of fundamentals to forecast exchange rates is to consider different economic models with other fundamentals. It turned out in the most recent years that exchange rate models based on Taylor-rule fundamentals perform well in ascertaining the predictability[7] of the exchange rates at a short horizon (Engel and West [2006], Molodtsova and Papell [2009], Molodtsova et al. [2011], Giacomini and Rossi [2010], Rossi and Inoue [2012] though Rogoff and Stavrakeva [2008] disagree) but do not find that these perform much better in terms of forecasting and find sometimes that they give strictly worse results[8]. For this reason we try out our methods on the same fundamentals though we do not find them better than the "classic" fundamentals (see Appendix C).

Another successful fundamental was the behavior of net foreign assets as in Gourinchas and Rey [2007] or Corte et al. [2012]. The fundamentals to conduct these tests are available at 3–month frequencies resulting in fewer observations that can be used so we do not investigate them here. Other studies assessed the forecasting ability of exchange rate models of the 1990s such as Cheung et al. [2005], or differences in the term structures of forward premia such as Clarida et al. [2003]. Given the scope of our exercise, we did not evaluate these models with our machine-learning methods, but it may be a useful research agenda for the future. Some other attempts, that are less relevant for our current study, involved work on what data was available at what instant while forming the forecasts (see for example Ince [2014]) – though these did not lead to a qualitative difference in the predictions obtained.

[7] Predictability is a different concept than forecastability. In Molodtsova and Papell [2009] it is about testing whether the estimated coefficients of a considered model are jointly significantly different from zero when explaining changes in the exchange rate. It does not mean that a model that exhibits predictability necessarily provides better forecasts (in the literature typically it does not). The focus of these and many other attempts in general is rather to assess whether fundamentals play a role in exchange rate determination as it can be motivated theoretically why the forecasts they produce in terms of an evaluation criterion such as root mean square errors (RMSE) may fare worse than those of a forecast based on no change of the exchange rate. (See Rossi [2013] for a discussion. Special tests were designed by West [1996], Clark and West [2006, 2007] for this purpose. See also Footnote 16.) In this paper, however, we are not interested in such understood predictability – we actually are interested whether we can produce better forecasts of the exchange rates than the no-change prediction. We are also not interested in validating a particular model – that is trying to fit the coefficients and check whether the signs and magnitudes are that those posited by theories; we simply try to extract from the fundamentals in question the information useful for the behavior of exchange rates.

[8] We do not use any models based on the evolution of net foreign assets such as Gourinchas and Rey [2007] because the fundamentals to conduct these tests are available at 3–month frequencies resulting in fewer observations that can be used.

1.2. Organization of the paper

First, in Section 2 we lay out the fundamentals that we shall consider. Then, in Section 3 we discuss the methods of the analysis and put them in perspective with the standard linear regressions. Next, in Section 4 we discuss the data while Section 5 contains the results. Section 6 concludes. An Appendix contains further details regarding the methods and more results tables.

2. Considered fundamentals

We consider the "classic" fundamentals stemming from the simple exchange rate models of the 1970s. The reasons are fourfold, as surveyed in Rossi [2013]: (i) these fundamentals come from exchange rate models that involve basic relationships in standard international economics such as the existence of arbitrage, (ii) they have been extensively used in the literature, (iii) studies have shown that at short-time horizons forecasting models based on these were not successful against the benchmark of no-change forecast[9], (iv) the data is widely available for long periods for a wide set of countries and does not require any transformation (like, for example, data on productivity).

2.1. General framework

The general forecasting model of the exchange rate change for a currency pair is given by

$$s_{t+1} - s_t = \alpha_t + \sum_{j=1}^{N} \beta_{j,t} f_{j,t} \,, \tag{1}$$

where s_t is the logarithm of the exchange rate (home currency units per unit of the foreign currency) at time t, the intercept α_t and the slope coefficients $\beta_{j,t}$ are to be picked based on any and all information available up to time t, while the $f_{j,t}$ are the N fundamentals considered at time t. Throughout the paper we will force[10] $\alpha_t = 0$. The time unit will be months.

By the exchange rate, we mean here either the end-of-the month value or the monthly average of the rate, depending on the data set.

[9]To remind our reader, no other set of fundamentals was shown as of yet to beat such forecasts in a consistent manner either.

[10]Affine models can be handled via one only of our two new forecating methods, namely, sequential ridge regression with discount factors, and did not offer an improvement upon the results shown in the paper. Details are available upon request. The other method, the exponentially weighted average strategy with discount factors, is not applicable to affine models.

The coefficients $\beta_{j,t}$ (and α_t when intercepts are considered, which is not the case here) are usually picked through rolling or recursive OLS regressions. Rossi [2013] states that "the literature has been focusing mainly on rolling or recursive window forecasting schemes (see West [2006]), where parameters are reestimated over time using a window of recent data", and Cheung et al. [2005] mentions "the convention in the empirical exchange rate modeling literature of implementing rolling regressions established by Meese and Rogoff [1983]." This was because they proved best and no other method could consistently beat them. In this paper, we revisit this convention and consider other methods for picking these coefficients. We do not write "estimate these coefficients" as such a wording refers to some underlying model with true parameters α and β. We will be interested solely in the forecasting performance and not at all in the existence or use of a model.

Before recalling how rolling and recursive OLS regressions proceed to that end and presenting alternative methods stemming from the field of machine learning, we discuss the fundamentals of interest.

2.2. PPP, UIRP and monetary model fundamentals

We are only interested in the predictive performance of our forecasting methods and we allow for different coefficients for home and foreign fundamentals relating to the same measured quantity, even if the models from which they come from could call for equal weighting theoretically. There is a good reason to do this as in our empirical work two series, even if pertaining to a similar economic concept, may be measured completely differently in any two countries (given that they are provided by independent institutions using diverse methodologies). Hence, the best weights picked may differ as the elasticities of response of investors to purportedly similar fundamentals in both countries may and should differ[11].

The first series of fundamentals is formed by inflation differentials, coming from the relative

[11] The most flagrant example are perhaps money stocks: for the United Kingdom and Sweden only M0 aggregates, and for Italy and the Netherlands only M2 are available for the entire period considered and not M1 as for other countries. M0, M1 and M2 money aggregates are typically correlated, but they obviously measure different things. Even for countries for which M1 measures are available, these contain different components depending on the country. Such issues unfortunately exist to some extent for every fundamental considered, and is a general problem in the literature. Due to the asymptotic properties of the methods we wanted to obtain the longest series possible for the largest number of currencies and had to – given the data available – sacrifice to some extent standardization.

purchasing power parity (PPP) model[12]. The associated forecasting equation is given by

$$\widehat{s}_{t+1} - s_t = \beta_{1,t}\pi_t - \beta_{2,t}\pi_t^\star \tag{2}$$

where π_t and $\pi_t^\star$ are respectively present home and foreign measures of 12-month inflation rates available (known) at time t. In what follows, a "$\star$" will denote the variables for the foreign country.

Our forecasting equations for the uncovered interest rate parity model (UIRP) are of the form

$$\widehat{s}_{t+1} - s_t = \beta_{1,t} i_{t\to t+1} - \beta_{2,t} i^\star_{t\to t+1}\,, \tag{3}$$

where $i_{t\to t+1}$ is the short run (money-market) interest rate at home and in the foreign country respectively. These would be the interest rates at which investors could place money at time t for the period t to $t+1$ and could be observed by them in real time.

The third series of fundamentals consists of variations of money stocks and outputs. The simplest monetary model (flexible price, Frenkel-Bilson model) states that exchanges rates can be modeled as linear combinations of the form

$$s_t = \alpha + \phi\big(m_t - m_t^\star\big) - \omega\big(y_t - y_t^\star\big)\,,$$

where m_t and $m_t^\star$ are the logarithms of the money stocks at time t while y_t and $y_t^\star$ are the logarithms of outputs. Here, α, ϕ and ω denote some true underlying parameters for the model. After lagging the fundamentals by a month (to account for known and present, not forward values), differencing the above equation[13], and allowing for decoupled fundamentals we obtain the forecasting equation

$$\widehat{s}_{t+1} - s_t = \beta_{1,t}\Delta m_t - \beta_{2,t}\Delta m_t^\star - \beta_{3,t}\Delta y_t + \beta_{4,t}\Delta y_t^\star \tag{4}$$

where $\Delta x_t = x_t - x_{t-1}$ denotes the change between periods $t-1$ and t for a variable x. In (4),

[12] The relative PPP model stipulates actually $s_{t+1} - s_t = \beta_{1,t}\Delta p_{t+1} - \beta_{2,t}\Delta p^\star_{t+1}$ where Δp_{t+1} is the change in the price level between periods t and $t+1$. However, as the change in the future price level is unknown at time t, we use past price changes (inflation) in our forecasting exercise.

[13] We proceeded this way as some of the methods we use, in particular, the exponentially weighted average strategy with discount factors, require direct predictions of the exchange rate change. An alternative is to find some"equilibrium" exchange rate driven by the aforementioned fundamentals and use the deviation of the current exchange rate from that "theoretical" exchange rate as the fundamental. Doing this does not change qualitatively our results.

the parameters $\beta_{1,t}$ and $\beta_{2,t}$ are to be picked over time, as in (2) and (3).

Hence, in our basic investigations we use as fundamentals[14]: (i) inflation differentials $\pi_t - \pi_t^\star$, or (ii) interest rate differentials $i_{t\to t+1} - i^\star_{t\to t+1}$, or (iii) differences in the money stock growths $\Delta m_t - \Delta m_t^\star$ and differences in the output growths $\Delta y_t - \Delta y_t^\star$. We also investigate whether all the fundamentals mentioned above taken together are able to predict changes in the exchange rate[15].

Finally, in Appendix C we also consider whether the fundamentals from a Taylor-rule based exchange-rate model (that has been found as successful in establishing the predictability of the exchange rate changes, as discussed in Section 1.1) are useful in forecasting as well. We use the most parsimonious version of equation (7) from Molodtsova and Papell [2009] as our forecasting equation:

$$s_{t+1} - s_t = \beta_{1,t}\pi_t^\star - \beta_{2,t}\pi_t + \beta_{3,t}\widetilde{y}_t^\star - \beta_{4,t}\widetilde{y}_t + \beta_{5,t} i^\star_{t-1\to t} - \beta_{6,t} i_{t-1\to t} \tag{5}$$

where $\widetilde{y}_t$ and $\widetilde{y}_t^\star$ are present measures of the output gaps. Therefore, our Taylor-rule fundamentals are the inflation, output gaps and the lagged interest rates.

The exact data series used are further discussed in Section 4.

Coupled fundamentals. In the forecasting equations (2)–(5) fundamentals of the home and foreign countries pertaining to the same concept can also get the same weight. For example, the PPP model in (2) will be then $\widehat{s}_{t+1} - s_t = \beta_{1,t}\big(\pi_t - \pi_t^\star\big)$. We will refer to this situation as coupled fundamentals and perform robustness checks using this formulation. Note that it still falls under the general umbrella (1), only with $N/2$ coefficients to pick instead of N and with the $f_{j,t}$ then referring to the differences between home and foreign fundamentals.

[14]The form in which the fundamentals are included does not seem to matter. We reran the PPP and monetary models for our main sample also using price or output indices in levels or the monetary stock: our qualitative conclusions do not change.

[15]We also investigated fundamentals from the other popular monetary flexible-price model that also involves differences in interest rates, which in our formulation would add terms $i_t - i_{t-1}$ and $i_t^\star - i_{t-1}^\star$ as predictors. We do not show the results as they were very close to the performance of the model shown in (4). We included these fundamentals, however, when considering forecasts with all fundamentals at hand to see whether aggregating information from many different series helps.

3. Methodology

3.1. Assessing the quality of the forecasts

As indicated above, forecasts $\widehat{s}_{t+1}$ of the 1-month ahead exchange rates s_{t+1} are based on the forecasting equations (2)–(5). A forecasting method consists of a rule for picking the coefficients $\beta_{j,t}$ over time based on past and present information. Several such methods are presented in Section 3.2, namely, the conventional rolling and recursive OLS regressions as well as two other methods stemming from the field of sequential learning.

We denote by T the total number of monthly values to be forecast, from months 1 to T. As is standard in the literature (see Molodtsova and Papell [2009] or Rossi [2013]) and for essentially the same reasons, namely, the consideration of rolling OLS regressions, we allow for a training period of length $t_0 = 120$ months (10 years) and only evaluate the accuracy of the forecasts on months $t_0 + 1 = 121$ to T. To that end, we consider the root mean square error,

$$\begin{aligned} \text{RMSE} &= \sqrt{\frac{1}{T-t_0}\sum_{t=t_0+1}^{T}\bigl(\widehat{s}_t - s_t\bigr)^2} \qquad (6) \\ &= \sqrt{\frac{1}{T-t_0}\sum_{t=t_0+1}^{T}\Bigl(\bigl(\widehat{s}_t - s_{t-1}\bigr)-\bigl(s_t - s_{t-1}\bigr)\Bigr)^2}, \end{aligned}$$

and note that (by substracting and adding the pivotal values s_{t-1}) this root mean square error is indifferently the one for the logarithms of exchange rates s_t or for the changes in logarithms of exchange rates $s_t - s_{t-1}$.

We will want to investigate whether the improvements in RMSE of one method over another one are statistically significant. Denote by $\widehat{s}_t$ and $\widehat{s}'_t$ the respective forecasts of two methods of interest. We aim to test the hypothesis H_0 that the difference in forecasting accuracy is not significant against the alternative hypothesis H_1 that the second method—the one outputting the forecasts $\widehat{s}'_t$—is significantly better on average. To that end, the standard practice is to consider the instantaneous differences in accuracy

$$d_t = \bigl(\widehat{s}_t - s_t\bigr)^2 - \bigl(\widehat{s}'_t - s_t\bigr)^2 .$$

We denote by

$$\overline{d}_T = \frac{1}{T - t_0} \sum_{t=t_0+1}^{T} d_t$$

the empirical average of the differences and by

$$\overline{\sigma}_T^2 = \frac{1}{T - t_0} \sum_{t=t_0+1}^{T} \left(d_t - \overline{d}_T\right)^2$$

their empirical variance.

Some descriptive statistics. To get a first feeling of whether H_0 should be rejected or not, one can take a look at the quantiles of the series of the d_t. E.g., in Tables 10–11 of Appendix C, we see that in the case of the sequential ridge regression with discount factors or the exponentially weighted average strategy with discount factors, the distribution of the differences d_t is shifted toward positive values: the 75% and 90% quantiles are larger in absolute values than the 25% and 10% quantiles, while in addition, the median is positive. This tendency is especially visible for the sample with the average exchange rates. This is not the case for rolling or recursive OLS regressions. Additional comments on these matters are provided in Section 5.1.

A general test for comparing the predictive accuracies. Diebold and Mariano [1995] presented a test[16] relying on mild and direct assumptions on the behavior of the differences d_t. This test uses the differences in the forecasting errors as primitives, even though the latter can be serially correlated. We state their results with a rectangular lag, as they advocated to do so.

More precisely, they showed that under an assumption of covariance stationary and of short memory of the differences d_t, for a properly chosen truncation lag denoted by $H \geqslant 0$, the test statistics

$$S_{\mathrm{DM},H} = \sqrt{T - t_0}\, \frac{\overline{d}_T}{\sqrt{\overline{\sigma}_T^{H,2}}}\,,$$

[16] The tests by West [1996], Clark and West [2006, 2007] are designed for comparing models, while we are interested here only in comparing forecasts. See Diebold [2012], Rossi [2013] for discussions. Further, the tests by Clark and West have been designed and studied only for the case of rolling and recursive OLS regressions, while in our case we obviously are interested in alternative methods. This is underlined in the original papers and pointed out again by Rogoff and Stavrakeva [2008]. Note, finally, that Wright [2008] implements neither the Clark-West nor the Diebold-Mariano tests to assess the predictive performance of his new method; he only offers a simulation study on artificially regenerated data.

where

$$\overline{\sigma}_T^{H,2} = \frac{1}{T-t_0} \sum_{t=t_0+1}^{T} \left(d_t - \overline{d}_T\right)^2 + \frac{2}{T-t_0} \sum_{\tau=1}^{H} \sum_{t=\tau+t_0+1}^{T} \left(d_t - \overline{d}_T\right)\left(d_{t-\tau} - \overline{d}_T\right),$$

converge to a $\mathcal{N}(0,1)$ distribution under H_0 while converging to $+\infty$ under H_1. Diebold [2012] insists on how general the method is to compare the predictive accuracy of forecasts between any two methods, as long as the mild assumption stated above, namely, covariance stationarity of the differences in accuracy d_t, holds. He explains in Section 2.2 of the mentioned reference why this assumption is natural and often met in practice.

The choice of the truncation lag H was partially left open; Diebold and Mariano suggested to pick it as a function of the length of the short memory (of the autocovariance degree). Estimating by $\widehat{H}$ a proper H based on our data then substituting its value would lead to considering the test statistic $S_{\mathrm{DM},\widehat{H}}$, which would not be guaranteed anymore converge to a $\mathcal{N}(0,1)$ distribution under H_0. We instead take a more robust approach to reject H_0, that is, we build a more conservative test than the original test based on some good, a priori value of H. Namely, we consider

$$S_{\mathrm{DM}} = \sqrt{T-t_0}\,\frac{\overline{d}_T}{\sqrt{\displaystyle\max_{H\in\{0,1,\ldots,20\}} \overline{\sigma}_T^{H,2}}}\,, \tag{7}$$

which is smaller than any of the corresponding original statistics $S_{\mathrm{DM},H}$. The limiting distribution under H_0 is smaller than a $\mathcal{N}(0,1)$ distribution. Yet, we compute the p–values using quantiles of the normal distribution, which is very conservative. Despite all, we will be able to reject the hypothesis H_0 of equal accuracy abilities in many circumstances.

Note that the maximal value 20 for H was set on our data set because it corresponds roughly to the maximal value of $\sqrt{T-t_0}$ on our data. The p–values associated with the test thus constructed will be reported in the tables in columns labeled "DM p–value".

3.2. Forecasting methods (1/2): classical ones

Getting back to the forecasting equations (2)–(5), we now present the different forecasting methods considered in this paper. We will do so in some generality, encompassing all these equations under the umbrella (1):

$$\widehat{s}_{t+1} - s_t = \sum_{j=1}^{N} \beta_{j,t} f_{j,t} \, .$$

We recall that in our view, the coefficients $\beta_{j,t}$ are to be picked according to some rule; they do not need to be understood as estimating some unknown underlying true value.

The no-change forecasting method. The first strategy consists of choosing $\beta_{j,t} = 0$ for all j at each round t, that is, of forecasting $\widehat{s}_{t+1}$ by s_t. We call it the no-change forecasting method.

Rolling OLS regression. This is the most standard technique in the literature—"the convention" as states, e.g., Cheung et al. [2005]. The idea is to truncate the available information to account for the most recent relationships between variables that can change through time because of policy changes (for example, a change to Taylor-rule based monetary policy), structural changes in the economy (such as shifting relationships between the money stock and inflation), etc. Because of this forecasting method, we need a training period, which we set to $t_0 = 120$ months as is standard in the literature (see Molodtsova and Papell [2009]). The rolling OLS regression picks, for months $t \geqslant t_0$,

$$(\beta_{1,t}, \, \ldots, \, \beta_{N,t}) \in \mathop{\arg\min}_{\beta_1,\ldots,\beta_N \in \mathbb{R}} \sum_{\tau=t-t_0+1}^{t} \left(s_\tau - s_{\tau-1} - \sum_{j=1}^{N} \beta_j f_{j,\tau-1} \right)^2 .$$

Recursive OLS regression. This is another standard technique in the literature. It consists of choosing, for months $t \geqslant 1$,

$$(\beta_{1,t}, \, \ldots, \, \beta_{N,t}) \in \mathop{\arg\min}_{\beta_1,\ldots,\beta_N \in \mathbb{R}} \sum_{\tau=1}^{t} \left(s_\tau - s_{\tau-1} - \sum_{j=1}^{N} \beta_j f_{j,\tau-1} \right)^2 ,$$

i.e., all past time instances, not only the t_0 most recent ones, are used to form the prediction.

3.3. Forecasting methods (2/2): new ones from machine learning

The new forecasting methods considered in this study stem from the field of machine learning, where they are already standard methods for the robust online prediction of quantitative phenomena by aggregation of basic predictors (fundamentals). The monograph by Cesa-Bianchi and Lugosi [2006] summarizes the research performed around them in the period 1989–2006.

These methods have been applied exactly as they are stated below (i.e., we provide no tweak on these methods) in the following fields: forecasting of the air quality (see, e.g., Mauricette et al. [2009], Mallet [2010], Debry and Mallet [2014]); the forecasting of electricity consumption (see, e.g., Devaine et al. [2013], Gaillard and Goude [2015]); the forecasting of the production of oil reservoirs (work in progress). We underline that thus, these methods are not ad hoc methods constructed solely for the problem of predicting exchanges rates.

The theoretical out-of-sample guarantees that they do come with are of the following form: for all possible bounded sequences of exchange rates and of fundamentals, their predictions are such that

$$\sum_{t=0}^{T-1} \left(s_{t+1} - s_t - \sum_{j=1}^{N} \beta_{j,t} f_{j,t} \right)^2 - \inf_{\beta^\dagger \in \mathcal{F}} \sum_{t=0}^{T-1} \left(s_{t+1} - s_t - \sum_{j=1}^{N} \beta_j^\dagger f_{j,t} \right)^2 \leqslant B(\mathcal{F}, T) \qquad (8)$$

with $B(\mathcal{F}, T) \ll T$ and where $\mathcal{F} \subset \mathbb{R}^N$ is some comparison class (the forecasting methods presented below are independent of the choice of $\mathcal{F}$, only the bound $B(\mathcal{F}, T)$ is sensitive to it). We explain below what we mean by a comparison class: a set of candidates for the underlying expression of the exchange rates in terms of linear combinations of fundamentals. With the algorithms presented below, such linear combinations can be given by $\mathcal{F}$ equal to the set of all point mass combinations (weights that equal 1 for one fundamental and are null for all others) or to some bounded Euclidean ball of $\mathbb{R}^N$ (e.g., all linear weights with Euclidian norm bounded by some constant U, and then, U steps in the bound).

In particular, from (8), dealing separately with the training period of size t_0 (for which an error bounded by something of the order of t_0 is made in the worst case), dividing by $T - t_0$, and taking square roots, we get the following guarantee on out-of-sample RMSEs:

$$\limsup_{T \to \infty} \left\{ \sqrt{\frac{1}{T-t_0} \sum_{t=t_0}^{T-1} \left(s_{t+1} - s_t - \sum_{j=1}^{N} \beta_{j,t} f_{j,t} \right)^2} - \inf_{\beta^\dagger \in \mathcal{F}} \sqrt{\frac{1}{T-t_0} \sum_{t=t_0}^{T-1} \left(s_{t+1} - s_t - \sum_{j=1}^{N} \beta_j^\dagger f_{j,t} \right)^2} \right\} \leqslant 0 \,. \qquad (9)$$

Let us comment in words about the properties of these out-of-sample guarantees. First, they rely on no stochastic modeling, they are achieved for all possible bounded sequences of exchange rates and of fundamentals: these performance bounds are deterministic. The bound $B(\mathcal{F}, T)$ actually also depends on the range in which the exchange rates and the fundamentals lie; but it is a uniform bound. Second, what they truly ensure is that the forecasting method has asymptotically an average performance as good as or even better than the one of the best constant linear combination in $\mathcal{F} \subset \mathbb{R}^N$, i.e., the best fixed model with coefficients in $\mathcal{F}$. But of course, as mentioned above, such a model does not need to exist, since no assumption of stochastic modeling is required. It just turns out that the methods presented below mimic the performance of the best model if applicable. Put differently, we can interpret the infimum in (8) (the error suffered by the best pick in the comparison class) as measuring some approximation error (how well in hindsight the fundamentals can predict the exchange rates) while the $B(\mathcal{F}, T)$ term is a sequential estimation error (the price to pay for facing a sequential rather than a batch problem).

