The Out-of-Sample Exchange Rate Predictive Ability of Macroeconomic Fundamentals, 1976-2016

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Abstract

Attempts to predict exchange rates using macroeconomic fundamentals have had mixed results since the 1983 papers of Meese and Rogoff, which state that no model can outperform a random walk at predicting exchange rates over all time periods. Most of the literature as of yet has found little support for traditional economic predictors such as uncovered interest rate parity conditions and purchasing power parity conditions. However, in the past 15 years researchers have found support for Taylor rule fundamental models in their ability to outperform a random walk in predicting exchange rates. In this paper I find issues with the favourable empirical evidence in support of the Taylor rule fundamental model, particularly with researchers using data in their models that would not be available to forecasters at the time. I adjust the Taylor rule fundamental model by only including data that would be observable to forecasters. In a horse race comparison, I compare the Taylor rule fundamental model to the more traditional macroeconomic fundamental models in their ability to beat a random walk, and their ability to predict the directional change of the exchange rate. I find that when I adjust the Taylor rule fundamental model only to include data observable to forecasters at the time, the model no-longer outperforms a random walk at predicting exchange rates, and is not superior to traditional macroeconomic fundamentals.

Keywords: predictability, exchange rates, macroeconomic fundamentals, Taylor rules, random walk, directional change.

1 Introduction

The inability of empirical forecasting methods to consistently beat a random walk in predicting exchange rates has troubled researchers since the seminal papers of Meese and Rogoff(1983,a,b). Although financial theory states that there is a relationship between traditional macroeconomic fundamentals and exchange rates, the empirical research does not support this. This inability of macroeconomic fundamentals to outperform a random walk at predicting the exchange rate since rates were allowed to float in 1970 is known as the Meese and Rogoff puzzle. More recent empirical research [1] claims to have found empirical support for models using Taylor rule fundamentals to out-perform a random walk at forecasting the exchange rate. However, I find that some of these papers use data in their models that would not be observable to forecasters at the time, which would make their claim for true superior exchange rate forecasting ability in comparison to the random walk false. In this paper I make adjustments to the Taylor rule fundamental model in order to ensure it only uses data that would be available to forecasters at the time. I compare the adjusted models to the original model using the same data set and find that the favorable predictive power of the original model drops out using the adjusted models. I also compare the adjusted models to traditional macroeconomic fundamental models [2] and find that the adjusted Taylor

[1] Molodtsova and Papell (2008), Engel and West (2005, 2006), and Giacomini and Rossi (2010).

[2] Uncovered Interest Rate Parity, Purchasing Power Parity, Monetary Fundamental Model.

rule fundamental models are not superior to the traditional macroeconomic fundamental models in out-performance of a random walk, or directional accuracy. The outcome of this research shows that the Meese and Rogoff puzzle still holds and is not solved by the Taylor rule fundamental model.

Correct exchange rate forecasting is important for policy makers in finance ministries and central banks because knowledge of whether a domestic currency is going to appreciate or depreciate against foreign currencies can assist the decision in whether to pursue contractionary or expansionary monetary policy. A strong currency has a similar drag on the economy as a high interest rate, and therefore a policy maker may want to delay contractionary monetary policy if the domestic currency is forecasted to appreciate in value. A policy maker can also use forecasted information about exchange rate movements to influence their negotiations in trade deals with other economies. For example, if the foreign currency is forecasted to depreciate in value in relation to the domestic currency, foreign exports will become more competitive. The policy maker can use this information to negotiate for trade measures that would protect domestic production.

Correct exchange rate forecasting is also important for the private sector. For firms and investors correct foreign exchange forecasting can help mitigate exchange rate risk, enabling the firm to engage in international buying and selling activities with the knowledge of where the exchange rate will move in the future. For example, if a Japanese automobile firm needs to purchase manufacturing parts from a firm in China in renminbi, they will face the risk of change in the yen/renminbi exchange rate between price quote, billing, and time of delivery. However, if the Japanese firm can accurately predict the spot rate [3] change, or at least the direction the exchange rate will move, then they can substantially mitigate their exchange rate risk through the use of financial derivative products such as futures, or operational means such as timing their foreign purchases for forecasted times of a more favorable exchange rate. In addition to mitigating exchange rate risk, the exchange rate is also a measure of competitiveness for an economy, and Investors can use forecasting information to guide decisions on whether or not to invest in an economy. Exchange rate prediction is also important for traders, if traders are able to correctly forecast the magnitude or even direction of the exchange rate, they can buy and sell currency and currency derivative products in order to profit, or efficiently hedge clients other activities.

2 An Introduction to Empirical Exchange Rate Forecasting Methods

In this section I explain how to determine the out-of-sample predictability of the exchange rate using a simplified empirical macroeconomic model.

[3]spot rate is defined as the price of the domestic currency in terms of one unit of foreign currency.

In-sample forecasting uses data within a sample period to estimate coefficients that produce forecasts of values within the same sample period. Out-of-sample forecasting forecasts outside the sample period used to estimate the coefficients.

Since I am looking at out-of-sample predictive ability in this paper, I use a rolling window method to forecast. This involves breaking down the entire data set into 2 periods, an in-sample period (rolling window) and an out-of-sample period. The regression is estimated using the rolling window, and I forecast one period into the out-of-sample region. The rolling window then moves along one observation, disregarding the first in-sample observation, and taking into account the realized value for the first out-of-sample observation. This means that the rolling window size stays fixed. This process is repeated until there are no longer any out-of-sample observations. The following equation 1 is a simple example of an exchange rate forecasting model:

$$s_{t+1} - s_t = \alpha + \beta(X_t - X_t^*) + e_{t+1} \tag{1}$$

Where, $s_{t+1} - s_t$ is the change in the (log) spot rate from period t to period $t + 1$. It is standard in the literature to forecast the change in the spot rate since the spot rate is a non-stationary variable, and taking the difference makes the dependent variable more stationary which gives our estimates more economic meaning.

