

Forecasting Exchange Rates Out-of-Sample with Panel Methods and Real-Time Data[†]

Onur Ince^{*}

University of Houston

Abstract

This paper evaluates out-of-sample exchange rate forecasting with Purchasing Power Parity (PPP) and Taylor rule fundamentals for 9 OECD countries vis-à-vis the U.S. dollar over the period from 1973:Q1 to 2009:Q1 at short and long horizons. In contrast with previous work, which reports “forecasts” using revised data, I construct a quarterly real-time dataset that incorporates only the information available to market participants when the forecasts are made. Using bootstrapped out-of-sample test statistics, the exchange rate model with Taylor rule fundamentals performs better at the one-quarter horizon and panel specifications are not able to improve its performance. The PPP model, however, forecasts better at the 16-quarter horizon and its performance increases with the panel framework. The results are in accord with previous research on long-run PPP and estimation of Taylor rule models.

Keywords: Exchange Rate Forecasting, Taylor Rules, Real-Time Data, Out-of-Sample Test Statistics

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^{*} Department of Economics, University of Houston, Houston, TX 77204-5882. Tel: +1 (713) 743-3854. Email: oince@mail.uh.edu

1. Introduction

Following the collapse of the Bretton-Woods system, the introduction of flexible exchange rate regimes attracted much attention to the area of international macroeconomics in an attempt to explain exchange rate behavior. Theoretical papers such as Dornbusch (1976), which extended the Mundell-Fleming model to incorporate rational expectations and sticky prices and introduced overshooting as an explanation for high exchange rate variability, and empirical work such as Frankel (1979), which found success in estimating empirical exchange rate models, inspired research in this field by pointing out the ability of macroeconomic models to explain exchange rate variability.

The seminal papers by Meese and Rogoff (1983a, 1983b) put an end to the atmosphere of optimism in exchange rate economics by concluding that empirical exchange rate models do not perform better than a random walk model out-of-sample. Their finding is still hard to overturn more than two decades later. Cheung, Chinn and Pascual (2005), for example, examine out-of-sample performance of the interest rate parity, monetary, productivity-based and behavioral exchange rate models, and suggest that none of the models consistently outperforms the random walk at any horizon.

Are empirical exchange rate models really as bad as we think? Recent studies have found evidence of exchange rate predictability using either panels or innovative modeling approaches. Engel, Mark, and West (2007) use panel specifications of the monetary, Purchasing Power Parity (PPP) and Taylor (1993) rule models, Rossi (2006) uses the monetary model in the presence of a structural break, Gourinchas and Rey (2007) use an external balance model, Molodtsova and Papell (2009) use a heterogeneous symmetric Taylor rule with smoothing, and Cerra and Saxena (2008) use a broad panel specification of the monetary model.

A common problem with the papers discussed above is their reliance on ex-post revised data for the forecasting analysis. Although it seems obvious that out-of-sample exchange rate forecasting should be evaluated using real-time data, which reflects information available to market participants, it is still very rare in the exchange rate literature. Almost all existing studies on exchange rate forecasting exploit revised data which contains future information, due to revisions and additions of new data, that is not available to either policymakers or market participants. Out-of-sample forecasting evaluations based on ex-post revised data yield misleading inferences about the exchange rate models and information problems of market agents are not accounted in the analysis.

The first paper to use real-time data to evaluate nominal exchange rate predictability is Faust, Rogers and Wright (2003). Examining the predictive ability of Mark's (1995) monetary model using real-time data for Japan, Germany, Switzerland and Canada vis-à-vis the U.S, they report that the models consistently perform better using real-time data than fully revised data. However, none of the models perform better than the random walk model. More recently, Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008, 2009) find evidence of predictability with Taylor rule fundamentals using real-time data for the Deutschmark/dollar and Euro/dollar exchange rates.

There are no studies on exchange rate forecasting with real-time data for a reasonably large number of countries over the post Bretton Woods period because of the limited availability of real-time data for countries other than the U.S. In this paper, I construct a quarterly real-time dataset that contains 9 OECD countries (Australia, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, the United Kingdom) vis-à-vis the U.S. dollar over the period from 1973:Q1 to 2009:Q1 to evaluate both short and long-horizon out-of-sample forecasting performance of the linear exchange models using PPP and Taylor rule fundamentals. I construct real-time prices and inflation from the International Financial Statistics (IFS) country pages using the consumer price index (CPI), and estimate real-time output gaps with the industrial production index.

A problem associated with recent papers presenting evidence of exchange rate predictability is that these studies employ a test developed by Clark and West (2006) (henceforth, CW test). They propose an adjustment to the Diebold and Mariano (1995) and West (1996) (henceforth, DMW test) statistic that corrects for size distortions. If two models are non-nested, the DMW test is appropriate to compare the mean square forecast errors (MSFE's). Applying DMW tests to compare the MSFE's of two nested models, however, leads to non-normal test statistics, and using standard normal critical values usually results in very poorly sized tests with far too few rejections of the null. This is a problem for out-of-sample exchange rate forecasting because, since the null is a random walk, all tests with structural models are nested. While the CW adjustment produces a test with correct size, Rogoff and Stavrakeva (2008) argue that it cannot evaluate forecasting performance because it does not test the null hypothesis of equal MSFE's of the random walk and the structural model. In order to satisfy the conditions for a "good" exchange rate forecasting model, empirical studies need to present evidence that the exchange rate model has MSFE that is significantly smaller than that of the random walk model, which cannot be done solely with CW test in the case of

forecasting bias.¹ They advocate the use of DMW tests with bootstrapped critical values to produce correctly sized tests.

Engel, Mark and West (2007) find that panel error-correction exchange rate models with PPP fundamentals are able to produce large improvements in out-of-sample forecasting at longer horizons.² Because they use ex-post revised data, the exchange rate models in their study contain future information that was not available to market participants. “Forecasting” exercises involving future news in the information set of the linear model cannot be evaluated as an out-of-sample forecasting exercise. Forecasts with real-time data, however, do not contain any unrealized future information in the information set of the linear model, and thus are a true out-of-sample forecast.

Molodtsova and Papell (2009) find evidence of out-of-sample predictability with the Taylor model at short horizon using single-equation estimation. Although they use ex-post revised data to calculate inflation, they estimate output gaps with quasi-real-time data in order to capture the information available to central banks as closely as possible. Quasi-real-time data is constructed with ex-post revised data, but the trends do not contain future observations and the data points are used with a lag for estimation. While quasi-real-time data does not contain future observations, it captures revisions which are not available to market participants. Therefore, forecasting exercises with quasi-real time data are also not true out-of-sample forecasts.

