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Onur Ince
Appalachian State University

Tanya Molodtsova
Emory University

Department of Economics
Appalachian State University
Boone, NC 28608
Phone: (828) 262-6123
Fax: (828) 262-6105
www.business.appstate.edu/economics

Real-Time Out-of-Sample Exchange Rate Predictability†

Onur Ince*

Tanya Molodtsova**

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Abstract

This paper revisits the long-standing Meese and Rogoff puzzle by examining the importance of real-time data for exchange rate forecasting. Most of the existing literature on exchange rate predictability uses recent historical data, which are not available to the public at the time the forecasts are made. This paper evaluates short- and long-horizon out-of-sample exchange rate predictability using Purchasing Power Parity (PPP) and Taylor rule fundamentals for 16 OECD currencies during the post-Bretton Woods era. Comparing the results with real-time and revised data, the evidence of short-run exchange rate predictability with Taylor rule models is stronger with real-time data. The models with Taylor rule fundamentals outperform the naïve no-change model at the 1-quarter horizon for 8 out of 16 currencies vis-à-vis the U.S. dollar with real-time data and for 6 out of 16 currencies with revised data, with the strongest evidence coming from specifications that incorporate heterogeneous coefficients. The evidence of short-run predictability is much stronger with Taylor rule models than with conventional purchasing power parity model regardless of which type of data is used. The out-of-sample performance of both PPP and Taylor rule fundamentals improves at longer horizons, with PPP model performing best in the long run. At the 16-quarter horizon, the models with Taylor rule fundamentals outperform the random walk for 10 out of 16 currencies vis-à-vis the U.S. dollar with either type of data, while the PPP model outperforms the naïve no-change model for 13 out of 16 currencies with real-time data and for 11 out of 16 currencies with revised data.

JEL Classifications: C2, E5, F3

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* Department of Economics, Appalachian State University, Boone, NC 28608. Tel: +1 (828) 262-4033 Email: inceo@appstate.edu

** Department of Economics, Emory University, Atlanta, GA 30322-2240. Tel: +1 (404) 727-8808 Email: tmolodt@emory.edu

1. Introduction

In the past decades, there have been multiple efforts to connect exchange rates with macroeconomic fundamentals in the literature on exchange rate forecasting. Despite numerous attempts, the pessimistic finding of Meese and Rogoff (1983a, 1983b) that standard macroeconomic models of exchange rate determination of the 1970s vintage cannot outperform the naïve "no change" model is still hard to overturn. Mark (1995) has drawn attention back to macroeconomic exchange rate models by finding evidence of exchange rate predictability at long horizons. In a comprehensive study, Cheung, Chinn, and Pascual (2005) examine the out-of-sample performance of the interest rate parity, monetary, productivity-based and behavioral exchange rate models and conclude that none of the models consistently outperforms the random walk at any horizon.

Recent breakthroughs in exchange rate literature emphasize the importance of expectations in determining exchange rates. Engel and West (2005) demonstrate that the present-value exchange rate models put relatively less weight on the current fundamentals and much more weight on their expectations, which implies that current fundamentals might affect exchange rates indirectly through induced changes in expectations about the future fundamentals. If exchange rate changes are driven by expectations, then both correctly modeling monetary policy and using data that accurately reflect market participants' expectations is critical.[1]

Until recently, the role of monetary policy has been overlooked in exchange rate literature. In this paper, we depart from standard monetary models of the 1970s and examine Taylor rule-based exchange rate models with real-time data. The simplest Taylor (1993) rule states that the central bank sets the short-run nominal interest rate in response to changes in inflation and output gap. Engel and West (2006) demonstrate that the Taylor rule and uncovered interest rate parity (UIRP) condition imply that there is a relation between real exchange rate and Taylor rule fundamentals. The authors provide empirical support for this model using DM/dollar rate over the 1979-1998 period. Mark (2009) considers a similar model, but allows for monetary policy inertia, and adaptive learning behavior of the market participants. Molodtsova and Papell (2009) examine the out-of-sample predictability of nominal exchange rate changes using Taylor rule fundamentals, including output gaps and inflation, for 12 countries from 1973 to 2006. While real-time data were not available during the post-Bretton Woods period for most of the countries, they find strong evidence of short-run predictability with quasi-revised data.[2] Engel, Mark, and West (2007) use a more constrained version of the Molodtsova and Papell (2009) specification and find less evidence of short-horizon predictability, but more evidence of long-horizon predictability than Molodtsova and Papell. Using a Taylor rule with pre-specified coefficients for the inflation differential,

[1] Both of these concerns are addressed in Engel, Mark, and West (2007).

[2] With "quasi-revised" data, output gaps are calculated based on revised data that are updated each period so as not to use ex post data.

output gap differential, and real exchange rate, they construct the interest rate differential implied by the policy rule and use the resultant differential for exchange rate forecasting. We use a single equation version of their model, which we call the Taylor rule differentials model. Wang and Wu (2012) estimate forecast intervals using Taylor rule-based exchange rate models for 9 OECD countries. Using revised data, they find evidence of superior out-of sample performance of the Taylor rule models, especially at long horizons.

Although expectations, the key driving force in exchange rate behavior, are formed in real time, the vast majority of existent studies on exchange rate predictability have used ex post revised data to evaluate the out-of-sample performance of empirical exchange rate models. The use of fully revised data could lead to misleading inference by not accurately reflecting the information that was available to the market participants at each point in time. As emphasized in Rossi (2006), relying on ex post data to forecast economic variables that are driven by persistent shocks might result in poor measures of agents' probability distributions. This problem is exacerbated when the variable is subject to long lasting regime shifts, which might be caused for example by monetary policy shifts.

The choice between first-release real-time data, which contain only new information about macroeconomic fundamentals, and revised data, which consists of the information in the latest available quarter, has not been extensively studied in the context of exchange rate predictability. In a triangular format of a real-time dataset, where each row corresponds to a calendar date and each column corresponds to a vintage date, first-release real-time data is constructed from the diagonal elements of a real-time data matrix and contains only the latest available observations at each period.[3] This type of data might be potentially useful for explaining how the public reacts to news about macroeconomic fundamentals.[4]

The limited availability of real-time data for countries other than the U.S. has prevented researchers from using real-time data to evaluate exchange rate models over the post Bretton-Woods period. Those few studies that do use real-time data to study exchange rate predictability suffer from one of the following problems, or both. First, the results are often based on relatively short samples and/or small subsets of currencies. Second, the comparisons of the results with real-time and revised data are rarely provided.

The first group of studies, originated by Faust, Rogers, and Wright (2005), evaluate out-of-sample predictability of various exchange rate models with real-time and revised data for a limited set of

[3] Following Croushore (2006) among others, the term "vintage" refers to a date in which a time series of data becomes known to the public. Corradi, Fernandez and Swanson (2009) use the term vintage to denote data that have passed through the same number of revisions.
[4] The alternative to using the first-release real-time data is real-time-vintage data that uses all the information in each vintage, so that the data is fully updated each period. The advantage of this type of data is that it is not subject to the "definitional change" problem, because data from only one vintage is used for estimation. Due to the varying number of lags over time and across variables, we do not use real-time data vintage data in this paper.

currencies. Faust, Rogers, and Wright (2005) examine the predictive ability of the monetary model using real-time data for Japan, Germany, Switzerland and Canada vis-à-vis the U.S. dollar and conclude that, while the models consistently perform better with real-time data than fully revised data, they do not perform better than the random walk model. Nikoslko-Rzhevskyy, Molodtsova, and Papell (2008) study U.S. dollar/ Deutschemark nominal exchange rate predictability using Taylor rule-based model and find strong evidence of exchange rate predictability at the one-quarter horizon using real-time, but not revised data. Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012) examine the out-of-sample performance of purchasing power parity (PPP), monetary, and Taylor rule models for Canada, Japan, and the U.K. vis-à-vis the U.S. dollar with revised and real-time data and find that the Taylor rule models work relatively better than the PPP and monetary models.

The second group of studies that use real-time data to evaluate exchange rate forecasts do not compare the results with real-time and revised data. Ince (2012), constructing a real-time dataset for 10 OECD countries, examines real-time predictive ability of the Taylor rule and PPP models in Engel, Mark, and West (2007) within a panel framework and concludes that while PPP model forecasts exchange rates better at long horizons, the forecasting ability of Taylor rule fundamentals is higher at short horizons and disappears completely in the long run. Although Taylor rule model performs better in the short-run, using panel methodology does not improve the forecasting ability of Taylor rule fundamentals. Similarly, Molodtsova, Nikolsko-Rzhevskyy, and Papell (2011), use real-time data to show that inflation and either the output gap or unemployment, variables which normally enter central banks' Taylor rules, can provide evidence of out-of-sample predictability for the U.S. Dollar/Euro exchange rate from 1999 to 2007.

The objective of this paper is to evaluate out-of-sample exchange rate predictability for PPP and Taylor rule fundamentals with real-time and revised data for 16 OECD countries over the post-Bretton Woods period from 1973:Q3 to 2012:Q3. The availability of a comprehensive real-time dataset provides an opportunity to examine how the two types of data perform out-of-sample. In order to examine the implications of using real-time data for exchange rate predictability, we ask the following three questions: (1) How does the out-of-sample performance of the PPP and Taylor rule models differ with real-time and revised data? (2) How is model selection affected by the use of real-time or revised data? (3) Does the out-of-sample performance of the models improve at long horizons with both types of data? Since data revisions change the data that are used to estimate the models, the choice of data can affect the estimated coefficients and alter model selection.[5]

The real-time data that is used in this paper is taken from OECD Original Release and Revisions Database after 1999:Q1 and from the Real-Time Historical Database for the OECD prior to 1999. Starting

[5] Stark and Croushore (2002) demonstrate how each of these mechanisms works in practice.

in 1973:Q3, we estimate the models using a rolling window of 8 years (32 quarters), so that the first one-quarter-ahead forecast is made for 1981:Q3 and the last for 2012:Q3 for non-EMU countries and for 1998:Q4 for EMU countries, generating a total of 125 and 70 forecasts, respectively. In order to construct Taylor rule fundamentals, we need to define the output gap, and we use deviations from linear trend, quadratic trend, Hodrick-Prescott (1997) filter, and Baxter-King (1999) filter.[6]

We evaluate the out-sample predictive ability of models with Taylor rule differentials in Engel, Mark and West (2007) and Ince (2012) and with Taylor rule fundamentals in Molodtsova and Papell (2009) against the driftless random using the Clark and West (2006) statistics with standard normal critical values. Combining all the specifications of Taylor rule models, we find evidence of exchange rate predictability at the 1-quarter horizon for 8 out of 16 exchange rates with real-time data, and 6 out of 16 countries with revised data. Comparing the out-of sample performance of different Taylor rule models, the models that allow for heterogeneity in inflation and output gap coefficients perform the best at the 1-quarter horizon with both types of data. The evidence of exchange rate predictability is much weaker with the PPP fundamentals model, which outperforms the random walk only for 1 country out of 16 at the 1-quarter horizon regardless of whether real-time or revise data is used.

Following Mark (1995), it has become standard practice to investigate long horizon out-of-sample exchange rate predictability. While Engel, Mark, and West (2007) find more evidence of predictability at long horizon than at short horizon using both PPP and Taylor rule models with revised data, Ince (2012) does not find that extending the forecast horizon helps to improve the predictability of Taylor rule specifications in Engel, Mark and West (2007) with real-time data, while increasing the evidence of predictability with PPP fundamentals, and Molodtsova and Papell (2009) find that the evidence of predictability disappears at longer than 3-month horizon with revised data.