On the right-hand side of this equation, is the predictor term, $(X_t - X_t^*)$, where X is the predictor of interest of the domestic economy and X^* is the predictor of interest of the foreign economy. This bracket term could also include multiple predictors of interest. The error term, e_{t+1}, captures the difference between the forecasted change in the spot rate and the actual change in the spot rate.

As the rolling window moves along the time series, I take note of the error terms that I obtain from the regressions. These error terms (e_{forc}) are then compared with the error terms of a random walk model (e_{rw}). A random walk states that there is no change in the spot rate from one period to the next, therefore, e_{rw} can be defined as any change that did occur in the spot rate from period t to $t+1$. Point estimates such as the root mean squared forecasting error (RMSFE) can be used to compare the error terms of the forecasting model with the random walk.

$$RMSFE = \frac{1}{N} \sum (e_{t+1})^2 \tag{2}$$

The point estimate provides an idea of how the forecasting model and random walk model error terms compare but states nothing about statistical significance.

In order to determine statistically significant outperformance of a random walk, tests such as the Diebold-Mariano (1995) test, or the Clark-West (2007) test (C.W.)[4] can be used. The C.W. tests against the null hypothesis of equal variance of errors between the forecasting model and the random walk model. Where $MSPE_f$ is the mean squared prediction

[4] A discussion of statistical tests used can be found in section 3.2.2.

error of the forecasting model and $MSPE_{rw-adj}$ is the mean squared prediction error of the random walk with an adjustment term that adjusts for an upward bias on estimators that occurs when comparing two models that are nested[5]. This test can be shown by equations 3 and 4:

$$H_0 : MSPE_f = MSPE_{rw-adj} \tag{3}$$

$$H_1 : MSPE_f < MSPE_{rw-adj} \tag{4}$$

If the null hypothesis of equal variance of errors is rejected, then I can infer that the forecasting model has a smaller variance of error than the random walk, and therefore outperforms the random walk at predicting the exchange rate at some level of significance.

3 Literature Review

Rossi (2013) summarizes the out-of-sample exchange rate predictability literature since the 1970s. She argues that whether exchange rates are predictable depends on the variables included in the model, the specifics of the model framework and the forecast evaluation method. Rossi (2013) states that linear models with fewer parameters tend to perform the best. An important conclusion of Rossi (2013) is that no model is able to beat the random walk consistently, across all countries and time periods.

I begin a review of the literature by discussing the financial theory behind traditional exchange rate forecasting models, and then present a summary

[5] Every model of interest is nested with the random walk, since the random walk term states that $s_{t+1} = s_t$.

of the empirical findings of the models. I then do the same for the recent favorable Taylor rule fundamental exchange rate forecasting model.

3.1 Traditional Fundamental Models

3.1.1 Uncovered Interest Rate Parity

Fisher (1896) analyses how interest rates are related to various units of account. Uncovered interest rate parity is an equality condition that states that the change in the spot rate is equal to the difference in interest rates between the two economies.

This can be explained by considering an example: Consider a situation in which an American investor has the choice to invest their funds in the United States, or the United Kingdom. The investor could invest their funds domestically in the United states earning $(1 + i_{u.s,t})$, or they could take their funds abroad to the United Kingdom, and earn $\frac{1}{S_t}(1 + i_{u.k,t})(E(S_{t+1}))$. In a world of perfect capital markets (no transaction costs, no taxes, perfect information, perfect competition), the resulting value of the 2 investment options should be the same. Otherwise there is an opportunity for arbitrage.
This can be modelled empirically by equation 5:

$$E(s_{t+h} - s_t) = \alpha + \beta(i_t - i_t^*) + e_{t+1} \tag{5}$$

Where, s_t is the (log) of the exchange rate h is the forecast horizon, i_t^* is the foreign interest rate, and i_t is the domestic. The financial theory states that the β should be positive and equal to 1, while $\alpha = 0$.

The empirical evidence for UIRP is not favourable. Meese and Rogoff (1983) find no statistically significant outperformance of the random walk by UIRP, with β coefficients that are negative and not equal to 1. This is inconsistent with the financial theory stated above. In Meese and Rogoff (1988), they find no outperformance of the random walk, but with a β that is positive in sign. Cheung, Chinn, and Pascual (2005) also find little statistically significant evidence for coefficient estimates in UIRP empirical models. Alquist and Chinn (2008) similarly find little statistically significant support for coefficient estimates in UIRP empirical models. Molodtsova and Papell (2008) find more favourable evidence for the UIRP model, with four out of twelve countries significantly beating the random walk model.

To conclude, estimates of UIRP models typically yield a negative β (where theory predicts β should be positive), and such models generally fail to outperform a random walk in predicting exchange rates.

