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Ince, O. & Molodtsova, T. (2015). Out-of-Sample Exchange Rate Predictability with Real-Time Data. Available at: https://www.researchgate.net/publication/283939306_Out-of-Sample_Exchange_Rate_Predictability_with_Real-Time_Data

Out-of-Sample Exchange Rate Predictability with Real-Time Data[†]

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Abstract

This paper evaluates short-run out-of-sample exchange rate predictability with real-time data for 15 OECD countries from 1973 to 2013. We consider the Taylor rule fundamentals model, where the variables that enter the Taylor rule are used to forecast exchange rate changes, and the Taylor rule differentials model, where a Taylor rule with postulated coefficients is used in the forecasting regression. We find evidence of predictability with the Taylor rule fundamentals model for 9 out of 15 countries. The Taylor rule differentials model performs worse, and the evidence of predictability is the weakest with the conventional monetary and PPP models.

Keywords: exchange rates, out-of-sample exchange rate predictability, real-time data, Taylor rules

JEL Classifications: E5, F3, C2

[†] We thank David Papell, Bent Sorensen, Michael McCracken, Jim Nason, Masao Ogaki, Alex Nikolsko-Rzhevskyy, Dean Croushore, Tara Sinclair, Simon van Norden, Ken West, and participants at the 9th Annual Missouri Economics Conference, the 29th Annual International Symposium on Forecasting, Southern Economic Association Conference 2012, Conference on Exchange Rates at Duke University, and the seminars at Georgia Institute of Technology, Emory University, and Appalachian State University for helpful comments and discussions.

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1. Introduction

In the past decades, there have been multiple efforts in the literature on exchange rate forecasting to connect the exchange rate behavior with macroeconomic fundamentals. However, the pessimistic finding of Meese and Rogoff (1983a, 1983b) that standard macroeconomic models of exchange rate determination cannot outperform the naïve "no change" model is still hard to overturn. Mark (1995) used error correction methods to evaluate Purchasing Power Parity (PPP), Interest Rate Parity (IRP), and monetary models and found evidence of exchange rate predictability at long horizons of sixteen quarters, but no systematic evidence of predictability at short horizons of one quarter. While Mark's long-horizon results have been subsequently both questioned and confirmed, the short-horizon results remained persistent. In a comprehensive study, Cheung, Chinn, and Pascual (2005) concluded that none of the standard exchange rate models consistently outperforms the random walk at short horizons.

Recent studies have found superior short-run exchange rate predictability with the Taylor rule models against the random walk benchmark. Following Engel and West (2006), Molodtsova and Papell (2009) introduce a variant of the Taylor rule into an exchange rate forecasting regression and report evidence of predictability for 11 of the 12 currencies at the one-month-ahead horizon. Engel, Mark, and West (2008) use postulated rather than estimated coefficients in Molodtsova and Papell (2009) model and find weaker evidence of exchange rate predictability with Taylor rule models at the one-quarter horizon. In a recent survey of the literature on exchange rate predictability, Rossi (2013) concludes that Taylor rule models perform better out-of-sample than a number of conventional alternatives. Finally, Ince, Molodtsova, and Papell (2016) demonstrate that evidence of exchange rate predictability with Taylor rule fundamentals in Molodtsova and Papell (2009) does not disappear after the crisis.

However, the problem with the existing studies on exchange rate predictability is that virtually all of them use ex-post revised data to evaluate the out-of-sample performance of empirical exchange rate models. Revised data does not accurately reflect information that was available to the market participants when they formulated their forecasts, and, therefore, cannot be used for evaluating the models out-of-sample. As shown in Engel and West (2005), the present-value exchange rate models put relatively less

weight on current fundamentals and more weight on their expectations. If exchange rate changes are driven primarily by expectations, then using the data that accurately reflects the information set of market participants at each point in time is essential.

Limited availability of real-time data for countries other than the U.S. has prevented researchers so far from using it to evaluate exchange rate models in a multi-country setting. Few studies that used real-time data resorted to the analysis of individual currencies, making it impossible to generalize their findings. One notable exception is Ince (2014), who examines predictability of the Taylor rule model in Engel, Mark, and West (2008) for 9 OECD countries using real-time data and confirms their finding that the evidence of exchange rate predictability is weak at the one-quarter horizon. Furthermore, the financial crisis raises additional questions about the prospects of the Taylor rule models during the post-2008 period.

Among the early studies, Faust, Rogers, and Wright (2005) examine the predictive ability of the monetary model using real-time data for Japan, Germany, Switzerland and Canada and conclude that the model does not perform better than the random walk model. Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008, 2011) evaluate real-time out-of-sample predictability of the U.S. dollar/ Deutschemark and U.S. Dollar/Euro exchange rates and find strong evidence of predictability with Taylor Rule fundamentals at the one-quarter forecast horizon. Using real-time data for the U.S. Dollar/Euro rate, Molodtsova and Papell (2013) incorporate credit spreads and financial conditions indexes into the Taylor rule models in Molodtsova and Papell (2009) and Engel, Mark and West (2008), and find that predictability of the U.S. Dollar/Euro exchange rate with Taylor rule models does not disappear after the crisis.

This paper is the first multi-country study of exchange rate predictability with real-time data that includes post-2008 period. We evaluate the out-of-sample performance of the Taylor rule, monetary and Purchasing Power Parity (PPP) models using real-time data for 15 currencies vis-à-vis the U.S. dollar over the period from 1973:Q1 to 2013:Q3. The availability of a long-term real-time dataset that covers all major macroeconomic variables allows us to examine short-term predictability of various Taylor rule and conventional specifications. Two classes of the Taylor rule model include the Taylor rule fundamentals model initiated by Molodtsova and Papell (2009) and the Taylor rule differentials model developed by

Engel, Mark, and West (2008). Both models subtract a Taylor rule for the foreign country from a Taylor rule for the United States, but the former estimates the coefficients on the variables that comprise the Taylor rule, domestic and foreign inflation, output gaps, and lagged interest rates and/or the real exchange rate, and the latter uses posited rather than estimated coefficients in the forecasting equation.

We merge real-time data from the *Real-Time Historical Database for the OECD* prior to 1999 and the data from the *OECD Original Release and Revisions Database* after 1999. Rogoff and Stavrakeva (2008) and Inoue and Rossi (2012) argue that the evidence of exchange rate predictability may depend on the choice of the forecast window. To avoid selecting the forecast window ad-hoc, we estimate exchange rate forecasting regressions using two different windows. Starting in 1973:Q1, we estimate exchange rate models using 32- and 40-quarter rolling windows. To define the output gap, we use deviations from linear trend, quadratic trend, Hodrick-Prescott (1997) filter, Baxter-King (1999) filter, and Christian-Fitzgerald (2003) filter.[1]

We use the Clark and West (CW) (2006) test of equal predictability to assess the performance of the models against the random walk without drift.[2] Under nested hypotheses, this methodology has become standard and is preferred to tests introduced by Diebold and Mariano (1995) and West (1996 (henceforth, DMW tests). CW statistics avoid the problem of very poorly sized tests with far too few rejections of the null of no predictability when the DMW tests are used with standard normal critical values. It is worth noting an important distinction between forecasting and predictability, emphasized by Inoue and Kilian (2004) and Rogoff and Stavrakeva (2008). Using the CW statistics, we examine predictability, whether the vector of coefficients on the macroeconomic fundamentals is jointly significantly different from zero in a regression with the change in the exchange rate on the left-hand-side. Therefore, we are using out-of-sample methodology to evaluate exchange rate models, not to examine whether the model could be potentially used by FOREX traders to make profits.

