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The Monetary Model of Exchange Rates is Better than the Random Walk in Out-of-Sample Forecasting

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Abstract

It is demonstrated that the monetary model of exchange rates is better than the random walk in out-of-sample forecasting if forecasting accuracy is measured by metrics that take into account the magnitude of the forecasting errors and the ability of the model to predict the direction of change. It is suggested that such a metric is the numerical value of the Wald test statistic for the joint coefficient restriction implied by the line of perfect forecast. The results reveal that the monetary model outperforms the random walk in out-of-sample forecasting for four different exchange rates.

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Introduction

Since the publication of the highly-cited paper of Meese and Rogoff (1983), it has become something like an undisputable fact of life that conventional exchange rate determination models cannot outperform the naïve random walk model in out-of-sample forecasting. This view is still widely accepted to the extent that it is typically argued that the Meese-Rogoff findings, which are "yet to be overturned", constitute a puzzle. Evans and Lyons (2004) describe the Meese-Rogoff finding as "the most researched puzzle in macroeconomics". Furthermore, Frankel and Rose (1995) argue that the negative results have had a "pessimistic effect" on the field of exchange rate modelling in particular and international finance in general. Likewise, Bacchetta and van Wincoop (2006) point out that the poor explanatory power of existing exchange rate models is most likely the major weakness of international macroeconomics.

Several reasons have been put forward for the failure of exchange rate forecasting models to outperform the random walk, including simultaneous equations bias, sampling errors, stochastic movements in the true underlying parameters, misspecification, non-linearities, improper modelling of expectations and over-reliance on the representative agent paradigm. What seems to be overlooked in the literature is the fact that forecasting accuracy is typically measured in terms of the root mean square error (RMSE) and similar metrics without paying attention to the ability of the model (and the random walk) to predict the direction of change in the exchange rate. Moosa (2013a) has recently demonstrated that we should expect nothing but the finding that exchange rate models cannot outperform the random walk when forecasting accuracy is measured in terms of the RMSE. Although some economists have produced results showing that it is possible to outperform the random walk in terms of the RMSE, they did that by using dynamic specifications that boil down to the introduction of a

random walk component to the model, hence beating the random walk by using a random walk process (Moosa, 2013b).

The objective of this paper is to demonstrate that by measuring forecasting power in terms of the magnitude of the error as well as the ability to predict the direction of change, it can be shown that the monetary model outperforms the random walk in out-of-sample forecasting. A measure of forecasting accuracy is proposed for this purpose.

A Proposed Measure of Forecasting Accuracy

Figure 1 is the four-quadrant prediction-realisation diagram where the predicted change in the exchange rate, $\hat{s}_t - s_{t-1}$, is plotted against the actual change, $s_t - s_{t-1}$. Each dot represents a combination of an actual change and the corresponding predicted change. This device allows us to observe the magnitude of the forecasting error as well as the ability of the underlying model to predict the direction of change. The line of perfect forecast, which is a 45-degree line passing through the origin, has the equation $\hat{s}_t - s_{t-1} = s_t - s_{t-1}$. The magnitude of the error is represented by the distance between a dot and the line of perfect forecast. Errors of direction are represented by the points falling in the second and fourth quadrants. They occur when the model predicts a positive change but the actual change turns out to be negative (second quadrant) and when the model predicts a negative change but the actual change turns out to be positive (fourth quadrant). Formally, an error of direction occurs if the condition $(\hat{s}_t - s_{t-1})(s_t - s_{t-1}) < 0$ is satisfied. For example, Figure 1 is the prediction-realisation diagram of a model that is good on direction because fewer points fall in the second and fourth quadrants than the first and third quadrants.

The literature typically examines forecasting accuracy in terms of magnitude or direction separately (predominantly in terms of magnitude). For example, the magnitude of error is measured in terms of the RMSE while errors of direction are measured in terms of direction accuracy, which is the percentage of times the model predicts the direction correctly. Suppose then that we are comparing two models, one of which is good on magnitude and bad on direction and the other (such as the model in Figure 1) is the other way round. Can we say which model is better overall? Not unless we have some sort of a combined measure of forecasting accuracy that involves some sort of a trade-off between magnitude and direction.