3.1.2 Purchasing Power Parity

Purchasing power parity (PPP) builds on the law of one price. The law of one price states that, in perfect capital markets, the price of a homogenous good in two different economies should be the same once the exchange rate has been accounted for. PPP extends the law of one price to apply not just to one homogenous good, but to a basket of goods, one example could be the Consumer Price Index (CPI), although the production price index may be a better predictor since it includes more traded goods. If PPP holds, then a domestic unit of currency is able to purchase the same amount of goods domestically as abroad, once converted into foreign currency. This means that the purchasing power of a unit of the domestic currency is the same in both the domestic and foreign country. The empirical model for PPP is similar to UIRP, modelled here by equation 6:

$$s_{t+1} - s_t = \alpha + \beta(p_t - p_t^*) + e_{t+1} \tag{6}$$

Here p^* is the (log) price of a basket of goods in the foreign economy, and p is the (log) price of a basket of goods in the domestic. The financial theory states that $\alpha = 0, \beta = 1$.

The empirical literature is not very supportive of PPP. Chinn, Cheung and Pascual (2005) find no out-of-sample significant out-performance of the random walk. In regards to PPP, it is possible that we do not find true parity due to imperfect capital markets, and the stickiness of prices (prices take time to adjust to changes in fundamentals).

3.1.3 Monetary Fundamentals

The monetary fundamental models link relative money demand, money supply, economic output (gross domestic product), interest rates, and prices (CPI, PPI), to exchange rates. There are many different ways to model monetary fundamentals, and each model will perform differently. A general framework for monetary fundamentals and their impact on exchange rates was proposed by Frenkel (1976), whose approach analyzes the role of money and assets on determination of the exchange rate. However, a more widely used framework has since been developed by Mark (1995), and is used by Molodtsova and Papell (2008) for evaluating out-of-sample predictability of the exchange rate using monetary fundamentals. This method states that the change in the spot rate is a function of the deviation of the spot rate from its fundamental equilibrium value. The fundamental equilibrium value is determined by the traditional monetary and asset fundamentals; money supply, the (log) of the price level(CPI), income (GDP or Industrial Price Index), and the interest rate. Molodtsova and Papell's (2008) model can be seen in equation 7 below:

$$s_{t+1} - s_t = \alpha + \beta Z_t + e_{t+1} \tag{7}$$

Where $Z = f_t - s_t$, f_t is the fundamental long run equilibrium of the exchange rate that has been defined by the fundamental variables stated in equation 8 below:

$$f_t = (m - m^*) - w(y - y^*) \tag{8}$$

Where m is money supply, using M1 data, and y is income, using GDP or the industrial production index.

Empirical findings are mixed on the ability of monetary fundamental models to predict exchange rates. Meese and Rogoff (1983) find no out-of-sample statistically significant out-performance of the random walk, as do Chinn and Meese (1995), Chinn, Cheung and Pascual (2005), and Alquist and Chinn (2008). However, Molodtsova and Papell (2008) find that a monetary fundamental model outperforms a random walk for four out of twelve countries. Mark (1995) finds favourable results at forecasting long horizons (further than one year), but the robustness of the results have been questioned by many including Berkowitz and Giorgianni (2001), who have concerns due to a small sample size possibly creating a bias of the β coefficient towards 0.

3.2 Promising Recent Models

Over the past fifteen years, two promising recent exchange rate forecasting models have been developed. The first is a Taylor rule fundamental model, and the second is an external imbalance measure model. These models have had more success in beating a random walk in forecasting exchange rates than traditional models based on macroeconomic fundamentals. Although I discuss the literature behind the Taylor rule model, the external imbalance measure model of Gourinchas and Ray (2007) is out of the scope of this paper and is not included.

3.2.1 Taylor Rule Fundamental Models

Taylor's (1993) Taylor rule states that the Federal Reserve determines the nominal interest rate by taking into account the difference between the current inflation rate and the target inflation rate, and the difference between potential and actual output (GDP). Molodtsova and Papell (2008) present the Taylor rule as equation 9 below:

$$i^* = \pi + \phi(\pi - \pi^*) + \gamma y + r^* \tag{9}$$

Here i^* is the short term nominal interest rate target, π is the inflation rate, π^* is the target inflation rate, y is the output gap, and r^* is the assumed equilibrium level of the real interest rate.

The Taylor rule posits that the short term target interest rate will increase if π increases relative to π^*, and/or if output is above the potential level. This makes intuitive sense since a central bank uses interest rate hikes to cool down an overheating economy, one that would be exhibiting high inflation and output.

Molotsova and Papell (2008) argue that π^* and r^* can be combined into a simple constant term $\mu = r^* - \phi\pi^*$, and equation 9 becomes equation 10:

$$i^* = \mu + \lambda\pi + \gamma y \tag{10}$$

Where $\lambda = 1 + \phi$, and since $\lambda > 1$, the real interest rate increases with inflation, satisfying the Taylor rule. Molodtsova and Papell (2008) state that foreign models include a real exchange rate term. This term, q, is included as an assumption that foreign central banks set a target level exchange rate in order to equilibrate purchasing power parity. Theoretically the foreign central bank would raise the nominal interest rate should, *ceteris paribus*, the real exchange rate depreciate from the value that allows purchasing power parity to hold. The model of Molodtsova and Papell (2008) that performs the best did not include a real exchange rate term on the right-hand side, therefore that model does not assume that foreign central banks target the real exchange rate to make PPP hold. Molodtsova and Papell (2008) continue to follow Clarida, Gali, and Gertler (1998) in formulating a model of the Taylor rule that encompasses the possibility that interest rates rise gradually to achieve the target level. This can be thought of as central banks not immediately raising interest rates to the target level, but slowly adjusting with incremental hikes over time. This can be captured by introducing a lagged interest rate term on the right-hand side of the equation. Slow adjustment of interest rates over time is referred to as interest-rate smoothing.