This paper evaluates out-of-sample forecasting with PPP and Taylor Rule fundamentals using my newly constructed real-time dataset for 9 OECD countries vis-à-vis the U.S. dollar with single-equation and panel error-correction frameworks based on bootstrapped DMW and CW test statistics.³ The out-of-sample forecast results with PPP fundamentals confirm the findings in Engel, Mark and West (2007) that the predictability of the PPP model increases with the panel specification and the PPP model has higher predictive power at long horizons. Evidence of long-term predictability with the PPP model is found for 6 out of 9 countries against the driftless random walk and for all the countries against the random walk with drift with panel framework. The exchange rate model with PPP fundamentals using panel data outperforms the driftless random walk for 5 out

¹ Rogoff and Stavrakeva (2008) consider the scale bias where the observed value is over- or under predicted by a certain percent.

² Engel, Mark and West (2007) use monetary and Taylor Rule models as well. However, the out-of-sample predictability of the PPP model dominates the other two models at longer horizons.

³ I would like to evaluate the out-of-sample forecasting ability of the monetary model. However, it is not possible to find coherent series of real-time money supply for all the countries.

of 9 countries and the random walk with drift for all the countries in the sample at the 16-quarter horizon.

The predictability of Taylor fundamentals, in contrast, is greatest with the single-equation specification, and the Taylor rule model has higher forecasting power at a short horizon as indicated in Molodtsova and Papell (2009). Evidence of short-term predictability with Taylor rule model is found for 1 out of 9 countries against the driftless random walk and for 4 out of 9 countries against the random walk with drift with single-equation estimation. The exchange rate model with Taylor rule fundamentals using a single-equation framework outperforms the driftless random walk for 1 out of 9 countries and the random walk with drift for 5 out of 9 countries at the one-quarter horizon.

The results are in accord with previous research on PPP and estimation of Taylor rule models. The PPP model works best with the panel specification at the 16-quarter horizon. Research on PPP shows no evidence at short-run PPP, and Papell (1997) finds considerably more support for long-run PPP with panel methods than with univariate tests. Panel models exploit the information contained in the high correlation between nominal and real exchange rates for the countries in our sample. The Taylor rule model performs better with single-equation estimation at the one-quarter horizon. Monetary policy rules implemented by central banks since the early-to-mid 1980s set interest rates for relatively short periods and are different from each other. Clarida, Gali and Gertler (1998) provide empirical evidence of how interest rate reaction functions differ among OECD countries. Gerdesmeier, Mongelli and Roffia (2007) compare the monetary policies implemented by the Eurosystem, the Fed and the Bank of Japan, and also find differences. Imposing identical monetary rules across all countries in a panel structure does not produce successful out-of-sample exchange rate forecasts, thus estimating the Taylor rule model with a single-equation framework performs better.

2. Data

The real-time quarterly data used in this study covers the post-Bretton Woods period from 1973:Q1 to 2009:Q1 for 10 OECD countries: Australia, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, the United Kingdom, and the United States. The dataset is constructed from the country tables of IMF's *International Financial Statistics* (IFS) books, regularly published on a monthly basis since 1948. Seasonally adjusted industrial production index (IFS line 66c) is used as a

measure of countries' income, since quarterly GDP data are not consistently published and not available for some countries for much of the time span. The price level in the economy is measured by the consumer price index (CPI) (IFS line 64) and seasonally adjusted by applying a one-sided moving average of the current observation and 3-lagged values. The inflation rate is the annual inflation rate calculated using the CPI over the previous 4 quarters. Nominal exchange rates are taken from the IFS CD-ROM (IFS line ae) defined as the end-of-period U.S. dollar price of a unit of foreign currency. Exchange rates for the Euro area after 1998 are normalized by fixing foreign currency per dollar to the Euro/Dollar rate as in Engel, Mark and West (2007).

The real-time data has the usual triangular format with vintage dates on the horizontal axis and calendar dates for each observation on the vertical axis. The series of real-time inflation and output gaps are constructed from the diagonal elements of the real-time data matrix and contain only the latest available observations at each period. For each country, this data represents a vector of quarterly observations from 1973:Q1 to 2009:Q1, thus resulting in 145 observations.

The output gap is calculated as the percentage deviation of actual output from a Hodrick-Prescott (1997) (HP) trend.⁴ The industrial production index series in each data vintage that is used to estimate the output gap goes back to 1958:Q1 for all countries. For the first data point, the trend is calculated using the data for 1958:Q1-1973:Q1, for the second data point, it is calculated using the data for 1958:Q1-1973:Q2, and so on. As with any method that uses a one-sided filter, the estimations might be subject to end-of-sample uncertainty which is exacerbated with real-time data, consisting of the last observations in each data vintage. To take into account the end-of-sample uncertainty in output gap estimation using real-time data, I use Watson's (2007) correction and forecast the industrial production series 12 quarters ahead before calculating the trend.⁵

3. Methodology

The econometric analysis in this study is based on panel estimation of the predictive regression,

$$s_{it+k} - s_{it} = \beta_k z_{it} + \varepsilon_{it+k} \quad (1)$$

⁴ The smoothness parameter for HP filter is 1600 for quarterly data.

⁵ While Watson (2007) also suggests to backcast the series, the series in each data vintage extends through 1958:Q1, which is long enough to remove the distortions in the beginning of the sample created by a one-sided filter.

where $z_{it} = f_{it} - s_{it}$ and $\varepsilon_{it} = \zeta_i + \theta_t + u_{it}$.⁶ In the predictive regression, s_{it} denotes the natural log of the nominal exchange rate, measured as the domestic price of U.S. dollar (which serves as base currency) for country i at time t . The deviation of the exchange rate from its equilibrium value is denoted by z and f stands for the fundamental in the exchange rate model that is determined either by PPP or Taylor rule. The forecast horizon k , takes the value of 1 for short-horizon and 16 for long-horizon regressions. The regression error, ε_{it} , has unobserved components, where ζ_i is the individual specific effect, θ_t is the time-specific effect, and u_{it} is the residual idiosyncratic error.

