

Forecasting Exchange Rates using an Optimal Portfolio Model with Time Varying Weights.

Mzingisi Peace Mapasa

Masters of Management in Finance and Investments.

Witwatersrand Business School

Faculty of Commerce, Law and Management

Johannesburg

2050

Supervisor

Prof. Christopher Malikane

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Abstract

This paper presents a mean variance based model of exchange rate determination and forecasting using the return differential of an optimal portfolio composed of money, bond, and stock market returns. We use the simple OLS estimation technique for the estimation and a recursive rolling regression technique to generate the out-of-sample forecasts. We employ an autoregressive technique to estimate the mean returns and time varying variance covariance matrices to generate time varying portfolio return weights. The out-of-sample forecast analysis, using the CW statistic suggests that our Optimized Uncovered Rate of Return Parity model outperforms the naïve random walk model in forecasting one month ahead nominal exchange rates for all the countries in the study. The results also show that the un-optimized model is also able to outperform the naïve random walk in all the countries at one month ahead forecasting horizon. These findings imply that the inclusion of the three market variables in modelling exchange rates improves the forecasting ability of exchange rate models.

1. Introduction

Almost three decades after the seminal work of Meese and Rogoff (1983) on exchange rate determination, researchers still find it impossible to reject the random walk hypothesis. The empirical literature on nominal exchange rate still points to the fact that the current exchange rate is often the best predictor of future exchange rates and that there is still a disconnect between the exchange rate and macroeconomic fundamentals. This exchange rate disconnect was first documented in the seminal work of Meese and Rogoff (1983, 1988) which has ever since generated a prolonged era of pessimism in exchange rate economics by concluding that empirical exchange rate models that include macroeconomic fundamentals do not perform better than a naïve random walk in out-of-sample forecasting of exchange rates. In their paper, they examine the out-of-sample performance of three empirical exchange rate models among major currencies during the post-Bretton Woods period and conclude that the random walk performs better than economic models of exchange rate determination developed in the 1970's.

The real success of the work by Meese and Rogoff (1983, 1988) is that the questions posed in their work remain largely controversial. This work triggered extensive literature which has seen the development of sophisticated economic models and elaborate economic techniques aimed at establishing that economic fundamentals have the power to explain variations in exchange rate. While, starting with Mark (1995), who finds evidence of greater predictability at longer horizons, with the findings later criticized by Kilian (1999), recent studies by Bacchetta, Wincoop, and Beutler (2010) evaluate whether parameter instability can indeed account for the Meese and Rogoff puzzle; they conclude that time-varying parameters have virtually no effect on the out-of-sample forecasting performance of exchange rate models and that the basic problem is not much the instability in the relationship between exchange rates and fundamentals, but its weakness. Furthermore, Flood and Rose (1995) find that there is no clear tradeoff between exchange rates volatility and the volatility of a variety of different macroeconomic variable (e.g. interest rates, relative prices, money reserves, and stock returns).

This paper draws motivation from many studies that have tried to shed light on this issue through consideration of different variables and extension of data to capture different exchange rate regimes. Among them, Alquist and Chinn (2008) examines the relative predictive power of the sticky price monetary model, uncovered interest parity, and a transformation of the net exports variable and finds evidence that uncovered interest parity outperforms a random walk at long

horizons. Other studies include Cheung, Chinn and Pascual (2005) who examines the out-of-sample performance of the monetary, interest rate parity, and productivity based exchange rate models and concludes that forecasting performance and the results are not necessarily indicative of the ability of these models to explain exchange rate behavior. Mark and Sul (2001) study the long-run relationship between nominal exchange rates and monetary fundamentals and find that the results generally support the hypothesis of cointegration.

Our contribution to the literature on exchange rates determination is twofold. Firstly, we present a simple optimal portfolio model with assets weights which are time varying. The model considers the returns of a portfolio made up of the returns from short term instruments such as the money market, returns from bonds, and returns from stock market in the attempt to try and explain movements in the exchange rate. We use the mean-variance portfolio developed by Markowitz (1952) to estimate the minimum variance portfolio with the assumption that there is no existence of any other assets in the portfolio, in that, no redundant assets exist. To account for the fact that weights on asset returns in the portfolio are time varying, we estimate time varying variance covariance matrices. In addition, we also test an un-optimized model with similar variables and then also add to literature by testing the performance of the models in emerging markets.

We follow a similar specification to that of the Uncovered Interest Parity (UIP) relationship, but modifying the equation such that the exchange rate depends on the return differential of an optimal portfolio made up of returns from the money market, bond market, and the stock market. We develop the optimized uncovered rate of return parity (URRP) which implies that investors reallocate their portfolios to the country with the highest returns. It follows that the currency of the country with the highest returns appreciates since funds will tend to flow to the country with the highest returns. In this paper, we consider two portfolios dominated in two different currencies: that is one dominated in domestic currency, and another dominated in foreign currency (US dollars). We employ the simple OLS estimation technique and a rolling regression technique for out-of-sample forecasting. To evaluate the superior predictability of the model over the naïve random walk we use test statistics; MAP, RMSE, MAPE, and the CW statistic.