The Taylor rule fundamental forecasting model is essentially a complex interest rate differential equation, captured by equations 11 and 12:

$$s_{t+1} - s_t = (i_t - i_t^*) \tag{11}$$

Where;

$$i_t - i_t^* = \alpha - w_{u\pi}\pi_t + w_{f\pi}\pi_t^* - w_{uy}y_t + w_{fy}y_t^* - w_{ui}i_{t-1} + w_{fi}i_{t-1}^* + e_{t+1} \tag{12}$$

This equation is what is used to forecast the change in the exchange rate. The interest rate differential signs provide insight into Molodtsova and Papell's (2008) predictions that anything that causes domestic central bank to raise interest rates relative to the foreign central bank will cause the domestic currency to appreciate.

Molodtsova and Papell (2008) find that Taylor rule fundamental models are good forecasters of the exchange rate, significantly beating the random walk in eight to eleven countries out the twelve for which the model is tested, depending on how the model is specified. Engel and West (2005, 2006) and Giacomini and Rossi (2010) also find evidence in support of using Taylor rule fundamentals to predict exchange rates.

3.2.2 Disagreement About Recent Favourable Results: the importance of test statistic choice.

There is some disagreement in the literature as to what extent Taylor rule fundamentals are able to solve the Meese-Rogoff puzzle of an inability of fundamental forecasting models to out-perform a random walk in forecasting exchange rates. Rogoff and Stavrakeva (2008) discuss the robustness of the empirical results in favor of the Taylor rule fundamental models out-performing a random walk in forecasting exchange rates out-of-sample.

Rogoff and Stavrakeva claim that the recent results in favour of Taylor rule fundamental models and their ability to out-perform a random walk are not statistically robust since the Clark West (2007) test used by Molodtsova and Papell (2008) tests a different null hypothesis than the traditional Diebold-Mariano test.

The Diebold-Mariano statistic was derived by Diebold and Mariano (1995). It has since been widely used in the literature, and was accepted to be one of the standard tests in comparing forecasting accuracy. Let $\hat{y}_f$ be the forecasted value of the series y by the model, and let $\hat{y}_{rw}$ be the forecasted value of the series y by the random walk, which will essentially just be y_{t-1}. The Diebold-Mariano tests against the null hypothesis of equal forecast accuracy $E(e_f) = E(e_{rw})$, where the e term is the error associated with each model. This null hypothesis tests whether the population mean of the loss differential function is equal to 0, where the loss differential is a function of the forecasted value and the realized value; $g(y, \hat{y}_f) = g(e_f)$. Molodtsova and Papell (2008) state that the Diebold-Mariano statistic is not normally distributed when comparing nested models. This is a problem for testing the forecasting model against the random walk, as every model is nested with the random walk model. The nested problem creates a positive bias on the estimated coefficients.

Clark and West (2006 and 2007) have developed the Clark and West test that is approximately asymptotically normally distributed with nested models. The C.W. statistic can be derived as follows: Again, let $\hat{y}_f$ be the model forecasts we are interested in, let $\hat{y}_{rw}$ be the random walk forecasts, and let y be the realized values. The Clark West statistic tests against the null hypothesis of equal mean squared prediction errors (MSPE):

$$H_0 : MSPE_f = MSPE_{rw-adj} \tag{13}$$

$$H_1 : MSPE_f < MSPE_{rw-adj} \tag{14}$$

Where,
$MSPE_f = \sum(y_t - \hat{y}_{f,t})^2$ and,
$MSPE_{rw-adj} = \sum(y_t - \hat{y}_{rw,t})^2 - \sum(\hat{y}_{f,t} - \hat{y}_{rw,t})^2$.
Rejection of the null hypothesis implies that the mean squared prediction error of the forecasting model is less than that of the random walk, which can be inferred as out-performance of the random walk by the forecasting model.
Stavrakeva and Rogoff (2008) state that while the asymptotic C.W. statistic is computationally more appealing than the more complex task of

bootstrapping traditional problematic statistics such as the Diebold-Mariano statistic, they argue that the robustness of results based on the asymptotic C.W. should be checked using a bootstrapped D.M. statistic. Rogoff and Stavrakeva (2008) do state that the asymptotic C.W. statistic is well defined for models using a fixed rather than recursive rolling window. This means that the C.W. statistic is well defined for frameworks where the rolling window in-sample size is fixed, and not allowed to deviate. My research keeps the in-sample size fixed at 120 data points, and therefore the C.W. statistic is appropriate for evaluating the models I examine. Rogoff and Stavrakeva (2008) recreate the results of Papell and Molodtsova (2008), while recreating the tests on the Taylor rule fundamental model, they bootstrap the C.W. (2007) statistic, and use further bootstrapping of traditional statistics such as the Diebold Mariano statistic. Their results show little significant outperformance of the random walk. Rogoff and Stavrakeva (2008) argue that their results show that the significance of the Taylor rule fundamental predictability is overstated, since the bootstrapped tests are more powerful and of larger size than the asymptotic C.W. statistic used by Papell and Molodtsova (2008).

4 Methodology

In this paper I examine the exchange rate predictive ability of macroeconomic fundamentals. I consider three traditional macroeconomic models[6], and the more recent Taylor rule fundamental model[7].