We investigate long horizon out-of-sample predictability by estimating 16-quarter-ahead exchange rate forecasting regressions.[7] First, the evidence of long-run exchange rate predictability is strongest with PPP and heterogeneous Taylor rule fundamentals models using both types of data. Second, the advantage of using real-time rather than revised data virtually disappears at long horizons for Taylor rule models and remains for PPP model. Combining all the specifications of Taylor rule models, we find evidence of exchange rate predictability at the 16-quarter horizon for 10 out of 16 exchange rates with either type of data. Comparing the out-of sample performance of different Taylor rule specifications, the models that allow for heterogeneity in inflation and output gap coefficients perform the best at the 16-quarter horizon with both types of data. The evidence of exchange rate predictability is stronger with the PPP fundamentals model than with Taylor rule model. The PPP model outperforms the driftless random

[6] We follow Ince and Papell (2012) in selecting these four measures of the output gap.
[7] The same forecast horizon is used in Engel, Mark, and West (2007) and Ince (2012).

walk at the 16-quarter horizon for 13 out of 16 exchange rates with real-time data, and 11 out of 16 countries with revised data.

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 its fundamental value. Thus, the h-period-ahead change in the log exchange rate can be modeled using the following regression

$$s_{t+h} - s_t = \alpha_h + \beta_h z_t + \nu_{t+h,t}, \tag{1}$$

where $z_t = f_t - s_t$

and f_t is the long-run equilibrium level of the nominal exchange rate determined by macroeconomic fundamentals. The variable 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.

2.1 PPP Fundamentals

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. Unfortunately, we cannot evaluate the monetary models due the poor quality of real-time data for money supply. 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. Engel, Mark, and West (2007) and Ince (2012) have evaluated the model with PPP fundamentals with revised and real-time data, respectively, and found that the evidence of predictability is much weaker with PPP fundamentals than with Taylor rule fundamentals at the 1-quarter horizon. The performance of the PPP model improves at longer horizons.

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,

$$f_t = (p_t - p_t^*) \tag{2}$$

where p_t is the log of the national price level. We substitute the PPP fundamentals (2) into equation (1), and use the resultant equation for forecasting.

2.2 Taylor Rule Differentials

We also consider exchange rate models that explicitly link the exchange rates and a set of macroeconomic variables that arise when central banks follows the interest rate setting rule, such as the Taylor rule. According to the simplest Taylor (1993) formulation, the monetary policy rule that central banks follow can be specified as,

$$i_t = \pi_t + \phi(\pi_t - \bar{\pi}) + \gamma y_t + \bar{r} \ , \tag{3}$$

where i_t is the target level of the short-term nominal interest rate, π_t is the inflation rate, $\bar{\pi}$ is the target level of inflation, y_t is the output gap, the percent deviation of actual industrial production from an estimate of its potential level, and $\bar{r}$ is the equilibrium level of the real interest rate.[8]

According to the Taylor rule, the central bank raises the target for the short-term nominal interest rate if inflation rises above its desired level and/or output is above potential output. The target level of the output deviation from its natural rate y_t is 0 because, according to the natural rate hypothesis, output cannot permanently exceed potential output. The target level of inflation is positive because it is generally believed that deflation is much worse for an economy than low inflation. The parameters $\bar{\pi}$ and $\bar{r}$ in equation (3) can be combined into a constant term, $\mu = \bar{r} - \phi\bar{\pi}$, which results in the following equation,

$$i_t = \mu + \lambda\pi_t + \gamma y_t \tag{4}$$

where $\lambda = 1 + \phi$. Because $\lambda > 1$, the real interest rate is increased when inflation rises, and so the Taylor principle is satisfied.

Following Clarida, Gali, and Gertler (1998), lagged interest rates are usually included in estimated Taylor rules to account for partial adjustment of the federal funds rate to the rate desired by the Federal Reserve. Since allowing for smoothing does not help in exchange rate forecasting, we do not include lagged interest rates.

Engel, Mark, and West (2007) estimate a Taylor rule based model, which we call the Taylor rule differentials model to differentiate it from the Taylor rule fundamentals model. They posit the coefficients for the Taylor rule and subtract the interest rate reaction function for the foreign country from that for the U.S. to obtain implied interest rate differentials,

$$i_t - i_t^* = 1.5(\pi_t - \pi_t^*) + 0.5(y_t - y_t^*) + 0.1(s_t + p_t^* - p_t) \tag{5}$$

where the constant is equal to zero assuming that the inflation target and equilibrium real interest rate are the same for the U.S. and the foreign country.

The implied interest rate differential can be used to construct an exchange rate forecasting equation,

$$s_{t+h} - s_t = \alpha_h + \beta_h \left(1.5(\pi_t - \pi_t^*) + 0.5(y_t - y_t^*) + 0.1(s_t + p_t^* - p_t)\right) + \nu_{t+h,t} \tag{6}$$

We estimate a variant of the Taylor rule differentials model in equation (6) with four measures of the output gap, linear, quadratic, Hodrick-Prescott, and Baxter-King output gaps. We use two types of the Taylor rule differentials. The *symmetric* Taylor rule differentials use Taylor's original coefficients on the

[8] While we do not explicitly incorporate time-varying inflation and/or equilibrium real interest rates, the use of rolling regressions allows for changes in the constant.

inflation and output gap differentials and do not include the real exchange rate.[9] The *asymmetric* Taylor rule differentials add the real exchange rate.

2.3 Taylor Rule Fundamentals

The models with Taylor rule fundamentals are constructed 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.,

$$i_t - i_t^* = \alpha + \lambda(\pi_t - \pi_t^*) + \gamma(y_t - y_t^*) + \eta_t \tag{7}$$

where asterisks denote foreign country variables and α is a constant. It is assumed that the coefficients on inflation and the output gap are the same for the U.S. and the foreign country, but the inflation targets and equilibrium real interest rates are allowed to differ.

We estimate the following exchange rate forecasting equation without making any assumptions about the sign and/or the magnitude of the coefficients,[10]

$$s_{t+h} - s_t = \omega + \omega_\pi(\pi_t - \pi_t^*) + \omega_y(y_t - y_t^*) + \nu_{t+h,t} \tag{8}$$

where asterisks denote foreign variables. We call this specification the Taylor rule fundamentals model with *homogenous* coefficients. The assumption of equal coefficients is not necessary to produce a forecasting equation, and we relax this assumption in a specification with heterogeneous coefficients. Alternatively, equation (8) is estimated with four right-hand side variables, thus relaxing the assumption that the coefficients on inflation and the output gap are the same for the U.S. and the foreign country. Since we do not know by how much a change in the interest rate differential (actual or forecasted) will cause the exchange rate to adjust, we do not have a link between the magnitudes of the coefficients in equations (7) and (8).

3. Data

We use quarterly real-time data from 1973:Q3 to 1998:Q4 for 9 European Monetary Union (EMU) countries (Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Portugal, and Spain) and from 1973:Q3 to 2012:Q3 for 7 non-European Monetary Union countries (Australia, Canada, Japan, Norway, Sweden, Switzerland, and the United Kingdom) vis-à-vis the United States. The real-time data

[9] Instead of using the coefficient on the output gap of 0.5, Engel, Mark, and West (2007) use the coefficient of 0.1. This change does not affect our result.

[10] We do not try to determine the signs or the magnitudes of the coefficients in equation (8). This question is addressed in empirical research on the forward premium and delayed overshooting puzzles by Eichenbaum and Evans (1995), Faust and Rogers (2003) and Scholl and Uhlig (2008), and the results in Gourinchas and Tornell (2004) and Bacchetta and van Wincoop (2010), who show that an increase in the interest rate can cause sustained exchange rate appreciation if investors either systematically underestimate the persistence of interest rate shocks or make infrequent portfolio decisions. A more extensive discussion of the link between higher inflation and forecasted exchange rate appreciation can be found in Molodtsova and Papell (2009).

comes from two sources: the OECD Original Release and Revisions Database after 1999:Q1 and the Real-Time Historical Database for the OECD prior to 1999.[11] The former database provides time series data for 21 key economic variables originally published in each monthly edition of the Main Economic Indicators from February 1999. The Real-Time Historical Database for the OECD is compiled by Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012). It contains the data 13 real-time variables for 26 OECD countries from 1962:Q2 to 1998:Q4, which can be directly merged with publicly available data from OECD Original Release and Revisions Database. The choice of 16 countries that are considered in this paper is determined by the quality of real-time data.

The dataset has a standard triangular format with the vintage date on the horizontal axis and calendar dates on the vertical. The real-time data is constructed from the diagonal elements of real-time data matrix and do not incorporate historical revisions, containing only the latest available observation in each period. This type of data is also called “first-release data” and it has a potential to explain how the public reacts to news about macroeconomic fundamentals. For each country and variable this data represents a vector of quarterly observations from 1973:Q3 to either 1998:Q4 or 2012:Q3, thus resulting in 102 observations for EMU countries and 157 observations for non-EMU countries. Molodtsova, Nikolsko-Rzhevskyy and Papell (2008) use first release real-time data to evaluate the U.S. dollar/Deutschemark nominal exchange rate predictability with Taylor rule fundamentals and find strong evidence of predictability at the one-quarter horizon during the 1979-1998 period. This type of data is also used in Ince (2012).

For each forecasting regression, we use 32 quarters to estimate the relationship between the fundamentals and the change in the exchange rate, and then use the estimated coefficients to forecast the exchange rate one- or sixteen-quarter ahead. We use rolling regressions with 32-quarter window to predict 70 exchange rate changes from 1981:Q3 to 1998:Q4 for European countries and 125 exchange rate changes from 1981:Q3 to 2012:Q3 for non-European countries. Since we use first-release data, the both the estimated coefficients and the forecasts are obtained using real-time data.[12]

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 4 quarters. The index of industrial production is used to measure the level of output. The output gap depends on the measure of potential output. Since there is no presumption about which definition of potential output is used by central banks or by the public, we consider percentage deviations of actual output from a linear time

[11] 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 is available at http://www.dallasfed.org/institute/oecd/index.cfm.

[12] An alternative method of constructing real-time data is to use real-time vintage data that includes all information available in point in time and, thus, incorporates revisions. With that method, the estimated coefficients would use partially revised data. Since the data is released with varying number of lags, we do not use real-time data vintage for comparison.

trend, a quadratic time trend, a Hodrick-Prescott (1997) (HP) trend, and a Baxter-King (BK) trend as alternative definitions.[13] 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, Ireland, and Spain. The industrial production data starts in 1970:Q4 for Australia, in 1960:Q1 for Japan and Switzerland, in 1966:Q1 for Ireland, and in 1965:Q1 for Spain. To mitigate the end-of-sample uncertainty problem, which is present while estimating HP and BK filters and exacerbated with real-time data, we use Watson's (2007) correction method and forecast the industrial production series 12 quarters ahead using an AR (8) model before calculating the trend.[14]

The nominal exchange rate, defined as the U.S. dollar price of a unit of foreign currency, is taken from the PACIFIC Exchange Rate Service website. We use point in time, rather than quarterly averaged, exchange rates to avoid inducing serial correlation in exchange rate changes. This, however, does not specify which point in time exchange rate should be used. Because of lags in data collection, real-time data for period *t* actually represents data through period *t-1*. While the variables are released at different times, all of the data that we use is released in the second month in the quarter (February, May, August, and November). For the purpose of evaluating forecasts that are made in real-time, we want to minimize the time between the release of the data and the start of the forecast (or else market participants will have time to incorporate information before the forecasts are made). Therefore, we use the end-of-the-second-month exchange rate.