One may wonder where the catch is—the type of guarantee exhibited above seems too good to be true. Actually, getting close to or slightly better than the performance of the best model is not necessarily good enough for obtaining great forecasts: the best model can have a poor performance. This may be in particular true in the setting of exchange rates where fundamentals are known to have a questionable value for modeling purposes. This all is in contrast with the other fields of application mentioned above such as forecasting of electricity consumption or air quality. Finally, we note that it can be shown that out-of-sample guarantees like (9) cannot be achieved by rolling OLS regression[17]. Performance guarantees on the latter forecasting methods thus requires a stochastic modeling of the sequence of exchange rates.

Is it better to use coupled or decoupled fundamentals? The short answer will be: there is no theoretical reason to prefer one or the other. Indeed, while the approximation errors of the decoupled version are always smaller than the ones of the coupled versions (just because they correspond to an infimum taken on a larger set), the bounds $B(\mathcal{F}, T)$ on the sequential estimator errors in (8) always increase with the number N of independent fundamentals, thus are larger with decoupled than with coupled fundamentals. As the total errors suffered by our forecasting methods are the sums of these two errors, their behavior as N increases is unclear—and actually, they can either increase or decrease.

[17] Available upon request.

EWA: the exponentially weighted average strategy with discount factors. It was introduced by Vovk [1990], Littlestone and Warmuth [1994] as early as in the beginning of the 90s and further understood and studied by, among others, Cesa-Bianchi et al. [1997], Cesa-Bianchi [1999], Auer et al. [2002]. We present a slight generalization in which past prediction instances get slightly more weight when they are more recent. This forecasting method relies on different parameters: a sequence (η_t) of positive numbers referred to as the learning rates; a nonnegative number γ referred to as the discount factor; a positive number $\kappa > 0$ referred to as the discount power. It picks the weights according to

$$\beta_{j,t} = \frac{1}{Z_t} \exp\left(-\eta_t \sum_{\tau=1}^{t} \left(1 + \frac{\gamma}{(t+1-\tau)^\kappa} \right) \bigl(s_\tau - s_{\tau-1} - f_{j,\tau-1} \bigr)^2 \right) \tag{10}$$

where Z_t is a normalization factor[18],

$$\begin{aligned} Z_t = 2 \, \exp\left(-\eta_t \sum_{\tau=1}^{t} \left(1 + \frac{\gamma}{(t+1-\tau)^\kappa} \right) \bigl(s_\tau - s_{\tau-1} \bigr)^2 \right) & \\ + \sum_{j=1}^{N} \exp\left(-\eta_t \sum_{\tau=1}^{t} \left(1 + \frac{\gamma}{(t+1-\tau)^\kappa} \right) \bigl(s_\tau - s_{\tau-1} - f_{j,\tau-1} \bigr)^2 \right). & \end{aligned}$$

Because of this factor Z_t and of the exponent function in the definition equations of the $\beta_{j,t}$, this strategy is referred to as the exponentially weighted average strategy (EWA strategy in short). Note that the obtained weights form a sub-convex weight vector: the components $\beta_{j,t}$ are nonnegative and sum up to something smaller than or equal to 1. (The missing mass to 1 is to be interpreted as a measure of the confidence that no change will take place between s_t and s_{t+1}.)

A study of the theoretical out-of-sample guarantees of EWA in the presence of the γ factors was offered in Stoltz [2010, Theorem 3], see also Cesa-Bianchi and Lugosi [2006, § 2.11], and can be instantiated as follows in our context. For all choices of γ and choices of κ and of non-increasing sequences (η_t) such that, as $t \to +\infty$,

$$t \, \eta_t \longrightarrow +\infty \qquad \text{and} \qquad \eta_t \sum_{\tau=1}^{t} \frac{1}{\tau^\kappa} = \mathcal{O}\bigl(\eta_t \, t^{1-\kappa} \bigr) \longrightarrow 0 \,, \tag{11}$$

[18] This is the version for decoupled experts. With coupled experts, the number of summands is reduced by a factor of 2 in the defining sum over j and concomitantly the factor 2 in the first term in the definition of Z_t is to be replaced by 1.

the desired guarantee (9) holds, for the set $\mathcal{F} = \mathcal{M}$ of all point-mass vectors. For instance, $\eta_t = 1/\sqrt{t}$ and $\kappa = 2$ would be suitable choices but many other choices associated with the desired theoretical guarantees exist.

More precisely, the bound $B(\mathcal{M}, T)$ of (8) equals

$$B(\mathcal{M}, T) = \frac{2 \ln N}{\eta_T} + \sum_{t=1}^{T} \frac{\eta_t}{2} L^2 + L \sum_{t=1}^{T} \bigl(\exp(2L\eta_t B_{t-1}) - 1 \bigr)$$

where

$$B_{t-1} = \sum_{\tau=1}^{t-1} \frac{\gamma}{s^\kappa}$$

and L is a bound on the quadratic errors $(s_t - s_{t-1})^2$ and $(s_t - s_{t-1} - f_{j,t-1})^2$ as t and j vary.

EWA in practice: how to choose its parameters. Instead of reporting in our simulation study the performance of the EWA method for several well-chosen sets of parameters, as is usual in the machine-learning literature, we re-use a more operational approach developed in Devaine et al. [2013] and only report the results obtained for one instance of the method. The latter selects at each time instance t, in a data-driven way (detailed below), parameters $\eta_t > 0$ and $\gamma_t > 0$ to be used in (10) (for $\gamma_t > 0$: instead of the fixed parameter γ initially considered); we choose $\kappa = 2$, which is common in the literature and which allows us to have a theoretical bound given condition (11). The parameters η_t and γ_t are respectively selected in the grids $\mathcal{E}$ and $\mathcal{G}$, where

$$\mathcal{E} = \bigl\{ m \times 10^k, \;\; m \in \{1, 2, 5\} \text{ and } k \in \{-4, -3, -2, -1\} \bigr\} \cup \{1\},$$
$$\mathcal{G} = \{0\} \cup \bigl\{ m \times 10^k, \;\; m \in \{1, 2, 5\} \text{ and } k \in \{1, 2\} \bigr\} \cup \{1\,000\}.$$

To predict instance $t + 1$, we resort to (10) with the pair of parameters in the grids $\mathcal{E}$ and $\mathcal{G}$ whose associated EWA strategy performed best in total on instances 1 to t.

SRidge: sequential ridge regression with discount factors. The issue with recursive linear regressions is that they tend to overfit past data, i.e., they lead to good in-sample predictions but poor out-of-sample ones. Two ways to prevent this overfitting are the following. First, one can consider only a fraction of the past data, typically the past H data points (in particular, if one believes that the exchange rate is a process with a memory bounded by H); this is done with rolling

OLS regressions. However, as mentioned above, it can be shown that rolling OLS regressions do not enjoy the desired guarantee (9).

Second, one can still consider all past data but add what is called a regularization term to the squared error, to help controlling (reducing) the range of the components $\beta_{j,t}$ of the linear vector picked, and/or put a higher weight on more recent observations for them to matter more. We implement below this second path, with a forecasting method called sequential ridge regression with discount factors.

The ridge regression was introduced by Hoerl and Kennard [1970] in a stochastic (non-sequential) setting. What follows relies on recent new analyses of the ridge regression in the machine learning community; see the original papers by Vovk [2001], Azoury and Warmuth [2001] as well as the survey in the monograph by Cesa-Bianchi and Lugosi [2006]. The sequential ridge regression (without discount factors and for a constant regularization factor $\lambda \geqslant 0$) picks the weights

$$(\beta_{1,t}, \, \ldots, \, \beta_{N,t}) \in \underset{\beta_1,\ldots,\beta_N \in \mathbb{R}}{\arg\min} \left\{ \lambda \sum_{j=1}^{N} \beta_j^2 + \sum_{\tau=1}^{t} \left(s_\tau - s_{\tau-1} - \sum_{j=1}^{N} \beta_j f_{j,\tau-1} \right)^2 \right\} . \tag{12}$$

We state the associated performance bound (8). It is in terms of the classes $\mathcal{F}_U$ of linear weights with Euclidean norm bounded by $U > 0$ (where the bound holds for all $U > 0$ simultaneously). We denote by L a bound on the exchange rates of and on the fundamentals: a value such that $s_t \in [-L, L]$ and $f_{j,t} \in [-L, L]$. Then, for all $U > 0$, the bound $B\big(\mathcal{F}_U, T\big)$ of (8) equals

$$B\big(\mathcal{F}_U, T\big) = \lambda U^2 + 2NL^2 \left(1 + \frac{NTL^2}{\lambda}\right) \ln \left(1 + \frac{TL^2}{N\lambda}\right).$$

In particular, when λ is well chosen (e.g., of the order of $1/\sqrt{T}$), one has

$$B\big(\mathcal{F}_U, T\big) = \mathcal{O}\big(\sqrt{T} \ln T\big) \ll T .$$

The recursive linear regression corresponds to the special case when $\lambda = 0$, but no theoretical bound is offered in this case.

As announced above, we used a common variant of the classical ridge regression presented above so as to focus more on recent observations. This is obtained via discounting: the sequential ridge regression (with discount factor γ and for a constant regularization factor $\lambda \geqslant 0$) picks the weights

$$(\beta_{1,t},\,\ldots,\,\beta_{N,t}) \in \operatorname*{arg\,min}_{\beta_1,\ldots,\beta_N\in\mathbb{R}} \left\{ \lambda \sum_{j=1}^{N} \beta_j^2 + \sum_{\tau=1}^{t} \left(1+\frac{\gamma}{(t+1-\tau)^2}\right) \left(s_\tau - s_{\tau-1} - \sum_{j=1}^{N} \beta_j f_{j,\tau-1}\right)^2 \right\}.$$

We took above the same discount power $\kappa = 2$ as in the case of EWA. Again, the parameters λ and γ are to be calibrated well: instead of reporting the performance for various pairs of fixed possible values, we resort to a more operational approach and select parameters λ_t and γ_t to be used for month $t+1$ based on past data. We do so ni the same way as described above for EWA and consider to that end the same grid $\mathcal{G}$ for the γ parameters and the grid for λ given by

$$\Lambda = \{0\} \cup \big\{ m \times 10^k,\ \ m \in \{1,2,5\} \text{ and } k \in \{1,2,3\} \big\} \cup \{10\,000\}\,.$$

4. Data and fundamentals used

Our main sample includes major floating exchange rates between March 1973–December 2014 (at most we have 502 data points per currency). We use two types of exchange rates. The first sample contains average monthly exchange rates used for example by Molodtsova and Papell [2009]. The second sample has end-of-month exchange rates. The average exchange rates have less variance than end-of-month rates; most available fundamentals (such as prices, output, but also the interest rates available from the IFS data set) are also averages. It makes hence sense to scrutinize the performance of the methods for both types of data. We also use a supplementary sample for March 1973–June 2006 taken directly from Molodtsova and Papell [2009] in order to compare our methods with the fundamentals taken from a Taylor-rule based exchange rate model that are deemed in the literature as generally being the most successful in obtaining predictability[19] of the exchange rate at the short 1–month horizon. For the sample 1973–2014 we try to extend the same data series for the fundamentals as used in Molodtsova and Papell [2009], but some of them were discontinued. As a result, we tried to find the closest substitutes possible for the entire period 1973–2014 from similar sources (IMF, OECD) through Datastream. The exchange rates are taken

[19]As explained in Footnote 7 predictability does not imply forecastability; the Taylor models studied in the existing literature were not able most of the time to deliver the latter for short-period horizons.

from the Federal Reserve Bank of Saint Louis database (for the average rates) and the IMF IFS database (for the end-of-month series). A detailed description of the data is given in Appendix A.

We principally study the behavior of 12 major floating currencies that are active throughout the 1973–2014 period. The introduction of the Euro in 1999 constrains the sample for some continental Europe currencies (FRF/USD, DEM/USD, ITL/USD, NLG/USD, PTE/USD). Even for the active currencies (USD/GBP, JPY/USD, CHF/USD, CAD/USD, SEK/USD, USD/AUD, DNK/USD), however, it was not possible to obtain fundamentals series for the entire 1973–2014 period (see details for each series in Appendix A).

Our fundamentals were formed as follows. The inflation differentials are calculated as 12–month changes in consumer price indexes (CPI). We use a money market rate or 3–month interest rate differentials for the interest rate based fundamentals. For differences in the money stock growth and output growth we use the preceding 12–month trends in these variables. We do not detrend, filter or seasonally adjust the data. The output gaps for the Taylor-rule fundamentals are percentage deviations from "potential" output that was computed including (i) a linear trend, (ii) a quadratic trend, (iii) a linear and quadratic trends, or (iv) a Hodrick-Prescott filter using the data available prior to the date for which the output gap was calculated.

5. Results

5.1. Main results

As discussed above, we use two samples with different exchange rate series (end-of-month and monthly-averages exchange rates), both present in the existing literature[20]. Our base results are shown in Tables 1–2 for the end-of-month and average exchange rate samples respectively. We show there the RMSE $\times 100$ of the no change prediction[21] (column 1), the Theil[22] ratios (columns 2, 4, 6 and 8) of predictions and the corresponding p–values of the Diebold and Mariano [1995]

[20]There is no reason to favor one over the other. For the end-of-month series the no change can be reinterpreted as a random walk with no drift prediction. However, most fundamentals available (and also used in the literature) are actually monthly averages, so for the end-of-month rates the random walk is given an advantage. What is more, the higher variance due to noise of the end-of-month exchange rates (for which there are numerous explanations, see for example Evans and Lyons [2005]) makes it inherently more difficult to uncover patterns even if they exist.

[21]These may differ for the same currency pair for different fundamentals given that the latter are available for different periods (see the data Tables 7– 8 in the Appendix A), so the forecasted periods may vary.

[22]In our context, this is the ratio of the RMSE predicted by the model and that of the no change prediction; a ratio below 1 means the particular method gave lower RMSE than the no change prediction.

tests of the hypothesis H_0 that the difference in the forecasting performance is not significant against the alternative hypothesis H_1 that the method under scrutiny is significantly better on average (DM p–value; columns 3, 5, 7 and 9), as discussed[23] in Section 3.1. We do so for the rolling OLS, recursive OLS, sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors, respectively, as our forecasting methods, and for the sets of fundamentals discussed in 2.2: PPP fundamentals, UIRP fundamentals, monetary model fundamentals, and all these fundamentals altogether.

Monthly-averaged exchange rates sample. We start with discussing Table 1. We observe that both methods give better RMSE than the no change prediction for all currency pairs for all fundamentals considered. These improvements can be statistically significant for sequential ridge regression with discount factors as witnessed by the DM test at the $10\,\%$ level in 11 out of 12 cases for the PPP fundamentals or when using all considered fundamentals (lowest subtable of Table 1). The RMSE improvements in comparison to the no-change prediction are slightly better for sequential ridge regression with discount factors than for the exponentially weighted average strategy with discount factors, and for some currency pairs and models reach up to $7\,\%$ (for example, the Italian lira / the U.S. dollar for the monetary fundamentals). The only currency pair for which we cannot find a model that improves the RMSE in a statistically significant way is the Portuguese Escudo / U.S. dollar; perhaps this is also due to the fact that the series available for this pair were the shortest in the sample (for example, the data on money aggregates was available only for 1979–1998, and 1983–1998 for interest rates) and it was not possible for the methods to fully establish their superior performance given the 120-month training period.

End-of-month changes sample. We first notice looking at Table 2 that the quadratic variation of the end-of-month exchange rates (as measured by the RMSE) is higher than that of the average monthly exchange rates. Probably due to this larger noise the sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors methods are not able to forecast the exchange rates better in many circumstances in comparison to the no change prediction using the same fundamentals as before. Still, table 2 shows that on this sample,

[23] We recall that we chose the truncation lag H for each Diebold and Mariano [1995] test in a conservative and data-driven way, see the maximum in the denominator of (7). Realized values of the argument of this maximum are available upon request.

we obtain better predictions than the no change prediction for the sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors methods using the PPP or UIRP fundamentals. The improvements, however, are small (not higher than $1.3\,\%$ in terms of the RMSE) and most of the time we cannot reject the hypothesis that the compared forecasting methods perform similarly. The exponentially weighted average strategy with discount factors is more successful as a method; both for the PPP and the UIRP it can improve upon the no change prediction for 10 out of 12 currency pairs. In the case of the PPP fundamentals, this performance is statistically superior at the $10\,\%$ level in 5 out of 12 cases. The sequential ridge regression with discount factors is less successful, being able to outperform the no-change prediction 7 out of 12 cases for the PPP fundamentals and 6 out of 12 for the UIRP fundamentals. There is no evidence that using the monetary fundamentals nor all fundamentals one could improve upon the no change prediction with the methods scrutinized.

Remarks about the performance of our methods. The conclusions from Tables 1–2 are striking. For the end-of-month sample we can claim forecastability of the exchange rates for the PPP and UIRP fundamentals using the exponentially weighted average strategy with discount factors, a feat that no study claimed so far at such a short range. In the average exchange rate sample, using the sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors we are able to beat the no change in terms of the RMSE improvement for *all* currency pairs for the period 1973–2014 for *all* fundamentals considered. The gains are not higher than ca. $7\,\%$ in terms of the RMSE: we are not able to extract much more information from the fundamentals than what a no-change prediction contains. Yet, comparing to the existing literature as surveyed by Rossi [2013] these gains are substantial.

When we combine all fundamentals together – in the spirit of the information aggregation ability of machine learning techniques – we do not gain in terms of forecasting accuracy. Sometimes the forecasts turn to be actually less precise according to the RMSE criterion (cf. the end-of-month sample). This may be an indication that the fundamentals we study contain pretty much the same information[24]. There is also a cost suffered by our methods while adding fundamentals that do not

[24]Theoretically, with additional assumptions there are links between the theories from which our "classic" fundamentals are taken. Interest rates could be high in a high inflation environment, and with the same risk premium both UIRP and PPP would predict a depreciation of a such a currency. If inflation is primarily a monetary phenomenon, high monetary growth would be correlated with high inflation and interest rates.

perform well – hence parsimony seems to be preferred in our setting as found in other studies of exchange rate predictability using other methods. To rephrase this discussion in the terms used in Section 3.3, the potential decrease in the approximation error when considering all fundamentals is too small to be compensated by a larger sequential estimation error linked to dealing with more fundamentals.

Performance of the rolling and recursive OLS strategies. The same fundamentals seem not to have any forecasting power when evaluated using the classical methods considered in the literature, either the rolling or recursive OLS regressions, no matter what sample we use. For neither of the currency pairs we obtain an improvement in terms of RMSE upon the no change prediction (which is already rare) that is statistically significant at conventional levels using the DM tests. This is in line with the common knowledge and the conclusion from the existing empirical literature that fundamentals do not allow for systematic improvements in forecasting (see Rossi [2013]).

Direct comparison of the machine learning and OLS strategies. Instead of making an indirect comparison between our forecasting methods and the ones typically used in the literature we can directly compare their performance by comparing the Theil ratios (of the machine learning method RMSE with respect to the OLS methods) and perform an appropriate DM test. The results of this exercise are shown in Tables 3–4. The first conclusion is that both methods do globally better than the OLS methods while comparing the Theil ratios no matter what type of fundamentals on what sample are considered (so even for monetary models and all fundamentals for the end-of-month sample when the machine learning methods were not successful in beating the no change prediction). Interestingly, largest gains are obtained when all fundamentals are used (last subtable of each table) – up to 17 % in terms of RMSE (for the SEK/USD pair in the averaged data of sequential ridge regression with discount factors vs. rolling OLS). This is partly because of the weak performance of the OLS methods as the number of fundamentals used grows, which was recognized by the literature (Rossi [2013]), while the effect of this growing number is milder in the case of our machine learning methods (see, e.g., Mauricette et al. [2009]). The advantage of both sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors is especially visible for the averaged exchange rate sample where the RMSE improvements are statistically significant at conventional levels for the vast majority of cases.

Finally, we note that some descriptive statistics show that this average good performance of our new methods does not come at the cost of local disasters, on the contrary: the forecasting errors seem to be uniformly better over time. Indeed, when computing the quantiles of the difference between the forecasting error of the no change minus the one of the methods under scrutiny, as is reported in Tables 10–11 of Appendix C, we see that these differences are uniformly much larger for the sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors than for the recursive or rolling OLS regressions when the methods exhibit forecastability for a given currency pair. By "uniformly" we mean here that quantiles of the same order for two series of differences are almost always ranked in the same manner, the ones corresponding to the sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors being larger than the ones for the rolling or recursive OLS regressions.

5.2. Robustness checks

We conducted several robustness checks to verify whether our results are not due to some quirk related to the samples that we constructed. This included several exercises[25].

First, we tried the "coupled" version of the fundamentals as well, that is, the models in the form without taking into account the possibility that one of the country series pertaining to a particular fundamental would have a different weight in the regression. The results can be seen in Tables 12–13 of Appendix C. We also considered 6–month inflation, money stock or output changes in the decoupled version to see whether a different way of constructing fundamentals matters. All the above exercises did not change qualitatively our results.

Next, we reran the basic models from Tables 1–2 on our data trimmed to shorter samples 1980–2014, post-Plaza accord period 1985–2014, the post ERM-crisis period 1992–2014 and 1973–2006 so as to see whether the inclusion of a particular period (e.g., high inflation period of 1970s, or post financial crisis period) drives the results. We show the results for the 1980-2014 sample in Tables 16–17. We also conducted a separate exercise on the 1973–2006 data taken directly from Molodtsova and Papell [2009], shown in Table 18 (our averaged exchange rate sample is an extension of their data set till 2014, as noted in Section A). What we observe in general is

[25] All results not shown due to space limitations are available upon request.

that the good forecasting properties of our methods still hold, albeit the observed gains against the no-change prediction are typically smaller. Trimming at the beginning of the sample affects especially the European currencies that became part of the Euro. This may indicate that in practice, longer data series are in general beneficial for the (asymptotic) guarantees to kick in, as indicated in Section 3.3.

We also tried to work with what we call "absolute" fundamentals. This means that instead of inflation differentials we directly used price, money and output levels as substitutes for the PPP and monetary model fundamentals[26]. The results here are weaker. We can still obtain improvements with the sequential ridge regression with discount factors. A problem arises, though, with the exponentially weighted average strategy with discount factors in that the forecast errors involving deviations of the exchange rates from the absolute fundamentals considered are much larger that those for relative fundamentals used in our original exercise; and the weights assigned to the absolute fundamentals by the method tend to be small (i.e., the predictions output by the method are close to the ones of no change). This is a documented fact: the method does not admit well fundamentals that err too much in comparison to one (here, the no-change prediction) that performs well. This is in contrast with the sequential ridge regression with discount factors, which can correct the fundamentals for proper scaling.