[1] Since there is no presumption in the literature as to which measure of the output gap is used by the central bank, we estimate the models using five measures of the output gap in Ince and Papell (2013).

[2] Although other benchmarks could be potentially interesting to consider, we use the most commonly used alternative in the literature. Among the random walk with and without drift, we have chosen a more conservative benchmark, the driftless random walk, which is harder to outperform out-of-sample.

Using real-time data, we find that out-of-sample exchange rate predictability with Taylor rule fundamentals does not fall apart after the financial crisis. Overall, we estimate 20 specifications of the Taylor rule fundamentals model. Four specifications of the model, with or without the real exchange rate and with or without the lagged interest rate in the Taylor rule, are estimated using five measures of the output gaps. The Taylor rule fundamentals models that produce the strongest evidence of exchange rate predictability is the model that does not include interest rate smoothing and the real exchange rate. For that model, the no predictability null of the random walk without drift can be rejected for 9 of 15 countries with a 40-quarter window, and for 8 of 15 countries with a 32-quarter window. Overall, we find much stronger evidence of short-term predictability than Engel, Mark, and West (2008) and Ince (2014), but somewhat weaker evidence than Molodtsova and Papell (2009).[3]

We find much weaker evidence of predictability with the Taylor rule differentials model that uses a Taylor rule with postulated rather than estimated coefficients in the forecasting regressions. For the best-performing model with interest rate smoothing and no real exchange rate, the no predictability null can be rejected for 4 of 15 countries with a 40-quarter window, and for 1 of the 15 countries with a 32-quarter window. The evidence is about as strong as in Ince (2014) and Engel, Mark, and West (2008).[4] Therefore, the results suggest that weaker evidence of short-term predictability with the Taylor rule model in these studies can be explained by the use of the Taylor rule differentials model instead of the Taylor rule fundamentals model. Not surprisingly, the conventional exchange rate models perform even worse. The no predictability null can be rejected for 1 of 15 countries with the Purchasing Power Parity model and with the two monetary models that assume that the coefficient on the relative output equals to either 0 or 1.

After evaluating exchange rate predictability at one-quarter horizon, we examine how the choice of the forecast origin and forecast horizon within a given quarter affects the predictability of exchange rate models. While the same quarterly real-time data is available for forecasting exchange rate within a quarter,

[3] Since we use quarterly real-time data and, as we know, data frequency affects out-of-sample performance of the models, our results are directly comparable to the results in Engel, Mark, and West (2008) and Ince (2014).

[4] Although we do not report the results with revised data, the evidence of exchange rate predictability is about the same with real-time and revised data. The results are available from the authors upon request.

the forecast origin and horizon might change. We evaluate exchange rate predictability using five different definitions of exchange rate changes. Using two most successful Taylor rule specifications, we find that the Taylor rule fundamentals models perform the best when the data frequency coincides with the forecast horizon. This finding could be explained by the fact that the market participants are aware that the actual interest rate slowly adjusts to its target level posited by the Taylor rule within a quarter.

2. Exchange Rate Models

Starting with Mark (1995), most widely used approach to evaluating exchange rate models out of sample is to represent a change in log nominal exchange rate as a function of its deviation from the fundamental value. Thus, the *h*-period-ahead change in the log exchange rate can be modeled using the following regression,

$$s_{t+h} - s_t = \alpha + \beta(f_t - s_t) + v_{t+h,t} \tag{1}$$

where s_t is the log of the U.S. dollar nominal exchange rate determined as the domestic price of foreign currency, so that an increase in s_t is a depreciation of the dollar, f_t is its long-run equilibrium level determined by macroeconomic fundamentals, and $v_{t+h,t}$ is the projection error.

2.1 Taylor Rule Fundamentals Model

We consider exchange rate models that explicitly link the exchange rate and a set of macroeconomic variables that appear in the interest rate setting rule of a central bank, such as the Taylor rule. According to the simplest Taylor (1993) specification, the monetary policy rule that central banks follow can be expressed as follows,

$$\bar{i}_t = \mu + \lambda\pi_t + \gamma y_t^g \tag{2}$$

where $\bar{i}_t$ is the target level of the short-term nominal interest rate, π_t is the inflation rate, y_t^g is the output gap, defined as the percentage deviation of the actual output from an estimate of its potential level.

Following Clarida, Gali, and Gertler (1998), it has become common practice to specify variants of the Taylor rule which allow for the possibility that the actual interest rate, i_t, adjusts gradually to achieve

its target level and/or include the real exchange rate, q_t. The rationale for including the real exchange rate is that the central bank sets the target level of the exchange rate to make PPP hold and increases (decreases) the nominal interest rate if the exchange rate depreciates (appreciates) from its PPP value.

$$i_t = (1-\rho)\bar{i}_t + \rho i_{t-1} + v_t \tag{3}$$

Substituting (2) into (3) gives the following equation,

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t^g + \delta q_t) + \rho i_{t-1} + v_t \tag{4}$$

The models with Taylor rule fundamentals are specified as in Molodtsova and Papell (2009). The implied interest rate differential is constructed by subtracting the interest rate reaction function for the foreign country from that for the U.S.,

$$i_t - i_t^* = \alpha + \alpha_{u\pi}\pi_t - \alpha_{f\pi}\pi_t^* + \alpha_{uy}y_t^g - \alpha_{fy}y_t^{g*} - \alpha_q q_t^* + \rho_u i_{t-1} - \rho_f i_{t-1}^* + \eta_t \tag{5}$$

where asterisks denote foreign variables, and subscripts *u* and *f* denote coefficients for the United States and the foreign country, respectively.

We estimate the following exchange rate forecasting equation without making any assumptions about the sign and/or the magnitude of the coefficients,

$$s_{t+h} - s_t = \omega - \omega_{u\pi}\pi_t + \omega_{f\pi}\pi_t^* - \omega_{uy}y_t^g + \omega_{fy}y_t^{g*} + \omega_q q_t^* - \omega_{ui}i_{t-1} + \omega_{fi}i_{t-1}^* + \varepsilon_{t+h,t} \tag{6}$$

Following equation (6), we evaluate 4 different specifications of the *Taylor rule fundamentals model* in forecasting exercises. If the foreign central bank doesn't target the exchange rate $\delta = \omega_q = 0$, we call the specification *symmetric*. Otherwise, it is *asymmetric*. If the actual interest rate adjusts to its target level within the period so that $\omega_{ui} = \omega_{fi} = 0$, the specification is stated with *no smoothing*. Otherwise, it is stated with *smoothing*.