3.1 PPP Fundamentals

Numerous studies that test for unit roots in real exchange rates using panels of industrialized countries have found strong rejections in the post-1973 period. The strong rejections of unit roots encourage testing the forecasting power of exchange rate models with PPP fundamentals. Recently, Engel, Mark and West (2007) have shown that PPP fundamentals forecast well at long horizons. Rogoff and Stavrakeva (2008) also conclude that PPP specification performs the best out of all the specifications they try.⁷

Under PPP fundamentals,

$$f_{it} = p_{0t} - p_{it} \quad (2)$$

where p_{0t} is the log of price level of U.S. which serves as base country and p_{it} is the log of price level of country i . I use the real-time CPI as a measure of the national price level. Substituting PPP fundamentals (2) into (1), I use the resultant equation for forecasting.

3.2 Taylor Rule Fundamentals

When central banks set the interest rate according to the Taylor rule, the linkage between the exchange rate and a set of fundamentals can be examined. According to Taylor (1993), central banks set the monetary policy as:

$$i_t^* = \pi_t + \phi(\pi_t - \pi^*) + \gamma y_t^g + r^* \quad (3)$$

where i_t^* is the target for the short-term nominal interest rate, π_t is the inflation rate, π^* is the target level of inflation, y_t^g is the output gap, or percent deviation of actual output from an estimate of its potential level, and r^* is the equilibrium level of the real interest rate. It is assumed that the target for

⁶ For single-equation framework, time-specific effect is zero.

⁷ Rogoff and Stavrakeva (2008) compare the forecasting power of the monetary model, the Taylor rule model and a structural model based on the Backus-Smith optimal risk sharing condition.

the short-term nominal interest rate is achieved within the period, so that there is no distinction between the actual and target nominal interest rate.

The parameters π^* and r^* in equation (3) can be combined into one constant term $\mu = r^* - \phi\pi^*$ and we have:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t^g \quad (4)$$

where $\lambda = 1 + \phi$. If the central bank sets the target the level of exchange rate to make PPP hold, equation (4) becomes:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t^g + \delta q_t \quad (5)$$

where q_t is the real exchange rate. The central bank increases (decreases) the nominal interest rates if the exchange rate depreciates (appreciates) from its equilibrium value under PPP assumption in the Taylor rule. Allowing interest rates to achieve its target level within the period:

$$i_t = \mu + \lambda\pi_t + \gamma y_t^g + \delta q_t \quad (6)$$

and i_t is the nominal interest rate. Subtracting the Taylor rule equation for the foreign country from that for the base country, the U.S. (denoted by "0"), equation (6) becomes:

$$i_{0t} - i_{it} = \lambda(\pi_{0t} - \pi_{it}) + \gamma(y_{0t}^g - y_{it}^g) + \delta(s_{it} + p_{it} - p_{0t}) \quad (7)$$

Imposing the uncovered interest rate parity condition $E_t s_{it+1} = i_{it} - i_{0t} + s_{it}$, the expected change in nominal exchange rates is equal to the interest differential:

$$E_t s_{it+1} = \lambda(\pi_{0t} - \pi_{it}) + \gamma(y_{0t}^g - y_{it}^g) + \delta(s_{it} + p_{it} - p_{0t}) + s_{it} \quad (8)$$

Molodtsova and Papell (2009) refer to specification (8) as homogenous asymmetric Taylor rule with no smoothing. They estimate the parameters λ, γ , and δ in equation (8) in a rolling regression framework. However, I follow the approach developed by Engel, Mark and West (2007). Rather than estimating the coefficients, they posit a Taylor rule such that $\lambda=1.5, \gamma=0.1$ and $\delta=0.1$. The Taylor rule fundamentals to be used in forecasting equation (1) become:

$$f_{it} = 1.5(\pi_{0t} - \pi_{it}) + 0.1(y_{0t}^g - y_{it}^g) + 0.1(s_{it} + p_{it} - p_{0t}) + s_{it} \quad (9)$$

It is well known in the literature that the uncovered interest rate parity condition does not hold in the short run. With an error correction specification, the exchange rate forecasting model, $E_t s_{it+k} - s_{it} = \beta_k (f_{it} - s_{it})$, is used to generate out-of-sample forecasts both at the short-horizon (where $k=1$) and the long-horizon (where $k=16$).

4. Out-of-Sample Forecasting

4.1 Estimation

To produce out-of-sample forecasts, the sample has to be split into two components, in-sample and out-of-sample. The in-sample component is used to estimate the parameters in equation (1) within both the single-equation and the panel frameworks. The remaining out-of-sample component is used for out-of-sample forecasting.

Following Mark and Sul (2001) and Engel, Mark and West (2007), I estimate the predictive regression by least squares dummy variable (LSDV) using observations through the end of the in-sample component, 1982:Q4. For $k=1$ ($k=16$), the predictive regression is used to forecast 1-step-ahead (16-step-ahead) exchange rate returns in 1983:Q1 (1986:Q4). Then, the in-sample component is updated recursively by extending the sample up to 1983:Q1 and equation (1) is re-estimated again. For $k=1$ ($k=16$), the predictive regression is used to forecast 1-step-ahead (16-step-ahead) exchange rate returns in 1983:Q2 (1987:Q1), and the loop continues until the last observation. At the end, 105 forecasts for $k=1$ and 90 overlapping forecasts for $k=16$ are derived with both PPP and Taylor rule fundamentals.

One crucial point for multi-period ahead forecasts in the panel framework is that the time effect needs to be forecasted. For k -period ahead forecasts, the time effect in period $t+k$ is calculated by taking the recursive mean of the time effect until period t , such as $\hat{\theta}_{t+k} = \frac{1}{t} \sum_{j=1}^t \hat{\theta}_j$.

4.2 Comparisons of Forecasts Based on MSFE

To compare the out-of-sample forecasting ability of the two nested models, this study focuses on the minimum mean-squared forecast error (MSFE) approach, which became dominant in the literature after Meese and Rogoff (1983a, 1983b). Forecasts of linear and random walk models are calculated as:

$$\begin{aligned} \text{Linear Model:} & \quad \Delta \hat{s}_{it+k} = \hat{\zeta}_i + \left(\frac{1}{t} \sum_{j=1}^t \hat{\theta}_j \right) + \hat{\beta} z_{it} \\ \text{Driftless Random Walk:} & \quad \Delta \hat{s}_{it+k} = 0 \\ \text{Random Walk with Drift:} & \quad \Delta \hat{s}_{it+k} = \hat{\alpha}_{it} \end{aligned} \tag{10}$$

where $\hat{\alpha}$ is the estimated drift term.⁸ Taking the difference between actual and predicted values of exchange rates gives the forecast error. The MSFE approach selects a model which has significantly smaller MSFE than the random walk with or without the drift.