Finally, we tried the actually realized fundamentals. That is, instead of "predicting" the next period change in fundamentals by their past values, we fed the actual values that were realized in course of economic activity. As in the literature started by Meese and Rogoff [1983], these do not lead to good or better forecasts.

A recent strand of literature identified Taylor rule fundamentals as useful in achieving exchange rate predictability (which is not the same as forecastability). Our focus is in the general ability of fundamentals to help forecasting exchange rates (compare Footnote 7). Nevertheless, we forecast exchange rates using such Taylor rule fundamentals in Section C, both on our sample and Molodtsova and Papell [2009] original data set, see Tables 14, 15 and 19. We find that i) these fundamentals do help in forecasting against the no-change prediction for the averaged exchange rate samples, which includes Molodtsova and Papell [2009] original data; but that ii) the performance of Taylor-rule exchange rate models is not superior to those based on the "classic"

[26]The UIRP model has no such counterpart. "Absolute" fundamentals A_t were created by adding price, money or output changes to an initial exchange rate in our data sets. Then the deviation of the actual nominal rate from its thus calculated "fundamental" value $A_t - s_t$ was used to predict $s_{t+1} - s_t$.

fundamentals.

5.3. Directional tests

A different, though secondary, measure of forecast quality that has been employed in the literature are "directional tests", i.e., tests whether the models are able to predict the direction of change of the exchange rate better than a fair coin toss. Although the machine learning methods are not constructed to be efficient in this regard as their focus is on controlling RMSE (see Section 3.3), we test how the predictions obtained by these methods fare in this dimension. In Tables 5–6 we exhibit the percentage success of either of the methods (OLS regressions as well as sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors) in forecasting the direction of change of exchange rates with the corresponding DM p-value of a test of the difference with a fair coin toss.

The patterns that emerge are interesting. Machine learning methods are able to predict the correct direction in several cases $60\,\%$ of the time (with a maximum of $63.4\,\%$) – improvements which are often statistically significant. Out of the two methods, the exponentially weighted average strategy with discount factors does better on both samples. The success in predicting RMSE goes typically hand in hand with the success of directional predictions. The worst performance is obtained for monetary fundamentals with in the end-of-month sample. This time, the OLS-based methods achieve some success (especially the rolling regression) in improving the direction of the change of the exchange rate when all fundamentals are considered (though it is significant at conventional levels for at most 7 out of 12 currency pairs for the average exchange rate sample). However, the percentage improvements over a coin toss are typically small, typically lower than for the machine learning methods for the same currency pair and never larger than $59.9\,\%$.

6. Conclusions

In this paper we apply methods stemming from the field of machine learning – sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors – to the perennial problem of exchange rate forecasting. In doing so, we obtain gains in forecasting using the standardly applied RMSE criterion for PPP, UIRP and monetary-models based fundamentals that were not found using traditionally applied estimation methods based on

OLS. The key is to use these machine-learning forecasting schemes to do what they are good for: produce forecasts – and not try to estimate some underlying model as was traditionally the case with more statistical methods. We conclude thus that a major problem of international economics – whether there is a short-term relationship between "classic" fundamentals and exchange rates – is answered in the affirmative under the condition that proper machine-learning techniques, e.g., the sequential ridge regression with discount factors or the exponentially weighted average strategy with discount factors, are applied. Our success points to a potential of such techniques for improving the evaluation of economic problems.

Machine learning techniques serve also to effectively aggregate information from many sources. A tempting exercise, beyond the scope of this paper, is to evaluate the forecasting performance including many more fundamentals than the "classic" ones considered here that were suggested by the literature – for example those based on productivity, interest rate yield curves, net foreign assets etc. Venturing further one could consider many more series that are not typically associated with exchange rate forecasting in the true spirit of machine learning.

As with any new method applied to exchange rate forecasting, it remains to be seen whether our results could be replicated for different currencies, samples, forecasting periods and fundamentals. Given the robustness of the results shown in this paper, however, we hope that the application of these methods to exchange rate forecasting will stand the test of time and will allow for better predictions and decision making in the future.

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Table 1: RMSE and Theil ratios of forecasts for linear models for the average exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.4410	1.0005	0.518	1.0040	0.874	**0.9735**	0.039 **	**0.9887**	0.025 **
JPY/USD	2.7039	1.0173	0.947	1.0007	0.688	**0.9816**	0.013 **	**0.9862**	0.002 ***
CHF/USD	2.7960	1.0116	0.891	1.0010	0.616	**0.9848**	0.009 ***	**0.9882**	0.003 ***
CAD/USD	1.5091	**0.9867**	0.148	**0.9965**	0.220	**0.9883**	0.071 *	**0.9964**	0.213
SEK/USD	2.5633	1.0108	0.761	1.0020	0.622	**0.9585**	0.014 **	**0.9865**	0.003 ***
DNK/USD	2.5355	1.0138	0.959	1.0011	0.580	**0.9817**	0.002 ***	**0.9835**	0.000 ***
USD/AUD	2.7434	**0.9969**	0.420	1.0015	0.625	**0.9710**	0.048 **	**0.9900**	0.056 *
FRF/USD	2.6411	1.0118	0.758	1.0018	0.556	**0.9809**	0.002 ***	**0.9829**	0.013 **
DEM/USD	2.7545	1.0148	0.837	1.0028	0.885	**0.9780**	0.003 ***	**0.9847**	0.010 ***
ITL/USD	2.6624	1.0087	0.702	1.0019	0.552	**0.9627**	0.008 ***	**0.9726**	0.050 **
NLG/USD	2.7517	1.0109	0.856	1.0022	0.918	**0.9811**	0.001 ***	**0.9839**	0.005 ***
PTE/USD	2.6956	**0.9964**	0.469	**0.9859**	0.375	**0.9713**	0.235	**0.9465**	0.151
UIRP fundamental									
USD/GBP	2.4410	1.0241	0.852	1.0037	0.655	**0.9688**	0.034 **	**0.9809**	0.037 **
JPY/USD	2.7039	1.0054	0.622	**0.9974**	0.352	**0.9717**	0.011 **	**0.9809**	0.032 **
CHF/USD	2.8195	1.0135	0.742	**0.9975**	0.439	**0.9790**	0.007 ***	**0.9797**	0.006 ***
CAD/USD	1.5091	1.0086	0.763	1.0013	0.643	**0.9965**	0.154	**0.9986**	0.306
SEK/USD	2.5626	1.0600	0.964	1.0136	0.911	**0.9601**	0.024 **	**0.9733**	0.039 **
DNK/USD	2.5355	1.0220	0.942	1.0071	0.774	**0.9776**	0.001 ***	**0.9784**	0.002 ***
USD/AUD	2.7414	1.0142	0.762	1.0060	0.720	**0.9746**	0.043 **	**0.9861**	0.103
FRF/USD	2.6411	1.0212	0.895	1.0141	0.829	**0.9687**	0.003 ***	**0.9765**	0.024 **
DEM/USD	2.7545	1.0216	0.806	1.0049	0.676	**0.9683**	0.001 ***	**0.9716**	0.004 ***
ITL/USD	2.6624	1.0143	0.707	1.0166	0.797	**0.9419**	0.036 **	**0.9578**	0.056 *
NLG/USD	2.7517	1.0424	0.760	**0.9999**	0.499	**0.9605**	0.001 ***	**0.9737**	0.019 **
PTE/USD	2.2481	**0.9963**	0.420	**0.9991**	0.484	**0.9695**	0.146	**0.9617**	0.157
Monetary model fundamentals									
USD/GBP	2.4410	1.0349	0.972	1.0173	0.889	**0.9647**	0.079 *	**0.9757**	0.034 **
JPY/USD	2.7042	**0.9999**	0.497	1.0016	0.536	**0.9683**	0.022 **	**0.9692**	0.013 **
CHF/USD	2.8377	1.0219	0.885	1.0059	0.645	**0.9815**	0.110	**0.9787**	0.052 *
CAD/USD	1.5083	1.0366	0.887	1.0075	0.779	**0.9746**	0.026 **	**0.9872**	0.154
SEK/USD	2.5626	1.0665	0.999	1.0289	0.948	**0.9487**	0.045 **	**0.9714**	0.003 ***
DNK/USD	2.5553	1.0517	0.997	1.0252	0.949	**0.9749**	0.012 **	**0.9689**	0.013 **
USD/AUD	2.7547	1.0256	0.900	1.0098	0.890	**0.9661**	0.035 **	**0.9807**	0.089 *
FRF/USD	2.5229	1.0615	0.981	1.0738	0.982	**0.9787**	0.126	**0.9954**	0.390
DEM/USD	2.7624	1.0174	0.770	1.0038	0.579	**0.9562**	0.020 **	**0.9514**	0.008 ***
ITL/USD	2.6458	1.0411	0.932	1.0165	0.798	**0.9300**	0.036 **	**0.9661**	0.019 **
NLG/USD	2.7517	1.0342	0.966	1.0076	0.699	**0.9598**	0.001 ***	**0.9709**	0.029 **
PTE/USD	2.2342	1.0103	0.574	1.0485	0.865	**0.9590**	0.205	**0.9778**	0.293
All fundamentals									
USD/GBP	2.4410	1.0635	0.983	1.0330	0.927	**0.9632**	0.027 **	**0.9741**	0.033 **
JPY/USD	2.7042	1.0424	0.945	1.0129	0.700	**0.9626**	0.002 ***	**0.9661**	0.005 ***
CHF/USD	2.8377	1.0650	0.975	1.0221	0.809	**0.9797**	0.063 *	**0.9751**	0.032 **
CAD/USD	1.5083	1.0052	0.568	1.0068	0.765	**0.9738**	0.032 **	**0.9885**	0.134
SEK/USD	2.5626	1.1506	0.950	1.0656	0.900	**0.9557**	0.004 ***	**0.9882**	0.302
DNK/USD	2.5553	1.0859	0.996	1.0248	0.917	**0.9691**	0.001 ***	**0.9641**	0.003 ***
USD/AUD	2.7547	1.0209	0.743	1.0224	0.900	**0.9631**	0.027 **	**0.9749**	0.030 **
FRF/USD	2.5229	1.1137	0.980	1.0599	0.942	**0.9736**	0.065 *	**0.9786**	0.186
DEM/USD	2.7624	1.0367	0.777	1.0157	0.663	**0.9542**	0.004 ***	**0.9485**	0.002 ***
ITL/USD	2.6458	1.0054	0.556	1.0438	0.918	**0.9351**	0.040 **	**0.9518**	0.027 **
NLG/USD	2.7517	1.0251	0.735	1.0182	0.715	**0.9614**	0.001 ***	**0.9654**	0.013 **
PTE/USD	2.2342	**0.9571**	0.197	1.0609	0.848	**0.9649**	0.156	**0.9769**	0.283

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 2: RMSE and Theil ratios of forecasts for linear models for the end-of-month exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.9051	1.0025	0.615	1.0032	0.887	**0.9998**	0.452	**0.9975**	0.335
JPY/USD	3.1023	1.0144	0.956	1.0010	0.866	**0.9999**	0.183	**0.9953**	0.107
CHF/USD	3.3428	1.0117	0.969	1.0009	0.631	**0.9994**	0.205	**0.9947**	0.063 *
CAD/USD	1.9982	**0.9988**	0.438	**0.9991**	0.351	1.0003	0.696	1.0011	0.987
SEK/USD	3.2290	1.0089	0.835	1.0009	0.590	1.0001	0.527	**0.9969**	0.204
DNK/USD	3.1200	1.0112	0.979	1.0008	0.580	**0.9997**	0.258	**0.9944**	0.051 *
USD/AUD	3.3786	**0.9984**	0.442	1.0009	0.600	1.0007	0.751	1.0001	0.512
FRF/USD	3.1978	1.0120	0.858	1.0036	0.668	1.0007	0.602	**0.9957**	0.197
DEM/USD	3.3136	1.0139	0.854	1.0035	0.931	**0.9994**	0.189	**0.9915**	0.041 **
ITL/USD	3.1907	1.0070	0.727	1.0019	0.574	1.0002	0.510	**0.9891**	0.099 *
NLG/USD	3.3319	1.0096	0.910	1.0023	0.980	**0.9995**	0.172	**0.9901**	0.023 **
PTE/USD	3.2207	1.0018	0.525	**0.9936**	0.408	**0.9916**	0.368	**0.9886**	0.348
UIRP fundamental									
USD/GBP	2.9051	1.0222	0.887	1.0044	0.739	1.0028	0.742	1.0024	0.589
JPY/USD	3.1023	1.0060	0.675	**0.9983**	0.359	**0.9993**	0.266	**0.9918**	0.153
CHF/USD	3.3747	1.0106	0.789	**0.9985**	0.442	**0.9994**	0.370	**0.9925**	0.075 *
CAD/USD	1.9982	1.0055	0.786	1.0009	0.678	1.0003	0.708	1.0010	0.941
SEK/USD	3.2263	1.0514	0.964	1.0110	0.912	**0.9948**	0.280	**0.9890**	0.255
DNK/USD	3.1200	1.0186	0.958	1.0042	0.799	1.0005	0.609	**0.9954**	0.255
USD/AUD	3.3793	1.0131	0.828	1.0058	0.757	1.0048	0.736	**0.9980**	0.400
FRF/USD	3.1978	1.0206	0.955	1.0112	0.875	1.0014	0.586	**0.9951**	0.328
DEM/USD	3.3136	1.0209	0.907	1.0052	0.723	**0.9986**	0.256	**0.9888**	0.141
ITL/USD	3.1907	1.0117	0.727	1.0116	0.790	1.0056	0.642	**0.9867**	0.222
NLG/USD	3.3319	1.0388	0.849	1.0036	0.697	**0.9997**	0.403	**0.9903**	0.185
PTE/USD	2.8024	**0.9970**	0.438	**0.9968**	0.434	**0.9965**	0.403	**0.9932**	0.353
Monetary model fundamentals									
USD/GBP	2.9051	1.0350	0.997	1.0165	0.932	1.0004	0.517	1.0008	0.531
JPY/USD	3.1046	1.0106	0.767	1.0046	0.631	1.0025	0.613	**0.9955**	0.330
CHF/USD	3.3887	1.0249	0.954	1.0103	0.785	1.0023	0.690	1.0102	0.932
CAD/USD	1.9994	1.0396	0.935	1.0104	0.893	1.0124	0.838	1.0070	0.899
SEK/USD	3.2263	1.0556	0.999	1.0222	0.970	1.0047	0.656	1.0076	0.801
DNK/USD	3.1675	1.0435	0.997	1.0186	0.965	1.0041	0.844	1.0062	0.964
USD/AUD	3.3926	1.0284	0.963	1.0108	0.948	1.0017	0.829	1.0060	0.766
FRF/USD	3.1041	1.0575	0.987	1.0502	0.987	1.0010	0.570	1.0100	0.755
DEM/USD	3.3286	1.0192	0.873	1.0121	0.804	1.0026	0.665	1.0009	0.526
ITL/USD	3.2797	1.0233	0.876	1.0150	0.820	1.0003	0.515	1.0035	0.592
NLG/USD	3.3319	1.0305	0.945	1.0085	0.754	**0.9978**	0.234	**0.9988**	0.462
PTE/USD	2.7703	1.0053	0.548	1.0504	0.988	1.0071	0.606	1.0152	0.759
All fundamentals									
USD/GBP	2.9051	1.0715	0.999	1.0281	0.952	**0.9984**	0.386	1.0033	0.610
JPY/USD	3.1046	1.0478	0.964	1.0101	0.724	1.0010	0.557	**0.9971**	0.380
CHF/USD	3.3887	1.0784	0.993	1.0244	0.909	1.0033	0.911	1.0043	0.652
CAD/USD	1.9994	1.0403	0.958	1.0106	0.895	1.0035	0.859	1.0018	0.991
SEK/USD	3.2263	1.1642	0.969	1.0691	0.883	1.0083	0.955	**0.9963**	0.406
DNK/USD	3.1675	1.0643	0.999	1.0195	0.951	1.0036	0.854	1.0053	0.949
USD/AUD	3.3926	1.0420	0.949	1.0197	0.913	1.0021	0.815	1.0029	0.609
FRF/USD	3.1041	1.0934	0.979	1.0407	0.908	1.0073	0.856	1.0065	0.635
DEM/USD	3.3286	1.0411	0.886	1.0281	0.846	1.0037	0.725	**0.9952**	0.375
ITL/USD	3.2797	1.0025	0.530	1.0392	0.883	1.0024	0.612	1.0043	0.588
NLG/USD	3.3319	1.0449	0.923	1.0292	0.901	**0.9982**	0.246	**0.9920**	0.276
PTE/USD	2.7703	1.0138	0.631	1.0580	0.968	1.0047	0.603	**0.9955**	0.397

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 3: RMSE and Theil ratios of the machine learning methods vs. rolling and recursive regressions for the average exchange rates sample.

Currency pair	SRidge vs.				EWA vs.			
	Rolling regression		Recursive regression		Rolling regression		Recursive regression	
	Ratio of RMSEs	DM p-value	Ratio of RMSEs	DM p-value	Ratio of RMSEs	DM p-value	Ratio of RMSEs	DM p-value
PPP fundamental								
USD/GBP	**0.9730**	0.056 *	**0.9696**	0.023 **	**0.9883**	0.148	**0.9848**	0.009 ***
JPY/USD	**0.9648**	0.002 ***	**0.9808**	0.009 ***	**0.9693**	0.003 ***	**0.9854**	0.001 ***
CHF/USD	**0.9735**	0.006 ***	**0.9838**	0.011 **	**0.9769**	0.004 ***	**0.9872**	0.002 ***
CAD/USD	1.0016	0.536	**0.9917**	0.116	1.0098	0.742	**0.9999**	0.488
SEK/USD	**0.9482**	0.049 **	**0.9565**	0.007 ***	**0.9760**	0.094 *	**0.9845**	0.013 **
DNK/USD	**0.9683**	0.001 ***	**0.9806**	0.003 ***	**0.9701**	0.000 ***	**0.9824**	0.008 ***
USD/AUD	**0.9740**	0.105	**0.9695**	0.029 **	**0.9931**	0.329	**0.9885**	0.017 **
FRF/USD	**0.9695**	0.039 **	**0.9792**	0.047 **	**0.9715**	0.036 **	**0.9812**	0.047 **
DEM/USD	**0.9637**	0.048 **	**0.9753**	0.005 ***	**0.9703**	0.033 **	**0.9820**	0.002 ***
ITL/USD	**0.9545**	0.007 ***	**0.9609**	0.002 ***	**0.9642**	0.002 ***	**0.9708**	0.000 ***
NLG/USD	**0.9706**	0.008 ***	**0.9790**	0.000 ***	**0.9733**	0.006 ***	**0.9818**	0.001 ***
PTE/USD	**0.9748**	0.035 **	**0.9852**	0.058 *	**0.9498**	0.002 ***	**0.9600**	0.001 ***
UIRP fundamental								
USD/GBP	**0.9460**	0.045 **	**0.9653**	0.040 **	**0.9578**	0.068 *	**0.9773**	0.066 *
JPY/USD	**0.9664**	0.019 **	**0.9742**	0.025 **	**0.9750**	0.068 *	**0.9828**	0.087 *
CHF/USD	**0.9659**	0.047 **	**0.9815**	0.107	**0.9666**	0.047 **	**0.9822**	0.122
CAD/USD	**0.9880**	0.198	**0.9952**	0.162	**0.9902**	0.238	**0.9974**	0.293
SEK/USD	**0.9057**	0.017 **	**0.9472**	0.011 **	**0.9182**	0.019 **	**0.9603**	0.019 **
DNK/USD	**0.9565**	0.004 ***	**0.9707**	0.008 ***	**0.9573**	0.004 ***	**0.9715**	0.010 ***
USD/AUD	**0.9610**	0.060 *	**0.9688**	0.013 **	**0.9723**	0.101	**0.9802**	0.032 **
FRF/USD	**0.9486**	0.004 ***	**0.9553**	0.004 ***	**0.9563**	0.009 ***	**0.9630**	0.018 **
DEM/USD	**0.9479**	0.020 **	**0.9636**	0.007 ***	**0.9511**	0.030 **	**0.9669**	0.021 **
ITL/USD	**0.9286**	0.003 ***	**0.9265**	0.016 **	**0.9443**	0.003 ***	**0.9421**	0.011 **
NLG/USD	**0.9214**	0.096 *	**0.9606**	0.038 **	**0.9341**	0.132	**0.9738**	0.135
PTE/USD	**0.9731**	0.140	**0.9703**	0.113	**0.9652**	0.136	**0.9625**	0.125
Monetary model fundamentals								
USD/GBP	**0.9322**	0.014 **	**0.9484**	0.018 **	**0.9428**	0.005 ***	**0.9592**	0.012 **
JPY/USD	**0.9685**	0.027 **	**0.9668**	0.025 **	**0.9693**	0.020 **	**0.9676**	0.019 **
CHF/USD	**0.9605**	0.001 ***	**0.9757**	0.024 **	**0.9577**	0.002 ***	**0.9730**	0.021 **
CAD/USD	**0.9401**	0.026 **	**0.9673**	0.031 **	**0.9523**	0.078 *	**0.9798**	0.140
SEK/USD	**0.8896**	0.001 ***	**0.9220**	0.006 ***	**0.9109**	0.000 ***	**0.9441**	0.005 ***
DNK/USD	**0.9270**	0.000 ***	**0.9510**	0.004 ***	**0.9213**	0.003 ***	**0.9451**	0.017 **
USD/AUD	**0.9420**	0.003 ***	**0.9567**	0.013 **	**0.9562**	0.015 **	**0.9712**	0.029 **
FRF/USD	**0.9220**	0.007 ***	**0.9114**	0.004 ***	**0.9377**	0.007 ***	**0.9270**	0.004 ***
DEM/USD	**0.9399**	0.003 ***	**0.9526**	0.013 **	**0.9351**	0.007 ***	**0.9478**	0.020 **
ITL/USD	**0.8933**	0.001 ***	**0.9149**	0.041 **	**0.9280**	0.005 ***	**0.9504**	0.010 ***
NLG/USD	**0.9280**	0.000 ***	**0.9525**	0.004 ***	**0.9388**	0.000 ***	**0.9635**	0.010 ***
PTE/USD	**0.9492**	0.112	**0.9146**	0.013 **	**0.9679**	0.259	**0.9326**	0.090 *
All fundamentals								
USD/GBP	**0.9057**	0.001 ***	**0.9324**	0.023 **	**0.9160**	0.001 ***	**0.9430**	0.017 **
JPY/USD	**0.9234**	0.000 ***	**0.9504**	0.011 **	**0.9268**	0.002 ***	**0.9539**	0.010 ***
CHF/USD	**0.9198**	0.004 ***	**0.9585**	0.039 **	**0.9156**	0.002 ***	**0.9540**	0.025 **
CAD/USD	**0.9688**	0.113	**0.9672**	0.032 **	**0.9834**	0.279	**0.9818**	0.105
SEK/USD	**0.8306**	0.026 **	**0.8969**	0.031 **	**0.8588**	0.023 **	**0.9274**	0.026 **
DNK/USD	**0.8924**	0.000 ***	**0.9456**	0.003 ***	**0.8878**	0.000 ***	**0.9408**	0.002 ***
USD/AUD	**0.9433**	0.017 **	**0.9420**	0.007 ***	**0.9549**	0.050 *	**0.9536**	0.004 ***
FRF/USD	**0.8742**	0.012 **	**0.9186**	0.015 **	**0.8787**	0.021 **	**0.9233**	0.027 **
DEM/USD	**0.9204**	0.049 **	**0.9394**	0.068 *	**0.9149**	0.046 **	**0.9338**	0.063 *
ITL/USD	**0.9301**	0.010 **	**0.8959**	0.010 **	**0.9467**	0.039 **	**0.9118**	0.008 ***
NLG/USD	**0.9378**	0.042 **	**0.9442**	0.051 *	**0.9417**	0.062 *	**0.9482**	0.072 *
PTE/USD	1.0081	0.580	**0.9095**	0.029 **	1.0206	0.687	**0.9208**	0.051 *

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 4: RMSE and Theil ratios of the machine learning methods vs. rolling and recursive regressions for the end-of-month exchange rates sample.