2.2 Taylor Rule Differentials Model

Engel, Mark, and West (2008, 2015) suggest a Taylor rule model, which we call the *Taylor rule differentials* model to differentiate it from the Taylor rule fundamentals model. The model posits the coefficients for the Taylor rule, so that the implied interest rate differential is

$$i_t - i_t^* = 1.5(\pi_t - \pi_t^*) + 0.5(y_t^g - y_t^{g*}) + 0.1(s_t + p_t^* - p_t) \tag{7}$$

An exchange rate forecasting equation is constructed as follows,

$$s_{t+h} - s_t = \alpha_h + \beta_h\left(1.5(\pi_t - \pi_t^*) + 0.5(y_t^g - y_t^{g*}) + 0.1(s_t + p_t^* - p_t\right) + v_{t+h,t} \tag{8}$$

2.3 Monetary and PPP Models

The monetary fundamentals model specifies exchange rate behavior in terms of relative demand for and supply of money in the two countries. Assuming purchasing power parity, UIRP, and no rational speculative bubbles, the fundamental value of the exchange rate can be derived,

$$f_t = (m_t - m_t^*) - k(y_t - y_t^*) \tag{9}$$

where m_t and y_t are the logs of money supply and income in period *t*; and asterisks denote foreign country variables. We construct the monetary fundamentals with a fixed value of the income elasticity, *k*, which is equal to either 0 or 1.

We examine the predictive ability of PPP model, which is a building block for the monetary model and an important representative of the 1970s and 1980s models. The PPP has been studied extensively in the recent decades, with numerous studies finding evidence in support of long-run PPP in the post-Bretton Woods period.[5] The Purchasing Power Parity (PPP) fundamentals model posits that the exchange rate will adjust over time to eliminate deviations from long-run PPP. Under PPP fundamentals,

$$f_t = (p_t - p_t^*) \tag{10}$$

where p_t is the log of the national price level. We substitute the monetary and PPP fundamentals in (9) and (10) into equation (1), and use the resultant equations for forecasting.

3. Data

The exchange rate models discussed in Section 2 are estimated using quarterly real-time data from 1973:Q1 through 1998:Q4 for eight Euro Area countries (Austria, Belgium, France, Germany, Italy, Netherlands, Portugal, and Spain) and through 2013:Q3 for seven non-euro countries (Australia, Canada,

[5] Engel, Mark, and West (2008) and Ince (2014) evaluated the model with PPP fundamentals and found that the evidence of predictability is much weaker with the PPP than with the Taylor rule fundamentals at the 1-quarter horizon.

Japan, Norway, Sweden, Switzerland, and the United Kingdom).[6] Our choice of countries is determined by the availability of real-time data for the post Bretton-Woods period. Exchange rates of the chosen countries are taken from the *PACIFIC Exchange Rate Service*.[7]

We combine two sources of real-time data to construct macroeconomic fundamentals. The real-time data from 1973:Q1 to 1998:Q4 is from the *Real-Time Historical Database for the OECD*.[8] The dataset is compiled by Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012). It contains quarterly data on 13 real-time variables for 26 OECD countries from 1962:Q2 to 1998:Q4 and can be directly merged with the data from the *OECD Original Release and Revisions Database*. The latter dataset provides the data for 21 key economic variables originally published in monthly editions of the *OECD Main Economic Indicators* from February 1999.

Both datasets have a standard triangular format with the vintage dates on the horizontal axis and the calendar dates on the vertical. The term vintage is used to denote each calendar date for which we have data as they were observed at the time. The real-time data is constructed from the diagonal elements of the real-time data matrix by pairing vintage dates with the last available observations. This type of data, sometimes referred to as the *first-release* data, is very useful in analyzing market reaction to news about macroeconomic fundamentals. Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) and Ince (2014) find evidence of superior predictability with first-release real-time data.

For each country and variable, the data represents a vector of quarterly observations from 1973:Q1 to either 1998:Q4 or 2013:Q3, thus resulting in 103 total observations for EMU countries and 163 observations for non-EMU countries. For each forecasting regression, we use 40- and 32-quarter windows to estimate the relationship between fundamentals and the change in the exchange rate, and then use the estimated coefficients to forecast the exchange rate change one-quarter ahead. Thus, we use rolling

[6] Some of the models are estimated using shorter samples. Notes under the tables list these exceptions. Our sample contains all countries considered in Molodtsova and Papell (2009) except for Denmark, all countries in Ince (2014), and all countries in Engel, Mark, and West (2008) except for Denmark, Finland, Greece, and South Korea.
[7] The data can be accessed at http://fx.sauder.ubc.ca/.
[8] The OECD Original Release and Revisions Database is publicly available at http://stats.oecd.org/mei, and the Real-Time Historical Database for the OECD can be accessed at http://www.dallasfed.org/institute/oecd/index.cfm.

regressions to predict 64 (72) exchange rate changes from 1983:Q1 (1981:Q1) to 1998:Q4 for European countries and 123 (131) exchange rate changes from 1983:Q1 (1981:Q1) to 2013:Q3 for non-European countries. Since we use first-release data, both the estimated coefficients and the forecasts are obtained using real-time data.[9]

The consumer price index (CPI) is used to measure the price level in each country. The inflation rate is the annual inflation rate calculated using the CPI over the previous four quarters. The index of industrial production is used to measure the level of output. The output gap depends on the estimate of potential output. Since there is no consensus about which definition of potential output is used by central banks or the public, we consider percentage deviations of the actual output from linear, quadratic, Hodrick-Prescott (1997) (HP), Baxter and King (1999) (BK), and Christiano and Fitzgerald (2003) (CF) trends as alternative measures.[10] The industrial production index that is used to estimate the output gap goes back to 1956:Q1 in each vintage for all countries except Australia, Japan, Switzerland, and Spain.[11]

Quarterly vintages in the *Real-Time Historical Database for the OECD* contain data that was published in the middle month of each quarter (February, May, August, and November). Because of lags in data collection and publication, the vintage dates are not synchronized with the release dates and each vintage includes the data collected from each country during the previous month. For the purpose of evaluating forecasts that were made in real-time, we want to minimize the time between the release of the data and the start of the forecast, otherwise market participants would have had time to incorporate relevant information before the forecasts were made. Therefore, we consider exchange rate forecasts that originate at the end of January, April, July, and October.

[9] An alternative method of constructing real-time data is to use *current-vintage* data that includes all information available in a point in time and, thus, incorporates previous revisions.

[10] We use a smoothing parameter of 1600 to detrend quarterly output series using the HP filter. To mitigate the end-of-sample uncertainty problem, which is present with the HP, BK, and CF filters, we use Watson (2007) correction method and forecast the industrial production 12 quarters ahead using an AR (8) model before calculating the trend.

[11] The industrial production data starts in 1970:Q4 for Australia, in 1960:Q1 for Japan and Switzerland, and in 1965:Q1 for Spain.

4. Forecast Comparison Based on MSPE

We are interested in comparing the mean squared prediction errors (MSPEs) from two nested models. The benchmark model is a driftless random walk, while the alternative is a linear model with Taylor rule, monetary, or PPP fundamentals. Under the null, the population MSPEs are equal. The procedure introduced by Diebold and Mariano (1995) and West (1996) (DMW) uses sample MSPEs to construct a *t*-type statistics, which is assumed to be asymptotically normal. While the asymptotic DMW test works well with non-nested models, Clark and McCracken (2001, 2005) and McCracken (2007) show that the limiting distribution of the DMW test for nested models under the true null is not standard. As a result, severely undersized DMW tests can cause far too few rejections of the null of no predictability.

Clark and West (2006) propose to adjust the DMW statistic, in order to correct for size distortions with nested models. The CW statistic is shown to be standard normal, with actual sizes close to the nominal size. The null hypothesis for the CW test is that the exchange rate follows a random walk while the alternative hypothesis is that the exchange rate can be described by a linear model. We report the CW statistics with standard normal critical values, which has become standard practice in the literature. Rejecting the random walk null in favor of the linear model provides evidence of predictability.