4.3 Out-of-Sample Test Statistics

To measure the relative forecast accuracy of the linear model against the driftless random walk and the random walk with drift, I use two alternative test statistics: the Diebold-Mariano and West (DMW) and the Clark-West (CW) statistics.

4.3.1 The Diebold-Mariano and West (DMW) Test

Suppose that a martingale difference process and a linear model are given as:

Model 1: $y_t = e_t$

Model 2: $y_t = X_t' \beta + e_t$ where $E_{t-1}(e_t) = 0$

where the dependent variable is the change in the exchange rate. Under the null hypothesis, population parameter $\beta = 0$ and exchange rate follows a random walk. For simplicity let us concentrate on one-step-ahead forecasting. Assume that sample size is $T+1$; the first R observations are used for estimation and P is equal to the number of forecasts. So we have, $T+1=R+P$, where $T+1=145$, $R=40$ and $P=105$ for one-step-ahead forecasting. Information prior to t is used to forecast for period $t=R, R+1, R+2, \dots, T$. The first forecast is for the period $R+1$ and the final forecast is for the period $T+1$.

The estimated forecasts for the random walk and the structural model are 0 and $X_{t+1}' \hat{\beta}_t$ and $\hat{\beta}_t$ is the regression estimate of β_t . After estimating the forecasts, the respective forecast errors for the models are $\hat{e}_{1,t+1} = y_{t+1}$ and $\hat{e}_{2,t+1} = y_{t+1} - X_{t+1}' \hat{\beta}_t$. Thus, the sample MSFE's of the two models become:

$$\hat{\sigma}_1^2 = P^{-1} \sum_{t=T-P+1}^T y_{t+1}^2 \quad \text{and} \quad \hat{\sigma}_2^2 = P^{-1} \sum_{t=T-P+1}^T (y_{t+1} - X_{t+1}' \hat{\beta}_t)^2 \quad (11)$$

⁸ The recursive mean of the time effect in parenthesis for the linear model is removed in the single-equation case.

Diebold and Mariano (1995) and West (1996) construct a t-type statistics which is assumed to be asymptotically normal and the population MSFE's are equal under the null. Defining the following equations,

$$\begin{aligned}\hat{f}_t &= \hat{e}_{1,t}^2 - \hat{e}_{2,t}^2 \\ \bar{f} &= P^{-1} \sum_{t=T-P+1}^T \hat{f}_{t+1} = \hat{\sigma}_1^2 - \hat{\sigma}_2^2 \\ \hat{V} &= P^{-1} \sum_{t=T-P+1}^T (\hat{f}_{t+1} - \bar{f})^2\end{aligned}\quad (12)$$

The DMW test statistic is

$$DMW = \frac{\bar{f}}{\sqrt{P^{-1}\hat{V}}}\quad (13)$$

The asymptotic DMW test works fine with non-nested models. However, 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. Undersized DMW tests cause too few rejections of the null and may miss the statistical significance of the linear exchange rate model against the random walk.

4.3.2 The Clark- West (CW) Test

Clark and West (2006, 2007) show that the sample difference between the MSFE's of two nested models in DMW test is biased downward from zero in favor of the random walk.

$$\hat{\sigma}_1^2 - \hat{\sigma}_2^2 = P^{-1} \sum_{t=T-P+1}^T \hat{f}_{t+1} = P^{-1} \sum_{t=T-P+1}^T y_{t+1}^2 - P^{-1} \sum_{t=T-P+1}^T (y_{t+1} - X'_{t+1} \hat{\beta}_t)^2 = 2P^{-1} \sum_{t=T-P+1}^T y_{t+1} X'_{t+1} \hat{\beta}_t - P^{-1} \sum_{t=T-P+1}^T (X'_{t+1} \hat{\beta}_t)^2 \quad (14)$$

Under the null hypothesis, the exchange rate follows a random walk, such that $e_{1,t+1} = e_{2,t+1} = y_{t+1}$. Since the independent variables are not correlated with the disturbance term, the first term in

equation (14) is equal to zero.⁹ Clark and West (2006, 2007) show that $-P^{-1} \sum_{t=T-P+1}^T (X'_{t+1} \hat{\beta}_t)^2 < 0$

because estimating the parameters of the alternative model under the true null (which are zero) brings noise into the forecasting process. Clark and West (2006) recommend an adjusted DMW statistic that adjusts for the negative bias in the difference between the two MSFE. Defining the adjustments as follows,

$$\begin{aligned} \hat{f}_{t+1}^{ADJ} &= \hat{e}_{1,t+1}^2 - \left[\hat{e}_{2,t+1}^2 - (X'_{t+1} \hat{\beta}_t)^2 \right] \\ \bar{f}^{ADJ} &= P^{-1} \sum_{t=T-P+1}^T \hat{f}_{t+1}^{ADJ} = \hat{\sigma}_1^2 - \left[\hat{\sigma}_2^2 - P^{-1} \sum_{t=T-P+1}^T (X'_{t+1} \hat{\beta}_t)^2 \right] \\ \hat{V} &= P^{-1} \sum_{t=T-P+1}^T (\hat{f}_{t+1}^{ADJ} - \bar{f}^{ADJ})^2 \end{aligned} \quad (15)$$

the CW test statistic is

$$CW = \frac{\bar{f}^{ADJ}}{\sqrt{P^{-1} \hat{V}^{ADJ}}} \quad (16)$$

The CW test has become one the most popular out-of-sample test statistic in the exchange rate literature. However, Rogoff and Stavrakeva (2008) show that the CW test cannot always be interpreted as a minimum MSFE test as the DMW test. Their study presents a proof that in the presence of forecast bias, the null hypothesis of the CW and the DMW tests are not necessarily the same.¹⁰ If one can reject the null of CW test, the true nature of exchange rate does not follow a random walk. Nevertheless, even if the true model follows some other model rather than a random walk, one can still apply the DMW statistics to test whether the random walk and the structural model have equal MSFEs.