The Taylor rule fundamental model has more favorable empirical evidence for outperformance of the random walk. However, I find that some favorable research uses data in their models that would not be observable to forecasters. On the right-hand-side of the Taylor rule fundamental model is the predictor y, which is the output gap. As previously mentioned in section 3.2.1, the output gap is the deviation of actual output from potential output. There is no data available for potential output, and therefore some estimation needs to be done to determine potential output. Some research such as Molodtsova and Papell (2008) state that they determined potential output by trending actual output on data following the observation that potential output is to be determined for. For example, Molodtsova and Papell (2008) determined potential output for 1971 using data from the years 1971,72 and 73. They fitted an exponential and Hodrick Prescott trend line on the actual industrial production index for those years to determine what the potential industrial production index could have been for 1971. Other favorable research such as Engel and West (2005) and Giacomini and Rossi (2010) do not state what data or methods they used to determine potential output.

I make adjustments to the original Taylor rule fundamental model of Molodtsova and Papell (2008) to only include data that would have been observable to forecasters. I forecast potential output by using a rolling

[6] UIRP, PPP, monetary fundamental model, explanations can be found in sections 3.1.1, 3.1.2, and 3.1.3.

[7] Explanation for Taylor rule fundamental model found in section 3.2.1.

window, univariate, autoregressive method to forecast the change in the industrial production index using data from the three years (36 data points) prior to the observation I am forecasting. I add this forecasted change to the actual industrial production index to determine potential output. This is the adjustment made for AR potential output Taylor rule fundamental model, where only a single adjustment is made. I also create a second adjusted model, where I not only use autoregressive methods to forecast potential output, but use similar methods to forecast the inflation target, once for each economy using CPI, and once for PPI. The inflation term in the RHS of this exchange rate forecasting model is defined to be the deviation of the inflation rate from the target value, where the target value is obtained using a rolling window univariate, autoregressive method. This model is defined as AR potential output and inflation target Taylor rule fundamental model, where a double adjustment is made.

I use the out-of-sample forecasting method[8] outlined in section 2 for each model[9] using data obtained from the IMF, various Central Banks, and the Federal Reserve. The forecast horizon is 1 month ahead, which is standard in the literature surrounding prediction using macroeconomic fundamentals. All the data is in monthly format, and I determine the in-sample window to be 120 observations (10 years). The in-sample window starts at 1976-1986. The out-of-sample region is from 1986-2016, 371 out-of-sample

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[8]A generic example for the rolling window program can be found in appendix B

[9]UIRP, PPP, monetary fundamental model, original Taylor fundamental model of Molodtsova and Papell (2008), AR potential output Taylor rule fundamental model, AR potential output and inflation target Taylor rule fundamental model.

observations. I use the Clark West (2007) test to determine if there is any statistically significant outperformance of the random walk by any of the models in exchange rate predictive ability. I use the Pesaran Timmermann (1992)[10] test to compare directional predictive ability of the models.

5 Empirical Results:

Table 1 shows the p-values for the Clark West (2007) test and the Pesaran Timmermann (1992) test for the uncovered interest rate parity model (UIRP), where a significant C.W. result implies outperformance of the random walk model in exchange rate prediction, and a significant P.T implies directional exchange rate predictive ability of the model.

Table 1: **Uncovered Interest Rate Parity**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada	0.3072	0.0069***
U.K	0.8388	0.7850
Switzerland	0.9026	0.3632
Japan	0.1066	0.1098

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the Uncovered Interest Rate Parity Model from section 3.1.1, where the empirical model is: $s_{t+1} - s_t = \alpha + \beta(i_t - i_t^*) + e_{t+1}$. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

Table 1 shows results that are consistent with past literature on the uncovered interest rate parity model's ability to outperform a random walk

[10]An outline of the PT test can be found in appendix A

in exchange rate prediction. There is no significant outperformance of a random walk using this model. These results are consistent with literature by Meese & Rogoff (1983a,b), Cheung Chinn and Pascual (2005), and Alquist and Chinn (2008). The UIRP model does have significant directional predictive ability for the USD/CAD exchange rate. A reason for this could be that Canadian monetary policy follows the United States policy very closely, which may have an impact on the predictability of exchange rates using interest rates as predictors.

Table 2 shows the p-values for C.W and P.T tests for the purchasing power parity model (PPP), where the consumer price index (CPI) differential of the two economies on either side of the bilateral exchange rate was used as the predictor. There is no significant outperformance of the random walk in

Table 2: **Purchasing Power Parity, using the Consumer Price Index**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada	0.8892	0.1325
U.K	0.2607	0.7849
Switzerland	0.4092	0.4530
Japan	0.6815	0.1103

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the Purchasing Power Parity Model from section 3.1.2, where the empirical model is: $s_{t+1} - s_t = \alpha + \beta(p_t - p_t^*) + e_{t+1}$. The predictor in this model is the consumers price index. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

predicting exchange rates by the purchasing power parity model using CPI as the predictor. This is consistent with existing literature on purchasing power parity such as results of Cheung, Chinn, and Pascual (2005). There is also no significant directional predictive ability using this model.

Table 3 shows the p-values for the C.W. and P.T. using the PPP model where production price index (PPI) is chosen as the predictor.

Table 3: **Purchasing Power Parity, using the Production Price Index**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada	0.4326	0.8235
U.K	0.2345	0.9275
Switzerland	0.0569*	0.3034
Japan	0.8217	0.2370

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the Purchasing Power Parity Model from section 3.1.2, where the empirical model is: $s_{t+1} - s_t = \alpha + \beta(p_t - p_t^*) + e_{t+1}$. The predictor in this model is the production price index. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

There is little significant outperformance of the random walk using PPI as the predictor for the PPP model. The only outperformance of a random walk by the PPP (PPI) model is on the USD/Switzerland exchange rate. A reason there could be more outperformance using PPI rather than CPI could be because the production price index includes more traded goods than the consumer price index, which could lead to more predictability of the exchange rate when using a price index differential model such as PPP.