5. Empirical Results

Using the CW tests of equal predictability, we evaluate out-of-sample exchange rate predictability of the models introduced in Section 2. The statistics are constructed using rolling regressions with real-time data. As discussed in Rogoff and Stavrakeva (2008) and Inoue and Rossi (2012), the performance of the exchange rate models might depend on the size of the estimation window. To avoid selecting a specific forecast window ad-hoc, we estimate the models using two window sizes of 40 and 32 quarters.[12] When a 40 (32)-quarter window is used, the models are estimated over the period 1973:Q1 – 1983:Q1 (1973:Q1 – 1981:Q1), reserving the remaining data for forecasting.

[12] Another way to address this issue would be to use the fluctuation test proposed by Giacomini and Rossi (2010). Since the results with two windows are not that different, we leave this investigation for future research.

5.1 Out-of-Sample Predictability with Taylor Rule Fundamentals

We estimate 20 specifications of the Taylor rule fundamentals model with heterogeneous coefficients on inflation and the output gap for the U.S. and the foreign country: with or without the real exchange rate (symmetric vs. asymmetric), and with or without the lagged interest rates (smoothing vs. no smoothing). For each class of models, we use five different measures of the output gap. Table 1 reports the results for 1-quarter-ahead forecasts of exchange rates using the symmetric Taylor rule fundamentals.

Panel A of Table 1 reports the results with no smoothing. With a 40-quarter rolling window, the model significantly outperforms the random walk for 4 out of 15 countries with a linear trend (Austria at the 5 percent significance level and Australia, Norway, and France at the 10 percent level), for 3 out of 15 countries with a quadratic trend (Australia, Switzerland, and Portugal at the 10 percent level), for 1 out of 15 countries with an HP trend (Australia at the 10 percent level), for 2 out of 15 countries with a BK trend (Australia and Norway at the 10 percent level), and for 3 out of 15 countries with a CF trend (Canada, Japan, and Sweden at the 10 percent level). Overall, the model significantly outperforms the random walk in 13 out of 75 cases and with at least one of the output gap specifications for 9 out of 15 countries.

With a 32-quarter rolling window, the results are similar. The model significantly outperforms the random walk for 8 out of 15 countries with a linear trend (Austria, Italy, Portugal, and Spain at the 5 percent level, and Norway, Sweden, Belgium, and France at the 10 percent level), for 2 out of 15 countries with a quadratic trend (Portugal and Spain at the 5 percent level), for 4 out of 15 countries with an HP trend (Italy, Portugal, and Spain at the 5 percent level, and France at the 10 percent level), for 6 out of 15 countries with a BK trend (Sweden, Italy, and Spain at the 5 percent level, and Norway, France, and Portugal at the 10 percent level), and for 5 out of 15 countries with a CF trend (Sweden at the 1 percent level, and France, Italy, Portugal, and Spain at the 10 percent level). Overall, the model significantly outperforms the random walk in 25 out of 75 cases and with at least one of the output gap specifications for 8 out of 15 countries.

Panel B of Table 1 reports the results for symmetric Taylor rule fundamentals model that includes the lagged interest rate. With a 40-quarter window, the model significantly outperforms the random walk for 4 out of 15 countries with a linear trend (Japan at the 5 percent level, and Australia, Norway, and Austria

at the 10 percent level), for 4 out of 15 countries with a quadratic trend (Australia at the 5 percent level, and Japan, Norway, and Switzerland at the 10 percent level), for 2 out of 15 countries with an HP trend (Japan and Switzerland at the 10 percent level), for 2 out of 15 countries with a BK trend (Japan and Norway at the 10 percent level), and for 1 out of 15 countries with a CF trend (Japan at the 5 percent level). The model significantly outperforms the driftless random walk in 13 out of 75 cases and with at least one of the output gap specifications for 5 out of 15 countries.

With a 32-quarter rolling window, the model significantly outperforms the random walk for 5 out of 15 countries with a linear trend (Norway, Sweden, Austria, and Spain at the 5 percent level, and Belgium at the 10 percent level), for 4 out of 15 countries with a quadratic trend (Austria at the 5 percent level, and Japan, Norway, and Spain at the 10 percent level), for 3 out of 15 countries with an HP trend (France, Italy, and Spain at the 10 percent level), for 4 out of 15 countries with a BK trend (Norway and Sweden at the 5 percent level, and Belgium and France at the 10 percent level), and for 4 out of 15 countries with a CF trend (Sweden at the 5 percent level, and Canada, Norway, and France at the 10 percent level). Overall, the model significantly outperforms the random walk in 20 out of 75 cases and with at least one of the output gap specifications for 9 out of 15 countries.

Table 2 reports the results for 1-quarter-ahead forecasts of exchange rates using asymmetric Taylor rule fundamentals. Panel A of Table 1 reports the results for the model with no smoothing. With a 40-quarter rolling window, the model significantly outperforms the random walk for 6 out of 15 countries with a linear trend (Switzerland, the U.K., and Austria at the 5 percent significance level, and Norway, France, and Italy at the 10 percent level), for 4 out of 15 countries with a quadratic trend (Australia, Sweden, Switzerland, and the U.K. at the 10 percent level), for 1 out of 15 countries with an HP trend (the U.K at the 10 percent level), for 2 out of 15 countries with a BK trend (Australia and Norway at the 10 percent level), and for no countries with a CF trend. Overall, the model significantly outperforms the random walk in 13 out of 75 cases and with at least one of the output gap specifications for 8 out of 15 countries.

When we use a 32-quarter rolling window, the model significantly outperforms the random walk for 4 out of 15 countries with a linear trend (Spain at the 1 percent level, and the U.K., Austria, and Italy at

the 5 percent level), for 4 out of 15 countries with a quadratic trend (Spain at the 1 percent level, and the U.K., Austria, and Italy at the 10 percent level), for 2 out of 15 countries with an HP trend (Italy and Spain at the 5 percent level), for 2 out of 15 countries with a BK trend (Spain at the 1 percent level and Italy at the 5 percent level), and for 4 out of 15 countries with a CF trend (Italy and Spain at the 5 percent level, and Sweden and France at the 10 percent level). The model significantly outperforms the random walk in 16 out of 75 cases and with at least one of the output gap specifications for 6 out of 15 countries.

Panel B of Table 2 reports the results for asymmetric Taylor rule fundamentals model with smoothing. With a 40-quarter window, the model significantly outperforms the random walk for 6 out of 15 countries with a linear trend (Norway, Switzerland, and Austria at the 5 percent level, and Australia, Japan, and the U.K, at the 10 percent level), for 5 out of 15 countries with a quadratic trend (Australia, Norway, and Switzerland at the 5 percent level, and Japan, and the U.K. at the 10 percent level), for 2 out of 15 countries with an HP trend (Switzerland and Japan at the 10 percent level), for 2 out of 15 countries with a BK trend (Japan and Norway at the 10 percent level), and for 2 out of 15 countries with a CF trend (Japan and Switzerland at the 10 percent level). The model significantly outperforms the random walk in 17 out of 75 cases and with at least one of the output gap specifications for 6 out of 15 countries.