⁹ $\sum_{t=T-P+1}^T y_{t+1} X'_{t+1} \hat{\beta}_t$ is zero, because the equality of $e_{1,t+1} = e_{2,t+1}$ under null hypothesis suggests that

$E(y_{t+1} X'_{t+1} \hat{\beta}_t) = E(e_{1,t+1} X'_{t+1} \hat{\beta}_t) = E(e_{2,t+1} X'_{t+1} \hat{\beta}_t)$. Since $E(e_{2,t+1} X'_{t+1}) = 0$ by assumption, we have $E(e_{2,t+1} X'_{t+1}) E(\hat{\beta}_t) = E(e_{2,t+1} X'_{t+1} \hat{\beta}_t) = 0$.

¹⁰ In the presence of scale bias, the null hypothesis of the CW and the DMW tests are different.

4.4 Bootstrapping Out-of-Sample Test Statistics

Size distortions of the DMW test in small samples can be reduced by bootstrapping the finite sample distribution of the test statistics. Kilian (1999) state that unlike asymptotic critical values, correctly specified (maintaining the cointegration between the exchange rate and fundamentals under the null hypothesis) bootstrap critical values adapt for the increase in the dispersion of the finite-sample distribution by itself. Kilian (1999) also suggest that the bootstrap is appropriate for multi-period ahead forecasts. Based on simulation evidence, Li and Maddala (1997) and Li (2000) also indicate bootstrapped tests have smaller size distortions and higher test power than asymptotic tests in cointegrating systems. Howbeit, Berkowitz and Kilian (2000) emphasize the importance of bootstrapping type implemented to preserve cointegrating relationships in the data. They argue that cointegration appears to be a parametric notion and parametric bootstraps are more accurate than non-parametric ones.

Mark and Sul (2001) and Rogoff and Stavrakeva (2008) apply bootstrapped out-of-sample tests to detect forecasting ability of linear exchange rate models against random walk in a panel framework. The bootstrap methods are similar in both studies. Mark and Sul (2001) implement parametric bootstrap and estimate error correction equations with seemingly unrelated regressions (SURs); however, Rogoff and Stavrakeva (2008) use semi-parametric bootstrap and estimate error correction equations with country specific OLS regressions.

Having insignificant bootstrapped DMW test statistics in certain cases, as opposed to highly significant asymptotic CW test, Rogoff and Stavrakeva (2008) criticize the asymptotic CW test to be oversized and has less power than the bootstrapped DMW test in the presence of forecast bias.¹¹ Oversized asymptotic CW test would cause too many rejections of the null hypothesis that exchange rate does not follow a random walk. It may detect spurious statistical significance and favor the alternative, structural exchange rate model. In this paper, I evaluate the out-of-sample forecasting ability of exchange rate fundamentals based on the bootstrapped DMW test, and the out-of-sample predictability of exchange rate fundamentals based on the bootstrapped CW test.

Rogoff and Stavrakeva's (2008) method of bootstrap (which imposes cointegration restriction between the exchange rate and the fundamentals) for each country is used in this study as follows:

¹¹ In the technical appendix of Clark and West (2007), the unadjusted power of the bootstrapped DMW test is higher than that of the asymptotic CW test for recursive regressions with one-step-ahead forecasts.

$$\Delta s_t = \varepsilon_t \tag{18}$$

$$\Delta z_t = \alpha + t + \gamma z_{t-1} + \sum_{j=1}^d \delta_j \Delta s_{t-j} + \sum_{j=1}^l \zeta_j \Delta z_{t-j} + u_t$$

where s_t is the nominal exchange rate and z_t is the deviation of exchange rate from fundamental as defined in equation (1). $\Delta s_t = s_t - s_{t-k}$ and $\Delta z_t = z_t - z_{t-k}$ where k is the forecast horizon, α is a constant and t is a trend. To control for autocorrelation in the error correction equation (ECE) lags of Δs_t and Δz_t are included. Akaike's information criterion is used for each country to determine the optimum number of d and l and to figure out whether to include a constant or a trend or both in the ECE. The sum of coefficients on lags of Δz_t is restricted to 1. s_t and z_t are simulated recursively after re-sampling the estimated residuals (ε_t and u_t). To reduce the bias caused by the initial values of the recursion, the first 100 observations are thrown away and a new sample is created. Applying the estimation procedure again, test statistics are calculated with the pseudo-data. This process is repeated 1000 times and semi-parametric bootstrap distribution is derived. Since the tests considered are one-sided tests, the p-values of DMW and CW tests are the percentage of the bootstrapped distribution above the estimated test statistic using the realized data.

5. Empirical Results

This section summarizes one- and 16-quarter-ahead out-of-sample predictive and forecasting performance of the linear exchange rate model with PPP and Taylor Rule fundamentals to that of the random walk model with and without drift using a newly constructed real-time dataset. The tables report the MSFE ratio, the ratio of MSFE of the structural model to that of the random walk, and the DMW and CW test statistics with their respective bootstrapped p-values.

It is important to interpret the results of the DMW and CW tests correctly. The DMW test is a minimum MSFE test that compares the MSFE of the linear exchange rate model to that of the random walk. A significant DMW test statistic implies that the linear exchange rate model produces a lower MSFE than the random walk. The forecasting ability of the structural model is higher and the structural model outperforms the random walk out-of-sample. On the other hand, the CW test is a test of predictability where a significant CW test statistic indicates that the coefficients in the linear exchange rate model are jointly different from zero, and the random walk null can be rejected in

favor of the linear model alternative. We call rejections of the equal MSFE null hypothesis with the DMW test evidence of forecasting ability, and rejections of the random walk null hypothesis with the CW test evidence of predictability.

5.1 PPP Fundamentals

One-quarter-ahead single-equation forecast results with the PPP model are presented in Table 1. No evidence of either out-of-sample predictability or forecasting ability is found for the PPP model against the driftless random walk for any exchange rate. The out-of-sample forecasting performance of the PPP model improves against the random walk with drift. Short-term predictability is found for Canada and Sweden, and the PPP model outperforms the random walk with drift for 4 countries (Canada, Germany, Japan, and Netherlands) at the one-quarter horizon.

Panel one-quarter-ahead forecasts using PPP fundamentals in Table 2 are only slightly better than single-equation forecasts in Table 1. The exchange rate model with PPP fundamentals using panel data significantly outperforms the driftless random walk only for Japan. The evidence of predictability and forecasting ability of the PPP model with panel estimation, just like in the single-equation case, increases against the random walk with drift at one-quarter horizon. Short-term predictability is found for 5 out of 9 countries (Australia, Canada, Germany, Japan, and Sweden) and the PPP model forecasts better than the random walk with drift for Australia and Sweden.