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 zero mean martingale difference process, while the alternative is a linear model with PPP or Taylor rule fundamentals. For h-step ahead change in the log exchange rate, the null and the alternative models can be written as,

Model 1: $s_{t+h} - s_t = \varepsilon_t$

Model 2: $s_{t+h} - s_t = X_t^{'}\beta + \varepsilon_t$, where $E_{t-h}(\varepsilon_t) = 0$

We want to test the null hypothesis that the MSPEs are equal against the alternative that the MSPE of the linear Model 2 is smaller than the MSPE of the driftless random walk Model 1. Under the null, the population MSPEs are equal. We need to use the sample estimates of the population MSPEs to draw the inference. The procedure introduced by Diebold and Mariano (1995) and West (1996) uses sample MSPEs to construct a t-type statistics, which is assumed to be asymptotically normal.

[13] We use a smoothing parameter equal to 1600 to detrend quarterly output series using the HP filter.
[14] While Watson (2007) suggests to backcast the series, the series in each data vintage extends through 1956:Q1, which is long enough to remove the distortions in the beginning of the sample.

While the asymptotic DMW test works fine with non-nested models, the size properties of the asymptotic DMW test have been widely criticized for 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 normal. Severely undersized DMW tests cause far too few rejections of the null when the models are nested and may miss the statistical significance of the linear exchange rate model against the random walk.

Clark and West (2006) propose to adjust the DMW statistic, in order to correct for the size distortions with nested models under the null. 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.[15] Clark and West (2007) show that, while the CW statistic is asymptotically normal if the parsimonious model is a random walk, it is not asymptotically normal in general. Even in the latter case, they advocate use of the CW statistic based on simulations which show that, for sufficiently large samples, standard normal critical values will provide actual sizes close to the nominal size.

We report the CW statistic, which has become standard in the literature on exchange rate predictability. Rejecting the random walk null in favor of the linear model alternative based on the CW statistic provides evidence of predictability for the model. As recommended in Clark and West (2006), the inference for long-horizon tests is done using West (1997) and Hodrick (1992) standard errors that take into account the overlapping nature of the data.

5. Empirical Results

We use real-time quarterly data from 1973:Q3 through 1998:Q4 for 9 European Monetary Union (EMU) countries (Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Portugal, and Spain) and from 1973:Q3 through 2012:Q3 for 7 non-European Monetary Union countries (Australia, Canada, Japan, Norway, Sweden, Switzerland, and the United Kingdom) vis-à-vis the United States. We evaluate out-of-sample exchange rate forecasting with PPP fundamentals, Taylor rule differentials, and Taylor rule fundamentals during the post-Bretton Woods period. The out-of-sample performance of PPP and Taylor rule specifications with real-time data is compared to the out-of-sample performance with fully revised data. As discussed in Section 4, we conduct one-quarter-ahead and sixteen-quarter-ahead exchange rate forecasts.

We use the Clark and West (CW) (2006) test for equal predictive ability. The statistics are constructed using rolling regressions with real time and revised data. We use quarterly data over the period 1973:Q3 – 1981:Q3 for estimation and reserve the remaining data for out-of-sample forecasting. To evaluate the out-of-sample performance of the models, we estimate them by OLS in rolling

[15] An alternative is to use the DMW statistic with bootstrapped critical values.

regressions and construct CW statistics. Each model is initially estimated using the first 32 quarters of data and the one- or sixteen-quarter-ahead forecasts are generated. Then the first data point is dropped, an additional data point is added at the end of the sample, and the model is re-estimated. A one- or sixteen-quarter-ahead forecast is generated at each step.

To illustrate the differences between real-time and revised variables, we examine real-time and revised inflation and HP output gaps by looking at the graphs of both series all the countries in the sample and the U.S. Figure 1 compares real-time inflation and HP output gaps with those available in 2012:Q3. Looking at the graphs, two observations are apparent. First, the differences between the two series vary in their magnitudes for different countries. Second, the differences between real-time and revised output gaps are substantially larger than those between real-time and revised inflation for all countries.[16]

The left-hand side of Table 1 illustrates these points in a more formal way by providing summary statistics for real-time and revised inflation, and linear, quadratic, HP, and BK output gaps. While, the average real-time and revised inflation rates are very close, the differences between the average real-time and revised output gaps are much more pronounced. Among the non-EMU countries, the largest difference between real-time and revised inflation rate of 0.34 percentage points is found for the U.K. and the smallest for Switzerland. Among the EMU countries, Portuguese real-time and revised inflation rate differ most, by 0.39 percentage points. Looking at the HP output gap as a representative measure of the output gap, the difference between the average real-time and revised output gap varies from 0.16 percentage points for Australia to 2.41 percentage points for Italy. These differences suggest that exchange rate forecasts based on real-time and revised data may differ substantially with most of the differences coming from the revisions in output gaps.

5.1 News versus Noise

The nature of data revisions can have important implications for exchange rate forecasting. Previous research on real-time data analysis has suggested that statistical agencies can revise data to either add news or reduce noise. If data revisions contain news, then initially released data represent optimal forecasts of the final realized values. Therefore, data revisions are orthogonal to initially released real-time data and reflect rational forecast errors. Alternatively, if data revisions reduce noise, data revisions represent measurement errors that are correlated with initially released data. In practice, revisions might combine properties of both “news” and “noise”.

The right-hand side of Table 1 reports the descriptive statistics on data revisions, defined as the difference between revised and real-time series. A positive value for the mean of the revision indicates that the variable was on average revised upwards, so that the arrival of new information or the correction

[16] These results are consistent with the findings in Orphanides (2003) for the U.S., Gerberding, Worms and Seitz (2005) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) for Germany, and in Ince (2012) for a set of 9 OECD countries.

of measurement errors (or both) made the statistical agency realize that the inflation rate and/or the output gap was higher than perceived in real-time. The mean revision for inflation is negative for 9 out of 16 countries in the sample. Based on the HP-filtered measure of the output gap, the output gap is on average revised upwards for all countries except Australia and Ireland.

Multiple studies have examined whether revisions of macroeconomic variables add news or reduce noise. Croushore (2009) summarizes this literature. Looking at the U.S. real-time data, Mankiw and Shapiro (1996) find that revisions to U.S. GDP add news. Orphanides (2001) finds that the data revisions for the U.S. inflation and output gap during the 5-year period between 1987 and 1992 represent mostly noise. Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) find that the revisions in U.S. inflation and output gap are mostly driven by noise. For Germany, they find that news dominate noise for both inflation and output gap measures.

To explore the nature of data revisions in our sample, we follow the methodology in Mankiw and Shapiro (1986). If the data revisions reduce noise, they should be uncorrelated with the revised data but correlated with the real-time series. The opposite should be true if the data revisions add news. The right-hand side of Table 1 shows the correlations between data revisions, defined as $X_{revised}$-$X_{real\text{-}time,}$ and the real-time and revised series for 16 countries and the U.S. The correlations in Table 1 indicate that the revisions in inflation represent mostly news for all countries, except Austria, Ireland, and Netherlands. The revisions in HP output gap display a similar pattern for all countries except Australia. While news dominates noise in revisions HP and BK output gaps for all countries, the revisions to linear and/or quadratic output gaps are dominated by noise for Australia, Canada, Sweden, Switzerland, U.K, Portugal, and Spain. The revisions to log price level are dominated by noise for all countries except Sweden, Belgium, France, and Germany. Revisions to real exchange rates, which are constructed based on the U.S. and foreign price levels and nominal exchange rate, mostly reduce noise for 7 out of 15 countries.

5.2 Out-of-Sample Predictability with PPP Fundamentals

Table 2 reports the CW statistics for the tests for equal predictive ability between the null of a martingale difference process and the alternative of a linear model with PPP fundamentals described in Section 2.1. The null and the alternative models are estimated at the 1-quarter and 16-quarter horizons with real-time and revised data. At the 1-quarter ahead horizon, the PPP model significantly outperforms the random walk only for 1 out 16 countries (Portugal at the 5% significance level) with real-time and revised data.

The evidence of predictability is much stronger with both types of data at the 16-quarter horizon. With real-time data, the model significantly outperforms the random walk for 13 out of 16 countries (Australia, Japan, U.K, and Portugal at the 1% significance level, Canada and Sweden at the 5% significance level, and Norway, Switzerland, Austria, Belgium, France, Netherlands, and Spain at the 10% significance level). With revised data, the model significantly outperforms the random walk for 11 out of 16 countries (Australia, Canada, Japan, U.K, and Portugal at the 1% significance level, Sweden at the 5% significance level, and Norway, Austria, Belgium, Netherlands, and Spain at the 10% significance level). Thus, the evidence of predictability is stronger with real-time data than with revised data. The only case where more evidence of predictability is found with revised data than with real-time data is Canada, for which the CW statistics improves from being significant at the 5% level to being significant at the 1% level. This should warn researchers who use revised data against finding misleading evidence of exchange rate predictability.

Overall, these results are in accord with the results in Engel Mark, and West (2007) and Ince (2012), who also find more evidence of exchange rate predictability with PPP fundamentals at long horizon than at short horizon.

5.3 Out-of-Sample Predictability with Taylor Rule Differentials

5.3.1 Short-Horizon Results

Following Engel, Mark, and West (2007), we evaluate out-of-sample exchange rate predictability with the Taylor rule differentials model described in Section 2.2 and the two types of data. Table 3 presents one-quarter-ahead out-of-sample forecasts with Taylor rule differentials model. Panels A and B of Table 3 report the results for symmetric and asymmetric specifications that either exclude or include real exchange rate. Following Clarida, Gali, and Gertler (1998), it has become standard in literature of monetary policy rules to posit that the foreign country central bank includes the difference between the exchange rate and the target exchange rate, defined by PPP, in its Taylor rule. Although asymmetric Taylor rule specifications have demonstrated limited success in exchange rate forecasting, we consider this specification for consistency with previous literature.

Two observations are apparent from the results. First, the performance of Taylor rule differentials models with real-time and revised data is very similar. Combining symmetric and asymmetric Taylor differentials specifications with four measures of output gap, the models significantly outperform the random walk for 4 out of 16 countries with either real-time data or revised data. Overall, the model significantly outperforms the random walk at 1-quarter horizon in 27 out of 128 cases with real-time data and in 24 out of 128 cases with revised data. Two observations are apparent from the results.

Second, including real-exchange rate in the model does not improve the out-of sample performance of the model. Symmetric Taylor rule differentials model significantly outperforms the random walk in 13 out of 64 cases with real-time data and 12 out of 64 cases with revised data. Asymmetric Taylor rule differentials model significantly outperforms the random walk in 14 out of 64 cases with real-time data and 12 out of 64 cases with revised data. Both symmetric and asymmetric models outperform the random walk with at least one of the four output gap specifications for 4 out of 16 countries with either real-time data or revised data.

These findings suggest that the choice between real-time and revised data is not crucial for evaluating exchange rate forecasts with Taylor rule differentials model. Although the total number of cases when the random walk null is rejected is slightly higher with real-time data, the total number of currencies for which 1-quarter ahead exchange rate predictability is found does not depend on the data choice. As in Molodtsova and Papell (2009) and Molodtsova, Nikolsko-Rzhevskyy and Papell (2011), the asymmetric model does not help to improve the predictive ability of the symmetric model. As we relax the assumption of imposed coefficients on inflation and output gap differentials in the next section, we consider only the symmetric specification of the Taylor rule model.

5.3.2 Long-Horizon Results

Following Mark (1995), it has become standard practice to investigate long horizon out-of-sample exchange rate predictability. The implications of using real-time data to evaluate exchange rate predictability can potentially differ at short and long horizon. If exchange rates are determined mostly by expected changes in fundamentals, using the data that were available to market participants is crucial for understanding how short- and long-run expectations are formed. Thus, real-time data are potentially important because they shape not only public estimates of current conditions, but also help to form short-term and long-term expectations of future economic conditions.