Currency pair	SRidge vs. Rolling regression: Ratio of RMSEs	SRidge vs. Rolling regression: DM p-value	SRidge vs. Recursive regression: Ratio of RMSEs	SRidge vs. Recursive regression: DM p-value	EWA vs. Rolling regression: Ratio of RMSEs	EWA vs. Rolling regression: DM p-value	EWA vs. Recursive regression: Ratio of RMSEs	EWA vs. Recursive regression: DM p-value
PPP fundamental								
USD/GBP	**0.9973**	0.369	**0.9966**	0.091 *	**0.9950**	0.305	**0.9943**	0.178
JPY/USD	**0.9857**	0.043 **	**0.9989**	0.111	**0.9812**	0.014 **	**0.9943**	0.060 *
CHF/USD	**0.9879**	0.025 **	**0.9986**	0.292	**0.9832**	0.007 ***	**0.9938**	0.055 *
CAD/USD	1.0016	0.578	1.0012	0.720	1.0023	0.613	1.0019	0.808
SEK/USD	**0.9913**	0.183	**0.9992**	0.379	**0.9881**	0.150	**0.9960**	0.207
DNK/USD	**0.9887**	0.020 **	**0.9989**	0.388	**0.9834**	0.009 ***	**0.9936**	0.121
USD/AUD	1.0023	0.583	**0.9998**	0.470	1.0017	0.565	**0.9993**	0.427
FRF/USD	**0.9888**	0.108	**0.9971**	0.313	**0.9839**	0.079 *	**0.9921**	0.176
DEM/USD	**0.9858**	0.140	**0.9960**	0.037 **	**0.9779**	0.064 *	**0.9880**	0.006 ***
ITL/USD	**0.9933**	0.123	**0.9983**	0.197	**0.9822**	0.064 *	**0.9872**	0.066 *
NLG/USD	**0.9900**	0.076 *	**0.9972**	0.010 ***	**0.9806**	0.006 ***	**0.9878**	0.007 ***
PTE/USD	**0.9898**	0.081 *	**0.9980**	0.284	**0.9867**	0.143	**0.9950**	0.322
UIRP fundamental								
USD/GBP	**0.9810**	0.155	**0.9984**	0.401	**0.9806**	0.203	**0.9980**	0.439
JPY/USD	**0.9934**	0.299	1.0010	0.588	**0.9859**	0.132	**0.9935**	0.236
CHF/USD	**0.9889**	0.188	1.0008	0.535	**0.9821**	0.104	**0.9940**	0.295
CAD/USD	**0.9948**	0.227	**0.9993**	0.359	**0.9955**	0.262	1.0001	0.516
SEK/USD	**0.9462**	0.032 **	**0.9840**	0.032 **	**0.9407**	0.053 *	**0.9782**	0.095 *
DNK/USD	**0.9822**	0.036 **	**0.9963**	0.156	**0.9772**	0.028 **	**0.9912**	0.140
USD/AUD	**0.9917**	0.244	**0.9990**	0.390	**0.9850**	0.155	**0.9922**	0.212
FRF/USD	**0.9812**	0.022 **	**0.9903**	0.135	**0.9750**	0.055 *	**0.9841**	0.131
DEM/USD	**0.9782**	0.079 *	**0.9935**	0.227	**0.9685**	0.061 *	**0.9837**	0.126
ITL/USD	**0.9941**	0.287	**0.9941**	0.155	**0.9753**	0.079 *	**0.9754**	0.077 *
NLG/USD	**0.9623**	0.150	**0.9961**	0.290	**0.9533**	0.121	**0.9868**	0.165
PTE/USD	**0.9995**	0.488	**0.9996**	0.487	**0.9962**	0.397	**0.9964**	0.367
Monetary model fundamentals								
USD/GBP	**0.9665**	0.017 **	**0.9841**	0.087 *	**0.9669**	0.036 **	**0.9846**	0.143
JPY/USD	**0.9920**	0.287	**0.9979**	0.422	**0.9850**	0.103	**0.9909**	0.205
CHF/USD	**0.9780**	0.033 **	**0.9921**	0.229	**0.9857**	0.142	**0.9999**	0.496
CAD/USD	**0.9738**	0.116	1.0020	0.555	**0.9686**	0.072 *	**0.9966**	0.347
SEK/USD	**0.9517**	0.000 ***	**0.9828**	0.058 *	**0.9545**	0.002 ***	**0.9857**	0.136
DNK/USD	**0.9622**	0.003 ***	**0.9858**	0.014 **	**0.9643**	0.007 ***	**0.9879**	0.067 *
USD/AUD	**0.9740**	0.044 **	**0.9910**	0.050 **	**0.9782**	0.080 *	**0.9953**	0.292
FRF/USD	**0.9466**	0.009 ***	**0.9532**	0.011 **	**0.9551**	0.025 **	**0.9617**	0.019 **
DEM/USD	**0.9837**	0.109	**0.9906**	0.162	**0.9821**	0.133	**0.9890**	0.234
ITL/USD	**0.9775**	0.088 *	**0.9855**	0.226	**0.9806**	0.150	**0.9887**	0.225
NLG/USD	**0.9683**	0.041 **	**0.9894**	0.191	**0.9693**	0.053 *	**0.9904**	0.244
PTE/USD	1.0018	0.518	**0.9588**	0.017 **	1.0098	0.598	**0.9665**	0.133
All fundamentals								
USD/GBP	**0.9318**	0.001 ***	**0.9711**	0.039 **	**0.9364**	0.001 ***	**0.9759**	0.100 *
JPY/USD	**0.9553**	0.031 **	**0.9909**	0.262	**0.9516**	0.016 **	**0.9871**	0.158
CHF/USD	**0.9303**	0.008 ***	**0.9793**	0.103	**0.9312**	0.007 ***	**0.9803**	0.105
CAD/USD	**0.9646**	0.047 **	**0.9930**	0.169	**0.9630**	0.050 **	**0.9913**	0.155
SEK/USD	**0.8660**	0.032 **	**0.9431**	0.131	**0.8557**	0.041 **	**0.9319**	0.123
DNK/USD	**0.9430**	0.002 ***	**0.9844**	0.084 *	**0.9446**	0.002 ***	**0.9861**	0.112
USD/AUD	**0.9617**	0.054 *	**0.9828**	0.085 *	**0.9625**	0.044 **	**0.9836**	0.115
FRF/USD	**0.9213**	0.026 **	**0.9679**	0.141	**0.9206**	0.017 **	**0.9671**	0.102
DEM/USD	**0.9641**	0.112	**0.9763**	0.150	**0.9559**	0.097 *	**0.9680**	0.127
ITL/USD	**0.9999**	0.499	**0.9646**	0.132	1.0018	0.524	**0.9665**	0.112
NLG/USD	**0.9552**	0.068 *	**0.9699**	0.080 *	**0.9493**	0.045 **	**0.9639**	0.040 **
PTE/USD	**0.9910**	0.402	**0.9496**	0.047 **	**0.9819**	0.313	**0.9409**	0.045 **

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 5: Directional tests: Percentages of changes predicted for linear models for the average exchange rates sample.

Currency pair	Rolling regression		Recursive regression		SRidge		EWA	
	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value
PPP fundamental								
USD/GBP	**0.514**	0.300	0.488	0.661	**0.585**	0.002 ***	**0.562**	0.009 ***
JPY/USD	0.496	0.552	0.475	0.761	**0.593**	0.001 ***	**0.559**	0.055 *
CHF/USD	**0.551**	0.071 *	0.491	0.586	**0.598**	0.002 ***	**0.598**	0.001 ***
CAD/USD	**0.543**	0.119	**0.514**	0.348	**0.543**	0.112	**0.522**	0.268
SEK/USD	0.499	0.515	0.496	0.540	**0.633**	0.000 ***	**0.598**	0.000 ***
DNK/USD	0.496	0.547	**0.549**	0.099 *	**0.598**	0.000 ***	**0.577**	0.002 ***
USD/AUD	**0.520**	0.337	0.463	0.825	**0.587**	0.002 ***	**0.522**	0.249
FRF/USD	0.455	0.826	**0.503**	0.480	**0.577**	0.017 **	**0.593**	0.005 ***
DEM/USD	0.466	0.758	0.418	0.949	**0.608**	0.001 ***	**0.608**	0.001 ***
ITL/USD	**0.534**	0.255	**0.503**	0.478	**0.598**	0.003 ***	**0.566**	0.090 *
NLG/USD	0.460	0.822	0.418	0.966	**0.603**	0.002 ***	**0.598**	0.003 ***
PTE/USD	0.481	0.637	**0.513**	0.397	**0.524**	0.312	**0.577**	0.031 **
UIRP fundamental								
USD/GBP	**0.507**	0.411	**0.541**	0.080 *	**0.562**	0.021 **	**0.538**	0.068 *
JPY/USD	**0.570**	0.021 **	**0.530**	0.155	**0.614**	0.000 ***	**0.612**	0.000 ***
CHF/USD	**0.596**	0.002 ***	**0.604**	0.001 ***	**0.617**	0.000 ***	**0.582**	0.003 ***
CAD/USD	**0.551**	0.072 *	**0.509**	0.396	**0.522**	0.241	0.472	0.765
SEK/USD	0.497	0.529	0.487	0.623	**0.611**	0.000 ***	**0.616**	0.000 ***
DNK/USD	0.483	0.706	**0.517**	0.317	**0.609**	0.000 ***	**0.575**	0.002 ***
USD/AUD	**0.517**	0.330	**0.517**	0.328	**0.588**	0.001 ***	**0.522**	0.240
FRF/USD	0.471	0.696	0.460	0.764	**0.593**	0.005 ***	**0.598**	0.003 ***
DEM/USD	**0.513**	0.408	**0.508**	0.439	**0.603**	0.002 ***	**0.614**	0.001 ***
ITL/USD	0.497	0.520	**0.503**	0.478	**0.603**	0.002 ***	**0.603**	0.002 ***
NLG/USD	**0.524**	0.303	**0.561**	0.079 *	**0.608**	0.001 ***	**0.598**	0.003 ***
PTE/USD	0.479	0.604	**0.521**	0.400	**0.563**	0.141	**0.634**	0.010 ***
Monetary model fundamentals								
USD/GBP	**0.501**	0.482	**0.514**	0.330	**0.598**	0.000 ***	**0.575**	0.004 ***
JPY/USD	**0.587**	0.001 ***	**0.555**	0.045 **	**0.605**	0.000 ***	**0.611**	0.000 ***
CHF/USD	**0.522**	0.289	**0.536**	0.178	**0.599**	0.001 ***	**0.602**	0.000 ***
CAD/USD	**0.526**	0.232	0.497	0.528	**0.561**	0.022 **	**0.529**	0.136
SEK/USD	**0.505**	0.439	0.471	0.783	**0.632**	0.000 ***	**0.624**	0.000 ***
DNK/USD	0.440	0.977	0.454	0.917	**0.577**	0.004 ***	**0.577**	0.007 ***
USD/AUD	**0.509**	0.409	0.494	0.574	**0.585**	0.002 ***	**0.582**	0.005 ***
FRF/USD	**0.508**	0.447	**0.525**	0.322	**0.575**	0.048 **	**0.600**	0.013 **
DEM/USD	**0.571**	0.038 **	**0.593**	0.009 ***	**0.627**	0.000 ***	**0.605**	0.003 ***
ITL/USD	0.468	0.684	**0.506**	0.445	**0.596**	0.007 ***	**0.615**	0.002 ***
NLG/USD	0.455	0.867	0.497	0.523	**0.598**	0.003 ***	**0.587**	0.007 ***
PTE/USD	0.471	0.648	0.457	0.736	**0.586**	0.073 *	**0.600**	0.060 *
All fundamentals								
USD/GBP	**0.567**	0.008 ***	**0.533**	0.119	**0.585**	0.001 ***	**0.577**	0.004 ***
JPY/USD	**0.582**	0.003 ***	**0.589**	0.002 ***	**0.613**	0.000 ***	**0.603**	0.000 ***
CHF/USD	**0.571**	0.010 ***	**0.538**	0.169	**0.596**	0.002 ***	**0.610**	0.000 ***
CAD/USD	**0.582**	0.001 ***	**0.505**	0.437	**0.571**	0.005 ***	**0.516**	0.275
SEK/USD	**0.547**	0.063 *	**0.553**	0.063 *	**0.626**	0.000 ***	**0.629**	0.000 ***
DNK/USD	**0.506**	0.425	**0.551**	0.051 *	**0.583**	0.001 ***	**0.589**	0.000 ***
USD/AUD	**0.554**	0.041 **	**0.506**	0.430	**0.582**	0.004 ***	**0.565**	0.018 **
FRF/USD	**0.500**	0.500	**0.550**	0.143	**0.583**	0.032 **	**0.583**	0.032 **
DEM/USD	**0.554**	0.107	**0.599**	0.005 ***	**0.616**	0.001 ***	**0.610**	0.001 ***
ITL/USD	**0.551**	0.107	**0.526**	0.282	**0.596**	0.007 ***	**0.590**	0.011 **
NLG/USD	**0.571**	0.068 *	**0.571**	0.046 **	**0.603**	0.002 ***	**0.603**	0.002 ***
PTE/USD	**0.543**	0.254	0.486	0.585	**0.614**	0.025 **	**0.571**	0.114

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 6: Directional tests: Percentages of changes predicted for linear models for the end-of-month exchange rates sample.

Currency pair	Rolling regression		Recursive regression		SRidge		EWA	
	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value	Proportion of changes predicted	DM p-value
PPP fundamental								
USD/GBP	**0.512**	0.334	0.493	0.599	0.470	0.835	**0.522**	0.273
JPY/USD	0.470	0.874	0.462	0.906	**0.546**	0.043 **	**0.543**	0.067 *
CHF/USD	**0.525**	0.208	0.488	0.635	**0.556**	0.024 **	**0.541**	0.085 *
CAD/USD	**0.528**	0.174	0.496	0.548	0.496	0.546	0.441	0.987
SEK/USD	**0.501**	0.484	0.480	0.719	0.493	0.573	**0.512**	0.343
DNK/USD	0.499	0.517	**0.525**	0.257	**0.564**	0.015 **	**0.559**	0.011 **
USD/AUD	0.494	0.562	0.497	0.530	0.483	0.696	0.480	0.747
FRF/USD	0.481	0.650	**0.540**	0.268	0.481	0.659	**0.571**	0.029 **
DEM/USD	0.455	0.847	0.481	0.672	**0.603**	0.010 ***	**0.608**	0.005 ***
ITL/USD	0.487	0.591	0.466	0.737	0.466	0.737	**0.577**	0.094 *
NLG/USD	**0.519**	0.357	0.455	0.818	**0.587**	0.025 **	**0.593**	0.025 **
PTE/USD	0.481	0.613	0.497	0.517	0.497	0.517	**0.550**	0.171
UIRP fundamental								
USD/GBP	0.496	0.546	**0.522**	0.216	0.480	0.727	**0.517**	0.298
JPY/USD	**0.546**	0.072 *	**0.522**	0.214	**0.562**	0.008 ***	**0.570**	0.003 ***
CHF/USD	**0.566**	0.008 ***	**0.547**	0.044 **	**0.550**	0.040 **	**0.563**	0.023 **
CAD/USD	**0.551**	0.024 **	**0.522**	0.220	0.493	0.575	0.483	0.697
SEK/USD	0.497	0.534	0.471	0.821	**0.508**	0.388	**0.539**	0.075 *
DNK/USD	**0.501**	0.483	0.483	0.689	**0.512**	0.345	**0.564**	0.006 ***
USD/AUD	**0.500**	0.500	**0.514**	0.332	0.470	0.837	0.492	0.614
FRF/USD	0.497	0.516	0.460	0.760	**0.561**	0.046 **	**0.593**	0.005 ***
DEM/USD	**0.508**	0.447	**0.540**	0.209	**0.593**	0.028 **	**0.608**	0.005 ***
ITL/USD	0.497	0.519	0.466	0.742	0.450	0.827	**0.603**	0.016 **
NLG/USD	**0.556**	0.100 *	**0.561**	0.068 *	**0.593**	0.017 **	**0.593**	0.014 **
PTE/USD	0.479	0.639	0.437	0.797	0.437	0.859	**0.507**	0.453
Monetary model fundamentals								
USD/GBP	**0.501**	0.480	**0.535**	0.138	**0.509**	0.383	**0.517**	0.333
JPY/USD	**0.532**	0.125	**0.524**	0.227	**0.542**	0.082 *	**0.558**	0.017 **
CHF/USD	0.497	0.536	**0.541**	0.079 *	**0.541**	0.092 *	**0.533**	0.115
CAD/USD	**0.513**	0.304	0.489	0.646	0.487	0.659	0.487	0.688
SEK/USD	0.432	0.993	0.474	0.759	**0.537**	0.076 *	**0.524**	0.228
DNK/USD	0.437	0.977	0.480	0.701	0.480	0.710	0.489	0.638
USD/AUD	**0.526**	0.212	0.489	0.665	0.477	0.754	0.497	0.537
FRF/USD	**0.525**	0.334	0.467	0.721	**0.558**	0.099 *	**0.550**	0.135
DEM/USD	**0.559**	0.056 *	**0.576**	0.035 **	**0.559**	0.142	**0.548**	0.114
ITL/USD	0.449	0.813	0.442	0.877	**0.513**	0.405	**0.538**	0.197
NLG/USD	0.434	0.892	**0.513**	0.394	**0.582**	0.043 **	**0.534**	0.180
PTE/USD	0.457	0.717	0.386	0.972	0.371	0.986	0.471	0.669
All fundamentals								
USD/GBP	**0.556**	0.019 **	0.491	0.627	0.496	0.550	0.488	0.623
JPY/USD	**0.537**	0.078 *	**0.537**	0.137	**0.566**	0.014 **	**0.558**	0.012 **
CHF/USD	**0.525**	0.207	**0.514**	0.328	**0.541**	0.084 *	**0.547**	0.055 *
CAD/USD	**0.558**	0.032 **	**0.503**	0.463	0.495	0.561	0.455	0.926
SEK/USD	**0.505**	0.428	0.495	0.564	0.487	0.650	**0.542**	0.050 **
DNK/USD	**0.529**	0.191	**0.511**	0.358	0.443	0.948	0.483	0.700
USD/AUD	**0.517**	0.285	**0.520**	0.264	0.472	0.800	**0.500**	0.500
FRF/USD	**0.567**	0.078 *	**0.550**	0.172	**0.500**	0.500	**0.533**	0.239
DEM/USD	**0.537**	0.231	**0.508**	0.424	**0.542**	0.142	**0.576**	0.064 *
ITL/USD	**0.513**	0.398	**0.513**	0.394	0.429	0.901	**0.558**	0.073 *
NLG/USD	**0.513**	0.385	**0.540**	0.174	**0.582**	0.044 **	**0.561**	0.106
PTE/USD	0.486	0.578	0.414	0.908	0.471	0.684	0.471	0.682

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Appendix for online publication

A. Detailed data description

B. Notes about the computations and forecasts

C. Additional graphs and tables

A. Detailed data description

The original dataset of Molodtsova and Papell [2009] was extended to the period 1973–2014 whenever possible – when the series were not discontinued. Series that had to be substituted have Datastream as the principal source. For those, as there were typically more series available without a clear advantage over one another, only the ones that were eventually used to generate predictions presented in the paper are listed (we did not get qualitatively different results using the alternatives). Data was obtained through Datastream on 30/01/2014. When the code from the original data series was known it was given instead. All series are monthly unless noted.

Quarterly series were transformed into monthly ones by a local quadratic interpolation. This means that a local quadratic polynomial was fit for each set of three adjacent quarterly observations; then, the monthly observations right before and after the center quarterly observation (the second one in the set) were filled in using the value of the quadratic polynomial. The output gap was estimated for each country with at least 24 data points. For the Hodrick-Prescott filter we used $\lambda = 129600$ as advocated by Ravn and Uhlig [2002].

The exact data series (and the periods for which they could be used) are described in detail in the following table.

Table 7: Data series description, part I.

Description	Series name	Intermediate source (if any)	Original source	Earliest date after March 1973 when the series is available	End date
Nominal exchange rate, U.S. – U.K.	EXUSUK		FRED	Mar-73	Dec-14
Nominal exchange rate, Japan -- U.S.	EXJPUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Switzerland – U.S	EXSZUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Canada -- U.S.	EXCAUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Sweden – U.S.	EXSDUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Denmark – U.S.	EXDNUS		FRED	Mar-73	Dec-14
Nominal exchange rate, U.S. – Australia	EXUSAL		FRED	Mar-73	Dec-14
Nominal exchange rate, France – U.S.	EXFRUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Germany – U.S.	EXGEUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Italy – U.S.	EXITUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Netherlands – U.S.	EXNEUS		FRED	Mar-73	Dec-14
Nominal exchange rate, Portugal – U.S.	EXPOUS		FRED	Mar-73	Dec-14
End-of-month nominal exchange rate, U.S.-U.K	UKI..AG.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Japan -- U.S.	JPI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Switzerland -- U.S.	SWI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Canada -- U.S.	CNI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Sweden -- U.S.	SDI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Denmark -- U.S.	DKI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, U.S.-- Australia	AUI..AG.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, France -- U.S.	FRI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Germany -- U.S.	BDI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Italy -- U.S.	ITI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Netherlands -- U.S.	NLI..AE.	Datastream	IFS	Mar-73	Dec-14
End-of-month nominal exchange rate, Portugal -- U.S.	PTI..AE.	Datastream	IFS	Mar-73	Dec-14
M1 money supply, n.s.a., U.S.	USI59MA.A	Datastream	IFS	Mar-73	Nov-14
Notes and coins in circulation outside the Bank of England, n.s.a., U.K.	UKAVAA..	Datastream	Bank of England	Mar-73	Dec-14
M1 money supply, billions of yens, n.s.a, Japan	JPI59MA.A	Datastream	IFS	Mar-73	Nov-14
Narrow money, billions of Swiss franks, n.s.a., Switzerland	SWI34...A	Datastream	IFS	Mar-73	Oct-14
M1 money supply, billions of Canadian dollars, n.s.a., Canada	CNI59MADA	Datastream	IFS	Mar-73	Oct-14
M0 money supply, millions of Swedish kronors, n.s.a., Sweden	SDM0....A	Datastream	Statistics Sweden	Mar-73	Dec-14
M1 money supply, millions of Danish kroners, n.s.a., Denmark	DKOMA027A	Datastream	MEI, OECD	Mar-73	Feb-14
M1 money supply, millions of Australian dollars, n.s.a., Australia	AUOMA027A	Datastream	MEI, OECD	Mar-73	Feb-14
M1 money supply, billions of French franks, n.s.a., France	13259MA.ZF..	Molodtsova and Papell (2009)	IFS	Dec-77	Dec-98
M1 money supply, billions of Deutsche marks, s.a., Germany	13459MACZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
M2 money supply, billions of Italian liras, n.s.a., Italy	13659MB.ZF...	Molodtsova and Papell (2009)	IFS	Dec-74	Dec-98
M2 money supply, billions of Dutch guilders, n.s.a., Netherlands	13859MB.ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
M1 money supply, billions of Portuguese escudos, n.s.a., Portugal	18259MA.ZF...	Molodtsova and Papell (2009)	IFS	Dec-79	Dec-98

Table 8: Data series description, part II.