The low predictive and forecasting power at the one-quarter horizon of the PPP model using panel and single-equation estimations is not surprising. Existing studies concerning the half-life of PPP, the expected number of years for a PPP deviation to decay by 50%, find half-lives of around 2.5 years.¹² Accounting for the slow adjustment of real exchange rates in advanced economies, one would expect the predictability and forecasting ability of PPP model to be low at short horizons.¹³

Sixteen-quarter-ahead out-of-sample forecasts of the PPP model with single-equation estimation are presented in Table 3. The evidence of long-term predictability is stronger compared to one-quarter-ahead forecasts using the single-equation framework with rejections of the random walk null found for 4 countries (France, Germany, Netherlands, and Sweden). The PPP model,

¹² See Wu (1996), Papell (1997, 2002), Murray and Papell (2002), Choi, Mark and Sul (2006) for details concerning the half-lives of PPP deviations.

¹³ The correlations between real and nominal exchange rates are very high for almost all the countries in our sample.

however, does not significantly forecast better than the driftless random walk for any exchange rate. More evidence of long-term predictability is found against the random walk with drift. Out-of-sample exchange rate predictability is found for 7 out of 9 countries (Australia, Canada, France, Germany, Japan, Netherlands, and Sweden) and the PPP model forecasts better than the random walk with drift for Australia, Canada and Netherlands. The out-of-sample predictability and forecasting ability of the PPP model with a single-equation framework is clearly improved at the 16-quarter horizon compared to one-quarter horizon.

The PPP model performs best with the panel specification at the 16-quarter horizon. As reported in Table 4, the evidence of predictability is found for 6 out of 9 countries (Canada, France, Germany, Japan, Netherlands, and Sweden), and the PPP model forecasts better than the driftless random walk for 5 countries (Canada, Germany, Japan, Netherlands and Sweden). Panel forecasts at long horizon are even more striking against the random walk with drift. Out-of-sample predictability and forecasting ability is found for all the countries in the sample, as the exchange rate model with PPP fundamentals significantly outperforms the random walk with drift for each country using panel data. Because the commonality of high correlation between real and nominal exchange rates for the countries in the sample can be captured with the panel specification, panel estimation becomes more efficient and the predictability and forecasting ability of the panel exchange rate model with PPP fundamentals is much higher than the single-equation framework.

5.2 Taylor Rule Fundamentals

Following Engel, Mark, and West (2007), predictive regressions using Taylor rule model are estimated where the coefficients on inflation, output gap, and real exchange rate are fixed at certain values. One-quarter-ahead single-equation forecasts with Taylor rule are reported in Table 5. Evidence of short-term predictability and forecasting ability is found only for Japan. The exchange rate model with Taylor fundamentals works much better against the random walk with drift. Evidence of out-of-sample predictability and forecasting ability is found for 4 out of 9 countries (Australia, Canada, Japan, and Sweden), and evidence of forecasting ability is found for Netherlands.

Comparing Tables 5 and 6, evaluating the performance of Taylor rules in a panel framework does not improve the results, as incorporating different monetary policies operated by central banks

in a panel framework does not help to forecast exchange rates out-of-sample.¹⁴ One-quarter ahead forecasting results for the Taylor rule model with a panel framework are reported in Table 6. No evidence of out-of-sample predictability or forecasting ability against the driftless random walk, as neither the equal MSFE nor the random walk null hypotheses can be rejected for any exchange rate. The results are stronger against the random walk with drift. Evidence of predictability is found for 4 out of 9 countries (Australia, Canada, Japan, and Sweden), and the Taylor rule model using panel estimation forecasts better than the random walk with drift for 5 out of 9 countries (Australia, Canada, Germany, Japan, and Sweden).

Table 7 presents 16-quarter-ahead single-equation forecasts using the Taylor rule model. There is no evidence of forecasting ability, and evidence of long-term predictability is found only for Germany against the driftless random walk. The single equation forecasts with the Taylor rule model perform better against the random walk with drift. Evidence of long-term predictability is found for Netherlands and Sweden, and evidence of forecasting ability for 5 out 9 countries (Australia, Canada, Japan, Netherlands, and Sweden).

Panel forecasts with the Taylor rule model at the 16-quarter horizon perform poorly. As reported in Table 8, no evidence of either long-term predictability or forecasting ability is found against the random walk, with or without drift, for any of the countries in the sample. These results are in accord with previous work using revised or quasi-real-time data. Molodtsova and Papell (2009) report that the evidence of short term predictability disappears at longer horizons with a single equation Taylor rule model, and Engel, Mark and West (2007) do not find more evidence of predictability with panel models.

6. Conclusions

The vast majority of empirical studies on exchange rate forecasting over the post-Bretton Woods period use ex-post revised data. Since this data contains future information that is not available to policymakers and market participants at the time forecasts are made, it cannot be used to evaluate predictability and forecasting ability of exchange rate models out-of-sample. The use of

¹⁴ See Clarida, Gali and Gertler (1998) and Gerdesmeier, Mongelli and Roffia (2007) for comparisons of interest rate reaction functions among countries.

real-time data overcomes this problem and mimics the information set of market agents as closely as possible.

The purpose of this paper is to investigate how real-time data affects out-of-sample exchange rate forecasts of PPP and the Taylor rule models at short and long horizons with single-equation and panel frameworks. Our results show that panel estimation increases the predictability and the forecasting ability of the PPP model relative to single-equation estimation. The high correlation between real and nominal exchange rates of the countries in our sample is better captured by the panel specification and estimating the predictive regression with panel data increases the predictive and forecasting power of the PPP model. At the 16-quarter horizon, evidence of predictability is found with panel estimation for 6 out of 9 countries against the driftless random walk and for all of the countries against the random walk with drift based on the bootstrapped CW test. The PPP model using panel data outperforms the driftless random walk for 5 out of 9 countries and outperforms the random walk with drift for all the countries in the sample based on the bootstrapped DMW test. One-quarter-ahead forecasts of the exchange rate model with PPP fundamentals are weaker than long-horizon forecasts. The good predictability and forecasting ability of the PPP model at longer-horizons is in accord with estimated half-lives of PPP deviations of around 2.5 years. The predictability and the forecasting ability of the PPP model at longer horizons with panel estimation confirms the findings in Engel, Mark and West (2007).