One possible way to combine the ability to predict magnitude and direction is to adjust the RMSE by a factor that reflects direction accuracy, which would produce the adjusted root mean square error proposed by Moosa and Burns (2012). The alternative combined measure of magnitude and direction accuracy proposed here is found in the prediction-realisation diagram. Consider Figure 2, which shows the line of perfect forecast, a line representing an exchange rate model and a line representing the random walk with a positive drift factor. The line representing the model is the best-fit line, obtained by regressing the predicted change on the actual change. The three lines have the general equation $\hat{s}_t - S_{t-1} = \alpha + \beta(S_t - S_{t-1})$. By imposing the restrictions $(\alpha, \beta) = (0,1)$ we obtain the equation for the line of perfect forecast. The coefficient restrictions are violated by the equation of the line representing the model shown in Figure 2 because $\alpha > 0$ and $0 < \beta < 1$. For the random walk line, the coefficient restrictions are violated because $\alpha > 0$ and $\beta = 0$.

Any violation of the coefficient restrictions defining the line of perfect forecast implies less than perfect forecasts, invariably involving magnitude and direction errors. Either of the conditions $\alpha \neq 0$ and $\beta \neq 1$ may imply a combination of errors of magnitude and direction.

For example, suppose that $\beta = 1$ but α is becoming increasingly positive. The more positive α is, the greater will be the distance between the model line and the line of perfect forecast, implying bigger errors (magnitude wise). At the same time, as α becomes increasingly positive, a larger number of dots will fall in the second quadrant, implying increasingly large numbers of direction errors. Now suppose that $\alpha = 0$, but the model line becomes increasingly steeper—that is, β increases. As that happens, the distance between the model line and the line of perfect forecast widens, signifying bigger errors. If β $(= \tan^{-1} \phi)$ rises such that $\phi > \pi / 2$, then the dots will fall in the second and fourth quadrants, signifying errors of direction.

It follows, therefore, that a measure of forecasting accuracy that combines both magnitude and direction is the extent of deviation from the coefficient restriction $(\alpha, \beta) = (0,1)$. A Wald test of coefficient restrictions can be conducted to find out if the violation is statistically significant as implied by the χ^2 statistic. If it is then a comparison can be made between a model and the random walk on the basis of the numerical value of the χ^2 statistic, such that the bigger the value, the greater the violation of the coefficient restriction and the worse is the model with respect to predictive power as judged by magnitude and direction. For the random walk to outperform the model it must produce a smaller χ^2 statistic for the restriction $(\alpha, \beta) = (0,1)$ than the model. A further test is that of the null that the estimated coefficients for the model are equal to those of the random walk—that is, $H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$ where the subscripts *R* and *M* refer to the random walk and monetary model, respectively.

Forecast Generation

The basic flexible price monetary model of exchange rates is used to generate forecasts. It is specified in logarithmic form as follows:

$$s_t = \alpha_0 + \alpha_1(m_{a,t} - m_{b,t}) + \alpha_2(y_{a,t} - y_{b,t}) + \alpha_3(i_{a,t} - i_{b,t}) + \varepsilon_t \tag{1}$$

where s is the log of the exchange rate, m is the log of the money supply, y is the log of industrial production, i is the interest rate, and a and b refer to the countries having a and b as their currencies, respectively (the exchange rate is measured as the price of one unit of b— that is, a/b). The model is estimated over part of the sample period, $t = 1, 2, \ldots m$, then a one-period ahead forecast is generated for the point in time $m+1$. The forecast log exchange rate is

$$\hat{s}_{m+1} = \hat{\alpha}_0 + \hat{\alpha}_1(m_{a,m+1} - m_{b,m+1}) + \hat{\alpha}_2(y_{a,m+1} - y_{b,m+1}) + \hat{\alpha}_3(i_{a,m+1} - i_{b,m+1}) \tag{2}$$

where $\hat{\alpha}_i$ is the estimated value of α_i. Hence the forecast level of the exchange rate is

$$\hat{S}_{m+1} = \exp(\hat{s}_{m+1}) \tag{3}$$

The process is then repeated by estimating the model over the period $t = 1, 2, \ldots m+1$ to generate a forecast for the point in time $m+2$, $\hat{s}_{m+2}$, and so on until we get to $\hat{s}_n$, where n is the total sample size. This process, therefore, involves recursive regression, which is preferred to rolling regression from an efficiency point of view.