While Engel, Mark, and West (2007) find more evidence of predictability at long horizon than at short horizon using Taylor rule differentials models with revised data, Molodtsova and Papell (2009) with revised data and Ince (2012) with real-time data do not find that extending forecast horizon helps to improve predictability of the Taylor rule models. We investigate long horizon out-of-sample predictability by estimating 16-quarter-ahead exchange rate forecasting regressions. This horizon is chosen to match the forecast horizon in Engel, Mark, and West (2007) and Ince (2012).

Table 4 presents sixteen-quarter-ahead out-of-sample forecasts with symmetric and asymmetric Taylor rule differentials model similar to the models considered in Engel, Mark, and West (2007) and Ince (2012). The out-of-sample performance of the models does not improve with the forecast horizon. Combining symmetric and asymmetric Taylor differentials specifications with four measures of output gap, the models still significantly outperform the random walk for 4 out of 16 countries with either real-time data or revised data. Overall, the total number of rejections of the random walk null at 16-quarter horizon drops to 22 out of 128 cases with real-time data and 21 out of 128 cases with revised data.

The overall pattern is the same as with short-horizon results. Including real-exchange rate in the model does not improve the out-of sample performance of the model. Symmetric Taylor rule differentials model significantly outperforms the random walk in 11 out of 64 cases with real-time data and 10 out of 64 cases with revised data. Asymmetric Taylor rule differentials model significantly outperforms the random walk in 11 out of 64 cases with either type of data. Both symmetric and asymmetric models outperform the random walk with at least one of the four output gap specifications for 4 out of 16 countries with either real-time data or revised data.

The only country, for which evidence of predictability (at the 10% significance level) is found with revised data, but not with real-time data, is Canada. This should warn researchers against the possibility of finding misleading evidence of exchange rate predictability at long horizons when revised data is used.

5.4 Out-of-Sample Predictability with Taylor Rule Fundamentals

5.4.1 Short-Horizon Results

Relaxing the assumption about imposed coefficients in the Taylor rule differentials model, we evaluate the out-of-sample predictability with Taylor rule fundamentals models described in Section 2.3. Since the inclusion of the real exchange rate does not improve the out-of-sample performance of the Taylor rule differentials model, we do not include the results with asymmetric Taylor rule models in this section. Table 5 presents one-quarter-ahead out-of-sample forecasts with Taylor rule fundamentals model. Without imposing specific values of the Taylor rule coefficients, Panels A and B report the results for Taylor rule fundamentals model that either restrict the coefficients on U.S. and foreign inflation and output gap to be the same (Panel A) or allow them to vary (Panel B). Two overall results are apparent. First, combining the results with real-time and revised data and with four measures of the output gap, the Taylor rule fundamentals model with heterogeneous coefficients provide stronger evidence of exchange rate predictability than the Taylor rule fundamentals model with homogeneous coefficients in six of the eight cases. Second, combining the results with homogenous and heterogeneous coefficients and with four measures of the output gap, the results with real-time data provide stronger evidence of exchange rate predictability than with revised data in five of the eight cases.

Combining Taylor rule fundamentals specifications with homogenous and heterogeneous coefficients and four measures of output gap, the models significantly outperform the random walk for 8 out of 16 countries with real-time data and for 6 out of 16 countries with revised data. Overall, the model significantly outperforms the random walk at 1-quarter horizon in 32 out of 128 cases with real-time data and in 24 out of 128 cases with revised data.

As in Molodtsova and Papell (2009), the model with heterogeneous coefficients performs the best out-of-sample. Taylor rule fundamentals model with homogenous coefficients significantly outperforms the random walk in 12 out of 64 cases with real-time data and 11 out of 64 cases with revised data. Taylor rule fundamentals model with heterogeneous coefficients significantly outperforms the random walk in 20 out of 64 cases with real-time data and 13 out of 64 cases with revised data. The model that restricts the coefficients on U.S. and foreign inflation and output gap to be the same outperforms the random walk with at least one of the four output gap specifications for 5 out of 16 countries with real-time data and 4 out of 16 countries with revised data. The model that allows the coefficients on U.S. and foreign Taylor rule variables to be vary outperforms the random walk with at least one of the four output gap specifications for 8 out of 16 countries with real-time data and 5 out of 16 countries with revised data.

Comparing these findings to the results in the previous section, it becomes apparent that the implications of using real-time data for evaluating exchange rate forecasts can vary substantially across specifications of the Taylor rule model. Both the total number of rejections of the random walk null and total number of countries for which 1-quarter ahead exchange rate predictability is found with at least one measure of the output gap are higher with real-time data than with revised data, with the largest difference for the best performing model with heterogeneous coefficients. The model with Taylor rule fundamentals and heterogeneous coefficients is found to perform the best out-of-sample in Molodtsova and Papell (2009) with revised data and Molodtsova, Nikolsko-Rzhevskyy and Papell (2011) with real-time data for the Euro/dollar exchange rate.

The differences in the out-of-sample performance of the model with real-time and revised data reflect the differences in the decision-making process of the forecasters. First-release real-time data represents market's reaction to news about macroeconomic fundamentals and helps in forming market expectations that are reflected in improved exchange rate forecasts, while revised data uses information that arrived after the forecasts were made and, therefore, does not mimic the information set that forecasters face. Focusing on the left-hand-side variable which is revised, Corradi, Fernandez, and Swanson (2007) find that first-release data are generally best predicted by first-releases. We find that first-release real-time data produces better short-horizon exchange rate forecasts than revised data even despite the end-of-sample uncertainty problem described above, which is likely to be more pronounced with first-release real-time data.

5.4.2 Long-Horizon Results

Table 6 presents sixteen-quarter-ahead out-of-sample forecasts with Taylor rule fundamentals model with homogenous and heterogenous coefficients. In contrast to the results with Taylor rule differentials models, the out-of-sample performance of the both models improve at longer horizon. Combining Taylor fundamentals specifications with homogenous and heterogeneous coefficient and with four measures of output gap, the models significantly outperform the random walk for 10 out of 16 countries with either real-time data or revised data. Overall, the total number of rejections of the random walk null at 16-quarter horizon increases to 54 out of 128 cases with real-time data and 53 out of 128 cases with revised data.

Relaxing the assumption about homogenous coefficients on U.S. and foreign inflation and output gap improve the out-of sample performance of the model. Taylor rule fundamentals model with homogenous coefficients significantly outperforms the random walk in 25 out of 64 cases with real-time data and 23 out of 64 cases with revised data, which more the doubles the number of rejections at the 1-quarter horizon. Taylor rule fundamentals model with heterogeneous coefficients significantly outperforms the random walk in 29 out of 64 cases with real-time data and 30 out of 64 cases with revised data. The model with homogenous coefficients outperforms the random walk with at least one of the four output gap specifications for 8 out of 16 countries with real-time data and for 7 out of 16 countries with revised data. The model with heterogeneous coefficients outperforms the random walk with at least one of the four output gap specifications for 9 out of 16 countries with either real-time data or revised data.

Although the overall pattern of the results is the same as with one-quarter ahead forecasts, as the performance of both Taylor rule fundamentals models improve at the sixteen-quarter horizon, the relative advantage of using real-time data over using revised data becomes less pronounced. This occurs because the increases in predictability are relatively stronger for the models estimated using revised data than real-time data. In addition to that, there are two countries, Canada and the U.K., for which evidence of predictability is found with revised data, but not with real-time data. This supports our initial result with PPP and Taylor rule differentials model that using revised data can lead to finding spurious evidence of exchange rate predictability at long horizon. Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012) find similar result with Taylor rule fundamentals model for the U.K. at the one quarter ahead horizon.

5.5 Summary of the Results

We have evaluated the out-of-sample performance of 1088 models, which include the models for 16 currencies with PPP model and 4 Taylor rule models that are estimated with 4 measures of output gap and 2 types of data at 2 forecast horizons. In order to summarize the results, Table 8 reports the number of significant CW statistics for each type of models. The table reports the number of significant CW statistics (at the 10% significance level or higher) for each specification in Tables 3-7, 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 Panel A, all the cells have 16 possible rejections. In Panels B – E, all the cells except “Overall” and “Number of Countries” have 16 possible rejections. The cells in the rows labeled “Overall” have 64 possible rejections, and the cells in the rows labeled “Number of Countries” have 16 possible rejections. In Panel F, all the cells except “Overall” and “Number of Countries” have 64 possible rejections. The cells in the rows labeled “Overall” have 256 possible rejections, and the cells in the rows labeled “Number of Countries” have 16 possible rejections.

The overall performance of the PPP model and Taylor rule models are summarized in Panels A and F, respectively. The Taylor rule models perform best at 1-quarter ahead horizon, while the PPP model performs best at 16-quarter horizon. These results confirm the findings in Engel, Mark, and West (2007) and Ince (2012). The evidence of short-horizon predictability with Taylor rule models and the evidence of long-horizon predictability with PPP model is relatively stronger with real-time data than with revised data. This emphasizes the importance of using the data that reflects the information set of the forecasters as close as possible for forecast evaluation.

The performance of Taylor differentials and Taylor rule fundamentals models are compared in Panels B-E. Among the Taylor rule models, the most successful specification is the Taylor rule fundamentals model, where the no predictability null can be rejected in 20 out of 64 cases with real-time data and 13 out of 64 cases with revised data at the 1-quarter ahead horizon. At the 16-quarter ahead horizon, the model with Taylor rule fundamentals performs the best, with 29 out of 64 rejections of the null with real-time data and 30 out of 64 cases with revised data. The results for the Taylor rule differentials models are weaker than for the Taylor rule fundamentals models, with the symmetric Taylor rule differentials model performing the worst. At 1-quarter ahead horizon, the random walk null is only rejected for 13 out of 64 sets of forecasts for the symmetric Taylor rule differentials model with real-time data, and for 12 out of 64 sets of forecasts for the symmetric Taylor rule differentials model with revised data. As the forecast horizon increases to 16 quarters, the number of rejections drops to 11 and 10 out of 64 cases with real-time and revised data, respectively.

6. Conclusions

Using the most comprehensive real-time dataset to date, which is constructed by merging the OECD Original Release and Revisions Database and Historical Real-Time Data for OECD described in Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012), we examine how the choice between real-time and revised data affects the out-of-sample evaluation of exchange rate models with PPP and Taylor rule fundamentals. While the former database covers the period starting in 1999:Q1 up to now, the latter contains real-time data prior to February 1999 and goes back to the early 1970s. The question of whether first-release data, which contain only new information about macroeconomic fundamentals, or revised data, which consists of the historical information in the most recently available vintage, should be used for evaluating exchange rate forecasts has not yet been studied extensively. We find that evidence of exchange rate predictability is stronger with real-time data than with revised data.

The availability of a comprehensive real-time dataset provides an opportunity to examine how the two types of data perform out-of-sample. As in Engel, Mark, and West (2007) and Ince (2012), we find that Taylor rule models are most successful at the 1-quarter ahead horizon, while the PPP model performs best at the 16-quarter horizon. Although the model selection does not depend on the choice of data, the evidence of short-horizon predictability with Taylor rule models and the evidence of long-horizon predictability with PPP model are relatively stronger with real-time data than with revised data. This emphasizes the importance of using the data that reflects the information set of the forecasters as close as possible.