In contrast, out-of-sample forecasting with panel models are unable to improve forecasts compared with single-equation estimation for the exchange rate model with Taylor rule fundamentals. As shown in Clarida, Gali and Gertler (1998), interest rate functions are different among the OECD countries, and so the assumption of identical monetary policy rules for all the central banks in panels is not very realistic. With both single-equation and panel error correction models, the predictability and the forecasting ability of the Taylor rule model is higher at the short-horizon, as in Molodtsova and Papell (2009). Evidence of short-term predictability with the Taylor rule model is found for 1 out of 9 countries against the driftless random walk and for 4 out of 9 countries against the random walk with drift. The exchange rate model with Taylor rule fundamentals using a single-equation framework outperforms the driftless random walk for 1 out of 9 countries and the random walk with drift for 5 out of 9 countries at one-quarter horizon.

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Table 1. Single Equation 1-Quarter-Ahead Forecasts Using PPP Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.0219	0.1770	0.5540	-0.6003	0.4520
Canada	1.0058	0.2108	0.3980	-0.3231	0.2340
France	1.0223	0.1191	0.3720	-0.6880	0.3000
Germany	0.9975	0.7763	0.2270	0.0987	0.1260
Italy	1.0739	0.2634	0.7000	-1.5571	0.8060
Japan	0.9918	0.9504	0.3160	0.3329	0.1420
Netherlands	1.0012	0.5748	0.2840	-0.0486	0.1360
Sweden	1.0217	0.6944	0.2900	-0.8252	0.4650
U.K.	1.0179	0.2829	0.3770	-0.5022	0.2860
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.0068	0.3595	0.2340	-0.2165	0.1670
Canada	0.9878	1.1801	0.0630	0.6040	0.0370
France	0.9978	0.6150	0.2290	0.1194	0.1300
Germany	0.9897	1.0355	0.1140	0.4836	0.0720
Italy	1.0197	-1.1403	0.8290	-1.4620	0.7400
Japan	0.9964	0.6673	0.1780	0.2881	0.0890
Netherlands	0.9925	0.9005	0.1330	0.3739	0.0780
Sweden	0.9991	1.1124	0.0770	0.0473	0.1050
U.K.	0.9970	0.5721	0.2170	0.1643	0.1130

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 2. Panel 1-Quarter-Ahead Forecasts Using PPP Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9870	1.0847	0.2880	0.4723	0.1900
Canada	0.9938	0.8499	0.2220	0.2249	0.1620
France	1.0084	0.0201	0.3390	-0.4093	0.2690
Germany	0.9876	1.1311	0.1840	0.4429	0.1340
Italy	1.0519	0.3837	0.4690	-0.9149	0.6950
Japan	0.9726	2.0353	0.0960	1.5247	0.0270
Netherlands	0.9926	0.8988	0.1790	0.3024	0.1190
Sweden	0.9907	0.7144	0.2930	0.3540	0.1460
U.K.	1.0042	0.6631	0.2820	-0.1231	0.3050
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9725	1.6333	0.0530	1.0345	0.0860
Canada	0.9761	1.5325	0.0750	0.6836	0.1760
France	0.9842	1.1510	0.1250	0.6060	0.2690
Germany	0.9799	1.3525	0.0970	0.7937	0.1670
Italy	0.9987	0.5847	0.2950	0.0490	0.4780
Japan	0.9772	1.4911	0.0550	0.8698	0.1100
Netherlands	0.9840	1.1972	0.1220	0.6509	0.1810
Sweden	0.9687	1.8830	0.0240	1.0867	0.0710
U.K.	0.9836	1.2211	0.1260	0.7057	0.2310

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 3. Single Equation 16-Quarter-Ahead Forecasts Using PPP Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.3393	1.1002	0.2600	-0.7412	0.5460
Canada	1.0883	0.6955	0.2590	-0.2140	0.2420
France	2.0458	2.0382	0.0150	-0.9436	0.5000
Germany	1.4950	2.6105	0.0040	-0.4662	0.3550
Italy	2.9815	0.6797	0.4280	-0.9610	0.6030
Japan	1.0300	1.0890	0.2940	-0.0642	0.3300
Netherlands	0.8441	2.4793	0.0090	0.1788	0.1300
Sweden	2.9874	2.2454	0.0130	-1.5296	0.7740
U.K.	2.1290	0.5006	0.3710	-0.6647	0.4180
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.7913	4.3300	0.0000	0.7716	0.0140
Canada	0.7596	2.2683	0.0060	0.8363	0.0200
France	1.1539	3.8812	0.0010	-0.2461	0.3350
Germany	1.3551	2.7336	0.0040	-0.3689	0.5680
Italy	1.1597	1.0209	0.1400	-0.1992	0.3050
Japan	1.0042	2.5483	0.0000	-0.0093	0.2070
Netherlands	0.7356	2.8317	0.0010	0.3482	0.0640
Sweden	1.7764	4.2205	0.0000	-1.0049	0.8730
U.K.	1.0219	0.9871	0.1420	-0.0269	0.2060

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 4. Panel 16-Quarter-Ahead Forecasts Using PPP Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.7614	1.6545	0.1080	0.6718	0.1250
Canada	0.6711	1.6328	0.0570	0.8875	0.0460
France	0.8818	1.2697	0.0600	0.2028	0.1290
Germany	0.4211	2.3768	0.0210	0.9245	0.0510
Italy	2.0116	0.4540	0.4780	-0.7276	0.6840
Japan	0.6032	2.6244	0.0170	1.5011	0.0210
Netherlands	0.4651	2.3258	0.0070	0.9939	0.0320
Sweden	0.4975	1.6649	0.0570	0.6658	0.0880
U.K.	1.4518	0.3979	0.3630	-0.3942	0.4370
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.4499	5.6980	0.0001	2.6217	0.0020
Canada	0.4684	3.6361	0.0020	2.0548	0.0020
France	0.4973	3.3588	0.0010	1.5287	0.0110
Germany	0.3817	2.5197	0.0050	1.0893	0.0170
Italy	0.7825	1.0278	0.0360	0.4021	0.0860
Japan	0.5881	4.1808	0.0010	1.5983	0.0040
Netherlands	0.4053	2.7490	0.0010	1.2681	0.0150
Sweden	0.2958	3.4463	0.0010	1.5690	0.0040
U.K.	0.6968	1.2608	0.0310	0.5513	0.0760