With a 32-quarter rolling window, the model significantly outperforms the random walk for 7 out of 15 countries with a linear trend (Spain at the 1 percent level, Norway and Austria at the 5 percent level, and Japan, Switzerland, the U.K, and Italy at the 10 percent level), for 3 out of 15 countries with a quadratic trend (Spain at the 5 percent level, and Austria and Italy at the 10 percent level), for 2 out of 15 countries with HP and BK trends (Italy and Spain at the 5 percent level), and for 1 out of 15 countries with a CF trend (Italy at the 10 percent level). Overall, the model significantly outperforms the random walk in 15 out of 75 cases and with at least one of the output gap specifications for 7 out of 15 countries.

The results presented in Tables 1 and 2 show that the two symmetric Taylor rule fundamentals models are the best-performing specifications with the highest number of countries for which the random walk null is rejected. Both models outperform the driftless random walk for 9 out of 15 countries with at least one output gap measure. Symmetric Taylor rule fundamentals model with heterogeneous coefficients

was also the best-performing model in Molodtsova and Papell (2009) and in Ince, Molodtsova, and Papell (2016).[13]

5.2 Out-of-Sample Predictability with Taylor Rule Differentials

Following Engel, Mark, and West (2008) and Ince (2014), we evaluate out-of-sample exchange rate predictability with the Taylor rule differentials model. As for the model with Taylor rule fundamentals, we estimate 20 specifications of the Taylor rule differentials model, with or without the real exchange rate, and with or without the lagged interest rates.[14] Table 3 contains the results for 1-quarter-ahead forecasts of the exchange rates using symmetric Taylor rule differentials. Overall, the evidence of predictability is weaker with Taylor rule differentials than with Taylor rule fundamentals.

Panel A of Table 3 reports the results for symmetric Taylor rule differentials model with no smoothing. With a 40-quarter rolling window, the model significantly outperforms the random walk in 6 out of 75 cases and with at least one of the output gap specifications for 2 out of 15 countries. The evidence of predictability is somewhat stronger when we include the lagged interest rates in the model. Panel B of Table 3 reports the results for symmetric Taylor rule differentials model with smoothing. With a 40-quarter window, the model significantly outperforms the random walk only for 1 out of 15 countries with all measures of potential output (Japan at either the 1 or 5 percent level). When a 32-quarter rolling window is used, the model significantly outperforms the random walk in 12 out of 75 cases and with at least one of the output gap specifications for 4 out of 15 countries.

5.3 Out-of-Sample Predictability with Monetary and PPP Fundamentals

For comparison purposes, Table 4 contains the CW statistics for the monetary and PPP fundamentals described in Sections 2.3. No evidence of predictability is found with any of the conventional models. The models significantly outperform the random walk only for Portugal with both window sizes. These results are in accord with the results in Molodtsova and Papell (2009), Engel, Mark, and West (2008),

[13] Although they don't use real-time data, they estimate the trend only using the data prior to the date for which the trend is estimated. Thus, they mimic the real-time nature of the decision-making process as closely as possible with revised data and call this type of data *quasi-real-time*.

[14] Since the performance of the model does not change when the real exchange rate in included in Equation (8), we omit these results to save space. The summary of the results is provided in Section 5.4.

Ince (2014), and Ince, Molodtsova, and Papell (2016), who also find more evidence of exchange rate predictability with Taylor rule models than with PPP and monetary models at short horizons.

5.4 Summary of the Results

We have evaluated 1290 exchange rate forecasts – for 15 currencies with 8 specifications of the Taylor rule model that were estimated with 5 measures of the output gap, 2 specifications of the monetary model, and the PPP model. We estimate each model with two window sizes. In order to summarize the results, Table 5 reports the number of significant CW statistics (at the 10% significance level or higher) for each specification in Tables 1-4, overall number of significant CW statistics for a given class of models, and the overall number of countries with significant CW statistics for at least one output gap measure.

The performance of the Taylor rule fundamentals models is summarized in Columns 1 and 3 of Panels A-D of Table 5. Looking at the results with a 40-quarter window, the most successful model is the symmetric Taylor rule fundamentals model without smoothing, where the no predictability null can be rejected for 9 out of 15 countries and in 13 cases out of 75. The symmetric Taylor rule fundamentals model with smoothing performs the best with a 32-quarter window, where the no predictability null is rejected for 9 out of 15 countries and in 20 cases out of 75.

The results for Taylor rule differentials models are summarized in Columns 2 and 4 of Panels A-D of Table 5. The evidence of predictability is very weak with a 40-quarter window. The two Taylor rule differentials models that exclude lagged interest rates perform the best, with the no predictability null rejected for 2 out of 15 countries and in only 3 cases out of 75. With the 32-quarter window, the two best-performing Taylor rule differentials models include smoothing. For these models, the no predictability null is rejected for 4 out of 15 countries and in 12 cases out of 75. There is virtually no evidence of predictability with the monetary and PPP models, where the random walk null rejected only for 1 out of 15 countries.

5.5 Robustness Check with Different Forecast Origins and Horizons

While the same real-time data might be available to policymakers and practitioners within a given quarter, the forecast origin and forecast horizon of interest might vary depending on their objectives. In this Section, we construct five definitions of the exchange rate change that can be used with the same quarterly

right-hand-side variables. If *t* is the end of the first month in a quarter, *t+1* is the end of the second month in a quarter, *t+2* is the end of the third month in a quarter, and *t+3* is the end of the first month in the following quarter, we can define five exchange rate changes, $s_{t+3} - s_t$, $s_{t+2} - s_t$, $s_{t+1} - s_t$, $s_{t+2} - s_{t+1}$, and $s_{t+3} - s_{t+2}$.[15] Quarterly exchange rate change, $s_{t+3} - s_t$, serves as a natural benchmark for comparison, since it is typically used in the literature with quarterly data.

Table 6 reports summary of the results for the symmetric Taylor rule fundamentals model with and without smoothing.[16] Overall, the results indicate that the Taylor rule models perform the best when the data frequency and the forecast horizon match. This finding might suggest that the market participants take into account the interest rate inertia, the fact that the actual interest rate gradually adjusts to its target level posited by the Taylor rule within a quarter. The result is also in line with McCracken (2013), who finds that the evidence of predictability for the Euro/U.S. dollar rate gets stronger as we move the forecast origin closer to the end of the quarter.

6. Conclusions

Using a comprehensive real-time dataset for 15 OECD countries, which is constructed by merging the *OECD Original Release and Revisions Database* and *Historical Real-Time Data for OECD*, we evaluate short-term out-of-sample exchange rate predictability with Taylor rule fundamentals, Taylor rule differentials, monetary, and PPP models during the post-Bretton-Woods period. Overall, the Taylor rule fundamentals model provides stronger evidence of exchange rate predictability than the Taylor rule differentials model, and much stronger evidence than the conventional models.

The best-performing Taylor rule fundamentals model does not include the real exchange rate and can either include or exclude the lagged interest rates in the central bank's Taylor rule. For that model, the evidence of out-of-sample exchange rate predictability is found for 9 out of 15 countries in our sample. The same model was also found the most successful specification in Molodtsova and Papell (2009) using the

[15] For example, if we are at the end of January of 1981, the same quarterly macroeconomic fundamentals can be used to forecast exchange rate changes from January 1981 to April 1981, from January 1981 to March 1981, from January 1981 to February 1981, from February 1981 to March 1981, and from March 1981 to April 1981.