Description	Series name	Intermediate source (if any)	Original source	Earliest date after March 1973 when the series is available	End date
Federal Funds Rate, United States	USI60B..	Datastream	IFS	Mar-73	Dec-14
Money Market Rate, U.K.	UKI60B..	Datastream	IFS	Mar-73	Nov-14
Money Market Rate, Japan	JPI60B..	Datastream	IFS	Mar-73	Dec-14
3-Month Euro Deposits, Switzerland	SWOIR075R	Datastream	MEI, OECD	Jan-74	Nov-14
Treasury Bills rate, Canada	CNI60C..	Datastream	IFS	Mar-73	Dec-14
Money Market Rate, Sweden	SDI60B..	Datastream	IFS	Mar-73	Oct-14
Money Market Rate, Denmark	DKI60B..	Datastream	IFS	Mar-73	Dec-14
Money Market Rate, Australia	AUI60B..	Datastream	IFS	Mar-73	Dec-14
Money Market Rate, France	13260B..ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Money Market Rate, Germany	13460B..ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Money Market Rate, Italy	13660B..ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Money Market Rate, Netherlands	13860B..ZF..	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Money Market Rate, Portugal	18260B..ZF..	Molodtsova and Papell (2009)	IFS	Jan-83	Dec-98
Industrial production, s.a., U.S.	USI66..CE	Datastream	IFS	Mar-73	Dec-14
Industrial production, s.a., U.K.	UKI66..CE	Datastream	IFS	Mar-73	Nov-14
Industrial production, s.a., Japan	JPI66..CE	Datastream	IFS	Mar-73	Oct-14
Industrial production, s.a., Switzerland, quarterly	SWQ66..BH	Datastream	IFS		
Industrial production, s.a., Canada	CNI66..CE	Datastream	IFS	Mar-73	Oct-14
Industrial production excluding construction, s.a., Sweden	SDOPRI35G	Datastream	MEI, OECD	Mar-73	Oct-14
Industrial production, s.a., Denmark	DKI66..BH	Datastream	IFS	Jan-74	Oct-14
Industrial production, s.a., Australia, quarterly	AUQ66..CE	Datastream	IFS		
Industrial production, s.a., France	13266..CZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Industrial production, s.a., Germany	13466..CZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Industrial production, s.a., Italy	13666..CZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Industrial production, s.a., Netherlands	13866..CZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Industrial production, s.a., Portugal	18266..BZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Consumer price index, U.S.	USI64...F	Datastream	IFS	Mar-73	Dec-14
Consumer price index (retail price index), U.K.	UKI64B..F	Datastream	IFS	Mar-73	Nov-14
Consumer price index, Japan	JPI64...F	Datastream	IFS	Mar-73	Nov-14
Consumer price index, Switzerland	SWI64...F	Datastream	IFS	Mar-73	Dec-14
Consumer price index, Canada	CNI64...F	Datastream	IFS	Mar-73	Nov-14
Consumer price index, Sweden	SDI64...F	Datastream	IFS	Mar-73	Dec-14
Consumer price index, Denmark	DKI64...F	Datastream	IFS	Mar-73	Dec-14
Consumer price index, quarterly, Australia	AUI64...F	Datastream	IFS	Mar-73	Aug-14
Consumer price index, France	13264...ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Consumer price index, Germany	Consumer prices: all items, 2000=100	Molodtsova and Papell (2009)	MEI, OECD	Mar-73	Dec-98
Consumer price index, Italy	13664...ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Consumer price index, Netherlands	13864...ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98
Consumer price index, Portugal	18264...ZF...	Molodtsova and Papell (2009)	IFS	Mar-73	Dec-98

B. Notes about the computations and forecasts

Calculations were performed with the Scilab 5.5.0 software. The “training” period for our methods was set at 120 months, which is standard in the literature. Correspondingly, the rolling OLS regressions were estimated with 120 months of past data at each instance. The computed coefficients of our models vary greatly over time and it is difficult to discern any time patterns – a feature known in the literature. This is not a surprise as our forecasting methods do not aim to estimate some model, they merely output efficient forecasts. The regularization and discount terms that are computed from past data are nonzero most of the time and they differ substantially between currencies, fundamentals used and time periods. Most of the time the best discount factors are high, above 10, which means that short-term trends are weighted most strongly during estimation.

We tried different grids from the ones in Section 3.3. All grids were logarithmic as is recommended by machine learning theory. We found that a larger grid typically yields small improvements in terms of RMSE over the initial grid we used – but not always as the RMSE of predictions can get worse. With a finer grid we may overfit the regularization and the discounting terms themselves. Smaller obtained RMSEs do not guarantee either obtaining better DM tests: all depends on the errors of individual predictions. It appears that there is a large set of said parameters where the quality of predictions (measured by the size of the RMSE) are qualitatively very similar and improve upon the OLS methods at hand.

C. Additional graphs and tables

This section provides complementary studies.

Taylor fundamentals. Previous research by Molodtsova and Papell [2009]) and the following literature showed that by using Taylor rule fundamentals one can obtain exchange rate predictability. For the sake of comparison with these studies, as Taylor rule fundamentals can be created from the data in our possession, we also reran such models based on (5) with these fundamentals for our basic sample and present them in Tables 14–15. We do not find forecastability on the end-of-month exchange rate sample. We find forecastability on the FRED average exchange rate sample but it is slightly worse than for the basic "classic" fundamentals. In Table 19 we use the Molodtsova and Papell [2009] data (to allow a direct comparison with their results). There is no forecastability with either rolling or recursive OLS methods. However (not reported) we find similar patterns as Molodtsova and Papell [2009] regarding predictability with the use of Clark-West (West [1996], Clark and West [2006, 2007]) tests designed for model comparison (confront Footnotes 7 and 16) in several instances for OLS-based methods. But such identified predictability does not help in forecasting exchange rates.

Machine learning methods and the detection of structural breaks. We chose the time period around the Plaza agreement (September 1985) in Table 9 to compare the performance of sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors with the OLS-based methods for the major currency pairs (USD/GBP, JPY/USD, DEM/USD and FRF/USD) that were the subject of the coordinated currency interventions that followed. This episode was picked because it involved several currencies and may represent a rare "known" structural break. Forecasts using the UIRP- and flexible-prices monetary models-based sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors react strongly to this "regime" change where major central banks started to intervene in currency markets to bring down the value of the U.S. dollar. In contrast, the predictions from the OLS methods or sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors based on the PPP fundamentals do so much more weakly and slowly (if at all). This substantiates our claim that our algorithm can accommodate quickly structural breaks that might be present in the data[27]. We obtain similar results for the end-of-month data.

Other tables with results discussed in text.

- Tables 10–11 report the quantiles of the differences in forecasting error between the no-change prediction and the methods under scrutiny.
- Tables 12–13 show the results for the exchange rate model fundamentals in their “coupled” form.
- Tables 14–15 show the results for the Taylor-rule based exchange rate model fundamentals in their “decoupled” (heterogenous) form to compare with the results from Molodtsova and Papell [2009].
- Tables 16–17 give the results for a subsample spanning all the observations since January 1980 till the end of our sample. Note: some results are not available for the PTE/USD pair as data on interest rates starts in 1983.
- Tables 18–19 report the results on the original Molodtsova and Papell [2009] 1973-2006 sample.

[27] We would like to thank Charles Engel for suggesting to perform such an exercise.

Table 9: Actual monthly exchange rate changes versus those forecasted by rolling, recursive and sequential ridge regression with discount factors and the exponentially weighted average strategy with discount factors for the PPP, UIRP and monetary model fundamentals around the Plaza agreement (September 1985) for major currencies for the average exchange rate sample.

Time	Actual natural logarithm monthly change (relative to the preceding month) in the exchange rate x 100	Predicted natural logarithm change of the monthly exchange rate x 100											
		Rolling regression	Recursive regression	SRidge	EWA	Rolling regression	Recursive regression	SRidge	EWA	Rolling regression	Recursive regression	SRidge	EWA
		PPP experts				UIRP experts				Monetary model with flexible prices			
USD/GBP													
avr-85	9.5205	-0.2245	-0.1878	0.1300	0.0000	-0.6009	-0.5556	0.5697	-0.2635	-0.3014	-0.4503	0.1275	0.4713
mai-85	0.8528	-0.2886	-0.2563	1.9048	0.2943	-0.2131	-0.2747	3.6255	0.6621	0.3399	0.0069	2.6418	0.5263
juin-85	2.5702	-0.2597	-0.2376	0.5773	0.2584	-0.1485	-0.2350	1.1701	0.6390	0.4835	0.0737	0.7916	0.5921
juil-85	7.5106	-0.2610	-0.2465	0.7263	0.2908	0.0003	-0.1359	1.4618	0.6050	0.6230	0.1734	1.2340	0.7348
août-85	0.2459	-0.2011	-0.2239	1.7780	0.2918	0.1249	-0.0409	2.9214	0.6321	0.3266	0.0288	3.3319	0.5578
sept-85	-1.4482	-0.1551	-0.1974	0.4860	0.1668	0.1252	-0.0453	0.9238	0.6336	0.1935	-0.0007	0.9612	0.6559
oct-85	4.1144	-0.1442	-0.1916	-0.0468	-0.0004	0.0819	-0.0776	-0.0736	0.0000	-0.1220	-0.1709	-0.1574	-0.0034
nov-85	1.2653	-0.1120	-0.1548	0.6791	0.2546	0.1226	-0.0376	1.3292	0.6406	-0.4584	-0.3716	1.4193	0.9174
déc-85	0.3536	-0.0990	-0.1253	0.3956	0.0796	0.1787	0.0008	0.8302	0.6452	-0.0612	-0.0322	0.9773	0.9325
janv-86	-1.4151	-0.0966	-0.1259	0.2072	0.0007	0.1089	-0.0442	0.3420	0.6621	-1.0470	-0.7422	0.2442	0.2768
févr-86	0.3714	-0.0937	-0.1068	-0.1562	-0.0356	0.1904	0.0032	-0.2210	-0.0396	-1.3067	-0.8689	-0.3564	-0.2003
mars-86	2.6027	-0.1106	-0.1362	0.0452	0.0000	0.2246	0.0301	0.1626	0.0000	-0.6994	-0.5346	0.0668	0.3105
JPY/USD													
avr-85	-2.3836	0.0880	0.0536	0.0089	0.0003	-0.0657	0.0890	0.0232	0.0000	-0.3014	0.0503	0.0263	0.0471
mai-85	-0.0461	-0.0005	0.0350	-0.1045	-0.2942	-0.0909	0.0868	-0.3200	-0.6621	0.3399	-0.1444	-0.2314	-0.4821
juin-85	-1.1545	0.0990	0.0502	-0.0199	-0.0020	-0.1276	0.0663	-0.0542	0.0000	0.4835	-0.0553	-0.0710	-0.1519
juil-85	-3.1447	-0.0586	0.0270	-0.0635	-0.2846	-0.2424	0.0068	-0.1729	-0.5807	0.6230	-0.0068	-0.2266	-0.3658
août-85	-1.5360	-0.0765	0.0223	-0.1832	-0.2918	-0.3132	-0.0073	-0.5047	-0.6321	0.3266	-0.1244	-0.6441	-0.7113
sept-85	-0.3938	-0.2414	0.0032	-0.1340	-0.2738	-0.3131	0.0070	-0.3585	-0.6336	0.1935	-0.2458	-0.4689	-0.7649
oct-85	-9.6914	0.0289	0.0277	-0.0509	-0.2356	-0.4152	-0.0216	-0.1736	-0.5555	-0.1220	-0.3639	-0.2181	-0.4503
nov-85	-5.0670	-0.0387	0.0101	-0.3811	-0.2549	-0.5683	-0.0791	-2.1351	-0.6406	-0.4584	-0.6294	-2.5959	-0.9174
déc-85	-0.6320	0.0815	0.0134	-0.3125	-0.2883	-0.8785	-0.1904	-1.7159	-0.6452	-0.0612	-0.7502	-2.0464	-0.9325
janv-86	-1.4392	0.1049	0.0142	-0.1351	-0.3049	-1.1638	-0.2740	-0.7296	-0.6621	-1.0470	-0.7856	-0.8405	-0.9569
févr-86	-7.8216	0.1267	0.0125	-0.1354	-0.3209	-0.8020	-0.1464	-0.6299	-0.6521	-1.3067	-0.7382	-0.7615	-0.9201
mars-86	-3.3880	-0.0517	-0.0129	-0.3811	-0.2533	-0.5572	-0.0779	-1.8235	-0.6305	-0.6994	-0.9359	-2.2024	-0.8723
DEM/USD													
avr-85	-6.3718	0.2340	0.0284	0.0866	0.2058	0.3786	0.2450	0.2044	0.2222	0.0319	0.1396	0.1272	-0.0247
mai-85	0.4739	0.2061	0.0148	-0.3201	-0.2962	0.3075	0.1992	-0.5840	-0.0538	0.1252	0.2284	-0.5575	-0.3651
juin-85	-1.4807	0.1905	0.0210	-0.0332	-0.0685	0.3027	0.1758	-0.0557	0.0098	0.0452	0.1746	-0.0381	-0.3916
juil-85	-5.1988	0.1295	0.0287	-0.0909	-0.1791	0.2780	0.1433	-0.1557	0.0017	-1.6376	-0.9217	-1.3419	-1.3289
août-85	-4.0236	0.1193	0.0142	-0.2892	-0.2916	0.2463	0.1951	-0.5157	-0.0333	-0.1205	-0.0294	-0.9543	-0.4445
sept-85	1.5768	0.0849	0.0079	-0.2629	-0.2750	0.2377	0.2166	-0.5722	-0.6242	0.1954	0.1787	-0.7839	-0.3161
oct-85	-7.0615	0.0869	0.0061	-0.0069	0.0000	0.2492	0.2438	0.0005	-0.0231	0.3880	0.3409	0.2028	-0.2443
nov-85	-1.8779	0.0282	0.0150	-0.3010	-0.2653	0.2198	0.2170	-0.6637	-0.6394	-0.1748	-0.1585	-1.4088	-0.9174
déc-85	-3.2582	0.0082	0.0197	-0.1691	-0.2934	0.2066	0.2038	-0.4058	-0.6003	-0.3469	-0.3174	-0.9595	-0.9231
janv-86	-2.9817	-0.0099	0.0170	-0.2195	-0.3085	0.1910	0.1986	-0.5021	-0.6418	0.5431	0.4108	-0.3753	-0.9544
févr-86	-4.4744	-0.0532	0.0179	-0.2210	-0.3181	0.1688	0.1762	-0.4875	-0.6307	-0.0780	-0.1218	-1.0797	-0.9201
mars-86	-2.4530	-0.1108	0.0072	-0.2372	-0.2610	0.1359	0.1323	-0.6320	-0.6261	-0.4612	-0.4187	-1.4225	-0.8723
FRF/USD													
avr-85	-6.5073	0.6470	0.5062	0.1995	0.3387	0.6574	0.4625	0.5326	0.7729	0.6422	0.6422	0.7009	0.8180
mai-85	0.4259	0.6503	0.5037	-0.4586	-0.1805	0.5712	0.3858	-0.4238	-0.3422	0.2692	0.2692	0.2155	-0.2007
juin-85	-1.5045	0.6476	0.4842	0.0022	0.0115	0.5770	0.3649	0.1462	0.1279	0.8395	0.8395	0.8260	0.3556
juil-85	-5.3892	0.6310	0.4616	-0.0972	-0.0485	0.5190	0.2780	0.0320	0.0288	0.5465	0.5465	0.5755	-0.0252
août-85	-3.6705	0.5530	0.4152	-0.4476	-0.1821	0.4881	0.3173	-0.3933	-0.2969	1.0379	1.0379	0.8375	-0.7154
sept-85	1.4856	0.4832	0.3661	-0.3569	-0.1541	0.4544	0.3150	-0.8138	-0.2601	0.8491	0.8491	0.2179	-0.8223
oct-85	-7.1293	0.4452	0.3421	0.0318	0.0270	0.4687	0.3461	0.1882	0.1680	0.7210	0.7210	0.7453	-0.0298
nov-85	-1.9358	0.3624	0.2652	-0.4338	-0.1777	0.4614	0.3552	-1.0426	-0.6030	-0.0966	-0.0966	-1.3423	-0.9174
déc-85	-2.8807	0.2838	0.1972	-0.2094	-0.1975	0.4862	0.3985	-0.5892	-0.4577	-1.2851	-1.2851	-1.4672	-0.9325
janv-86	-2.6744	0.2359	0.1591	-0.2329	-0.2256	0.4982	0.4255	-0.6462	-0.4962	-1.2759	-1.2759	-1.4634	-0.9569
févr-86	-4.4353	0.1333	0.0757	-0.2137	-0.3181	0.4608	0.3873	-0.6202	-0.4808	-1.2891	-1.2891	-1.4046	-0.9201
mars-86	-2.2765	0.0971	0.0516	-0.2543	-0.2610	0.4079	0.3350	-0.8690	-0.5541	-0.1187	-0.1187	-0.6030	-0.8723

Table 10: Quantiles of the differences in forecasting error between the random walk and the method under scrutiny for the average exchange rates sample. Distributions of errors that are shifted towards positive values indicate methods that outperfom the random walk.