In order to avoid the problem of choosing between the random walk with and without drift, the random walk model is estimated as an AR(1) process following the equation

$$s_t = a + bs_{t-1} + \varepsilon_t \tag{4}$$

Meese and Rogoff (1983) actually considered the issue of which random walk model to choose. The consensus view seems to be that the random walk with drift should be used only if the drift factor is statistically significant. In this study the random walk is estimated for another reason: without estimating equation (4), the Wald test cannot be conducted.

Data and Empirical Results

The empirical results are based on four exchange rates involving the U.S. dollar (USD), Japanese yen (JPY), British pound (GBP) and Canadian dollar (CAD). Two of the four exchange rates are against the dollar (JPY/USD and CAD/USD), and the other two are cross rates (JPY/CAD and GBP/USD). Monthly data (obtained from the IMF's *International Financial Statistics*) are used covering the period January 1990-July 2010. For the purpose of generating out-of-sample forecasts, the sample period is split at December 2005 into an estimation period and a forecasting period, so that forecasts are generated over the period January 2006-July 2010.

Figure 3 is the empirical counterpart of the theoretical prediction-realisation diagram shown in Figure 2. Four prediction-realisation diagrams are presented for each of the four exchange rates—each diagram exhibits the line of perfect forecast as well as the lines representing the forecasting power of the monetary model and the random walk. We can readily see that the random walk line is very close to the horizontal axis—this is because the drift factor is statistically insignificant.[1] In all cases the slope of the model line is closer to that of the line of perfect forecast than the random walk, which has a slope of zero.

Table 1 reports the results of the coefficient restrictions tests. To start with, the restrictions $\alpha = 0$ and $\beta = 1$ are rejected in all cases except for the model in the case of the CAD/USD rate. The joint restriction $(\alpha, \beta) = (0,1)$ is rejected in all cases, implying that the model and the random walk provide forecasts that are significantly inferior to perfect forecasts. The question is which forecasts are better, or less bad, those of the random walk or what the

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[1] The drift factor is effectively the mean percentage change in the exchange rate. It can be estimated by regressing the percentage change in the exchange rate (or the first log difference) on a constant. For the four exchange rates, the estimated values of the drift factor and the t statistics are as follows: JPY/USD (-0.53, -1.30), CAD/USD (-0.13, -0.26), JPY/CAD (-0.26, -0.39) and GBP/USD (0.28, 0.65).

model provides. The Meeses-Rogoff puzzle is that the random walk is better or less bad than any model, but this is not what we see here. The values of the χ^2 associated with the random walk are multiples of those associated with the monetary model. Since the numerical value of the χ^2 is indicative of the deviation of the values of α and β from 0 and 1 respectively, it follows that the model is less far away from perfect forecasts than the random walk—in other words, the model is better than the random walk. These results are confirmed by the coefficient restriction test of the null hypothesis $(\alpha_R, \beta_R) = (\alpha_M, \beta_M)$. In all cases the χ^2 statistic is significant, implying that the model is significantly better (or less bad) than the random walk. The monetary model and the random walk are not equally bad as compared with perfect forecasts. This finding casts doubt on the soundness of using market-based forecasting whereby the best forecast is the current level. It also has implications for the profitability of carry trade relative to a forecasting-based currency trading strategy.

Conclusion

It is typically claimed that exchange rate models cannot outperform the random walk in out-of-sample forecasting, as first suggested by Meese and Rogoff (1983). This result is associated with the measurement of forecasting accuracy by metrics that depend on the magnitude of the forecasting errors, while ignoring the ability of the model to predict the direction of change. However, when forecasting accuracy is measured by a metric that takes into account both magnitude and direction, it can be demonstrated that the monetary model of exchange rates can outperform the random walk. In this paper we suggest that such a metric is the numerical value of the test statistic for the joint coefficient restriction implied by the line of perfect forecast. For four different exchange rates, it was found that the monetary model outperforms the random walk in out-of-sample forecasting. The Meese-Rogoff puzzle

is only a puzzle if we judge forecasting accuracy by the magnitude of the forecasting error while ignoring the direction of change.