Comparing the results with real-time and revised data, the evidence of short-run exchange rate predictability with Taylor rule models is stronger with real-time data. The models with Taylor rule fundamentals outperform the naïve no-change model at the 1-quarter horizon for 8 out of 16 currencies vis-à-vis the U.S. dollar with real-time data and for 6 out of 16 currencies with revised data, with the strongest evidence coming from specifications that incorporate heterogeneous coefficients. The evidence of short-run predictability is much stronger with Taylor rule models than with conventional purchasing power parity model regardless of which type of data is used. The out-of-sample performance of both PPP and Taylor rule fundamentals improves at longer horizons, with PPP model performing best in the long run. At the 16-quarter horizon, the models with Taylor rule fundamentals outperform the random walk for 10 out of 16 currencies vis-à-vis the U.S. dollar with either type of data, while the PPP model outperform the naïve no-change model for 13 out of 16 currencies with real-time data and for 11 out of 16 currencies with revised data.

At long horizon, the evidence of predictability is found with revised data, but not with real-time data for two countries, Canada and the U.K in various Taylor rule specifications. This supports similar finding in Fernandez, Koenig, and Nikolsko-Rzhevskyy (2012) that using revised data can lead to finding spurious evidence of exchange rate predictability at long horizon.

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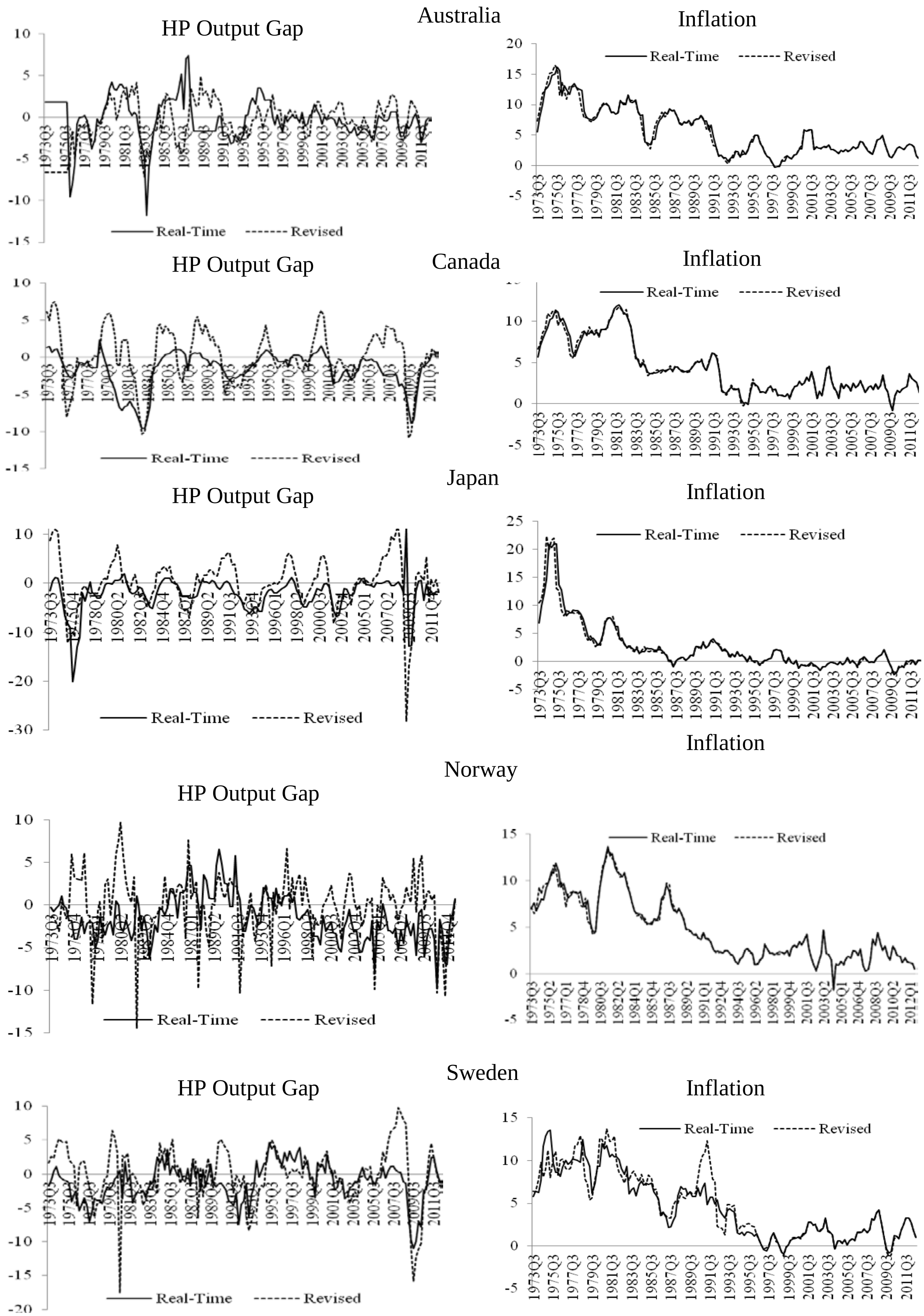