Currency pair	Rolling regression					Recursive regression					SRidge					EWA				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
PPP fundamental																				
USD/GBP	-1.30	-0.39	-0.01	0.33	1.12	-0.41	-0.13	0.00	0.10	0.34	-1.02	-0.22	0.03	0.36	1.68	-0.83	-0.16	0.00	0.26	1.25
JPY/USD	-2.05	-0.81	-0.03	0.40	1.36	-0.32	-0.14	-0.01	0.12	0.32	-1.16	-0.29	0.05	0.66	1.98	-0.82	-0.04	0.00	0.31	1.30
CHF/USD	-1.54	-0.43	0.01	0.41	1.22	-0.69	-0.26	-0.01	0.28	0.69	-0.73	-0.12	0.04	0.42	1.65	-0.88	-0.15	0.02	0.56	1.47
CAD/USD	-0.52	-0.14	0.01	0.22	0.66	-0.21	-0.10	0.01	0.11	0.23	-0.14	-0.05	0.01	0.08	0.24	-0.07	-0.02	0.00	0.02	0.09
SEK/USD	-2.41	-0.91	-0.10	0.76	2.42	-1.01	-0.39	-0.02	0.34	0.97	-0.98	-0.19	0.08	0.72	1.98	-0.51	-0.13	0.03	0.36	1.10
DNK/USD	-2.04	-0.73	-0.03	0.52	1.40	-1.10	-0.41	0.06	0.43	0.89	-0.53	-0.12	0.04	0.48	1.26	-0.81	-0.26	0.02	0.73	1.59
USD/AUD	-2.07	-0.77	-0.03	0.76	2.30	-0.68	-0.29	-0.03	0.20	0.71	-0.77	-0.18	0.03	0.42	1.54	-1.01	-0.27	0.00	0.40	1.29
FRF/USD	-1.96	-0.73	-0.09	0.49	2.05	-1.17	-0.41	-0.02	0.33	1.44	-0.59	-0.16	0.05	0.58	1.65	-1.13	-0.39	0.17	0.91	2.04
DEM/USD	-1.95	-0.71	-0.05	0.46	1.26	-0.45	-0.16	-0.03	0.10	0.32	-0.93	-0.25	0.10	0.68	1.86	-1.16	-0.26	0.13	0.80	1.83
ITL/USD	-2.17	-0.70	0.01	0.54	1.53	-1.81	-0.85	-0.04	0.70	1.79	-1.18	-0.21	0.10	1.11	2.57	-1.44	-0.30	0.01	1.18	2.80
NLG/USD	-1.57	-0.66	-0.06	0.35	1.26	-0.26	-0.09	-0.01	0.05	0.15	-0.75	-0.20	0.09	0.70	1.67	-1.04	-0.28	0.07	0.77	1.72
PTE/USD	-4.92	-1.93	-0.15	1.34	4.96	-4.02	-1.54	0.00	1.21	4.59	-2.59	-0.90	0.01	0.94	4.39	-2.91	-0.28	0.00	0.82	6.00
UIRP fundamental																				
USD/GBP	-1.99	-0.51	-0.02	0.49	2.22	-0.84	-0.21	0.01	0.26	1.15	-1.08	-0.19	0.01	0.35	2.85	-1.22	-0.16	0.00	0.40	2.06
JPY/USD	-2.20	-0.72	0.05	0.84	2.73	-1.14	-0.26	0.00	0.48	1.66	-1.09	-0.11	0.00	0.47	1.64	-1.19	0.00	0.00	0.24	1.88
CHF/USD	-2.97	-0.44	0.03	0.68	2.10	-1.75	-0.22	0.05	0.46	1.96	-1.71	-0.16	0.01	0.69	2.80	-1.59	-0.14	0.00	0.80	2.40
CAD/USD	-0.63	-0.29	0.02	0.21	0.56	-0.23	-0.08	0.00	0.07	0.22	-0.17	-0.05	0.00	0.05	0.21	-0.08	-0.03	0.00	0.03	0.11
SEK/USD	-2.90	-0.90	-0.01	0.63	1.95	-1.21	-0.40	-0.03	0.38	0.84	-1.14	-0.21	0.03	0.69	2.23	-1.02	-0.16	0.03	0.52	1.92
DNK/USD	-2.79	-0.60	-0.02	0.56	1.99	-1.97	-0.50	0.00	0.47	1.60	-0.96	-0.13	0.01	0.60	2.23	-1.12	-0.17	0.00	0.68	2.44
USD/AUD	-2.95	-0.91	-0.02	0.90	2.86	-1.31	-0.50	0.00	0.40	1.04	-1.08	-0.26	0.05	0.54	1.77	-0.93	-0.21	0.00	0.28	1.03
FRF/USD	-2.65	-1.07	-0.04	0.56	1.92	-2.72	-0.99	-0.12	0.72	2.09	-1.42	-0.47	0.16	1.45	3.15	-2.03	-0.51	0.19	1.47	2.79
DEM/USD	-2.26	-1.03	-0.01	0.79	2.23	-1.51	-0.24	0.00	0.39	1.34	-1.79	-0.47	0.16	1.46	3.12	-2.01	-0.43	0.05	1.36	3.13
ITL/USD	-4.37	-1.36	-0.02	1.12	3.50	-3.21	-1.13	-0.08	1.10	2.22	-2.61	-0.58	0.17	2.11	4.52	-1.99	-0.25	0.07	1.32	3.52
NLG/USD	-4.10	-1.11	-0.03	1.52	4.03	-2.34	-0.40	0.10	0.97	2.65	-1.84	-0.55	0.20	1.47	3.53	-2.15	-0.48	0.01	1.32	3.38
PTE/USD	-1.32	-0.49	-0.06	0.58	1.64	-1.44	-0.66	0.04	0.65	1.46	-1.49	-0.22	0.08	0.75	2.33	-2.59	-0.76	0.02	1.23	3.68
Monetary model fundamentals																				
USD/GBP	-3.73	-1.16	-0.06	0.61	2.03	-2.14	-0.73	-0.01	0.42	1.76	-2.73	-0.67	0.06	0.78	3.21	-1.66	-0.48	0.02	0.77	3.02
JPY/USD	-4.26	-0.88	0.02	1.25	4.25	-3.70	-1.12	-0.01	1.10	3.94	-3.02	-0.82	0.03	1.36	4.25	-2.14	-0.64	0.03	1.21	4.08
CHF/USD	-4.67	-1.39	-0.03	1.10	3.75	-3.00	-0.95	0.01	1.25	2.87	-2.85	-0.79	0.14	1.48	3.86	-2.72	-0.82	0.05	1.48	3.84
CAD/USD	-1.18	-0.49	-0.02	0.32	1.00	-0.45	-0.20	0.00	0.15	0.46	-0.47	-0.12	0.01	0.24	0.72	-0.23	-0.04	0.00	0.05	0.24
SEK/USD	-4.61	-1.67	-0.11	0.71	2.36	-2.03	-0.67	-0.04	0.27	1.00	-2.20	-0.60	0.13	1.43	3.20	-2.02	-0.40	0.10	1.23	2.95
DNK/USD	-2.88	-1.30	-0.20	0.39	1.21	-1.76	-0.57	-0.02	0.25	0.89	-1.81	-0.43	0.05	1.11	3.39	-2.57	-0.92	0.00	1.72	3.99
USD/AUD	-4.05	-1.32	-0.08	0.71	2.47	-1.64	-0.62	-0.03	0.32	1.13	-2.20	-0.52	0.05	0.98	3.49	-2.44	-0.55	0.03	1.03	3.16
FRF/USD	-5.79	-2.04	-0.08	1.08	2.94	-6.37	-1.42	-0.01	0.69	2.83	-2.49	-0.72	0.15	1.32	3.45	-2.09	-0.51	0.09	0.96	2.11
DEM/USD	-3.52	-1.31	0.10	1.37	3.63	-2.68	-0.95	0.12	1.19	3.04	-2.94	-1.07	0.31	1.82	5.31	-1.91	-0.55	0.18	1.72	3.63
ITL/USD	-4.90	-1.99	-0.10	0.82	2.69	-3.05	-0.92	-0.01	0.82	2.09	-2.44	-0.53	0.10	1.56	5.02	-2.40	-0.57	0.07	1.73	3.68
NLG/USD	-4.05	-1.39	-0.20	0.58	2.13	-2.75	-0.94	-0.01	0.79	2.12	-2.00	-0.67	0.25	1.80	4.35	-1.73	-0.62	0.12	1.38	3.20
PTE/USD	-4.00	-1.26	-0.24	1.21	4.33	-3.17	-1.84	-0.28	0.58	1.90	-2.64	-0.67	0.08	0.75	4.47	-3.76	-0.64	0.05	1.36	4.06
All fundamentals																				
USD/GBP	-6.24	-1.92	-0.11	1.43	4.00	-2.69	-0.79	-0.01	0.58	2.39	-2.14	-0.51	0.03	0.69	2.94	-2.21	-0.76	0.04	0.95	3.47
JPY/USD	-7.32	-2.65	-0.09	1.49	4.44	-6.23	-2.27	0.00	1.62	5.28	-2.34	-0.61	0.05	1.13	3.64	-1.88	-0.63	0.03	1.18	4.01
CHF/USD	-8.60	-2.73	-0.07	1.73	4.73	-4.83	-1.59	-0.01	1.50	4.28	-2.56	-0.82	0.13	1.65	3.72	-3.15	-1.00	0.07	1.96	4.25
CAD/USD	-1.71	-0.60	0.00	0.59	1.71	-0.63	-0.21	0.00	0.17	0.59	-0.36	-0.09	0.02	0.20	0.59	-0.18	-0.06	0.00	0.08	0.27
SEK/USD	-7.11	-2.23	-0.07	1.43	4.12	-3.13	-1.03	0.01	0.84	2.82	-1.69	-0.40	0.12	1.11	2.67	-2.17	-0.39	0.06	1.13	3.18
DNK/USD	-6.01	-2.44	-0.12	1.31	3.93	-2.79	-0.81	0.04	0.65	2.10	-1.41	-0.54	0.07	1.22	3.30	-2.91	-0.92	0.08	1.91	4.22
USD/AUD	-6.42	-1.99	-0.08	1.55	5.19	-3.06	-1.11	-0.02	0.62	2.17	-1.97	-0.44	0.05	0.83	2.70	-1.37	-0.37	0.02	0.62	2.33
FRF/USD	-8.71	-2.89	-0.11	1.75	5.16	-5.08	-2.56	0.02	1.86	4.34	-2.08	-0.72	0.15	1.29	3.63	-2.95	-1.31	0.14	1.92	4.06
DEM/USD	-6.28	-1.52	0.03	2.10	4.62	-6.13	-1.29	0.12	2.19	4.53	-2.35	-0.85	0.21	1.61	4.88	-2.71	-1.15	0.24	2.34	4.72
ITL/USD	-4.22	-1.44	0.02	1.35	4.35	-5.81	-1.77	-0.02	1.65	3.62	-2.11	-0.41	0.09	1.60	4.60	-1.68	-0.30	0.06	1.24	3.64
NLG/USD	-7.60	-2.15	0.08	2.23	6.32	-5.94	-1.40	0.05	1.73	4.65	-1.97	-0.60	0.19	1.74	4.21	-2.33	-0.72	0.26	1.87	3.78
PTE/USD	-3.05	-1.36	-0.02	1.87	3.80	-3.69	-1.95	-0.33	0.65	2.35	-1.70	-0.32	0.10	0.63	2.48	-2.72	-1.00	0.05	1.47	4.44

Table 11: Quantiles of the differences in forecasting error between the random walk and the method under scrutiny for the end-of-month exchange rates sample. Distributions of errors that are shifted towards positive values indicate methods that outperfom the random walk.

Currency pair	Rolling regression					Recursive regression					SRidge					EWA				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
PPP fundamental																				
USD/GBP	-1.32	-0.45	-0.01	0.41	1.00	-0.55	-0.14	0.00	0.12	0.50	-0.21	-0.06	0.00	0.04	0.25	-1.47	-0.38	0.00	0.37	1.65
JPY/USD	-2.32	-0.78	-0.06	0.53	1.75	-0.30	-0.13	-0.01	0.10	0.26	-0.02	0.00	0.00	0.01	0.02	-0.90	-0.11	0.00	0.24	1.06
CHF/USD	-1.81	-0.51	0.00	0.43	1.48	-0.78	-0.25	0.00	0.26	0.85	-0.14	-0.03	0.00	0.06	0.21	-1.34	-0.29	0.00	0.42	1.76
CAD/USD	-0.65	-0.21	0.00	0.19	0.76	-0.26	-0.11	-0.01	0.10	0.27	-0.06	-0.02	0.00	0.02	0.05	-0.05	-0.01	0.00	0.01	0.04
SEK/USD	-2.84	-1.02	-0.07	0.90	2.78	-1.11	-0.49	-0.03	0.42	1.28	-0.33	-0.09	0.00	0.08	0.37	-1.19	-0.23	0.00	0.32	1.41
DNK/USD	-2.28	-0.82	-0.02	0.63	1.56	-1.27	-0.60	0.01	0.45	1.24	-0.08	-0.01	0.00	0.03	0.10	-1.19	-0.30	0.03	0.46	1.57
USD/AUD	-2.25	-1.13	-0.03	0.92	2.66	-0.92	-0.36	-0.01	0.28	0.71	-0.24	-0.08	0.00	0.04	0.16	-1.00	-0.05	0.00	0.03	0.48
FRF/USD	-2.39	-0.81	-0.04	0.63	2.06	-1.17	-0.44	0.01	0.31	1.11	-0.26	-0.04	0.00	0.04	0.30	-1.63	-0.55	0.10	0.68	1.48
DEM/USD	-2.05	-0.71	-0.04	0.41	1.50	-0.44	-0.18	0.00	0.09	0.27	-0.11	-0.02	0.01	0.06	0.16	-1.53	-0.33	0.09	0.98	1.76
ITL/USD	-2.38	-0.83	-0.04	0.47	2.28	-2.17	-0.76	-0.16	0.66	2.39	-1.67	-0.57	-0.11	0.60	1.86	-1.46	-0.35	0.03	0.83	3.15
NLG/USD	-2.24	-0.53	-0.01	0.32	1.30	-0.29	-0.11	-0.01	0.06	0.15	-0.11	-0.02	0.00	0.05	0.14	-1.46	-0.39	0.05	0.90	1.85
PTE/USD	-5.02	-2.09	-0.21	1.54	4.88	-4.43	-1.38	-0.09	0.99	4.45	-3.72	-1.24	-0.13	1.12	4.33	-2.72	-0.70	0.00	0.75	3.94
UIRP fundamental																				
USD/GBP	-2.58	-0.64	-0.03	0.54	2.59	-0.92	-0.25	0.00	0.26	1.36	-0.29	-0.06	0.00	0.05	0.42	-2.26	-0.49	0.00	0.35	2.46
JPY/USD	-2.52	-0.92	0.03	0.97	3.19	-1.14	-0.27	0.00	0.39	1.64	-0.23	-0.02	0.00	0.04	0.25	-1.57	-0.08	0.00	0.16	1.78
CHF/USD	-3.41	-0.68	0.02	0.79	2.76	-1.76	-0.32	0.01	0.65	2.44	-0.41	-0.06	0.00	0.12	0.54	-1.67	-0.02	0.00	0.09	2.45
CAD/USD	-0.83	-0.26	0.02	0.29	0.69	-0.28	-0.10	0.00	0.10	0.24	-0.02	0.00	0.00	0.00	0.01	-0.05	-0.01	0.00	0.00	0.02
SEK/USD	-3.89	-1.40	-0.05	0.76	2.76	-2.09	-0.55	-0.03	0.21	1.55	-0.68	-0.12	0.00	0.10	0.72	-2.21	-0.57	0.00	0.38	2.06
DNK/USD	-2.66	-0.68	-0.02	0.47	1.98	-1.49	-0.39	-0.01	0.39	1.37	-0.05	-0.01	0.00	0.01	0.08	-1.92	-0.28	0.00	0.62	2.33
USD/AUD	-3.84	-1.13	-0.03	1.04	3.13	-1.60	-0.58	0.00	0.49	1.23	-0.63	-0.19	0.00	0.12	0.36	-0.26	0.00	0.00	0.00	0.08
FRF/USD	-3.36	-1.38	-0.01	0.62	2.26	-2.64	-1.02	-0.09	0.93	2.37	-0.92	-0.15	0.02	0.25	0.94	-3.57	-1.19	0.21	1.29	3.21
DEM/USD	-2.15	-0.74	-0.04	0.54	1.82	-1.10	-0.23	0.02	0.45	1.26	-0.46	-0.10	0.03	0.25	0.69	-3.47	-1.06	0.12	1.72	3.38
ITL/USD	-4.11	-1.69	-0.16	1.06	3.89	-3.51	-1.28	-0.20	0.88	2.82	-2.75	-0.82	-0.05	0.53	2.35	-3.90	-1.20	0.00	1.69	5.56
NLG/USD	-4.07	-1.02	0.00	1.04	3.35	-0.83	-0.21	0.04	0.39	1.07	-0.28	-0.05	0.01	0.15	0.31	-3.18	-1.01	0.07	1.61	3.64
PTE/USD	-2.10	-0.92	-0.11	0.67	2.60	-1.45	-0.78	-0.08	0.45	1.35	-0.70	-0.30	-0.02	0.26	0.74	-0.80	-0.28	0.00	0.22	0.57
Monetary model fundamentals																				
USD/GBP	-4.29	-1.28	-0.09	0.66	2.76	-2.29	-0.71	0.01	0.45	2.22	-1.32	-0.27	0.00	0.25	1.28	-2.49	-0.87	0.00	0.81	2.58
JPY/USD	-4.37	-1.04	-0.01	1.12	4.69	-3.85	-1.12	-0.01	1.00	4.25	-2.31	-0.54	0.01	0.67	2.47	-3.23	-0.90	0.00	1.18	3.61
CHF/USD	-5.61	-1.74	-0.09	1.44	4.82	-4.71	-1.25	0.01	1.43	4.21	-1.33	-0.37	0.01	0.50	1.36	-1.76	-0.48	0.01	0.58	1.45
CAD/USD	-1.86	-0.64	-0.01	0.36	1.09	-0.71	-0.26	-0.02	0.18	0.59	-0.11	-0.01	0.00	0.01	0.09	-0.09	-0.03	0.00	0.02	0.06
SEK/USD	-6.77	-2.37	-0.35	0.65	2.93	-3.05	-0.83	-0.05	0.42	1.35	-0.85	-0.11	0.00	0.17	0.72	-2.41	-0.79	0.00	0.71	2.45
DNK/USD	-5.15	-1.51	-0.14	0.52	1.76	-2.26	-0.66	-0.01	0.37	0.99	-0.02	-0.01	0.00	0.01	0.01	-0.80	-0.28	-0.01	0.21	0.67
USD/AUD	-4.72	-1.57	-0.01	1.03	3.66	-2.00	-0.67	-0.02	0.45	1.50	-0.24	-0.02	0.00	0.02	0.08	-1.67	-0.46	-0.01	0.43	1.49
FRF/USD	-5.48	-2.57	-0.12	1.18	3.26	-5.31	-2.22	-0.17	0.73	3.58	-1.30	-0.38	0.02	0.33	0.99	-2.97	-1.16	0.01	0.75	2.71
DEM/USD	-5.79	-1.40	0.08	1.73	3.64	-4.18	-0.94	0.08	1.47	3.15	-1.63	-0.22	0.01	0.45	1.18	-3.96	-1.69	0.01	1.47	4.39
ITL/USD	-4.61	-1.98	-0.40	0.95	3.87	-3.23	-1.41	-0.16	0.83	3.42	-1.20	-0.41	0.00	0.26	0.83	-4.10	-1.15	0.00	1.09	3.50
NLG/USD	-6.38	-2.11	-0.31	0.89	3.88	-3.81	-1.03	0.00	0.82	3.10	-0.57	-0.09	0.02	0.24	0.62	-3.00	-0.96	0.00	1.05	3.33
PTE/USD	-6.51	-1.60	-0.21	1.38	4.32	-3.80	-1.54	-0.29	0.42	1.30	-1.77	-0.41	-0.06	0.14	0.87	-2.08	-0.54	-0.01	0.66	1.76
All fundamentals																				
USD/GBP	-9.18	-2.66	-0.16	1.94	5.54	-3.11	-0.84	-0.07	0.66	2.94	-0.64	-0.16	0.00	0.19	0.84	-3.09	-0.93	-0.03	0.69	3.44
JPY/USD	-7.77	-2.95	-0.08	2.01	7.04	-5.78	-2.35	-0.05	1.99	5.71	-1.58	-0.38	0.02	0.55	2.03	-3.62	-1.08	0.01	1.21	3.46
CHF/USD	-11.91	-4.06	-0.32	2.19	6.89	-7.11	-2.06	-0.04	1.68	5.74	-0.70	-0.14	0.01	0.15	0.52	-3.87	-1.23	0.01	1.39	4.18
CAD/USD	-2.65	-0.88	0.00	0.64	1.88	-0.82	-0.28	-0.01	0.22	0.65	-0.06	-0.01	0.00	0.01	0.05	-0.09	-0.03	0.00	0.01	0.05
SEK/USD	-9.47	-3.49	-0.20	1.70	5.17	-4.71	-1.63	-0.14	1.18	4.07	-0.35	-0.08	0.00	0.06	0.34	-3.39	-1.40	0.01	1.37	3.72
DNK/USD	-7.65	-2.45	-0.13	1.43	5.47	-3.15	-0.95	-0.01	0.73	2.79	-0.04	-0.01	0.00	0.01	0.02	-0.53	-0.18	-0.01	0.12	0.33
USD/AUD	-9.14	-3.09	-0.15	2.00	5.79	-4.24	-1.31	0.00	0.86	2.52	-0.46	-0.11	0.00	0.07	0.26	-2.80	-0.26	0.00	0.17	1.44
FRF/USD	-8.52	-3.10	0.06	1.48	5.26	-6.58	-2.19	0.00	1.80	4.44	-1.53	-0.27	0.00	0.18	0.92	-4.64	-1.59	0.01	1.47	4.52
DEM/USD	-7.86	-2.38	-0.02	1.80	6.15	-5.68	-1.89	-0.05	1.75	5.06	-1.01	-0.09	0.00	0.11	0.83	-4.99	-1.86	0.05	1.95	4.78
ITL/USD	-6.21	-2.47	-0.16	1.24	6.67	-5.77	-1.98	-0.16	1.25	6.08	-1.55	-0.54	-0.06	0.33	1.33	-5.39	-1.67	0.03	1.38	6.05
NLG/USD	-9.23	-3.09	-0.45	2.36	8.71	-8.09	-2.47	0.00	1.49	5.67	-0.47	-0.08	0.02	0.23	0.73	-4.11	-1.01	0.02	1.67	4.23
PTE/USD	-4.84	-2.53	-0.25	1.63	4.40	-4.28	-1.87	-0.31	0.51	2.07	-0.68	-0.26	-0.02	0.15	0.57	-0.83	-0.36	-0.01	0.22	0.92

Table 12: RMSE and Theil ratios of forecasts using coupled fundamentals for the average exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.4410	1.0048	0.911	1.0045	0.908	**0.9945**	0.328	**0.9998**	0.447
JPY/USD	2.7039	1.0067	0.795	1.0008	0.812	**0.9813**	0.041 **	**0.9911**	0.005 ***
CHF/USD	2.7960	1.0029	0.762	1.0012	0.760	**0.9906**	0.194	**0.9967**	0.051 *
CAD/USD	1.5091	**0.9877**	0.160	**0.9972**	0.139	**0.9844**	0.042 **	1.0018	0.844
SEK/USD	2.5633	1.0008	0.534	1.0056	0.850	**0.9778**	0.006 ***	**0.9975**	0.134
DNK/USD	2.5355	**0.9999**	0.493	**0.9988**	0.251	**0.9853**	0.001 ***	**0.9973**	0.081 *
USD/AUD	2.7434	**0.9965**	0.405	1.0049	0.876	**0.9946**	0.031 **	**0.9984**	0.279
FRF/USD	2.6411	1.0055	0.635	1.0003	0.510	**0.9798**	0.041 **	**0.9932**	0.140
DEM/USD	2.7545	1.0084	0.879	1.0007	0.673	**0.9669**	0.009 ***	**0.9931**	0.070 *
ITL/USD	2.6624	1.0019	0.544	1.0011	0.527	**0.9720**	0.023 **	**0.9891**	0.142
NLG/USD	2.7517	1.0076	0.976	1.0016	0.846	**0.9796**	0.055 *	**0.9932**	0.076 *
PTE/USD	2.6956	**0.9884**	0.405	**0.9843**	0.369	**0.9787**	0.328	**0.9607**	0.184
UIRP fundamental									
USD/GBP	2.4410	1.0137	0.753	1.0007	0.525	**0.9651**	0.089 *	**0.9923**	0.085 *
JPY/USD	2.7039	1.0072	0.800	1.0025	0.704	**0.9857**	0.183	**0.9923**	0.083 *
CHF/USD	2.8195	1.0005	0.554	1.0005	0.606	**0.9824**	0.013 **	**0.9952**	0.057 *
CAD/USD	1.5091	1.0032	0.611	1.0007	0.726	**0.9919**	0.038 **	**0.9969**	0.163
SEK/USD	2.5626	1.0280	0.977	1.0045	0.767	**0.9561**	0.026 **	**0.9855**	0.098 *
DNK/USD	2.5355	1.0125	0.888	**0.9998**	0.485	**0.9933**	0.226	**0.9966**	0.091 *
USD/AUD	2.7414	1.0105	0.732	1.0075	0.825	**0.9650**	0.108	**0.9917**	0.085 *
FRF/USD	2.6411	1.0066	0.772	1.0045	0.677	**0.9715**	0.047 **	**0.9937**	0.113
DEM/USD	2.7545	1.0047	0.767	1.0028	0.672	**0.9760**	0.003 ***	**0.9904**	0.032 **
ITL/USD	2.6624	1.0057	0.632	**0.9982**	0.460	**0.9416**	0.051 *	**0.9694**	0.066 *
NLG/USD	2.7517	1.0043	0.641	1.0007	0.527	**0.9754**	0.050 **	**0.9940**	0.063 *
PTE/USD	2.2481	**0.9848**	0.206	**0.9920**	0.375	**0.9839**	0.348	**0.9777**	0.196
Monetary model fundamentals									
USD/GBP	2.4410	1.0200	0.874	1.0007	0.526	**0.9802**	0.190	**0.9919**	0.220
JPY/USD	2.7042	**0.9982**	0.451	1.0030	0.585	**0.9708**	0.025 **	**0.9794**	0.035 **
CHF/USD	2.8377	1.0042	0.644	1.0052	0.665	**0.9833**	0.097 *	**0.9771**	0.036 **
CAD/USD	1.5083	1.0254	0.776	1.0028	0.688	**0.9794**	0.053 *	**0.9978**	0.429
SEK/USD	2.5626	1.0311	0.979	1.0046	0.820	**0.9402**	0.056 *	**0.9797**	0.014 **
DNK/USD	2.5553	1.0164	0.961	1.0084	0.941	**0.9794**	0.011 **	**0.9873**	0.123
USD/AUD	2.7547	1.0185	0.782	1.0033	0.858	**0.9720**	0.095 *	**0.9930**	0.243
FRF/USD	2.5229	1.0536	0.965	1.0578	0.973	1.0120	0.663	**0.9998**	0.495
DEM/USD	2.7624	1.0353	0.980	1.0127	0.883	**0.9660**	0.079 *	**0.9558**	0.007 ***
ITL/USD	2.6458	1.0114	0.671	1.0069	0.667	**0.9523**	0.076 *	**0.9730**	0.046 **
NLG/USD	2.7517	1.0010	0.557	1.0020	0.665	**0.9826**	0.024 **	1.0052	0.708
PTE/USD	2.2342	**0.9800**	0.347	**0.9862**	0.368	**0.9445**	0.162	**0.9667**	0.209
All fundamentals									
USD/GBP	2.4410	1.0550	0.995	1.0169	0.954	**0.9737**	0.136	**0.9823**	0.068 *
JPY/USD	2.7042	1.0143	0.718	1.0079	0.732	**0.9689**	0.032 **	**0.9766**	0.018 **
CHF/USD	2.8377	1.0211	0.923	1.0096	0.753	**0.9814**	0.076 *	**0.9750**	0.029 **
CAD/USD	1.5083	1.0137	0.645	1.0059	0.856	**0.9804**	0.059 *	**0.9988**	0.463
SEK/USD	2.5626	1.1397	0.902	1.0747	0.843	**0.9619**	0.026 **	**0.9924**	0.358
DNK/USD	2.5553	1.0447	0.945	1.0104	0.889	**0.9767**	0.006 ***	**0.9793**	0.015 **
USD/AUD	2.7547	1.0279	0.821	1.0146	0.924	**0.9678**	0.061 *	**0.9898**	0.189
FRF/USD	2.5229	1.0935	0.934	1.0637	0.873	1.0134	0.648	**0.9903**	0.321
DEM/USD	2.7624	1.0608	0.993	1.0232	0.922	**0.9589**	0.029 **	**0.9539**	0.004 ***
ITL/USD	2.6458	1.0378	0.794	1.0381	0.841	**0.9339**	0.057 *	**0.9625**	0.046 **
NLG/USD	2.7517	1.0172	0.762	1.0053	0.659	**0.9753**	0.018 **	1.0051	0.703
PTE/USD	2.2342	**0.9855**	0.362	1.0377	0.909	**0.9590**	0.134	**0.9396**	0.103