[16] Although we don't report the detailed results to save space, they are available from the authors upon request.

quasi-revised data from 1983 through mid-2006, and in Ince, Molodtsova, and Papell (2016) using the same data extended to the end of 2014. The results indicate that the evidence of short-term predictability with the Taylor rule model is much stronger than in Engel, Mark, and West (2008) and Ince (2014), but somewhat weaker than in Molodtsova and Papell (2009). Using real-time data, we confirm that out-of-sample exchange rate predictability with Taylor rule fundamentals did not disappear after the financial crisis and the period when the federal funds rate was at the zero lower bound.

We find less evidence of predictability with the Taylor rule differentials model, where the coefficients in the Taylor rule are postulated rather than estimated in the forecasting regressions. Overall, the specification that includes interest rate smoothing and excludes real exchange rate performs the best. For that model, the null of no predictability can be rejected for 4 of 15 countries. Ince (2014) finds similar results for Taylor rule differentials model with real-time data and Engel, Mark, and West (2008) with revised data. Therefore, our results indicate that somewhat weaker evidence of short-term predictability with Taylor rule models in Ince (2014) and Engel, Mark and West (2008) can be explained by their use of the Taylor rule differentials model instead of the Taylor rule fundamentals model. Additionally, the conventional exchange rate models perform poorly.

In addition to one-quarter forecast horizon that is typically used with quarterly data, we consider two-month and one-month exchange rate changes that originate at the end of different months in a quarter. While the same real-time data might be available to policymakers and practitioners within a given quarter, the forecast origin and forecast horizon of interest might vary depending on their objectives. We find that the Taylor rule models perform the best when the data frequency and the forecast horizon are the same. Overall, these findings could indicate that the decisions of the market participants reflect gradual adjustment of the interest rate to its target level posited by the Taylor rule within a quarter.

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Table 1. Symmetric Taylor Rule Fundamentals Model

	Window Size = 40					Window Size = 32				
	Lin	*Quad*	*HP*	*BK*	*CF*	*Lin*	*Quad*	*HP*	*BK*	*CF*
A. No Smoothing										
Australia	**1.299**	**1.595**	**1.352**	**1.417**	0.502	0.176	0.477	0.658	0.433	0.070
Canada	0.454	0.657	0.872	0.773	**1.587**	-0.055	0.130	0.725	0.694	1.195
Japan	0.613	0.453	0.681	0.595	**1.538**	0.154	0.173	0.028	-0.402	0.201
Norway	**1.468**	1.178	0.361	**1.285**	1.017	**1.294**	1.129	0.106	**1.412**	1.076
Sweden	0.937	0.974	0.251	1.052	**1.466**	**1.468**	1.174	0.849	**2.107**	**2.439**
Switzerland	0.967	**1.456**	0.736	0.176	0.226	0.747	0.701	-0.074	-0.440	-0.650
U.K.	1.169	1.086	0.823	0.540	0.275	0.817	1.000	0.836	0.772	0.928
Austria	**1.851**	0.619	0.456	0.111	0.641	**1.946**	1.228	0.997	0.519	0.371
Belgium	1.088	0.549	-0.086	-0.377	-0.537	**1.337**	1.016	0.893	0.888	0.489
France	**1.483**	1.114	1.125	0.982	0.910	**1.294**	0.905	**1.382**	**1.534**	**1.496**
Germany	0.568	0.187	0.290	0.240	0.784	-0.185	-0.165	0.744	0.610	0.228
Italy	1.200	0.888	1.158	0.797	0.984	**1.793**	1.271	**1.778**	**1.690**	**1.600**
Netherlands	0.923	-0.206	-0.587	-0.486	0.308	0.216	0.565	-0.322	0.422	0.403
Portugal	1.210	**1.341**	1.144	0.826	0.668	**1.901**	**1.872**	**1.706**	**1.586**	**1.586**
Spain	0.939	0.746	0.476	0.418	-0.522	**2.294**	**2.102**	**1.917**	**1.831**	**1.513**
B. Smoothing										
Australia	**1.422**	**1.704**	0.763	0.731	0.228	0.728	0.766	0.113	-0.141	-0.447
Canada	0.872	0.791	0.617	0.389	1.232	0.962	0.913	0.894	0.671	**1.512**
Japan	**1.982**	**1.554**	**1.566**	**1.526**	**1.785**	1.081	**1.333**	0.848	0.683	0.527
Norway	**1.362**	**1.467**	1.024	**1.548**	1.047	**1.714**	**1.643**	0.790	**1.807**	**1.580**
Sweden	0.972	0.960	0.045	0.744	0.525	**1.702**	1.155	1.071	**1.736**	**1.743**
Switzerland	1.014	**1.571**	**1.500**	0.835	1.093	1.183	1.073	0.844	0.696	0.606
U.K.	0.552	0.746	0.556	0.478	0.081	1.005	0.855	0.948	0.988	0.987
Austria	**1.362**	0.796	0.252	-0.153	0.193	**1.810**	**1.703**	1.172	0.592	0.621
Belgium	0.597	0.161	-0.418	-0.574	-0.878	**1.376**	1.194	0.956	**1.315**	0.683
France	0.933	0.438	0.560	0.596	0.506	1.209	0.987	**1.511**	**1.358**	**1.624**
Germany	0.268	0.112	0.011	-0.243	-0.025	0.012	0.075	0.132	-0.142	-0.310
Italy	0.495	0.522	0.668	0.042	0.374	1.241	0.904	**1.557**	1.225	1.236
Netherlands	0.169	-0.147	-0.614	-0.993	-0.367	0.703	0.814	0.122	-0.158	-0.022
Portugal	-0.566	-0.018	-0.332	-0.034	-0.838	-0.890	-0.939	-0.529	-0.042	-0.207
Spain	-0.272	0.097	-0.459	-0.265	-1.428	**1.711**	**1.641**	**1.536**	1.260	0.851

Notes to Tables 1-3: The tables report CW statistics for the 1-quarter-ahead tests of equal predictive ability between the null of a driftless random walk and the alternative of a linear model with Taylor rule fundamentals (Tables 1 and 2) and Taylor rule differentials (Table 3). In Table 1, the alternative model is the model with symmetric Taylor rule fundamentals with and without smoothing, which is estimated with heterogeneous inflation and output coefficients using linear, quadratic, HP, BK, and CF trends to estimate potential output. Panel A reports the results of estimating Taylor rule fundamentals model with no smoothing, and Panel B contains the results with smoothing. The CW statistics where the alternative model significantly outperforms the random walk at 10, 5, or 1% significance level based on standard normal critical values for the one-sided test are marked in bold. All models are estimated in rolling regressions with 40- and 32-quarter windows to predict exchange rate changes from 1983:M1 (1983:M1) through 1998:Q4 for Euro Area countries and 2013:Q3 for the rest of the countries. The only exception is Australia, for which the first forecast date is 1983:Q3. The models with smoothing are estimated using data from 1975:Q1 for Canada, 1975:Q4 for Switzerland, 1983:Q1 for Portugal, 1974:Q4 for Spain and 1973:Q1 for the rest of the countries. The sample ends in 2009:Q3 for Norway, 1998:Q4 for Euro Area countries, and 2013:Q3 for the rest of the countries.