The remainder of the sections are organized as follows. In the next section, we briefly review the literature on exchange rate determination and forecasting. Section 3 describes empirical exchange rate model models considered and their foundation. Section 4 presents the methodology and describes the data used. Section 5 presents the findings of the study, and section 6 concludes.

1.1. Research problem

The predictability of exchange rate has always been elusive in the literature of international economics. In the past decade, there have been various attempts to connect the exchange rate movement with macroeconomic fundamentals in the literature of exchange rate forecasting. Post the Bretton-Woods regime, the introduction of floating exchange rates attracted a lot of attention in international macroeconomics, with different scholars attempting to explain the exchange rate behavior. The works by Meese and Rogoff (1983a, 1983b) were the first studies that originated the prolonged conundrum by concluding that empirical exchange rate models which include macroeconomic variables fail to perform better than the naïve no change random walk model in forecasting exchange rates. This paper tries to explain the movement of exchange rate by taking a different approach. We look at different variables to those used in previous studies, to forecast exchange rates.

1.2. Research objective

The main objective of this study is to evaluate out-of-sample exchange rate predictability using an optimal portfolio with time varying weights for four developed and four emerging countries vis-à-vis the U.S dollar over the period from January 1990 to December 2014. We further try to establish whether the inclusion of three financial market variables in forecasting exchange rates improves the predictability of exchange rates. We follow a similar specification to that of the Uncovered Interest Parity (UIP) relationship, but modifying the equation such that the exchange rate depends on the return differential of an optimal portfolio made up of returns from the money market, bond market, and the stock market. We develop the uncovered rate of return parity (URRP) which implies that investors reallocate their portfolios to the country with the highest returns.

1.3. Research Questions

This study sets out to answer the following questions;

- Does a model which is optimized show better exchange rate forecasting ability when compared to a naïve random walk model?

- Does a model which is optimized show better exchange rate forecasting ability when compared to an autoregressive model?
- Does a model which is optimized show better exchange rate forecasting ability when compared to a model with un-optimized parameters?

2. Literature Review

The literature on exchange rates is vast but starts with the seminal work of Meese and Rogoff (1983), where they study the out of sample forecasting accuracy of various structural and time series exchange rate models and find that the random walk performs better than all the estimated models at one to twelve months forecasting horizon. Cheung, Chinn and Pascual (2005) examine the out of sample performance of the interest rate parity, monetary, productivity-based and behavioral exchange rate models and conclude that none of the models consistently outperform the random walk at any horizon. Kilian (1999), Berben and van Dijk (1998), Bacchetta and Wincoop (2010), Berkowitz and Giorgianni (2001), Mark and Sul (2001) who all find that monetary fundamentals have weak prediction power for long run exchange rates.

Also, Engel, Mark and West (2007), and Engel, Mark and West (2009) do not find evidence of predictability of exchange rate at any horizon. Furthermore, Flood and Rose (1995) study the volatility of macroeconomic variables such as money and output and finds that there is no clear tradeoff between exchange rates volatility and the volatility of a variety of different macroeconomic variables. They conclude that exchange rate models based only fundamentals are unlikely to be very successful.

Possible explanations given for this exchange rate disconnect in Meese and Rogoff's study was that the failure of the models could be attributed to structural instability due to oil shocks, difficulties in modelling expectations of the explanatory variable, and short-sample problem. Other studies have also tried to shed some light on this matter by providing possible resolution to the difficulty of tying exchange rates to economic fundamentals. Specifically, Engel and West (2005) show analytically that exchange rate can be consistent with present-value asset pricing models and will approach a random walk as the discount factor approaches one. Engel and West (2006) construct a model which implies that the deviation of real exchange rate from its steady state depends on the present value of a weighted sum of inflation and output gap differentials, and find a positive correlation for the actual dollar-mark real exchange rate.

Several studies have proven to have potential in exchange rate forecasting literature in recent years. Molodtsova and Papell (2008) find that Taylor rule fundamentals find evidence of long term predictability for 11 out of 12 currencies vis-à-vis the U.S dollar over the post-Bretton Wood float. Della Corte, Sarno, and Tsiakas (2008) provides comprehensive review of the statistical and economic methods used for evaluating out-of-sample exchange rate predictability and finds that

empirical models based on uncovered interest parity, purchasing power parity and asymmetric Taylor rule perform better than the random walk in out-of-sample forecasting at long horizon. Engel and West (2005) explore the implications of monetary policy endogeneity for exchange rate determination. By endogenizing monetary policy and explicitly introducing the interest rate rule, these authors advance new and promising approach to modelling exchange rate behavior. Their positive findings are also affirmed by other similar studies pursuing a similar modelling strategy. For example, Mark (2009) studies a variant of the Taylor rule based exchange rate equation, which presents some encouraging results for the model. Waldman and Clarida (2008), Wang and Wu (2008) also present favorable findings on the empirical performance of several variant of the Taylor rule based exchange rate specification.