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 13: RMSE and Theil ratios of forecasts using coupled fundamentals for the end-of-month exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.9051	1.0050	0.965	1.0032	0.917	1.0006	0.618	1.0005	0.609
JPY/USD	3.1023	1.0058	0.826	1.0010	0.976	**0.9999**	0.437	**0.9973**	0.143
CHF/USD	3.3428	1.0027	0.847	1.0009	0.817	1.0000	0.803	**0.9996**	0.382
CAD/USD	1.9982	**0.9964**	0.280	**0.9991**	0.321	1.0000	0.530	1.0029	0.991
SEK/USD	3.2290	1.0015	0.599	1.0009	0.847	1.0016	0.782	1.0000	0.493
DNK/USD	3.1200	1.0001	0.513	1.0008	0.283	**0.9995**	0.409	**0.9989**	0.245
USD/AUD	3.3786	**0.9976**	0.405	1.0009	0.866	1.0006	0.852	1.0009	0.644
FRF/USD	3.1978	1.0072	0.749	1.0036	0.614	1.0005	0.527	**0.9981**	0.319
DEM/USD	3.3136	1.0063	0.891	1.0035	0.781	1.0000	0.774	**0.9968**	0.100 *
ITL/USD	3.1907	1.0026	0.589	1.0019	0.566	1.0011	0.547	**0.9959**	0.287
NLG/USD	3.3319	1.0056	0.984	1.0023	0.928	1.0000	0.940	**0.9976**	0.172
PTE/USD	3.2207	**0.9961**	0.449	**0.9936**	0.406	**0.9925**	0.397	**0.9821**	0.265
UIRP fundamental									
USD/GBP	2.9051	1.0132	0.813	1.0012	0.562	1.0045	0.634	**0.9976**	0.310
JPY/USD	3.1023	1.0062	0.816	1.0020	0.736	1.0012	0.816	**0.9993**	0.400
CHF/USD	3.3747	1.0009	0.641	1.0005	0.725	1.0000	0.691	**0.9990**	0.292
CAD/USD	1.9982	1.0027	0.667	1.0006	0.747	1.0001	0.863	1.0020	0.923
SEK/USD	3.2263	1.0242	0.975	1.0037	0.732	**0.9907**	0.211	**0.9868**	0.172
DNK/USD	3.1200	1.0119	0.931	1.0006	0.620	1.0002	0.839	1.0012	0.677
USD/AUD	3.3793	1.0097	0.793	1.0067	0.835	1.0075	0.826	**0.9999**	0.495
FRF/USD	3.1978	1.0085	0.858	1.0039	0.731	1.0019	0.621	**0.9984**	0.306
DEM/USD	3.3136	1.0036	0.866	1.0026	0.753	1.0001	0.841	**0.9962**	0.149
ITL/USD	3.1907	1.0060	0.680	**0.9996**	0.488	1.0055	0.661	**0.9869**	0.151
NLG/USD	3.3319	1.0044	0.757	1.0014	0.701	1.0022	0.594	**0.9978**	0.234
PTE/USD	2.8024	**0.9874**	0.223	**0.9917**	0.351	**0.9918**	0.347	**0.9899**	0.288
Monetary model fundamentals									
USD/GBP	2.9051	1.0201	0.953	1.0021	0.653	1.0050	0.696	1.0034	0.664
JPY/USD	3.1046	1.0042	0.669	1.0042	0.687	1.0065	0.780	**0.9965**	0.348
CHF/USD	3.3887	1.0029	0.622	1.0063	0.723	1.0015	0.590	1.0005	0.520
CAD/USD	1.9994	1.0254	0.822	1.0032	0.751	1.0065	0.849	1.0074	0.911
SEK/USD	3.2263	1.0283	0.981	1.0047	0.843	1.0138	0.841	1.0040	0.735
DNK/USD	3.1675	1.0151	0.948	1.0059	0.870	1.0008	0.800	1.0086	0.930
USD/AUD	3.3926	1.0180	0.845	1.0044	0.939	1.0008	0.673	1.0016	0.565
FRF/USD	3.1041	1.0460	0.983	1.0439	0.979	1.0280	0.982	1.0117	0.772
DEM/USD	3.3286	1.0312	0.994	1.0169	0.965	1.0001	0.510	**0.9827**	0.133
ITL/USD	3.2797	1.0051	0.602	1.0050	0.672	**0.9976**	0.360	**0.9951**	0.329
NLG/USD	3.3319	**0.9969**	0.407	**0.9984**	0.436	**0.9945**	0.199	1.0022	0.668
PTE/USD	2.7703	**0.9864**	0.332	**0.9965**	0.414	1.0045	0.696	**0.9991**	0.487
All fundamentals									
USD/GBP	2.9051	1.0515	0.999	1.0154	0.980	1.0000	0.500	**0.9977**	0.402
JPY/USD	3.1046	1.0190	0.844	1.0072	0.812	1.0039	0.739	**0.9951**	0.285
CHF/USD	3.3887	1.0190	0.958	1.0100	0.811	1.0020	0.643	**0.9975**	0.402
CAD/USD	1.9994	1.0274	0.860	1.0043	0.802	1.0060	0.831	1.0072	0.943
SEK/USD	3.2263	1.1676	0.902	1.0753	0.859	1.0060	0.847	**0.9852**	0.169
DNK/USD	3.1675	1.0307	0.977	1.0081	0.948	1.0005	0.788	1.0051	0.989
USD/AUD	3.3926	1.0310	0.913	1.0138	0.939	1.0021	0.840	1.0014	0.555
FRF/USD	3.1041	1.0761	0.978	1.0516	0.926	1.0291	0.950	1.0061	0.649
DEM/USD	3.3286	1.0501	0.996	1.0265	0.983	**0.9995**	0.384	**0.9815**	0.101
ITL/USD	3.2797	1.0226	0.768	1.0306	0.889	**0.9988**	0.455	**0.9955**	0.363
NLG/USD	3.3319	1.0125	0.726	1.0025	0.581	**0.9939**	0.179	**0.9978**	0.201
PTE/USD	2.7703	1.0170	0.732	1.0456	0.977	1.0023	0.545	**0.9990**	0.485

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 14: RMSE and Theil ratios of forecasts using Taylor-rule fundamentals for the average exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
Output gap fundamentals: deviations from a linear trend									
USD/GBP	2.4410	1.0588	0.990	1.0313	0.921	**0.9751**	0.046 **	**0.9798**	0.034 **
JPY/USD	2.7042	1.0262	0.823	1.0026	0.549	**0.9700**	0.001 ***	**0.9758**	0.002 ***
CHF/USD	2.8377	1.0764	0.995	1.0236	0.903	**0.9763**	0.005 ***	**0.9784**	0.001 ***
CAD/USD	1.5083	**0.9926**	0.319	**0.9909**	0.295	**0.9816**	0.042 **	**0.9939**	0.022 **
SEK/USD	2.5626	1.1004	0.908	1.0309	0.969	**0.9419**	0.029 **	**0.9786**	0.002 ***
DNK/USD	2.4891	1.0261	0.847	1.0168	0.863	**0.9755**	0.001 ***	**0.9730**	0.002 ***
USD/AUD	2.7547	**0.9970**	0.451	1.0145	0.817	**0.9731**	0.033 **	**0.9851**	0.024 **
FRF/USD	2.6411	1.0321	0.807	1.0236	0.812	**0.9684**	0.002 ***	**0.9712**	0.034 **
DEM/USD	2.7545	1.0420	0.882	1.0250	0.843	**0.9686**	0.001 ***	**0.9803**	0.037 **
ITL/USD	2.6624	1.0032	0.539	1.0188	0.830	**0.9441**	0.014 **	**0.9876**	0.181
NLG/USD	2.7517	1.0335	0.783	1.0141	0.736	**0.9662**	0.000 ***	**0.9735**	0.006 ***
PTE/USD	2.2342	1.0337	0.838	1.0922	0.941	**0.9637**	0.132	**0.9857**	0.148
Output gap fundamentals: deviations from a quadratic trend									
USD/GBP	2.4410	1.0516	0.983	1.0349	0.951	**0.9772**	0.066 *	**0.9799**	0.034 **
JPY/USD	2.7042	1.0191	0.744	1.0040	0.574	**0.9702**	0.001 ***	**0.9799**	0.002 ***
CHF/USD	2.8377	1.0703	0.993	1.0230	0.924	**0.9760**	0.004 ***	**0.9773**	0.001 ***
CAD/USD	1.5083	**0.9961**	0.438	**0.9906**	0.245	**0.9831**	0.097 *	**0.9921**	0.014 **
SEK/USD	2.5626	1.0912	0.882	1.0399	0.951	**0.9405**	0.027 **	**0.9778**	0.002 ***
DNK/USD	2.4891	1.0216	0.840	1.0170	0.961	**0.9749**	0.001 ***	**0.9726**	0.001 ***
USD/AUD	2.7547	**0.9967**	0.449	1.0110	0.745	**0.9704**	0.028 **	**0.9844**	0.021 **
FRF/USD	2.6411	1.0283	0.787	1.0233	0.813	**0.9684**	0.002 ***	**0.9698**	0.027 **
DEM/USD	2.7545	1.0528	0.929	1.0151	0.748	**0.9687**	0.001 ***	**0.9803**	0.040 **
ITL/USD	2.6624	1.0005	0.506	1.0176	0.811	**0.9441**	0.014 **	**0.9882**	0.200
NLG/USD	2.7517	1.0407	0.826	1.0066	0.650	**0.9662**	0.000 ***	**0.9746**	0.006 ***
PTE/USD	2.2342	1.0104	0.618	1.0760	0.970	**0.9637**	0.133	**0.9848**	0.127
Output gap fundamentals: deviations from a linear and a quadratic trend									
USD/GBP	2.4410	1.0450	0.976	1.0296	0.967	**0.9759**	0.051 *	**0.9794**	0.032 **
JPY/USD	2.7042	1.0232	0.831	1.0013	0.529	**0.9728**	0.002 ***	**0.9760**	0.003 ***
CHF/USD	2.8377	1.0491	0.972	1.0170	0.850	**0.9761**	0.004 ***	**0.9776**	0.001 ***
CAD/USD	1.5083	**0.9902**	0.332	**0.9905**	0.252	**0.9891**	0.072 *	**0.9924**	0.009 ***
SEK/USD	2.5626	1.0757	0.943	1.0378	0.976	**0.9409**	0.027 **	**0.9768**	0.001 ***
DNK/USD	2.4891	1.0240	0.876	1.0146	0.941	**0.9754**	0.002 ***	**0.9734**	0.002 ***
USD/AUD	2.7547	**0.9918**	0.376	1.0058	0.631	**0.9708**	0.028 **	**0.9836**	0.017 **
FRF/USD	2.6411	1.0303	0.757	1.0218	0.797	**0.9684**	0.002 ***	**0.9720**	0.039 **
DEM/USD	2.7545	1.0475	0.915	1.0098	0.644	**0.9684**	0.001 ***	**0.9794**	0.030 **
ITL/USD	2.6624	1.0049	0.553	1.0123	0.712	**0.9442**	0.014 **	**0.9885**	0.204
NLG/USD	2.7517	1.0351	0.804	1.0067	0.644	**0.9662**	0.000 ***	**0.9735**	0.006 ***
PTE/USD	2.2342	1.0099	0.617	1.0758	0.963	**0.9638**	0.132	**0.9858**	0.148
Output gap fundamentals: deviations from a Hodrick-Prescott filtered trend									
USD/GBP	2.4410	1.0527	0.977	1.0217	0.888	**0.9753**	0.047 **	**0.9794**	0.031 **
JPY/USD	2.7042	1.0231	0.815	1.0013	0.526	**0.9733**	0.002 ***	**0.9776**	0.005 ***
CHF/USD	2.8377	1.0554	0.990	1.0231	0.910	**0.9764**	0.005 ***	**0.9790**	0.002 ***
CAD/USD	1.5083	**0.9812**	0.201	1.0022	0.671	**0.9863**	0.054 *	**0.9941**	0.010 **
SEK/USD	2.5626	1.0878	0.969	1.0399	0.952	**0.9423**	0.030 **	**0.9783**	0.002 ***
DNK/USD	2.4891	1.0335	0.943	1.0098	0.817	**0.9764**	0.002 ***	**0.9730**	0.001 ***
USD/AUD	2.7547	**0.9897**	0.376	1.0146	0.814	**0.9727**	0.031 **	**0.9833**	0.016 **
FRF/USD	2.6411	1.0306	0.796	1.0264	0.835	**0.9685**	0.002 ***	**0.9712**	0.034 **
DEM/USD	2.7545	1.0535	0.965	1.0198	0.816	**0.9684**	0.001 ***	**0.9794**	0.030 **
ITL/USD	2.6624	**0.9990**	0.488	1.0148	0.765	**0.9442**	0.014 **	**0.9880**	0.192
NLG/USD	2.7517	1.0394	0.838	1.0123	0.746	**0.9663**	0.000 ***	**0.9733**	0.005 ***
PTE/USD	2.2342	1.0049	0.535	1.0609	0.924	**0.9638**	0.132	**0.9860**	0.154

***, **, and * denote statistical significance at the $1\,\%$, $5\,\%$, and $10\,\%$ levels.

Table 15: RMSE and Theil ratios of forecasts using Taylor-rule fundamentals for the end-of-month exchange rates sample.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
Output gap fundamentals: deviations from a linear trend									
USD/GBP	2.9051	1.0430	0.984	1.0276	0.953	1.0011	0.607	1.0030	0.622
JPY/USD	3.1046	1.0297	0.915	1.0048	0.624	**0.9996**	0.228	**0.9937**	0.187
CHF/USD	3.3887	1.0644	0.997	1.0216	0.941	**0.9986**	0.141	**0.9941**	0.143
CAD/USD	1.9994	1.0145	0.782	**0.9988**	0.455	1.0002	0.646	**0.9995**	0.315
SEK/USD	3.2263	1.1008	0.965	1.0241	0.992	**0.9971**	0.387	**0.9954**	0.211
DNK/USD	3.1037	1.0323	0.937	1.0136	0.890	1.0023	0.894	**0.9939**	0.219
USD/AUD	3.3926	1.0073	0.642	1.0126	0.852	1.0043	0.820	1.0009	0.562
FRF/USD	3.1978	1.0359	0.915	1.0277	0.909	1.0005	0.539	**0.9961**	0.382
DEM/USD	3.3136	1.0444	0.938	1.0303	0.931	**0.9987**	0.287	**0.9914**	0.210
ITL/USD	3.1907	1.0082	0.631	1.0216	0.944	1.0024	0.578	1.0067	0.665
NLG/USD	3.3319	1.0341	0.870	1.0212	0.900	**0.9998**	0.444	**0.9883**	0.143
PTE/USD	2.7703	1.0606	0.918	1.0976	0.976	**0.9970**	0.410	**0.9987**	0.426
Output gap fundamentals: deviations from a quadratic trend									
USD/GBP	2.9051	1.0387	0.973	1.0298	0.975	1.0010	0.597	1.0027	0.610
JPY/USD	3.1046	1.0238	0.870	1.0063	0.664	**0.9995**	0.177	**0.9943**	0.214
CHF/USD	3.3887	1.0601	0.989	1.0223	0.973	**0.9986**	0.143	**0.9927**	0.097 *
CAD/USD	1.9994	1.0184	0.799	**0.9991**	0.465	1.0002	0.643	**0.9993**	0.216
SEK/USD	3.2263	1.0756	0.943	1.0314	0.982	**0.9986**	0.445	**0.9951**	0.198
DNK/USD	3.1037	1.0270	0.870	1.0154	0.969	1.0005	0.847	**0.9933**	0.198
USD/AUD	3.3926	1.0063	0.615	1.0096	0.782	1.0043	0.817	1.0012	0.590
FRF/USD	3.1978	1.0333	0.909	1.0279	0.915	1.0005	0.539	**0.9964**	0.390
DEM/USD	3.3136	1.0456	0.949	1.0219	0.891	**0.9987**	0.286	**0.9908**	0.192
ITL/USD	3.1907	1.0029	0.549	1.0206	0.938	1.0024	0.578	1.0047	0.619
NLG/USD	3.3319	1.0356	0.883	1.0146	0.886	**0.9998**	0.445	**0.9883**	0.144
PTE/USD	2.7703	1.0501	0.822	1.0848	0.957	**0.9970**	0.413	**0.9988**	0.429
Output gap fundamentals: deviations from a linear and a quadratic trend									
USD/GBP	2.9051	1.0353	0.970	1.0262	0.987	1.0010	0.602	1.0014	0.557
JPY/USD	3.1046	1.0301	0.935	1.0042	0.628	**0.9996**	0.231	**0.9943**	0.212
CHF/USD	3.3887	1.0461	0.968	1.0178	0.923	**0.9986**	0.144	**0.9930**	0.104
CAD/USD	1.9994	1.0167	0.777	**0.9982**	0.430	1.0002	0.648	**0.9990**	0.163
SEK/USD	3.2263	1.0638	0.988	1.0272	0.991	**0.9982**	0.429	**0.9958**	0.231
DNK/USD	3.1037	1.0298	0.895	1.0136	0.935	1.0004	0.835	**0.9926**	0.175
USD/AUD	3.3926	1.0029	0.553	1.0052	0.663	1.0042	0.813	1.0021	0.638
FRF/USD	3.1978	1.0363	0.892	1.0263	0.903	1.0005	0.539	**0.9951**	0.354
DEM/USD	3.3136	1.0431	0.944	1.0174	0.796	**0.9987**	0.287	**0.9905**	0.185
ITL/USD	3.1907	1.0160	0.718	1.0182	0.883	1.0025	0.581	1.0075	0.684
NLG/USD	3.3319	1.0352	0.880	1.0171	0.862	**0.9998**	0.445	**0.9889**	0.156
PTE/USD	2.7703	1.0489	0.840	1.0811	0.961	**0.9970**	0.410	**0.9987**	0.426
Output gap fundamentals: deviations from a Hodrick-Prescott filtered trend									
USD/GBP	2.9051	1.0427	0.988	1.0203	0.951	1.0011	0.609	1.0026	0.606
JPY/USD	3.1046	1.0233	0.901	1.0034	0.590	**0.9996**	0.196	**0.9944**	0.219
CHF/USD	3.3887	1.0504	0.998	1.0220	0.961	**0.9986**	0.137	**0.9938**	0.134
CAD/USD	1.9994	1.0167	0.890	1.0041	0.826	1.0002	0.648	**0.9992**	0.168
SEK/USD	3.2263	1.0679	0.987	1.0300	0.981	**0.9972**	0.388	**0.9954**	0.210
DNK/USD	3.1037	1.0322	0.977	1.0086	0.805	1.0004	0.832	**0.9928**	0.181
USD/AUD	3.3926	1.0041	0.570	1.0121	0.841	1.0043	0.817	1.0019	0.633
FRF/USD	3.1978	1.0361	0.922	1.0283	0.913	1.0005	0.539	**0.9951**	0.354
DEM/USD	3.3136	1.0482	0.980	1.0239	0.895	**0.9987**	0.287	**0.9913**	0.207
ITL/USD	3.1907	1.0190	0.752	1.0218	0.926	1.0024	0.578	1.0077	0.687
NLG/USD	3.3319	1.0381	0.909	1.0174	0.895	**0.9998**	0.445	**0.9889**	0.155
PTE/USD	2.7703	1.0405	0.811	1.0530	0.963	**0.9970**	0.410	**0.9987**	0.429

***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

Table 16: RMSE and Theil ratios of the forecasts for a shorter-period sample (1980 onwards, average exchange rates sample).