Figure 1. Real-Time and Revised HP Output Gap and Inflation

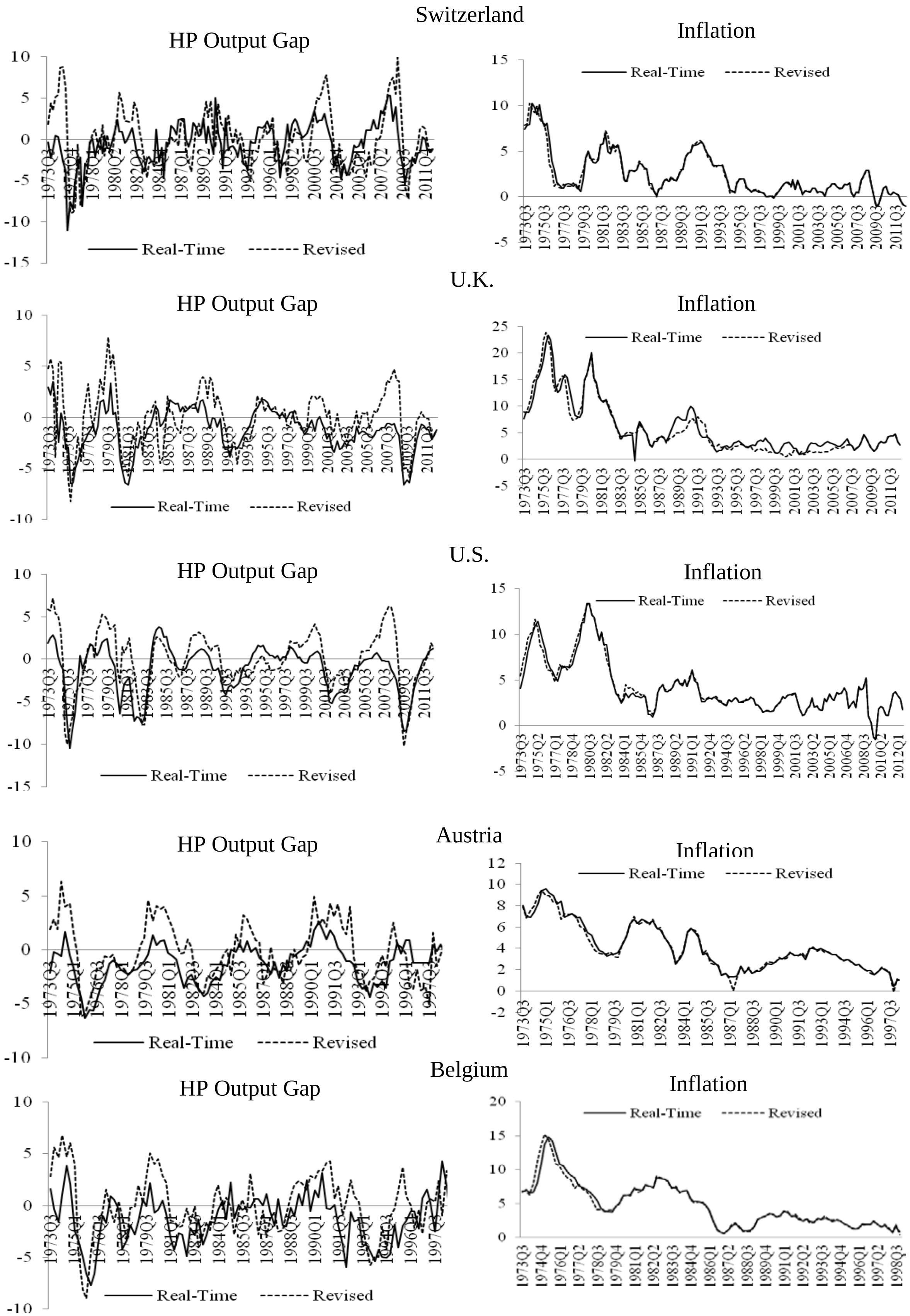

Figure 1. (Contd) Real-Time and Revised HP Output Gap and Inflation

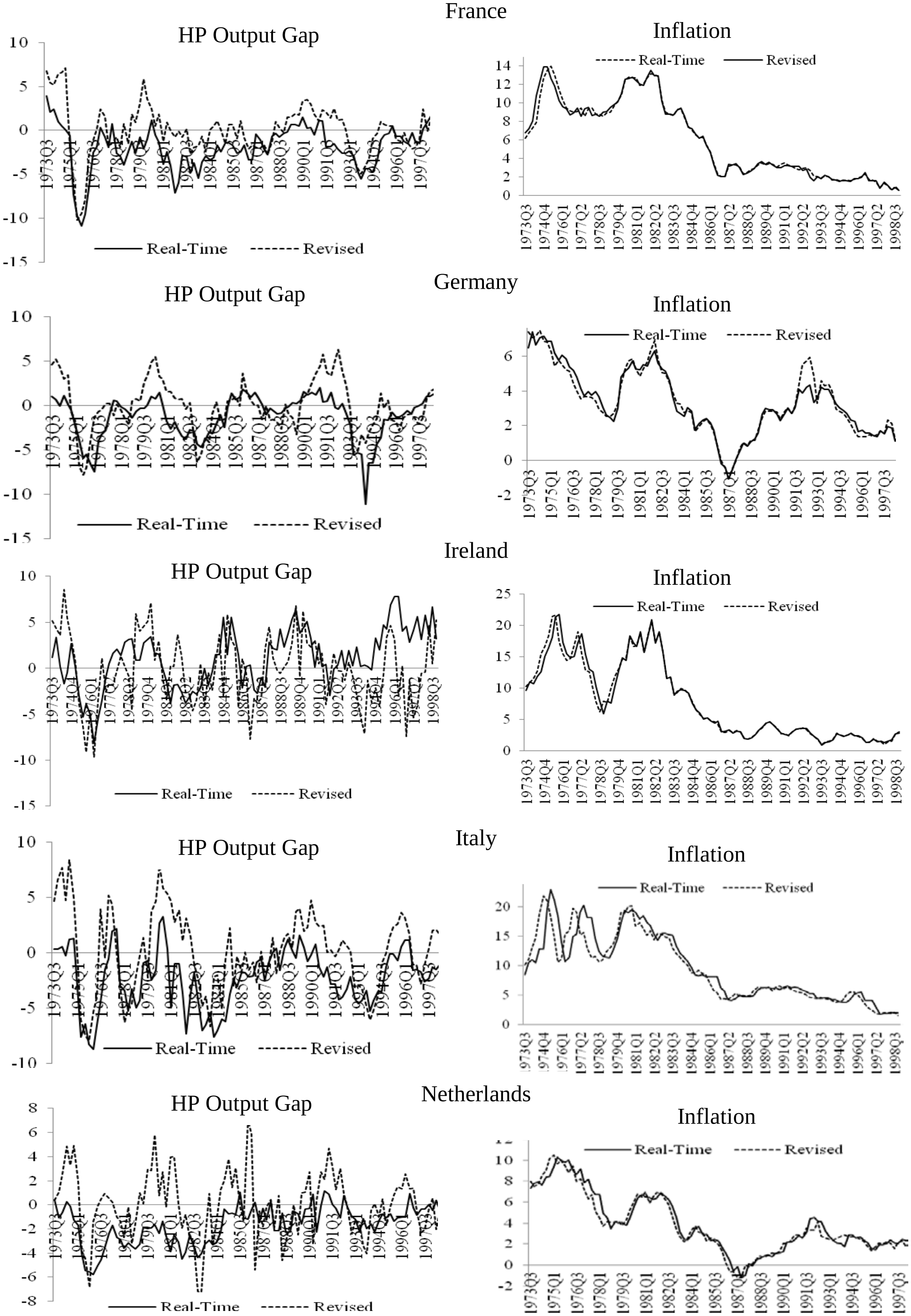

Figure 1. (Contd) Real-Time and Revised HP Output Gap and Inflation

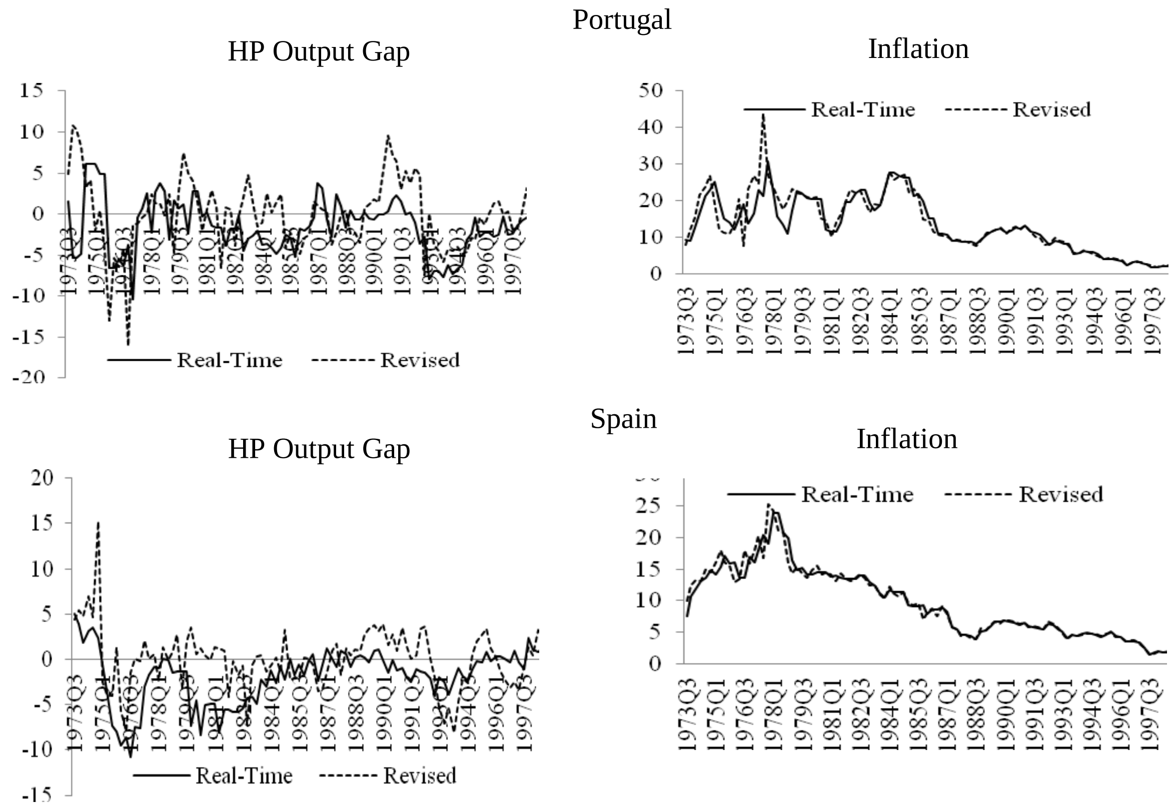

Figure 1. (Contd) Real-Time and Revised HP Output Gap and Inflation

Table 1. Descriptive Statistics for Real-Time Data, Revised Data, and Revisions

	Real-Time Data		Revised Data		Revisions, $X_{Revised} - X_{Real\text{-}Time}$			
	Mean	SD	Mean	SD	Mean	SD	Corr with $X_{Revised}$	Corr with $X_{Real\text{-}time}$
A. Inflation								
Australia	5.598	3.959	5.582	3.951	-0.016	0.729	0.109	-0.074
Canada	4.298	3.223	4.314	3.250	0.016	0.374	0.131	0.016
Japan	2.585	4.391	2.529	4.437	-0.056	1.075	0.164	-0.079
Norway	4.701	3.400	4.686	3.405	-0.015	0.430	0.075	-0.051
Sweden	4.566	3.754	4.792	3.939	0.226	1.486	0.310	-0.070
Switzerland	2.430	2.405	2.416	2.413	-0.014	0.461	0.112	-0.079
U.K.	5.983	5.032	5.641	5.208	-0.342	1.353	0.257	-0.003
U.S.	4.195	2.890	4.291	2.906	0.096	0.440	0.113	-0.039
Austria	4.082	2.245	4.025	2.234	-0.057	0.339	0.043	-0.108
Belgium	4.764	3.274	4.739	3.289	-0.025	0.606	0.118	-0.067
France	6.064	4.109	6.079	4.142	0.015	0.484	0.126	0.009
Germany	3.316	1.919	3.338	1.963	0.022	0.441	0.211	0.014
Ireland	7.843	6.207	7.844	6.207	0.001	1.028	0.082	-0.084
Italy	9.617	5.628	9.362	5.545	-0.255	2.317	0.173	-0.242
Netherlands	3.884	2.812	3.760	2.794	-0.124	0.645	0.086	-0.143
Portugal	13.400	7.344	13.786	8.078	0.386	3.667	0.418	-0.040
Spain	9.581	5.409	9.628	5.480	0.047	1.247	0.171	-0.058
B. Linear Output Gap								
Australia	0.517	4.387	-0.168	4.430	0.349	5.039	0.577	-0.566
Canada	10.319	12.311	2.772	12.141	13.091	9.379	0.368	-0.399
Japan	-29.031	11.631	6.738	22.699	35.769	13.314	0.922	0.654
Norway	-12.888	15.568	3.408	18.354	16.296	7.461	0.548	0.167
Sweden	-11.826	9.943	0.317	9.256	12.143	8.604	0.382	-0.510
Switzerland	-4.152	6.957	0.210	5.880	4.361	7.806	0.513	-0.688
U.K.	-8.003	6.883	1.283	8.227	9.287	2.782	0.613	0.328
U.S.	-8.235	5.932	1.214	8.517	9.449	4.804	0.738	0.250
Austria	-10.469	5.205	2.291	8.467	12.760	5.674	0.799	0.210
Belgium	-11.937	5.640	4.191	7.067	16.129	4.620	0.605	-0.062
France	-14.236	7.049	11.050	7.662	25.286	4.658	0.430	-0.193
Germany	-11.323	6.667	6.012	7.019	17.335	4.358	0.389	-0.244
Ireland	5.017	10.067	-12.477	12.205	-17.495	14.389	0.725	-0.550
Italy	-19.799	6.203	14.591	6.721	34.390	4.603	0.451	-0.254
Netherlands	-20.330	7.913	11.666	11.521	31.996	7.780	0.729	0.078
Portugal	-8.985	8.288	17.051	7.494	26.035	8.823	0.494	-0.618
Spain	-13.830	7.919	9.448	6.616	23.278	6.024	0.218	-0.579
C. Quadratic Output Gap								
Australia	-0.905	4.935	-0.178	4.422	0.727	6.778	0.686	-0.759
Canada	0.245	8.960	-0.184	7.601	-0.429	8.142	0.354	-0.609
Japan	6.771	8.410	-0.561	8.178	2.022	4.623	0.599	0.299
Norway	-3.308	9.342	-0.424	9.738	16.296	7.461	0.707	0.038
Sweden	7.248	10.371	-1.034	9.340	-8.282	12.152	0.561	-0.667
Switzerland	4.883	6.363	-0.190	6.167	-5.073	8.953	0.704	-0.725
U.K.	-0.813	5.492	-0.430	5.468	0.383	5.421	0.491	-0.498
U.S.	2.147	6.034	-0.642	6.814	-2.989	6.677	0.600	-0.429
Austria	-0.840	5.402	-1.652	8.175	-0.812	11.738	0.914	-0.790
Belgium	1.203	5.559	-0.865	6.817	-2.068	9.480	0.816	-0.705
France	-0.385	5.648	-1.128	6.955	-0.743	9.734	0.821	-0.712
Germany	-0.064	5.972	-1.117	6.475	-1.053	8.866	0.739	-0.683
Ireland	4.997	4.588	-5.014	8.855	-10.011	8.248	0.858	-0.141
Italy	4.161	5.717	-2.242	6.290	-6.403	7.508	0.670	-0.577
Netherlands	0.536	9.033	11.666	11.521	11.129	19.478	0.959	-0.933
Portugal	-1.891	5.352	0.208	5.931	2.099	6.577	0.638	-0.522
Spain	4.431	8.133	-0.485	10.256	-4.916	15.829	0.892	-0.822

Table 1 (Contd.) Descriptive Statistics for Real-Time Data, Revised Data, and Revisions

	Real-Time Data		Revised Data		Revisions, $X_{Revised} - X_{Real\text{-}Time}$			
	Mean	SD	Mean	SD	Mean	SD	Corr with $X_{Revised}$	Corr with $X_{Real\text{-}time}$
D. HP Output Gap								
Australia	-0.211	2.521	-0.535	2.597	-0.323	3.243	0.647	-0.619
Canada	-1.667	2.519	0.017	3.626	1.684	2.882	0.723	-0.103
Japan	-2.073	3.487	-0.051	5.197	2.022	4.623	0.754	-0.202
Norway	-1.484	2.650	-0.057	3.709	1.427	3.907	0.759	-0.412
Sweden	-1.049	2.770	0.046	4.162	1.095	3.640	0.756	-0.179
Switzerland	-0.518	2.598	0.037	3.571	0.554	3.180	0.710	-0.249
U.K.	-1.172	2.071	0.012	2.745	1.184	2.012	0.660	-0.097
U.S.	-1.142	2.791	-0.018	3.354	1.125	2.143	0.560	-0.094
Austria	-1.246	1.807	-0.151	2.638	1.096	1.963	0.729	-0.023
Belgium	-1.290	2.367	0.084	2.935	1.373	2.486	0.630	-0.269
France	-1.857	2.539	-0.007	2.934	1.850	1.949	0.521	-0.166
Germany	-1.239	2.448	-0.088	2.928	1.150	2.290	0.583	-0.238
Ireland	1.130	3.122	-0.132	3.746	-1.262	3.899	0.667	-0.448
Italy	-2.240	2.613	0.169	3.561	2.409	2.579	0.681	-0.059
Netherlands	-1.636	1.580	-0.031	2.742	1.605	2.586	0.826	-0.204
Portugal	-1.509	3.305	-0.041	4.302	1.469	4.592	0.726	-0.445
Spain	-1.790	3.035	0.090	3.297	1.880	3.460	0.597	-0.491
E. BK Output Gap								
Australia	-0.162	2.147	-0.502	2.315	-0.340	2.409	0.587	-0.489
Canada	-1.462	2.083	0.123	3.506	1.585	2.737	0.805	0.041
Japan	-2.112	3.892	0.167	4.910	2.279	4.402	0.656	-0.304
Norway	-1.325	1.862	0.054	2.841	1.379	2.948	0.794	-0.372
Sweden	-0.933	2.125	0.079	3.702	1.012	2.843	0.821	0.091
Switzerland	-0.221	3.427	0.049	3.186	0.270	3.626	0.500	-0.593
U.K.	-1.045	1.837	0.084	2.492	1.129	1.665	0.676	0.011
U.S.	-1.114	2.623	0.038	3.200	1.152	1.952	0.574	-0.044
Austria	-1.040	1.682	-0.108	2.393	0.932	1.941	0.717	-0.133
Belgium	-1.260	1.906	0.119	2.667	1.379	2.066	0.703	-0.100
France	-1.459	1.834	0.133	2.716	1.592	1.840	0.740	0.093
Germany	-1.151	2.254	0.008	2.725	1.159	2.114	0.592	-0.223
Ireland	0.947	2.717	-0.438	3.083	-1.385	3.028	0.605	-0.428
Italy	-2.111	2.220	0.270	3.220	2.381	2.319	0.724	0.006
Netherlands	-1.549	1.301	0.137	2.273	1.686	2.127	0.827	-0.189
Portugal	-1.123	2.225	0.198	3.519	1.320	2.879	0.776	-0.067
Spain	-1.602	2.639	0.284	2.736	1.886	2.694	0.528	-0.474