Table 2. Asymmetric Taylor Rule Fundamentals Model

	Window Size = 40					Window Size = 32				
	Lin	*Quad*	*HP*	*BK*	*CF*	*Lin*	*Quad*	*HP*	*BK*	*CF*
A. No Smoothing										
Australia	1.216	**1.502**	0.830	**1.377**	0.328	0.237	0.156	-0.728	-0.441	-0.688
Canada	0.018	0.238	0.388	0.437	0.036	-0.309	-0.155	-0.118	-0.139	0.001
Japan	0.269	0.348	0.197	-0.189	0.548	-0.027	-0.377	-0.452	-1.353	-0.466
Norway	**1.309**	1.266	-0.286	**1.300**	0.347	1.057	0.412	-1.506	0.299	-0.324
Sweden	1.012	**1.283**	-0.294	0.792	0.814	0.452	0.305	-0.358	1.051	**1.358**
Switzerland	**1.735**	**1.302**	0.123	-0.520	-0.007	0.854	0.169	-0.840	-1.098	-0.170
U.K.	**1.716**	**1.573**	**1.307**	1.003	0.888	**1.861**	**1.390**	1.019	0.795	1.121
Austria	**2.048**	1.039	0.416	-0.069	0.264	**2.096**	**1.324**	1.030	0.207	0.316
Belgium	1.058	0.614	0.158	-0.291	-0.429	0.220	0.315	0.325	0.306	0.385
France	**1.459**	1.131	1.202	0.870	0.656	0.418	0.032	0.929	1.073	**1.288**
Germany	0.260	-0.105	-0.041	-0.175	-0.203	-1.154	-1.133	-0.830	-0.966	-0.604
Italy	**1.340**	1.271	1.150	0.884	0.735	**1.882**	**1.454**	**2.117**	**1.924**	**1.813**
Netherlands	-0.544	-0.352	-1.423	-1.101	-0.248	-1.674	-0.806	-1.160	-0.248	0.208
Portugal	0.627	0.518	0.252	0.025	-0.476	1.163	1.111	1.009	0.720	0.581
Spain	1.252	0.948	0.078	0.824	-1.063	**2.757**	**2.410**	**2.067**	**2.375**	**1.683**
B. Smoothing										
Australia	**1.359**	**1.844**	0.762	1.075	0.446	0.807	0.783	-0.406	-0.514	-0.836
Canada	0.548	0.579	0.272	0.149	-0.060	0.568	0.545	-0.192	-0.370	0.385
Japan	**1.416**	**1.459**	**1.402**	**1.316**	**1.552**	**1.323**	1.197	1.149	0.843	0.622
Norway	**1.731**	**1.742**	0.378	**1.358**	0.136	**1.671**	1.169	-0.566	0.747	0.198
Sweden	1.160	1.039	-0.271	0.465	0.067	0.836	0.243	0.605	0.876	0.907
Switzerland	**2.077**	**2.131**	**1.596**	0.833	**1.458**	**1.370**	0.944	0.565	0.497	1.075
U.K.	**1.628**	**1.573**	1.156	0.888	0.627	**1.434**	1.060	0.769	0.771	1.105
Austria	**1.924**	1.123	1.171	-0.388	-0.070	**2.285**	**1.546**	1.215	0.265	0.199
Belgium	0.794	0.422	-0.285	-0.792	-0.783	0.441	0.408	0.279	0.523	0.309
France	0.669	0.373	0.348	0.193	0.282	0.035	-0.137	0.730	0.557	1.161
Germany	0.175	-0.070	-0.205	-0.415	-0.318	-0.865	-0.925	-0.927	-1.016	-0.704
Italy	0.845	1.070	1.269	0.899	0.398	**1.537**	**1.377**	**2.197**	**1.881**	**1.428**
Netherlands	-0.612	-0.495	-1.542	-1.637	-0.947	-0.688	-0.466	-0.539	-0.691	-0.214
Portugal	-0.385	0.358	-0.841	-0.716	-1.551	-0.923	-0.808	-0.685	-0.909	-0.581
Spain	-0.169	0.301	-1.252	-0.033	-2.150	**2.426**	**2.301**	**1.758**	**1.739**	1.250

Notes: The alternative model in this table is the model with asymmetric Taylor rule fundamentals with and without smoothing, which is estimated with heterogeneous inflation and output coefficients using linear, quadratic, HP, BK, and CF trends to estimate potential output. See also notes to Table 1.

Table 3. Symmetric Taylor Rule Differentials Model

	Window Size = 40					Window Size = 32				
	Lin	*Quad*	*HP*	*BK*	*CF*	*Lin*	*Quad*	*HP*	*BK*	*CF*
A. No Smoothing										
Australia	**1.443**	1.013	0.968	**1.437**	1.254	1.247	0.427	0.786	1.217	1.009
Canada	1.211	0.760	1.165	**1.293**	1.141	**1.313**	0.848	1.017	1.111	1.027
Japan	0.667	0.839	0.905	0.705	0.925	0.942	1.166	0.863	0.677	1.267
Norway	0.081	-0.321	-0.980	-0.192	-0.994	0.637	-0.237	-0.820	-0.502	-1.110
Sweden	-0.654	0.500	-0.371	-0.114	0.251	-0.219	0.766	0.948	1.094	1.263
Switzerland	0.720	1.030	0.875	0.410	0.458	0.044	0.187	-0.152	-0.633	-0.527
U.K.	-0.468	-0.995	0.028	0.034	-0.294	-1.544	-1.764	-1.200	-1.241	-1.370
Austria	-0.587	-0.502	-0.231	-0.207	0.057	-1.380	-1.439	-1.291	-1.404	-1.241
Belgium	-2.093	-2.055	-2.147	-1.833	-2.037	-1.441	-1.409	-1.509	-1.532	-1.579
France	0.523	0.388	0.166	-0.233	-0.580	0.745	0.572	0.859	0.444	0.102
Germany	-0.382	-0.032	0.370	0.506	0.814	-0.762	-0.679	-0.175	-0.090	0.114
Italy	0.166	-0.022	-0.094	-0.054	-0.208	0.562	0.316	0.739	0.704	0.797
Netherlands	-1.103	-0.962	-1.203	-0.664	-0.407	-0.753	-1.176	-1.114	-0.642	-0.426
Portugal	0.600	0.395	0.579	0.723	0.693	**1.855**	**2.014**	**1.962**	**1.992**	**2.000**
Spain	-1.456	-1.615	-1.694	-1.706	-1.623	0.304	0.083	0.143	0.181	0.266
B. Smoothing										
Australia	0.851	0.791	0.297	0.539	0.460	0.528	0.154	0.064	0.306	0.189
Canada	0.484	0.160	0.905	1.077	0.794	1.175	0.689	1.095	1.218	1.027
Japan	**2.398**	**2.455**	**2.138**	**1.902**	**2.087**	**2.657**	**2.848**	**2.271**	**2.063**	**2.363**
Norway	-0.759	-0.374	-0.833	-0.305	-1.104	0.769	0.965	0.055	0.389	-0.160
Sweden	-0.351	-0.385	-0.739	-0.533	-0.310	0.458	0.564	0.406	0.690	0.709
Switzerland	1.131	1.236	0.880	0.660	0.749	1.170	**1.331**	1.269	1.129	1.126
U.K.	-0.300	-0.386	-0.212	-0.151	-0.410	-0.395	-0.599	-0.417	-0.406	-0.518
Austria	-0.121	-0.252	-0.093	-0.232	-0.220	0.685	0.697	0.593	0.423	0.329
Belgium	-1.077	-1.187	-1.226	-1.077	-1.246	-0.003	-0.012	-0.205	-0.294	-0.492
France	0.904	0.465	0.493	0.077	-0.217	**1.681**	**1.686**	**1.652**	**1.335**	1.015
Germany	-0.711	-0.644	-0.629	-0.564	-0.300	-0.053	-0.155	-0.201	-0.288	-0.148
Italy	0.253	0.330	0.391	0.472	0.347	0.566	0.345	**1.303**	**1.384**	1.204
Netherlands	-0.219	-0.248	-0.278	-0.119	-0.113	0.330	0.229	0.180	0.297	0.383
Portugal	-1.369	-1.391	-1.468	-1.467	-1.588	-0.498	-0.547	-0.490	-0.501	-0.485
Spain	-1.899	-2.031	-1.936	-1.831	-1.728	-0.024	-0.635	-0.499	-0.335	-0.234

Notes: The alternative model in this table is the model with symmetric Taylor rule differentials with and without smoothing, which is estimated using linear, quadratic, HP, BK, and CF trends to estimate potential output. See also notes to Table 1.