Table 4 shows the p-values for the C.W. and P.T. when using the monetary fundamental model to predict the exchange rate, three different monetary fundamental models are run for each exchange rate. An exogenous weight (w) is attributed on the output differential term for the long run fundamental exchange rate value[11]. The model is run 3 times, where w is set to 0, 1 and 3.

Table 4: **Monetary Fundamental Model**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada W=0	0.7478	0.0943*
Canada W=1	0.9416	0.1678
Canada W=3	0.9469	0.2276
U.K. W=0	0.7809	0.6653
U.K. W=1	0.4087	0.6477
U.K. W=3	0.4142	0.6015
Japan W=0	0.7187	0.4231
Japan W=1	0.9163	0.1979
Japan W=3	0.9106	0.1683

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the Monetary Fundamental Model from section 3.1.3, where the empirical model is: $s_{t+1} - s_t = \alpha + \beta(Z_t) + e_{t+1}$. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

The results regarding monetary fundamentals ability to outperform a random walk at forecasting exchange rates are consistent with Meese and

[11]refer to equation 8 in section 3.1.3.

Rogoff (1983,a,b), Cheung Chinn and Pascual (2005), Alquist and Chinn (2008) and Chinn and Meese (1995). These results show no significant outperformance of a random walk using monetary fundamentals to forecast the exchange rate. This is in contrast to Mark (1995), Molodtsova and Papell (2009), who find some outperformance of the random walk using monetary fundamentals as predictors of the exchange rate. I find significant directional exchange rate predictive ability of the USD/CAD exchange rate using monetary fundamentals when only money supply is on the right hand side on the fundamental long run equilibrium value of the exchange rate. Again, this could be because monetary policy in Canada follows American monetary policy quite closely, so money supply differential of the two economies may provide some directional predictive ability of the exchange rate.

In conclusion to the results on traditional macroeconomic fundamental models ability to forecast the exchange rate, there is little to no significant outperformance of the random walk, and little to no directional accuracy. This is consistent with the majority of the past empirical literature on macroeconomic fundamentals and exchange rate prediction.

The results following are in regard to the recent promising Taylor rule fundamental exchange rate forecasting model. Table 5 shows the p-values for the C.W. and P.T. tests for the original Taylor rule fundamental exchange rate forecasting model where input data for potential output was found by placing a trend on actual industrial production index (IPI) data.

The two trends used were Hodrick Prescott (HP), and an exponential trend (EXP). The trends were placed on IPI data for the 3 years following the observation that I am attempting to estimate, meaning that this model is not a true forecasting model.

The results in table 5 show more significant predictive ability for 2 out of

Table 5: **Original Taylor Rule Fundamental Model**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada HP	0.0398**	0.187
Canada EXP	0.045**	0.0265**
U.K. HP	0.7811	0.507
U.K. EXP	0.1853	0.4628
Japan HP	0.0933*	0.0812*
Japan EXP	0.1185	0.0961*

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the original Taylor rule fundamental model from section 3.2.1, where the empirical model is: $s_{t+1} - s_t = \alpha - w_{u\pi}\pi_t + w_{f\pi}\pi_t^* - w_{uy}y_t + w_{fy}y_t^* - w_{ui}i_{t-1} + w_{fi}i_{t-1}^* + e_{t+1}$. This model uses a Hodrick Prescott trend and an Exponential trend to find y (the output gap), using data that would not be available to forecasters at the time. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

the three exchange rates using a Hodrick Prescott trend, and 1 out of the 3 using a exponential trend. There is also significant directional predictive ability for 2 out of the 3 exchange rates. These results are consistent with literature by Molodtsova and Papell (2009), Engel and west (2005, 2006), and Giacomini and Rossi (2010). However, the results displayed in table 5 were obtained using a model that used data that would not be available to forecasters at the time. Therefore, this model could not be used in real time exchange rate forecasting.

Table 6 shows the p-values for AR potential output and inflation target Taylor rule fundamental exchange rate forecasting model. Table 7 shows the p-values for the AR potential output Taylor rule fundamental exchange rate forecasting model.

Table 6: **AR Potential Output and Inflation Target Taylor Rule Fundamental Model**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada (CPI)	0.1992	0.117
Canada (PPI)	0.1448	0.56
U.K (PPI)	0.5386	0.0821*
Japan (CPI)	0.2944	0.6298
Japan (PPI)	0.5525	0.7018

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the AR potential output and inflation target Taylor rule fundamental model, where the empirical model is: $s_{t+1} - s_t = \alpha - w_{u\pi}\pi_t + w_{f\pi}\pi_t^* - w_{uy}y_t + w_{fy}y_t^* - w_{ui}i_{t-1} + w_{fi}i_{t-1}^* + e_{t+1}$. This model uses autoregressive methods to estimate potential output and the inflation target, using only data that would be available to forecasters at the time. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

The AR potential output and inflation target Taylor rule fundamental (table 6) model includes forecasted inflation target and potential output using rolling window, univariate, autoregressive methods. The AR potential output (table 7) model includes forecasted potential output using autoregressive methods, but keeps the inflation term as $(CPI_t - CPI_{t-1})$.