Notes: The statistics reported for each real-time and revised variable and its revision are: Mean, the mean, and SD, the standard deviation. For data revisions, the table reports Corr with $X_{Revised}$, Corr with $X_{Real\text{-}time}$ that are correlations of revisions with revised series and with real-time series. A positive value of the "mean" revision indicates that the variable was on average revised upwards. The data is from 1973:Q3 to 2012:Q3 for Non-EU countries, and from 1973:Q3 to 1998:Q4 for EU countries. The output gaps are estimated using the data from 1956:Q1 for all countries except Australia, Japan, Switzerland, Ireland, and Spain. The industrial production data starts in 1970:Q4 for Australia, in 1960:Q1 for Japan and Switzerland, in 1966:Q1 for Ireland, and in 1965:Q1 for Spain. Inflation and output gaps are measures in percentages, and the price level in logs.

Table 2. PPP Model

Country	Real-Time Data	Revised Data	Real-Time Data	Revised Data
	Short-Horizon Forecasts (h=1)		Long-Horizon Forecasts (h=16)	
Australia	-1.393	-1.384	2.821***	2.902***
Canada	-0.154	-0.938	1.878**	2.399***
Japan	-1.161	-1.179	2.878***	2.895***
Norway	0.470	0.550	1.602*	1.583*
Sweden	-0.073	-0.029	2.094**	2.031**
Switzerland	-0.737	-0.898	1.337*	1.242
U.K.	-0.011	0.008	3.311***	2.936***
Austria	-0.218	-0.294	1.452*	1.416*
Belgium	-0.711	-0.681	1.466*	1.475*
France	0.402	-0.352	1.550*	1.235
Germany	-0.303	-0.505	0.718	0.647
Ireland	0.133	0.078	0.434	0.564
Italy	0.390	0.405	1.127	1.068
Netherlands	-0.839	-0.983	1.468*	1.331*
Portugal	1.958**	1.925**	2.846***	2.867***
Spain	0.684	0.543	1.464*	1.472*

Notes: The table reports CW statistics for the tests of equal predictive ability between the null of a martingale difference process and the alternative of a linear model with Taylor rule fundamentals. The alternative model is the model with PPP fundamentals, which is estimated either at the short- or long horizons of 1 or 16 quarters, and either with real-time or revised data. West (1992) and Hodrick (1996) standard errors are used for the long-horizon CW tests. *, **, and *** indicate that the alternative model significantly outperforms the random walk at 10, 5, and 1% significance level, respectively, based on standard normal critical values for the one-sided test. Rolling regressions with 32-quarter windows are used to predict exchange rate changes from 1981:Q3 to 1998:Q4 and from 1981:Q3 to 2012:Q3 for EMU and non-EMU countries, respectively.

Table 3. Short-Horizon Forecasts with Taylor Rule Differentials Models

Country	Linear Trend	Quadratic Trend	HP Filter	BK Filter	Linear Trend	Quadratic Trend	HP Filter	BK Filter
	Real-Time Data				Revised Data			
				A. Symmetric Model				
Australia	2.105**	1.722**	1.968**	2.222**	0.803	1.807**	2.221**	2.163**
Canada	1.652**	1.451*	1.279	1.518*	0.780	1.797**	1.444*	1.802**
Japan	1.040	1.255	2.051**	2.003**	0.519	0.980	1.395*	1.651**
Norway	0.823	-0.230	-1.289	-1.110	-0.476	-0.518	-1.256	-1.078
Sweden	-0.492	0.417	0.754	0.692	0.536	0.510	0.409	0.124
Switzerland	-0.294	-0.095	-0.310	-0.781	-0.480	-0.686	-0.471	-0.530
U.K.	-1.004	-1.232	-0.793	-0.821	-0.265	-0.207	0.200	0.012
Austria	-0.837	-0.793	-0.848	-0.831	-0.551	-0.659	-0.480	-0.323
Belgium	-1.124	-1.102	-1.244	-1.140	-0.430	-0.434	-0.501	-0.731
France	0.088	-0.147	-0.029	-0.137	0.182	0.116	-0.141	-0.405
Germany	-0.478	-0.421	-0.188	-0.088	-0.474	-0.480	-0.336	-0.227
Ireland	-0.165	0.545	0.516	0.293	0.200	0.303	0.635	0.531
Italy	-0.088	-0.253	0.191	0.282	0.937	0.709	0.850	1.007
Netherlands	-0.594	-0.642	-0.696	-0.489	-0.532	-0.382	-0.466	-0.269
Portugal	1.686**	1.710**	1.723**	1.791**	2.047**	2.019**	2.000**	1.966**
Spain	-0.123	-0.077	-0.146	-0.405	0.612	0.699	0.352	0.266
				B. Asymmetric Model				
Australia	2.123**	1.751**	1.978**	2.230**	0.836	1.814**	2.224**	2.166**
Canada	1.655**	1.454*	1.282*	1.521*	0.785	1.802**	1.448*	1.807**
Japan	1.039	1.251	2.041**	1.995**	0.517	0.973	1.392*	1.649*
Norway	0.816	-0.242	-1.304	-1.119	-0.481	-0.522	-1.267	-1.084
Sweden	-0.496	0.411	0.735	0.672	0.524	0.496	0.393	0.107
Switzerland	-0.303	-0.103	-0.322	-0.792	-0.489	-0.695	-0.481	-0.539
U.K.	-1.002	-1.231	-0.790	-0.816	-0.248	-0.190	0.220	0.032
Austria	-0.843	-0.803	-0.859	-0.839	-0.554	-0.554	-0.483	-0.328
Belgium	-1.126	-1.104	-1.244	-1.140	-0.436	-0.440	-0.507	-0.736
France	0.090	-0.146	-0.026	-0.134	0.183	0.116	-0.143	-0.409
Germany	-0.481	-0.425	-0.192	-0.091	-0.481	-0.487	-0.340	-0.231
Ireland	-0.165	0.547	0.517	0.295	0.200	0.303	0.637	0.533
Italy	-0.096	-0.259	0.179	0.271	0.926	0.694	0.835	0.991
Netherlands	-0.598	-0.649	-0.703	-0.493	-0.536	-0.387	-0.472	-0.274
Portugal	1.687**	1.711**	1.724**	1.791**	2.046**	2.018**	2.000**	1.967**
Spain	-0.129	-0.085	-0.152	-0.409	0.603	0.692	0.342	0.256

Notes: The table reports CW statistics for the 1-quarter-ahead tests of equal predictive ability between the null of a martingale difference process and the alternative of a linear model with Taylor rule fundamentals. The alternative model is the symmetric or asymmetric Taylor rule differentials model, which is estimated either with real-time or revised data using quadratic, HP, and BK trends to estimate potential output. *, **, and *** indicate that the alternative model significantly outperforms the random walk at 10, 5, and 1% significance level, respectively, based on standard normal critical values for the one-sided test. Rolling regressions with 32-quarter windows are used to predict exchange rate changes from 1981:Q3 to 1998:Q4 and from 1981:Q3 to 2012:Q3 for EMU and non-EMU countries, respectively.

Table 4. Short-Horizon Forecasts with Taylor Rule Fundamentals Models

Country	Linear Trend	Quadratic Trend	HP Filter	BK Filter	Linear Trend	Quadratic Trend	HP Filter	BK Filter
	Real-Time Data				Revised Data			
A. Homogenous Coefficients								
Australia	1.549*	0.941	2.001**	1.795**	-0.253	1.201	1.619**	1.649**
Canada	1.366*	1.048	1.414*	1.211	1.351*	1.332*	0.834	1.371*
Japan	1.070	1.130	1.881**	1.684**	0.380	0.761	1.696**	1.674**
Norway	-0.306	-1.214	-1.750	-0.744	-1.254	-1.525	-1.748	-1.632
Sweden	0.439	0.441	0.516	1.330*	0.183	0.256	0.465	0.313
Switzerland	0.246	0.166	-0.705	-0.924	-1.040	-1.201	-1.542	-1.761
U.K.	-0.611	-0.977	-0.688	-0.687	-1.232	-1.245	-0.276	-0.610
Austria	-0.931	-1.072	-1.161	-1.248	-1.203	-1.199	-1.100	-0.996
Belgium	-0.943	-0.952	-0.962	-1.230	-1.216	-1.193	-1.011	-1.075
France	-0.728	-1.271	-0.660	-0.753	0.042	-0.225	-0.423	-0.358
Germany	-1.224	-1.166	-1.134	-0.980	-1.201	-1.194	-1.360	-1.266
Ireland	0.309	0.181	0.321	0.062	0.449	0.320	0.558	0.613
Italy	-0.402	-0.484	-0.551	-0.891	0.811	0.298	0.168	0.191
Netherlands	-0.979	-0.897	-0.920	-0.764	-0.421	-0.354	-1.053	-1.328
Portugal	1.840**	1.995**	1.846**	1.982**	1.972**	1.917**	1.839**	1.932**
Spain	-0.839	0.160	-0.133	-0.605	0.809	0.925	0.548	0.256
B. Heterogeneous Coefficients								
Australia	1.322*	2.194**	2.498***	2.004**	0.591	1.547**	2.252**	2.091**
Canada	0.919	1.144	2.104**	1.924**	1.627*	0.768	1.173	1.380*
Japan	0.876	1.095	1.252	0.849	0.687	1.228	0.648	0.584
Norway	1.152	0.911	-0.630	1.433*	0.568	0.922	-0.110	-0.478
Sweden	1.603*	1.753**	1.178	2.015**	1.401*	1.516*	1.339*	1.074
Switzerland	0.535	0.401	-0.551	-0.559	0.598	0.690	-0.357	-0.410
U.K.	0.000	-0.088	-0.591	-0.428	0.427	0.468	0.603	0.328
Austria	1.456*	0.910	0.823	0.456	0.044	0.260	0.308	1.159
Belgium	0.925	0.684	0.747	1.004	1.106	1.110	0.870	0.846
France	0.331	0.090	0.059	0.550	0.284	0.329	0.081	0.453
Germany	0.112	0.155	0.558	0.539	-0.297	-0.424	-0.806	-0.445
Ireland	0.443	0.137	0.043	0.412	0.205	0.506	0.083	0.001
Italy	1.007	0.876	1.512*	1.529*	0.958	0.798	0.473	1.170
Netherlands	-0.076	0.121	-0.627	-0.067	0.237	0.358	0.500	0.169
Portugal	1.574*	1.429*	1.411*	1.291*	1.941**	1.926**	1.614*	1.213
Spain	1.833**	1.765**	1.984**	1.201	1.999**	2.080**	1.246	1.193

Notes: The table reports CW statistics for the 1-quarter-ahead tests of equal predictive ability between the null of a martingale difference process and the alternative of a linear model with Taylor rule fundamentals. The alternative model is the model with Taylor rule fundamentals, which is estimated either with heterogeneous or homogenous inflation and output coefficients, and either with real-time or revised data using linear, quadratic, HP, and BK trends to estimate potential output. *, **, and *** indicate that the alternative model significantly outperforms the random walk at 10, 5, and 1% significance level, respectively, based on standard normal critical values for the one-sided test. Rolling regressions with 32-quarter windows are used to predict exchange rate changes from 1981:Q3 to 1998:Q4 and from 1981:Q3 to 2012:Q3 for EMU and non-EMU countries, respectively.