Table 4. Models with Monetary and PPP Fundamentals

	Window Size = 40			Window Size = 32		
	PPP	*Mon k=0*	*Mon k=1*	*PPP*	*Mon k=0*	*Mon k=1*
Australia	-1.605	-1.537	-1.529	-1.522	-1.473	-1.438
Canada	-0.644	-0.661	-0.355	-0.261	0.380	0.357
Japan	-0.861	-0.979	-1.139	-1.266	-0.766	-0.728
Norway	0.271	-0.742	-0.676	-0.298	-0.503	-0.844
Sweden	-0.029	-0.866	-0.605	-0.896	0.302	-0.214
Switzerland	-0.536	-1.880	-1.654	-0.771	-1.326	-0.907
U.K.	0.539	-1.385	-1.654	-0.099	-0.859	-1.256
Austria	-0.466	-2.298	-2.220	0.197	-1.624	-1.557
Belgium	-0.779	-3.219	-3.267	-0.635	-1.924	-2.438
France	0.590	0.062	0.372	0.213	0.482	0.417
Germany	-0.628	-1.872	-0.960	0.177	-1.184	-0.607
Italy	0.580	0.492	0.539	0.315	0.214	0.113
Netherlands	-0.879	-2.875	-2.247	-0.213	-2.573	-2.228
Portugal	**1.448**	**1.585**	**1.630**	**2.513**	**2.398**	**2.435**
Spain	1.017	0.191	0.055	0.813	0.480	0.482

Notes: The table reports 1-quarter-ahead CW tests of equal predictive ability between the null of a driftless random walk and the alternative of a linear model with macroeconomic fundamentals. The alternative models are the model with PPP and monetary fundamentals with a value of the income elasticity, *k*, set to 0 or 1. The CW statistics where the alternative model significantly outperforms the random walk at 10, 5, or 1% significance level based on standard normal critical values for the one-sided test are marked in bold. The models are estimated using data from 1973:Q1 through 1998:Q4 for Euro Area countries and 2013:Q3 for the rest of the countries.

Table 5. Summary of the Results

	Window Size = 40		Window Size = 32	
	Fundamentals	Differentials	Fundamentals	Differentials
A. Symmetric Taylor Rule Model with No Smoothing				
Linear Output Gap	4	1	8	2
Quadratic Output Gap	3	0	2	1
HP Output Gap	1	0	4	1
BK Output Gap	2	2	6	1
CF Output Gap	3	0	5	1
Overall	13	3	25	6
# of Countries	9	2	8	2
B. Symmetric Taylor Rule Model with Smoothing				
Linear Output Gap	4	1	5	2
Quadratic Output Gap	4	1	4	3
HP Output Gap	2	1	3	3
BK Output Gap	2	1	4	3
CF Output Gap	1	1	4	1
Overall	13	5	20	12
# of Countries	5	1	9	4
C. Asymmetric Taylor Rule Model with No Smoothing				
Linear Output Gap	6	1	4	2
Quadratic Output Gap	4	0	4	1
HP Output Gap	1	0	2	1
BK Output Gap	2	2	2	1
CF Output Gap	0	0	4	1
Overall	13	3	16	6
# of Countries	8	2	6	2
D. Asymmetric Taylor Rule Model with Smoothing				
Linear Output Gap	6	1	7	2
Quadratic Output Gap	5	1	3	3
HP Output Gap	2	1	2	3
BK Output Gap	2	1	2	3
CF Output Gap	2	1	1	1
Overall	17	5	15	12
# of Countries	6	1	7	4
E. Monetary and PPP Models				
PPP Model	1	-	1	-
Monetary Model: k=0	1	-	1	-
Monetary Model: k=1	1	-	1	-

Notes: The table reports the number of significant CW statistics (at the 10% significance level or higher) for each specification in Tables 1-4, overall number of significant CW statistics for a given class of models, and the overall number of countries with significant CW statistics for at least one output gap measure. In Panels A-D, all the cells except "Overall" and "# of Countries" have 15 possible rejections, the cells in the rows labeled "Overall" have 75 possible rejections, and the cells in the rows labeled "Number of Countries" have 15 possible rejections. In Panel E, all cells have 15 possible rejections.

Table 6. Summary of the Results for Different Forecast Origins and Horizons

	Window Size = 40					Window Size = 32				
	$S_{t+3}-S_t$	$S_{t+2}-S_t$	$S_{t+1}-S_t$	$S_{t+2}-S_{t+1}$	$S_{t+3}-S_{t+2}$	$S_{t+3}-S_t$	$S_{t+2}-S_t$	$S_{t+1}-S_t$	$S_{t+2}-S_{t+1}$	$S_{t+3}-S_{t+2}$
A. Symmetric Taylor Rule Fundamentals Model with No Smoothing										
Linear	4	5	2	0	1	8	5	0	2	2
Quadratic	3	3	0	0	1	2	1	0	2	2
HP	1	0	0	0	0	4	1	0	2	0
BK	2	1	1	0	0	6	3	1	1	3
CF	3	1	0	0	0	5	3	0	1	4
Overall	13	10	3	0	2	25	13	1	8	11
# of Countries	9	5	2	0	1	8	6	1	2	5
B. Symmetric Taylor Rule Fundamentals Model with Smoothing										
Linear	4	2	2	1	1	5	2	0	0	3
Quadratic	4	2	0	0	1	4	0	0	0	3
HP	2	2	1	1	0	3	0	0	0	2
BK	2	2	1	0	0	4	2	1	0	2
CF	1	2	1	0	1	4	2	1	0	2
Overall	13	10	5	2	3	20	6	2	0	12
# of Countries	5	3	2	1	2	9	3	1	0	5
C. Monetary Model: k=1										
# of Countries	1	1	1	1	0	1	1	0	1	1
D. PPP Model										
# of Countries	1	1	0	1	0	1	2	2	2	1

Notes: The table reports the number of significant CW statistics (at the 10% significance level or higher) for each specification in Tables 1-4, overall number of significant CW statistics for a given class of models, and the overall number of countries with significant CW statistics for at least one output gap measure in case of the Taylor rule models. In Panels A and B, all the cells except "Overall" and "# of Countries" have 15 possible rejections, the cells in the rows labeled "Overall" have 75 possible rejections, and the cells in the rows labeled "Number of Countries" have 15 possible rejections. In Panels C and D, all the cells have 15 possible rejections.