Table 7: **AR Potential Output Taylor Rule Fundamental Model**

	p-values	
Country	Clark-West Test	Pesaran-Timmermann Test
Canada (CPI)	0.3301	0.1865
Canada (PPI)	0.2189	0.5212
U.K (PPI)	0.5626	0.6061
Japan (CPI)	0.1921	0.2952
Japan (PPI)	0.1701	0.294

This table shows the p-values associated with the Clark West test and the Pesaran Timmermann test for the AR potential output Taylor rule fundamental model, where the empirical model is: $s_{t+1} - s_t = \alpha - w_{u\pi}\pi_t + w_{f\pi}\pi_t^* - w_{uy}y_t + w_{fy}y_t^* - w_{ui}i_{t-1} + w_{fi}i_{t-1}^* + e_{t+1}$. This model uses autoregressive methods to estimate potential output, using only data that would be available to forecasters at the time. A significant p-value for the Clark West test implies outperformance of the random walk, whereas a significant p-value for the Pesaran Timmermann test implies directional accuracy of the model.

The favourable evidence in support found in the original Taylor rule fundamental exchange rate forecasting model (Table 5) drops out in both cases. When only using data observable to forecasters, there is no outperformance of a random walk, and little to no significant directional predictive ability. In comparison to the results of the traditional macroeconomic fundamental models shown in table 1, 2, 3, and 4, these true forecasting Taylor rule models have no superior predictive ability. This is in contrast to literature in support for Taylor rule fundamentals exchange rate predictive ability, Molodtsova and Papell (2009), and Engel and West (2005). This does not say anything to contrast the favourable results of Engel, Mark and West (2014) in support of using factor methods for the Taylor rule fundamental model to predict exchange rates. Engel, Mark and

West (2014) also only used data that would be observable to forecasters to estimate potential output.

6 Conclusion

I find that Taylor rule fundamental exchange rate prediction models do not solve the Meese and Rogoff puzzle, and are not superior to traditional macroeconomic fundamental models in outperformance of a random walk or directional exchange rate predictive ability. Using the C.W. statistic, I find no significant outperformance of the random walk using Taylor rule fundamental models that only include data that is observable to forecasters. I find that the Taylor rule model that includes AR methods to estimate both data for potential output and the inflation target finds directional exchange rate predictive ability for only the USD/U.K. exchange rate, and only at the ten percent significance level. For future research, it is worth looking into localized predictability of these models. It could be that the Taylor rule fundamental model works over some periods and not others. A test of localized performance such as Giacomini and Rossi (2010) could inform on which models perform well over certain periods. The next step would be to look into what economic factors are occurring in the economies of interest and on the global scale when some models work and some do not. Another promising model has also been developed in the past ten years, the external imbalance measure model of Gourinchas and Ray (2007). There is a lack of literature surrounding this model, but the general consensus among literature on the model shows favourable outperformance of the random walk in regards to predictive ability of exchange rates. The implications of my results are in support for no empirical model being able to forecast the exchange rate consistently over all time periods, however, the promising literature surrounding the external imbalance measure model demands further investigation.

References

[1] Alquist, Ron., Chinn, Menzie. (2008). Conventional and Unconventional Approaches to Exchange rate Modelling and Assessment. *International Journal of Finance Economics.* Vol 13(1), pp. 2-13.

[2] Berkowitz, Jeremy, and Lorenzo Giorgianni. 2001. "Long-Horizon Exchange Rate Predictability?" *Review of Economics and Statistics* Vol 83 (1):

[3] Chen, Yu-Chin., Rogoff, S. Kenneth., Rossi, Barbara. (2010). Can Exchange Rates Forecast Commodity Prices. *The Quarterly Journal of Economics.* Vol. 125(3), pp. 1145-1194.

[4] Chinn, Menzie D., and Richard A. Meese. 1995. "Banking on Currency Forecasts: How Predictable Is Change in Money ?" *Journal of International Economics* Vol 38 (1-2): 161-78

[5] Clarida, Richard H., Jordi Gali, and Mark Gertler. 1998. "Monetary Policy Rules in Practice: Some Interna tional Evidence." *European Economic Review* Vol 42 (6): 1033-67.

[6] Clark, Todd E., and Kenneth D. West. 2006. "Using Out-of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis." *Journal of Econometrics* Vol 135 (1-2): 155-86.

[7] Clark, Todd E., and Kenneth D. West. 2007. "Approxi mately Normal Tests for Equal Predictive Accuracy in Nested Models." *Journal of Econometrics* Vol 138 (1): 291-311.

[8] Diebold, Francis X., and Roberto S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business and economic statistics* Vol 13(3): 253-63.

[9] Engel, Charles., Mark, Nelson., West, D. Kenneth. (2014). Factor Model Forecasts of Exchange Rates. *Econometric Reviews.* 0,(0). pp. 1-24.

[10] Engel, Charles., West, D. Kenneth. (2005). Exchange Rates and Fundamentals. *Journal of the Political Economy.* Vol. 113. No. 3, pp. 485-517.

[11] Ferraro, Domenico., Rogoff, S. Kenneth., Rossi, Barbara. (2015). Can Oil Prices Forecast Exchange Rates? An Empirical Analysis of the Relationship Between Commodity Prices and Exchange Rates. *Journal of International Money and Finance.* Vol 54, pp.116-141.

[12] Fisher, Irving. 1896. Appreciation and Interest. New York: *Macmillan for the American Economic Association.*

[13] Frenkel, Jacob A. 1976. "A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence." *Scandinavian Journal of Economics* Vol 78 (2): 200-224

[14] Giacomini, Raffaella., Rossi, Barbara. (2010). Forecast Comparisons in Unstable Environments. *Journal of Applied Econometrics.* Vol. 25, Issue 4, pp. 595-620.