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 5. Single Equation 1-Quarter-Ahead Forecasts Using Taylor Rule Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9914	1.2537	0.1310	0.2250	0.1050
Canada	1.0060	0.5849	0.2490	-0.2338	0.1790
France	1.0527	-1.3383	0.8700	-1.9355	0.8450
Germany	1.0147	0.6132	0.2690	-0.3617	0.2020
Italy	1.0597	-0.3097	0.6850	-1.4349	0.7300
Japan	0.9652	1.9937	0.0990	1.4085	0.0130
Netherlands	1.0048	0.4043	0.3110	-0.1809	0.1350
Sweden	1.0100	1.0844	0.1890	-0.2601	0.2220
U.K.	1.0333	-1.1452	0.8570	-1.6155	0.7630
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9786	1.6592	0.0330	1.2498	0.0070
Canada	0.9858	1.1145	0.0840	0.8788	0.0230
France	1.0213	-1.5723	0.9380	-1.7368	0.8580
Germany	1.0048	0.6663	0.2350	-0.1424	0.1520
Italy	1.0060	0.7238	0.1850	-0.1340	0.1420
Japan	0.9697	1.9859	0.0170	1.6030	0.0030
Netherlands	0.9934	0.7929	0.1700	0.2549	0.0660
Sweden	0.9773	1.6497	0.0340	1.1215	0.0100
U.K.	1.0092	-0.5116	0.5830	-0.7419	0.3400

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 6. Panel 1-Quarter-Ahead Forecasts Using Taylor Rule Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.0014	0.8280	0.3110	-0.0426	0.2910
Canada	1.0094	0.4920	0.2980	-0.4324	0.3490
France	1.0314	-0.5309	0.6530	-1.1586	0.7020
Germany	1.0022	0.3006	0.4450	-0.1204	0.3470
Italy	1.0725	0.1114	0.6420	-1.3378	0.8360
Japan	0.9848	1.2875	0.3400	0.5006	0.2660
Netherlands	1.0056	-0.0354	0.4800	-0.3726	0.3410
Sweden	1.0185	0.3264	0.4620	-0.6734	0.5500
U.K.	1.0292	-0.1793	0.5490	-0.9453	0.5620
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9884	2.0224	0.0230	1.8584	0.0120
Canada	0.9891	1.4148	0.0860	1.2825	0.0560
France	1.0006	0.0641	0.6290	-0.0969	0.5430
Germany	0.9924	1.5397	0.1440	1.4379	0.0980
Italy	1.0183	-1.3881	0.9480	-1.6899	0.9390
Japan	0.9894	1.8692	0.0300	1.7603	0.0220
Netherlands	0.9940	1.1742	0.1560	1.0690	0.1000
Sweden	0.9856	2.1221	0.0140	2.0224	0.0060
U.K.	1.0052	-0.4187	0.6880	-0.6499	0.5970

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 7. Single Equation 16-Quarter-Ahead Forecasts Using Taylor Rule Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.3755	0.3071	0.4490	-0.6126	0.4570
Canada	1.3806	-0.4763	0.6990	-1.3708	0.7140
France	3.1752	0.2036	0.4360	-1.4136	0.6790
Germany	1.0439	1.5246	0.0700	-0.0514	0.1770
Italy	3.7153	0.0230	0.6430	-1.4449	0.7670
Japan	0.9203	0.7005	0.4720	0.2044	0.2640
Netherlands	1.0795	0.8599	0.1800	-0.1441	0.1670
Sweden	1.5230	0.5261	0.4040	-0.6842	0.5150
U.K.	2.9587	-0.5476	0.7100	-1.3239	0.6230
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.8639	0.7102	0.1240	0.3535	0.0760
Canada	0.9302	0.4608	0.2190	0.3733	0.0910
France	1.5964	1.0529	0.2420	-0.7708	0.5450
Germany	0.8746	1.5925	0.1070	0.1755	0.1570
Italy	1.4247	-0.0450	0.5820	-0.5894	0.5720
Japan	0.8974	0.6737	0.1110	0.2698	0.0760
Netherlands	0.8547	1.3971	0.0850	0.3329	0.0820
Sweden	0.7617	1.4365	0.0470	0.6234	0.0390
U.K.	1.3117	-0.3061	0.6940	-0.4753	0.4540

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.

Table 8. Panel 16-Quarter-Ahead Forecasts Using Taylor Rule Fundamentals

No Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	1.4467	-0.0038	0.5820	-0.7712	0.5780
Canada	1.4097	-0.6368	0.7710	-1.4443	0.7830
France	2.0068	-0.8928	0.8210	-1.4713	0.8300
Germany	1.0488	0.2465	0.4700	-0.1870	0.3700
Italy	2.5953	-0.2666	0.7700	-1.3622	0.8480
Japan	0.9283	0.7547	0.4810	0.1388	0.3860
Netherlands	1.1738	-0.5536	0.7430	-0.8821	0.6090
Sweden	1.7350	-0.3142	0.7150	-1.0647	0.7340
U.K.	1.8665	-0.4944	0.7080	-0.9460	0.5980
Drift					
	MSFE ratio	CW	P-value	DMW	P-value
Australia	0.9086	0.3606	0.2920	0.2513	0.1400
Canada	0.9498	0.3397	0.3060	0.2625	0.1720
France	1.0088	0.1881	0.5730	-0.0258	0.5410
Germany	0.8786	0.7962	0.2610	0.5564	0.2070
Italy	0.9953	0.1283	0.5670	0.0105	0.4620
Japan	0.9052	0.2868	0.2450	0.1881	0.2010
Netherlands	0.9293	0.7348	0.2290	0.4532	0.1750
Sweden	0.8678	0.5384	0.1620	0.3829	0.1190
U.K.	0.8275	0.5368	0.2790	0.4247	0.1720

Notes: The table reports the MSFE ratio, defined as the ratio of MSFEs of the linear exchange rate model to that of the benchmark model (random walk with and without the drift), the CW statistics and the DMW statistics for the tests of equal MSFEs. All reported tests are one-sided. Bold font denotes the p-value of respective test statistic significant at 10 % level based on semi-parametric bootstrap. Starting in 1973:Q1, I estimate recursive regressions with a 40-quarter initial window to predict exchange rate changes from 1983:Q1 to 2009:Q1.