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Table 1: Tests of Coefficient Restrictions*

Exchange Rate	Model	Random Walk
JPY/USD		
$H_0 : \alpha = 0$	8.98	4.87
$H_0 : \beta = 1$	-2.80	-62.53
$H_0 : (\alpha, \beta) = (0,1)$	101.78	4201.10
$H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$	78.15	
CAD/USD		
$H_0 : \alpha = 0$	5.66	6.64
$H_0 : \beta = 1$	-1.34	-258.18
$H_0 : (\alpha, \beta) = (0,1)$	34.79	6705.50
$H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$	31.66	
JPY/CAD		
$H_0 : \alpha = 0$	-22.83	-7.77
$H_0 : \beta = 1$	-2.93	-117.23
$H_0 : (\alpha, \beta) = (0,1)$	522.93	13745.10
$H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$	520.96	
GBP/CAD		
$H_0 : \alpha = 0$	-14.21	-12.10
$H_0 : \beta = 1$	-2.47	-57.49
$H_0 : (\alpha, \beta) = (0,1)$	220.59	3693.10
$H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$	176.77	

* The test statistics for $H_0 : \alpha = 0$ and $H_0 : \beta = 1$ have a t distribution. The test statistics for $H_0 : (\alpha, \beta) = (0,1)$ and $H_0 : (\alpha_R, \beta_R) = (\alpha_M, \beta_M)$ are distributed as $\chi^2(2)$.
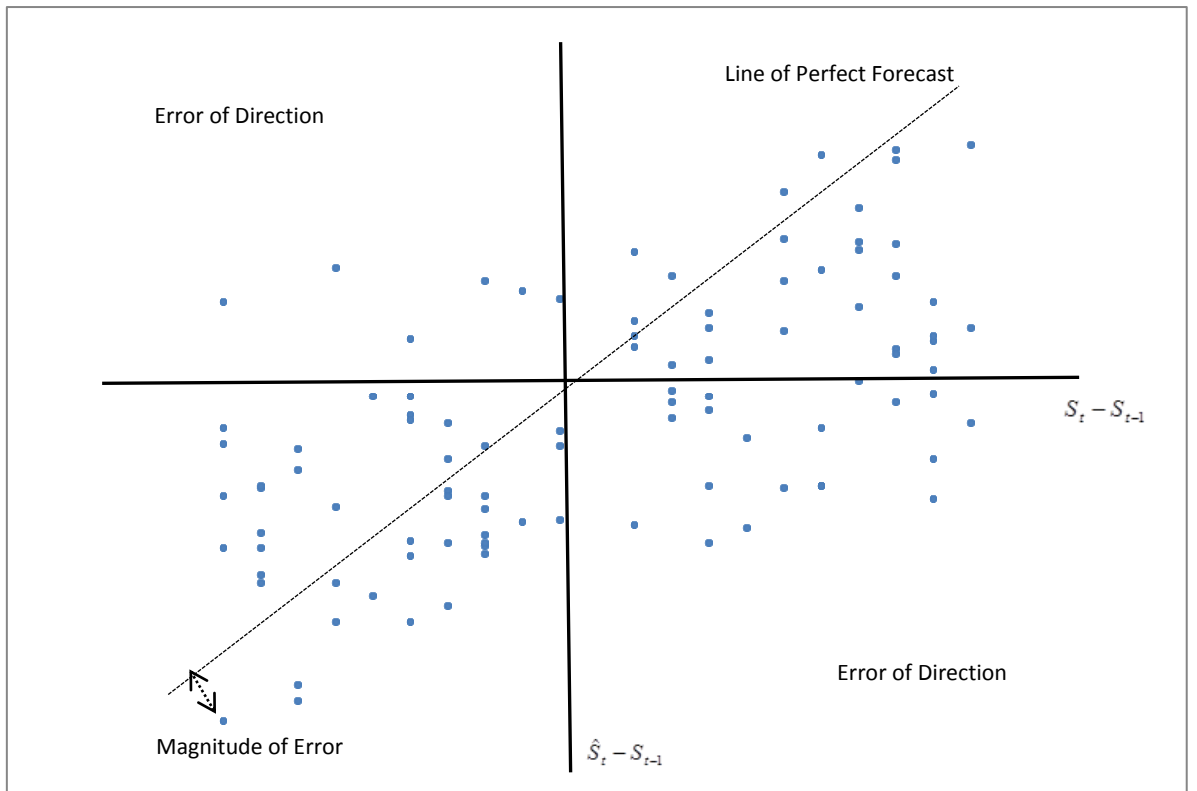
Figure 1: The Prediction-Realisation Diagram