[15] Gourinchas, Pierre-Oliver., Ray, Helen. (2007). International Financial Adjustment. *Journal of Political Economy.* Vol. 115, No. 4 pp. 665-703.

[16] Kenneth S. Rogoff Vania Stavrakeva, (2008). "The Continuing Puzzle of Short Horizon Exchange Rate Forecasting,"NBER Working Papers14071, *National Bureau of Economic Research, Inc.*

[17] Mark, Nelson C. 1995. "Exchange Rates and Funda mentals: Evidence on Long-Horizon Predictability." *American Economic Review* Vol 85 (1): 201-18

[18] Meese, Richard A., and Kennern S. Rogoff. 1988. "Was It Real? The Exchange Rate-Interest Differential Relation over the Modern Floating-Rate Period." *Journal of Finance* Vol 43 (4): 933

[19] Meese, Richard A., and Kenneth S. Rogoff. 1983a. "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics* Vo14 (1-2): 3

[20] Meese, Richard A., and Kenneth S. Rogoff. 1983b. "The Out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification?" *Exchange Rates and International Macroeconomics*, edited by Jacob A. Frenkel, 6

[21] Meese, Richard, and Kenneth Rogoff. (1983). Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?. *Journal of International Economics* 14: 3-24.

[22] Meese, Richard., Rogoff, Kenneth. (1988). Was it Real? The Exchange Rate-Interest Differential Relation Over the Modern Floating-Rate Period. *The Journal of Finance*, vol. 43, no. 4, pp. 933-948.

[23] Molodtsova, Tanya., Papell, H. David. (2008). Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals. *Journal of International Economics.* Vol 77, Issue 2, pp. 167-180.

[24] Pascual, G. Antonio., Chinn, Menzie., Cheung, Yin-Wong. (2005). Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?. *Journal of International Money and Finance.* Vol. 24, Issue 7, pp. 1150-1175.

[25] Pesaran, M., Timmermann, A. (1992). A Simple Nonparametric Test of Predictive Performance.Journal of Business *Economic Statistics*,Vol 10 no.4, pp. 461-465.

[26] Rossi, Barbara. (2013). Exchange Rate Predictability. *Journal of Economic Literature*, Vol 51 no.4 pp.1063-1119.

[27] Taylor, John B. 1993. "Discretion versus Policy Rules in Practice." *Carnegie-Rochester Conference Series on Public Policy* 39: 195-21

7 Appendix

7.1 Appendix A: Explanation of Pesaran Timmermann (1992) test of nonparametric performance

The PT test can be used to determine if a model has directional predictive ability. The PT test is implemented for exchange rate directional predictive ability as follows: Let y_t be the dependent variable, here the (log) change in the spot rate from $t-1$ to t. Let x_t be the forecasted change in the spot rate from $t-1$ to t. Let $\dot{y}_t = 1$ if $y_t > 0$, else 0. Let $\dot{x}_t = 1$ if $x_t > 0$, else 0. Let $\dot{z}_t = 1$ if $\dot{y}_t{}^*\dot{x}_t > 0$, else 0. This allows $\dot{z}_t$ to equal 1 if the exchange rate directional change was correctly forecasted by the forecasting model for period t, since if $\dot{y}_t$ and $\dot{x}_t$ are of the same sign, then $\dot{z}_t$ will be 1.

The next step is to derive the S_n statistic shown by equation 16:

$$S_n = \frac{\hat{P} - \hat{P}_*}{(v\hat{a}r(\hat{P}) - v\hat{a}r(\hat{P}_*))^{\frac{1}{2}}} \tag{15}$$

Where,

S_n is asymptotically normally distributed, N(0, 1).

$\hat{P} = \bar{\dot{z}}$, mean of $\dot{z}$.

$\hat{P}_y = \bar{\dot{y}}$, mean of $\dot{y}$.

$\hat{P}_x = \bar{\dot{x}}$, mean of $\dot{x}$.

$\hat{P}_* = \hat{P}_y\hat{P}_x + (1-\hat{P}_y)(1-\hat{P}_x)$.

Rejection of the null hypothesis that x cannot predict y implies that the model of interest has directional predictive ability at some confidence level.

7.2 Appendix B: General Rolling window Program Example:

The code shown below is the general framework for the rolling window program in EVIEWS. The code specifically is shown for using the UIRP model to forecast change in the Cad/USD exchange rate, but can easily be reformatted to suit other models and exchange rates.

```
Table(600,600) results

smpl @all

series s=usdcad

series ds=s(+1)-s

series rws = s(-1)-s(-1)

series x = iusa-icad

vector(371) forc

vector(371)actualos

smpl 121 491

actualos = ds

stom(rws,rwv)

smpl @all

for !n = 1 to 371

smpl !n 119+!n

equation eq01.ls ds c x

smpl 120+!n 120+!n

forecast name

results(!n+1, 1) = name(120+!n)

forc(!n)= name (120+!n)

next
```

7.3 Appendix C: C.W. Test Program Example

The code shown below is used for the automation of the C.W. test in EVIEWS using the programming function.

smpl @all

mtos(actualos,actualoss)

mtos(rwv,rws)

mtos(forc,forcs)

for !n = 1 to 371

smpl @all

series cw = $((actualoss - rws)^2) - (((actualoss - forcs)^2) - (rws - forcs)^2)$

equation eqcwols.ls cw c

next

smpl @all