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.2980	**0.9955**	0.386	**0.9978**	0.450	**0.9913**	0.091 *	**0.9905**	0.094 *
JPY/USD	2.6567	1.0123	0.832	1.0033	0.733	**0.9822**	0.127	**0.9893**	0.017 **
CHF/USD	2.6868	1.0141	0.871	1.0048	0.693	**0.9846**	0.044 **	**0.9903**	0.016 **
CAD/USD	1.6306	**0.9845**	0.129	**0.9936**	0.087 *	**0.9962**	0.096 *	**0.9958**	0.242
SEK/USD	2.6802	1.0073	0.671	**0.9932**	0.255	**0.9581**	0.041 **	**0.9859**	0.017 **
DNK/USD	2.4385	1.0112	0.879	1.0011	0.572	**0.9812**	0.009 ***	**0.9852**	0.002 ***
USD/AUD	2.6738	**0.9922**	0.338	**0.9948**	0.183	**0.9748**	0.090 *	**0.9908**	0.070 *
FRF/USD	2.4663	1.0163	0.785	1.0076	0.951	**0.9697**	0.029 **	**0.9906**	0.163
DEM/USD	2.5581	1.0315	0.907	1.0137	0.831	**0.9651**	0.044 **	**0.9861**	0.079 *
ITL/USD	2.7052	1.0042	0.666	**0.9995**	0.485	**0.9377**	0.045 **	**0.9755**	0.063 *
NLG/USD	2.5501	1.0182	0.906	1.0229	0.837	**0.9670**	0.066 *	**0.9870**	0.087 *
PTE/USD	2.5223	1.0223	0.813	1.0148	0.708	**0.9739**	0.041 **	**0.9787**	0.135
UIRP fundamental									
USD/GBP	2.2980	1.0430	0.918	1.0382	0.908	**0.9674**	0.318	**0.9847**	0.103
JPY/USD	2.6567	1.0178	0.800	1.0084	0.668	**0.9813**	0.035 **	**0.9847**	0.046 **
CHF/USD	2.6868	1.0255	0.816	1.0273	0.808	**0.9855**	0.038 **	**0.9858**	0.035 **
CAD/USD	1.6306	1.0121	0.834	1.0062	0.821	**0.9841**	0.068 *	1.0001	0.525
SEK/USD	2.6797	1.0600	0.943	1.0350	0.840	**0.9463**	0.041 **	**0.9748**	0.064 *
DNK/USD	2.4385	1.0258	0.935	1.0131	0.841	**0.9688**	0.021 **	**0.9804**	0.010 **
USD/AUD	2.6728	1.0112	0.694	**0.9996**	0.463	**0.9572**	0.058 *	**0.9915**	0.138
FRF/USD	2.4663	1.0247	0.912	1.0333	0.841	**0.9813**	0.053 *	**0.9735**	0.088 *
DEM/USD	2.5581	1.0450	0.824	1.0331	0.798	**0.9670**	0.032 **	**0.9747**	0.066 *
ITL/USD	2.7052	1.0081	0.606	1.0342	0.876	**0.9582**	0.077 *	**0.9450**	0.071 *
NLG/USD	2.5501	1.1305	0.876	1.0959	0.871	**0.9679**	0.059 *	**0.9744**	0.064 *
PTE/USD									
Monetary model fundamentals									
USD/GBP	2.2980	1.0330	0.962	1.0183	0.895	**0.9627**	0.143	**0.9888**	0.210
JPY/USD	2.6570	1.0118	0.741	1.0170	0.837	**0.9713**	0.069 *	**0.9804**	0.077 *
CHF/USD	2.7041	1.0246	0.857	1.0086	0.761	**0.9964**	0.425	**0.9913**	0.284
CAD/USD	1.6300	1.0381	0.876	1.0063	0.682	**0.9741**	0.037 **	**0.9966**	0.399
SEK/USD	2.6797	1.0502	0.995	1.0257	0.967	**0.9402**	0.072 *	**0.9759**	0.017 **
DNK/USD	2.4619	1.0410	0.994	1.0094	0.943	**0.9814**	0.110	**0.9768**	0.059 *
USD/AUD	2.6871	1.0240	0.854	1.0113	0.932	**0.9660**	0.066 *	**0.9785**	0.118
FRF/USD	2.4663	1.0413	0.897	1.0581	0.935	**0.9784**	0.154	**0.9879**	0.272
DEM/USD	2.5581	1.0305	0.823	1.0207	0.745	**0.9652**	0.167	**0.9493**	0.020 **
ITL/USD	2.7052	1.0258	0.763	1.0158	0.703	**0.9259**	0.083 *	**0.9725**	0.065 *
NLG/USD	2.5501	1.0494	0.925	1.0065	0.655	**0.9640**	0.048 **	**0.9766**	0.076 *
PTE/USD									
All fundamentals									
USD/GBP	2.2980	1.0849	0.990	1.0479	0.931	**0.9594**	0.067 *	**0.9835**	0.144
JPY/USD	2.6570	1.0558	0.970	1.0336	0.904	**0.9665**	0.018 **	**0.9746**	0.039 **
CHF/USD	2.7041	1.0965	0.989	1.0275	0.837	**0.9906**	0.277	**0.9891**	0.244
CAD/USD	1.6300	1.0026	0.532	1.0059	0.605	**0.9728**	0.039 **	**0.9959**	0.390
SEK/USD	2.6797	1.1499	0.921	1.1129	0.862	**0.9578**	0.015 **	**0.9945**	0.415
DNK/USD	2.4619	1.0976	0.993	1.0331	0.894	**0.9710**	0.013 **	**0.9638**	0.007 ***
USD/AUD	2.6871	1.0170	0.674	1.0241	0.887	**0.9604**	0.078 *	**0.9814**	0.134
FRF/USD	2.4663	1.1292	0.981	1.0676	0.945	**0.9706**	0.068 *	**0.9749**	0.177
DEM/USD	2.5581	1.1006	0.945	1.0596	0.864	**0.9597**	0.079 *	**0.9508**	0.028 **
ITL/USD	2.7052	1.0123	0.602	1.0424	0.815	**0.9387**	0.074 *	**0.9618**	0.138
NLG/USD	2.5501	1.1023	0.939	1.0880	0.933	**0.9646**	0.034 **	**0.9733**	0.063 *
PTE/USD									

***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

Table 17: RMSE and Theil ratios of the forecasts for a shorter-period sample (1980 onwards, end-of-month exchange rates sample).

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.6343	**0.9999**	0.497	**0.9981**	0.444	**0.9981**	0.197	**0.9981**	0.408
JPY/USD	3.0508	1.0098	0.855	1.0036	0.852	**0.9999**	0.353	**0.9980**	0.221
CHF/USD	3.2016	1.0140	0.958	1.0036	0.718	**0.9992**	0.272	**0.9951**	0.092 *
CAD/USD	2.1689	**0.9979**	0.403	**0.9975**	0.160	1.0000	0.569	1.0015	0.968
SEK/USD	3.3955	1.0067	0.753	**0.9964**	0.284	1.0006	0.567	**0.9951**	0.149
DNK/USD	3.0006	1.0097	0.926	1.0004	0.542	**0.9985**	0.177	**0.9918**	0.024 **
USD/AUD	3.2036	**0.9952**	0.369	**0.9962**	0.180	**0.9977**	0.319	**0.9977**	0.269
FRF/USD	3.0352	1.0136	0.867	1.0056	0.941	1.0045	0.843	**0.9944**	0.218
DEM/USD	3.0482	1.0290	0.906	1.0147	0.890	**0.9983**	0.205	**0.9897**	0.079 *
ITL/USD	3.2141	1.0025	0.627	**0.9994**	0.476	**0.9986**	0.384	**0.9959**	0.335
NLG/USD	3.0634	1.0143	0.914	1.0156	0.823	**0.9978**	0.290	**0.9912**	0.104
PTE/USD	3.1025	1.0164	0.834	1.0093	0.700	1.0063	0.657	**0.9986**	0.446
UIRP fundamental									
USD/GBP	2.6343	1.0400	0.926	1.0344	0.918	1.0184	0.835	1.0025	0.611
JPY/USD	3.0508	1.0151	0.832	1.0056	0.657	1.0004	0.578	**0.9951**	0.176
CHF/USD	3.2016	1.0183	0.844	1.0170	0.813	**0.9980**	0.127	**0.9933**	0.081 *
CAD/USD	2.1689	1.0066	0.820	1.0031	0.767	1.0000	0.708	1.0003	0.640
SEK/USD	3.3927	1.0504	0.940	1.0298	0.840	**0.9910**	0.160	**0.9833**	0.187
DNK/USD	3.0006	1.0208	0.943	1.0068	0.814	**0.9986**	0.135	**0.9938**	0.184
USD/AUD	3.2081	1.0110	0.763	1.0002	0.528	**0.9997**	0.433	**0.9986**	0.368
FRF/USD	3.0352	1.0234	0.926	1.0207	0.835	1.0001	0.505	**0.9902**	0.266
DEM/USD	3.0482	1.0358	0.867	1.0226	0.848	1.0000	0.500	**0.9853**	0.136
ITL/USD	3.2141	1.0044	0.571	1.0175	0.860	**0.9909**	0.212	**0.9789**	0.170
NLG/USD	3.0634	1.0884	0.883	1.0524	0.859	**0.9961**	0.246	**0.9877**	0.184
PTE/USD									
Monetary model fundamentals									
USD/GBP	2.6343	1.0335	0.991	1.0154	0.908	**0.9900**	0.264	1.0058	0.691
JPY/USD	3.0536	1.0216	0.918	1.0180	0.886	1.0058	0.707	**0.9999**	0.496
CHF/USD	3.2169	1.0305	0.947	1.0137	0.911	1.0046	0.824	1.0091	0.808
CAD/USD	2.1708	1.0395	0.920	1.0100	0.813	1.0131	0.832	1.0090	0.927
SEK/USD	3.3927	1.0467	0.993	1.0195	0.978	1.0087	0.668	1.0057	0.704
DNK/USD	3.0252	1.0407	0.991	1.0087	0.961	1.0010	0.753	1.0062	0.766
USD/AUD	3.2191	1.0277	0.918	1.0109	0.983	1.0014	0.630	1.0028	0.618
FRF/USD	3.0352	1.0488	0.952	1.0453	0.960	1.0006	0.538	1.0116	0.767
DEM/USD	3.0482	1.0220	0.784	1.0132	0.698	**0.9993**	0.464	1.0019	0.540
ITL/USD	3.2141	1.0179	0.733	1.0189	0.773	**0.9937**	0.306	1.0004	0.508
NLG/USD	3.0634	1.0459	0.923	1.0076	0.697	**0.9948**	0.239	1.0012	0.531
PTE/USD									
All fundamentals									
USD/GBP	2.6343	1.0881	0.999	1.0389	0.930	**0.9934**	0.203	1.0050	0.695
JPY/USD	3.0536	1.0604	0.979	1.0281	0.930	1.0029	0.652	**0.9978**	0.414
CHF/USD	3.2169	1.1053	0.996	1.0301	0.955	1.0034	0.763	1.0093	0.801
CAD/USD	2.1708	1.0377	0.936	1.0090	0.696	1.0035	0.845	1.0023	0.934
SEK/USD	3.3927	1.1693	0.954	1.1165	0.873	1.0104	0.914	**0.9895**	0.298
DNK/USD	3.0252	1.0763	0.998	1.0293	0.940	**0.9999**	0.476	1.0055	0.762
USD/AUD	3.2191	1.0404	0.906	1.0224	0.940	1.0002	0.520	**0.9981**	0.440
FRF/USD	3.0352	1.1011	0.971	1.0475	0.914	**0.9992**	0.438	1.0127	0.748
DEM/USD	3.0482	1.0721	0.911	1.0496	0.866	**0.9948**	0.233	**0.9938**	0.378
ITL/USD	3.2141	**0.9967**	0.474	1.0259	0.742	**0.9911**	0.219	**0.9905**	0.340
NLG/USD	3.0634	1.0656	0.944	1.0579	0.958	**0.9947**	0.221	**0.9942**	0.382
PTE/USD									

***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

Table 18: RMSE and Theil ratios of the forecasts with classic fundamentals using Molodtsova and Papell [2009] data set.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
PPP fundamental									
USD/GBP	2.4868	1.0032	0.586	1.0059	0.905	**0.9805**	0.093 *	**0.9888**	0.046 **
JPY/USD	2.7803	1.0172	0.926	1.0009	0.682	**0.9839**	0.054 *	**0.9864**	0.007 ***
CHF/USD	2.7955	1.0050	0.672	1.0025	0.739	**0.9731**	0.004 ***	**0.9842**	0.002 ***
CAD/USD	1.2612	**0.9869**	0.186	1.0050	0.801	**0.9976**	0.256	1.0021	0.917
SEK/USD	2.4678	1.0135	0.839	1.0082	0.808	**0.9700**	0.007 ***	**0.9847**	0.009 ***
DNK/USD	2.5955	1.0197	0.985	1.0055	0.840	**0.9832**	0.000 ***	**0.9819**	0.000 ***
USD/AUD	2.4487	1.0104	0.836	1.0096	0.907	**0.9905**	0.030 **	**0.9927**	0.169
FRF/USD	2.6311	1.0137	0.796	1.0036	0.617	**0.9814**	0.002 ***	**0.9838**	0.017 **
DEM/USD	2.7605	1.0147	0.835	1.0028	0.882	**0.9771**	0.002 ***	**0.9846**	0.010 ***
ITL/USD	2.6670	1.0092	0.716	1.0023	0.566	**0.9630**	0.007 ***	**0.9727**	0.043 **
NLG/USD	2.7535	1.0109	0.857	1.0025	0.951	**0.9784**	0.001 ***	**0.9849**	0.008 ***
PTE/USD	2.4642	**0.9995**	0.491	**0.9988**	0.480	1.0003	0.505	**0.9895**	0.345
UIRP fundamental									
USD/GBP	2.4868	1.0283	0.823	**0.9992**	0.473	**0.9618**	0.040 **	**0.9782**	0.052 *
JPY/USD	2.7803	1.0033	0.560	**0.9950**	0.281	**0.9634**	0.005 ***	**0.9782**	0.025 **
CHF/USD	2.7955	1.0062	0.584	1.0129	0.649	**0.9752**	0.083 *	**0.9710**	0.006 ***
CAD/USD	1.2612	1.0023	0.561	**0.9987**	0.452	**0.9978**	0.391	1.0032	0.937
SEK/USD	2.4678	1.0685	0.914	1.0222	0.923	**0.9464**	0.038 **	**0.9656**	0.066 *
DNK/USD	2.5955	1.0156	0.860	1.0047	0.654	**0.9738**	0.002 ***	**0.9735**	0.002 ***
USD/AUD	2.4487	1.0047	0.573	1.0028	0.567	**0.9795**	0.106	**0.9844**	0.152
FRF/USD	2.6311	1.0215	0.897	1.0143	0.830	**0.9704**	0.005 ***	**0.9766**	0.024 **
DEM/USD	2.7605	1.0217	0.807	1.0051	0.669	**0.9690**	0.001 ***	**0.9699**	0.004 ***
ITL/USD	2.6670	1.0148	0.715	1.0163	0.797	**0.9428**	0.039 **	**0.9584**	0.057 *
NLG/USD	2.7535	1.0431	0.763	1.0003	0.507	**0.9593**	0.001 ***	**0.9710**	0.013 **
PTE/USD	2.3017	**0.9851**	0.214	**0.9994**	0.472	**0.9827**	0.099 *	**0.9850**	0.129
Monetary model fundamentals									
USD/GBP	2.4868	1.0274	0.881	1.0125	0.823	**0.9662**	0.107	**0.9742**	0.041 **
JPY/USD	2.7803	**0.9974**	0.440	**0.9815**	0.124	**0.9639**	0.021 **	**0.9696**	0.042 **
CHF/USD	2.7955	1.0090	0.678	**0.9970**	0.424	**0.9696**	0.027 **	**0.9710**	0.035 **
CAD/USD	1.2612	1.0451	0.995	1.0161	0.913	**0.9982**	0.431	**0.9962**	0.273
SEK/USD	2.4678	1.0826	0.997	1.0383	0.946	**0.9267**	0.046 **	**0.9667**	0.002 ***
DNK/USD	2.5955	1.0438	0.977	1.0201	0.896	**0.9676**	0.004 ***	**0.9586**	0.001 ***
USD/AUD	2.4487	1.0197	0.883	1.0191	0.900	**0.9840**	0.173	**0.9928**	0.328
FRF/USD	2.5229	1.0615	0.981	1.0738	0.982	**0.9787**	0.126	**0.9954**	0.390
DEM/USD	2.7624	1.0174	0.770	1.0038	0.579	**0.9562**	0.020 **	**0.9514**	0.008 ***
ITL/USD	2.6458	1.0411	0.932	1.0165	0.798	**0.9300**	0.036 **	**0.9661**	0.019 **
NLG/USD	2.7535	1.0337	0.963	1.0079	0.697	**0.9594**	0.002 ***	**0.9711**	0.026 **
PTE/USD	2.3017	1.0618	0.892	1.0392	0.897	**0.9902**	0.364	**0.9777**	0.270
All fundamentals									
USD/GBP	2.4868	1.0693	0.968	1.0232	0.796	**0.9644**	0.044 **	**0.9692**	0.035 **
JPY/USD	2.7803	1.0303	0.853	**0.9942**	0.418	**0.9612**	0.003 ***	**0.9649**	0.017 **
CHF/USD	2.7955	1.0609	0.916	1.0244	0.744	**0.9671**	0.019 **	**0.9645**	0.015 **
CAD/USD	1.2612	1.0084	0.611	1.0154	0.828	**0.9962**	0.313	**0.9978**	0.261
SEK/USD	2.4678	1.2283	0.929	1.1167	0.931	**0.9513**	0.015 **	1.0009	0.511
DNK/USD	2.5955	1.0746	0.979	1.0268	0.901	**0.9662**	0.001 ***	**0.9636**	0.003 ***
USD/AUD	2.4487	1.0375	0.870	1.0145	0.755	**0.9772**	0.046 **	**0.9877**	0.233
FRF/USD	2.5229	1.1137	0.980	1.0599	0.942	**0.9736**	0.065 *	**0.9786**	0.186
DEM/USD	2.7624	1.0367	0.777	1.0157	0.663	**0.9542**	0.004 ***	**0.9485**	0.002 ***
ITL/USD	2.6458	1.0054	0.556	1.0438	0.918	**0.9351**	0.040 **	**0.9518**	0.027 **
NLG/USD	2.7535	1.0254	0.737	1.0198	0.735	**0.9583**	0.001 ***	**0.9660**	0.015 **
PTE/USD	2.3017	1.1243	0.955	1.0162	0.696	**0.9895**	0.306	**0.9690**	0.133

***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

Table 19: RMSE and Theil ratios of the forecasts with Taylor-rule fundamentals using Molodtsova and Papell [2009] data set.

Currency pair	No change	Rolling regression		Recursive regression		SRidge		EWA	
	RMSE x 100	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value	Theil ratio	DM p-value
Output gap fundamentals: deviations from a linear trend									
USD/GBP	2.4868	1.0434	0.925	1.0094	0.676	**0.9754**	0.085 *	**0.9760**	0.048 **
JPY/USD	2.7803	1.0125	0.656	**0.9913**	0.368	**0.9678**	0.002 ***	**0.9712**	0.003 ***
CHF/USD	2.7955	1.0829	0.986	1.0313	0.867	**0.9702**	0.007 ***	**0.9719**	0.001 ***
CAD/USD	1.2612	1.0038	0.548	**0.9749**	0.085 *	**0.9976**	0.340	**0.9995**	0.432
SEK/USD	2.4678	1.1360	0.881	1.0398	0.956	**0.9293**	0.061 *	**0.9776**	0.016 **
DNK/USD	2.5303	1.0210	0.792	1.0209	0.848	**0.9738**	0.003 ***	**0.9711**	0.007 ***
USD/AUD	2.4664	1.0133	0.650	1.0078	0.608	**0.9821**	0.166	**0.9833**	0.065 *
FRF/USD	2.6311	1.0352	0.831	1.0265	0.839	**0.9695**	0.002 ***	**0.9724**	0.042 **
DEM/USD	2.7605	1.0425	0.885	1.0272	0.866	**0.9688**	0.001 ***	**0.9799**	0.035 **
ITL/USD	2.6670	1.0040	0.549	1.0203	0.863	**0.9456**	0.017 **	**0.9905**	0.248
NLG/USD	2.7535	1.0351	0.794	1.0175	0.785	**0.9651**	0.000 ***	**0.9759**	0.013 **
PTE/USD	2.3017	1.1075	0.955	1.0007	0.511	**0.9858**	0.053 *	**0.9805**	0.237
Output gap fundamentals: deviations from a quadratic trend									
USD/GBP	2.4868	1.0374	0.913	1.0150	0.778	**0.9749**	0.082 *	**0.9755**	0.046 **
JPY/USD	2.7803	1.0050	0.561	**0.9881**	0.296	**0.9673**	0.002 ***	**0.9755**	0.002 ***
CHF/USD	2.7955	1.0729	0.978	1.0336	0.897	**0.9700**	0.007 ***	**0.9708**	0.000 ***
CAD/USD	1.2612	**0.9921**	0.397	**0.9798**	0.080 *	**0.9990**	0.382	**0.9980**	0.201
SEK/USD	2.4678	1.1376	0.879	1.0599	0.944	**0.9295**	0.061 *	**0.9768**	0.012 **
DNK/USD	2.5303	1.0194	0.787	1.0228	0.976	**0.9741**	0.004 ***	**0.9708**	0.006 ***
USD/AUD	2.4664	1.0220	0.744	1.0126	0.685	**0.9821**	0.166	**0.9846**	0.082 *
FRF/USD	2.6311	1.0313	0.814	1.0262	0.842	**0.9695**	0.002 ***	**0.9699**	0.029 **
DEM/USD	2.7605	1.0533	0.931	1.0168	0.773	**0.9689**	0.001 ***	**0.9797**	0.036 **
ITL/USD	2.6670	1.0013	0.517	1.0187	0.839	**0.9454**	0.017 **	**0.9888**	0.207
NLG/USD	2.7535	1.0422	0.834	1.0093	0.710	**0.9651**	0.000 ***	**0.9750**	0.008 ***
PTE/USD	2.3017	1.0683	0.964	1.0008	0.510	**0.9857**	0.052 *	**0.9804**	0.237
Output gap fundamentals: deviations from a linear and a quadratic trend									
USD/GBP	2.4868	1.0353	0.913	1.0135	0.786	**0.9751**	0.083 *	**0.9753**	0.047 **
JPY/USD	2.7803	1.0105	0.648	**0.9875**	0.243	**0.9683**	0.002 ***	**0.9719**	0.003 ***
CHF/USD	2.7955	1.0541	0.945	1.0327	0.923	**0.9699**	0.006 ***	**0.9708**	0.000 ***
CAD/USD	1.2612	**0.9845**	0.291	**0.9892**	0.219	**0.9991**	0.390	**0.9981**	0.251
SEK/USD	2.4678	1.1095	0.933	1.0638	0.983	**0.9295**	0.061 *	**0.9767**	0.011 **
DNK/USD	2.5303	1.0230	0.841	1.0225	0.971	**0.9741**	0.004 ***	**0.9685**	0.004 ***
USD/AUD	2.4664	1.0190	0.721	1.0088	0.640	**0.9820**	0.166	**0.9848**	0.085 *
FRF/USD	2.6311	1.0329	0.775	1.0244	0.823	**0.9695**	0.002 ***	**0.9721**	0.042 **
DEM/USD	2.7605	1.0479	0.917	1.0105	0.655	**0.9694**	0.001 ***	**0.9795**	0.031 **
ITL/USD	2.6670	1.0055	0.560	1.0131	0.731	**0.9457**	0.017 **	**0.9901**	0.238
NLG/USD	2.7535	1.0363	0.811	1.0082	0.679	**0.9651**	0.000 ***	**0.9752**	0.011 **
PTE/USD	2.3017	1.0651	0.950	**0.9955**	0.429	**0.9859**	0.053 *	**0.9807**	0.239
Output gap fundamentals: deviations from a Hodrick-Prescott filtered trend									
USD/GBP	2.4868	1.0460	0.917	1.0086	0.682	**0.9749**	0.081 *	**0.9756**	0.046 **
JPY/USD	2.7803	1.0216	0.741	**0.9877**	0.296	**0.9687**	0.002 ***	**0.9727**	0.005 ***
CHF/USD	2.7955	1.0587	0.971	1.0304	0.896	**0.9704**	0.007 ***	**0.9708**	0.000 ***
CAD/USD	1.2612	**0.9917**	0.378	1.0120	0.938	**0.9992**	0.395	**0.9980**	0.209
SEK/USD	2.4678	1.1056	0.951	1.0643	0.960	**0.9296**	0.062 *	**0.9777**	0.015 **
DNK/USD	2.5303	1.0357	0.930	1.0167	0.896	**0.9741**	0.004 ***	**0.9704**	0.006 ***
USD/AUD	2.4664	1.0190	0.710	1.0111	0.656	**0.9822**	0.168	**0.9847**	0.082 *
FRF/USD	2.6311	1.0333	0.817	1.0290	0.859	**0.9695**	0.002 ***	**0.9724**	0.042 **
DEM/USD	2.7605	1.0539	0.966	1.0219	0.843	**0.9694**	0.001 ***	**0.9791**	0.029 **
ITL/USD	2.6670	**0.9997**	0.497	1.0170	0.802	**0.9456**	0.017 **	**0.9898**	0.230
NLG/USD	2.7535	1.0406	0.844	1.0149	0.797	**0.9652**	0.000 ***	**0.9763**	0.014 **
PTE/USD	2.3017	1.0584	0.916	**0.9991**	0.488	**0.9860**	0.053 *	**0.9804**	0.236

***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.