Line of Perfect Forecast

Error of Direction

Error of Direction

$S_t - S_{t-1}$

Magnitude of Error

$\hat{S}_t - S_{t-1}$

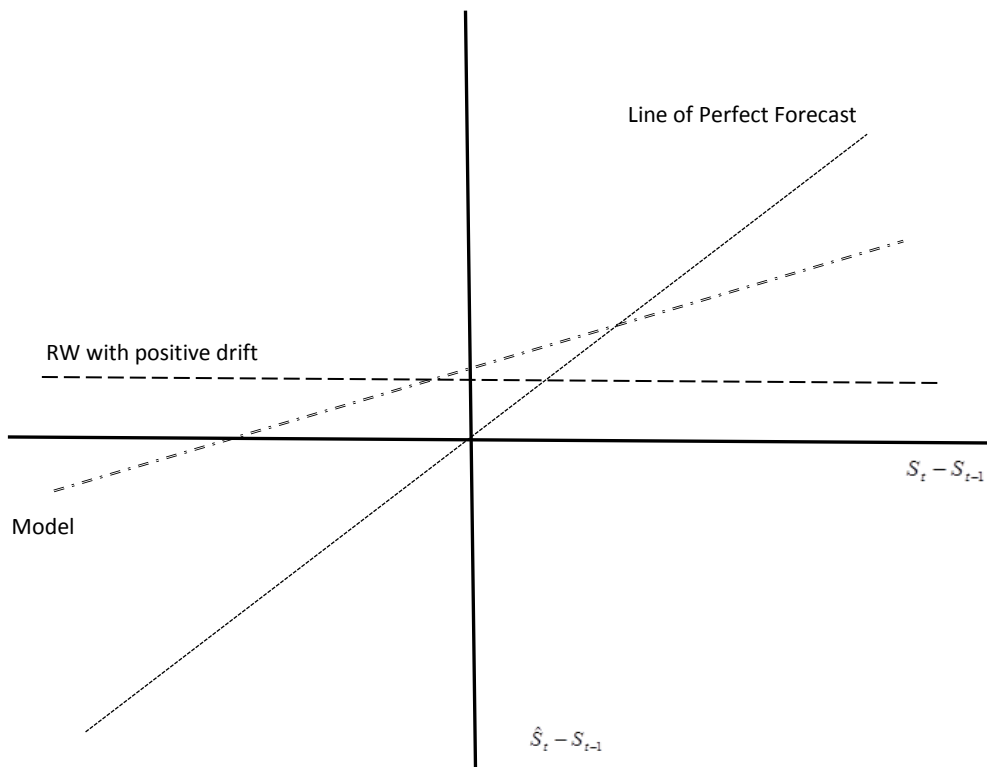**Figure 2: Prediction-Realisation of the Monetary Model and the Random Walk with Positive Drift**

Figure 3: Prediction-Realisation Diagrams for Four Exchange Rates

JPY/USD

Perfect forecast
Line of best fit (RW)
Line of best fit (Monetary Model)

CAD/USD

Perfect forecast
Line of best fit (RW)
Line of best fit (Monetary Model)

JPY/CAD

Perfect forecast
Line of best fit (RW)
Line of best fit (Monetary Model)

GBP/CAD

Perfect forecast
Line of best fit (RW)
Line of best fit (Monetary Model)