Table 5. Long-Horizon Forecasts with Taylor Rule Differentials Models

Country	Linear Trend	Quadratic Trend	HP Filter	BK Filter	Linear Trend	Quadratic Trend	HP Filter	BK Filter
	Real-Time Data				Revised Data			
A. Symmetric Model								
Australia	0.860	1.169	1.311*	1.346*	1.143	0.983	1.090	1.114
Canada	1.115	1.142	1.109	1.094	1.375*	1.315*	1.182	1.205
Japan	2.434***	2.597***	1.843**	1.771**	2.255**	2.184**	1.868**	1.851**
Norway	0.572	0.478	-0.046	-0.057	0.723	0.745	-0.039	0.096
Sweden	1.200	1.250	0.402	0.338	0.186	0.164	0.029	0.055
Switzerland	1.301*	1.380*	1.536*	1.441*	1.372*	1.406	1.393*	1.341*
U.K.	0.120	-0.112	-0.225	-0.195	-0.160	-0.150	-0.375	-0.311
Austria	1.097	1.182	1.187	1.182	1.255	1.269	1.251	1.223
Belgium	0.726	1.170	1.193	1.285*	1.219	1.233	1.248	1.290*
France	-0.545	-0.491	-0.497	-0.469	-0.441	-0.440	-0.381	-0.371
Germany	1.107	1.166	1.205	1.227	1.203	1.199	1.241	1.219
Ireland	-0.693	-0.766	-0.756	-0.738	-0.670	-0.729	-0.743	-0.754
Italy	-0.803	-0.794	-0.640	-0.624	-0.710	-0.773	-0.651	-0.644
Netherlands	-0.032	0.973	0.906	0.878	-0.049	0.039	1.069	1.003
Portugal	0.808	0.846	0.895	0.899	0.908	0.899	0.832	0.836
Spain	-0.416	-0.308	-0.382	-0.401	-0.408	-0.373	-0.414	-0.404
B. Asymmetric Model								
Australia	0.862	1.173	1.315*	1.350*	1.146	0.982	1.093	1.117
Canada	1.114	1.142	1.108	1.093	1.373*	1.314*	1.179	1.202
Japan	2.425***	2.588***	1.835**	1.763**	2.251**	2.179**	1.861**	1.844**
Norway	0.572	0.477	-0.054	-0.067	0.724	0.746	-0.041	0.097
Sweden	1.191	1.244	0.387	0.321	0.180	0.158	0.022	0.048
Switzerland	1.298*	1.375*	1.528*	1.432*	1.368*	1.404*	1.387*	1.335*
U.K.	0.117	-0.117	-0.228	-0.199	-0.150	-0.149	-0.378	-0.335
Austria	1.093	1.180	1.184	1.179	1.252	1.266	1.248	1.221
Belgium	0.718	1.166	1.189	1.280*	1.213	1.227	1.244	1.286*
France	-0.547	-0.494	-0.500	-0.473	-0.445	-0.444	-0.385	-0.375
Germany	1.101	1.162	1.202	1.223	1.200	1.196	1.239	1.216
Ireland	-0.691	-0.766	-0.755	-0.737	-0.672	-0.728	-0.742	-0.754
Italy	-0.802	-0.793	-0.643	-0.626	-0.713	-0.775	-0.654	-0.647
Netherlands	-0.038	0.968	0.899	0.871	-0.058	0.029	1.062	0.996
Portugal	0.807	0.846	0.895	0.899	0.908	0.899	0.832	0.836
Spain	-0.417	-0.311	-0.383	-0.403	-0.410	-0.375	-0.416	-0.406

Notes: The table reports CW statistics for the 16-quarter-ahead tests of equal predictive ability between the null of a martingale difference process and the alternative of a linear model with Taylor rule fundamentals. The alternative model is the symmetric or asymmetric Taylor rule differentials model, which is estimated either with real-time or revised data using quadratic, HP, and BK trends to estimate potential output. West (1992) and Hodrick (1996) standard errors are used for the long-horizon CW tests. *, **, and *** indicate that the alternative model significantly outperforms the random walk at 10, 5, and 1% significance level, respectively, based on standard normal critical values for the one-sided test. Rolling regressions with 32-quarter windows are used to predict exchange rate changes from 1981:Q3 to 1998:Q4 and from 1981:Q3 to 2012:Q3 for EMU and non-EMU countries, respectively.

Table 6. Long-Horizon Forecasts with Taylor Rule Fundamentals Models

Country	Linear Trend	Quadratic Trend	HP Filter	BK Filter	Linear Trend	Quadratic Trend	HP Filter	BK Filter
	Real-Time Data				Revised Data			
	A. Homogenous Coefficients							
Australia	1.834**	1.331*	1.427*	1.555*	1.580*	1.739**	2.170**	2.145**
Canada	1.170	1.150	1.145	1.076	1.596*	1.459*	1.256	1.311*
Japan	2.603***	2.723***	2.103**	1.994**	2.451***	2.497***	2.108***	2.093**
Norway	0.805	0.708	0.059	0.257	0.670	0.686	-0.085	0.164
Sweden	1.317*	1.353*	0.589	0.630	0.343	0.451	0.274	0.506
Switzerland	1.600*	1.612*	1.787**	1.695**	1.571*	1.643*	1.434*	1.439*
U.K.	0.263	-0.026	0.102	0.077	0.458	0.525	-0.132	-0.165
Austria	1.216	1.225	1.221	1.237	1.233	1.233	1.240	1.251
Belgium	1.771**	1.545*	1.561*	1.654**	1.592*	1.582*	1.570*	1.607*
France	0.452	-0.090	-0.115	-0.063	-0.453	-0.402	-0.430	-0.401
Germany	1.352*	1.376*	1.378*	1.400*	1.316*	1.318*	1.273	1.284*
Ireland	-0.620	-0.726	-0.655	-0.733	-0.234	-0.765	-0.787	-0.792
Italy	0.168	-0.015	-0.246	-0.236	-0.166	-0.009	-0.268	-0.173
Netherlands	1.230	1.325*	1.158	1.162	1.179	1.154	1.053	1.073
Portugal	1.313*	1.311*	1.123	1.072	1.337*	1.264	0.886	0.863
Spain	0.538	-0.043	-0.357	-0.343	-0.344	-0.005	-0.283	-0.202
	B. Heterogeneous Coefficients							
Australia	2.199**	1.883**	1.828**	2.079**	2.136**	2.196**	1.972**	1.926**
Canada	1.342*	1.382*	1.565*	1.601*	1.819**	1.505*	1.626*	1.732**
Japan	2.950***	2.922***	2.554***	2.417***	2.849***	2.845***	2.606***	2.582***
Norway	1.019	1.018	0.917	1.057	1.044	1.089	0.658	0.818
Sweden	1.579*	1.210	1.140	1.238	1.173	1.360*	0.976	1.009
Switzerland	1.737**	1.462*	1.798**	1.610*	1.862**	2.027**	1.568*	1.645**
U.K.	1.218	1.019	0.922	0.973	1.673**	1.741**	1.251	1.286*
Austria	1.273	1.124	1.106	1.078	1.276	1.259	1.125	1.126
Belgium	1.447*	1.416*	1.501*	1.454*	1.299*	1.290*	1.359*	1.450*
France	1.203	1.252	1.126	1.205	0.934	0.986	0.902	1.008
Germany	1.291*	1.218	1.303*	1.298*	1.166	1.116	1.176	1.185
Ireland	0.837	0.896	0.935	0.883	0.834	0.796	0.782	0.857
Italy	1.126	1.017	1.055	1.041	1.044	1.070	1.011	1.003
Netherlands	1.256	1.210	1.164	1.134	1.235	1.234	1.137	1.190
Portugal	3.010***	3.169***	2.946***	3.176***	3.016***	2.901***	3.178***	3.306***
Spain	1.444*	1.077	1.075	1.222	1.238	1.372*	1.138	1.260

Notes: The table reports CW statistics for the 16-quarter-ahead tests of equal predictive ability between the null of a martingale difference process and the alternative of a linear model with Taylor rule fundamentals. The alternative model is the model with Taylor rule fundamentals, which is estimated either with heterogeneous or homogenous inflation and output coefficients, and either with real-time or revised data using linear, quadratic, HP, and BK trends to estimate potential output. West (1992) and Hodrick (1996) standard errors are used for the long-horizon CW tests. *, **, and *** indicate that the alternative model significantly outperforms the random walk at 10, 5, and 1% significance level, respectively, based on standard normal critical values for the one-sided test. Rolling regressions with 32-quarter windows are used to predict exchange rate changes from 1981:Q3 to 1998:Q4 and from 1981:Q3 to 2012:Q3 for EMU and non-EMU countries, respectively.

Table 7. Summary of the Results

	Real-Time Data	Revised Data	Real-Time Data	Revised Data
	Short-Horizon Forecasts (h=1)		Long-Horizon Forecasts (h=16)	
A. PPP Model				
Overall	1	1	13	11
B. Symmetric Taylor Rule Differentials Model				
Linear Output Gap	3	1	2	3
Quadratic Output Gap	3	3	2	2
HP Output Gap	3	4	3	2
BK Output Gap	4	4	4	3
Overall	13	12	11	10
Number of countries	4	4	4	4
C. Asymmetric Taylor Rule Differentials Model				
Linear Output Gap	3	1	2	3
Quadratic Output Gap	3	3	2	3
HP Output Gap	4	4	3	2
BK Output Gap	4	4	4	3
Overall	14	12	11	11
Number of countries	4	4	4	4
D. Taylor Rule Fundamentals Model with Homogenous Coefficients				
Linear Output Gap	3	2	7	7
Quadratic Output Gap	1	2	8	6
HP Output Gap	4	3	5	4
BK Output Gap	4	4	5	6
Overall	12	11	25	23
Number of countries	5	4	8	7
E. Taylor Rule Fundamentals Model with Heterogeneous Coefficients				
Linear Output Gap	5	4	9	7
Quadratic Output Gap	4	4	6	9
HP Output Gap	5	3	7	6
BK Output Gap	6	2	7	7
Overall	20	13	29	29
Number of countries	8	5	9	9
F. All Taylor Rule Models				
Linear Output Gap	14	8	20	20
Quadratic Output Gap	11	12	18	20
HP Output Gap	16	14	18	14
BK Output Gap	18	14	20	19
Overall	59	48	76	73
Number of countries	8	6	10	10

Notes: The table reports the number of significant CW statistics (at the 10% significance level or higher) for each specification in Tables 2-6, 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 Panel A, all the cells have 16 possible rejections. In Panels B – E, all the cells except "Overall" and "Number of Countries" have 16 possible rejections. The cells in the rows labeled "Overall" have 64 possible rejections, and the cells in the rows labeled "Number of Countries" have 16 possible rejections. In Panel F, all the cells except "Overall" and "Number of Countries" have 64 possible rejections. The cells in the rows labeled "Overall" have 256 possible rejections, and the cells in the rows labeled "Number of Countries" have 16 possible rejections.