However, several literatures have shown that there is no unique way to model exchange rate forecasting behavior. These studies include those Bacchetta and van Wincoop (2006) Cheung et al. (2005), MacDonald and Ricci (2005), Taylor (2001), Kilian and Taylor (2001), Clarida, Gali, and Gertler (1998), Frankel and Rose (1995). More studies such as Mark (2009), Engel et al. (2007), Engel and West (2006) find an instant reaction of the exchange rates to macroeconomic surprises and they further emphasize that macroeconomic expectations and surprises by the central bank are the drivers of the short run exchange rates.

In the same light, Yuan (2011) models the effects of the macroeconomic determinants on the nominal exchange rate to be channeled through the transition probabilities in a Markovian process. From the model, He concludes that the deviation of exchange rate from its fundamental value alters the markets belief in the probability of the process staying in certain regime the following period. His results also confirm that fundamentals can affect the evolution of the dynamics of the exchange rate in a non-linear way through the transition probabilities and the volatility of the exchange rate is associated with significant ARCH effects which are subject to regime changes.

Moreover, Kilian and Taylor (2003) propose that the behavior of the exchange rate is well approximated by non-linear, exponential smooth transition autoregressive (ESTAR) model. Junttila and Korhonen (2011) who introduce a mixed monetary model (MMM) based on joining together some of the most relevant characteristics of the flexible and sticky price monetary model and analyzed the model using empirical approach involving a parametric non-linear error correction presentation for the data. Clostermann and Schnatz (2000) find the Dollar-Euro exchange rates to be dependent on interest rates, oil prices, fiscal deficits and the overall

productivity of the economy. Alberola, Cervero, Lopez, and Ubide (1999) find the exchange rates to be dependent on prices and net foreign assets.

So far, a vast literature has been devoted to construction and evaluation of the point forecast of exchange rates. Although this has been of great interest to policy makers, practitioners and academics, the behavior of exchange rates remains a grey area. While studies by Molodtsova, Nikolsko-Rzhevskyy, and Papell (2011) find evidence of exchange rate predictability using panel methods, Apergis, Zestos, and Shaltayev (2011) explores the causal links between the US Dollar-Euro exchange rate and three key macroeconomic variables and provide evidence in favor of the presence of a long-run relationship between the exchange rate and the spread between United States and Eurozone interest rates.

Salvatore (2005) attributes the failure of exchange rate models to the exclusion of relevant fundamentals and their inability to model market news and shocks. Della Corte (2008) finds exchange rate models to be explained better by monetary fundamentals rather than non-monetary factors. This is further validated by the works of Basher and Westerlund (2009), Groen (1999) and Frankel (1979) who all conclude that there exists a long-run relationship between the common factors of exchange rates and fundamentals.

3. Theoretical Framework

The first part of the paper deals with the optimal portfolio model that we develop to try explain variations in the exchange rate. According to the mean-variance portfolio theory, investors diversify their wealth among different assets in which they wish to minimize the risk but maximize investment returns. How investors allocate their wealth within different portfolios is addressed by the mean-variance portfolio optimization developed by Markowitz (1952). The variance of a portfolio made up of a combination of assets from the money market, bond market, and stock market is calculated as:

$$\sigma_p^2 = \mathbf{W}'\mathbf{\Omega}\mathbf{W} \quad (1)$$

Where $\mathbf{W} = [w_m \ w_b \ w_s]$ is a vector of asset weights in a portfolio and $\mathbf{\Omega} = E[(R_i - \mu_i)(R_i - \mu_i)']$, $i = (b, m, s)$ is a 3×3 variance covariance matrix of returns. The subscript p , b , m , and s are the returns from the optimal portfolio, returns from bonds, returns from money market, and returns from stocks respectively. The combination of the assets in the portfolio are balanced such that they yield maximum returns, since every investor seeks to maximize their returns. Taking into cognizance a constraint that we set, that the weights of all the three assets in the portfolio all add up to 1 and are non-negative.

To determine the optimal weights of the assets in the portfolio, the variance and covariance between these assets are firstly calculated as inputs. For any return $R_{i,t}$, we fit the model:

$$R_{i,t} = \delta_0 + \sum_{i=1}^n \delta_i R_{i,t-i} + \varepsilon_{i,t} \quad (2)$$

Where $\varepsilon_{i,t}$ is the error term, δ_0 is the constant, and $R_{i,t}$ is the returns on each asset in the portfolio at time t . We can then write the time varying variance covariance matrices as follows;

$$\begin{bmatrix} \varepsilon_{b,t}^2 & \varepsilon_{b,t}\varepsilon_{m,t} & \varepsilon_{b,t}\varepsilon_{s,t} \\ \varepsilon_{b,t}\varepsilon_{m,t} & \varepsilon_{m,t}^2 & \varepsilon_{m,t}\varepsilon_{s,t} \\ \varepsilon_{b,t}\varepsilon_{s,t} & \varepsilon_{m,t}\varepsilon_{s,t} & \varepsilon_{s,t}^2 \end{bmatrix} \begin{bmatrix} w_b \\ w_m \\ w_s \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad (3)$$

To determine the optimal weights of the assets in the portfolio, the variance and covariance between these assets are firstly calculated as inputs. Following Rong et al. (2010) and Abd El Aal (2011), the time-varying variance and covariance are calculated as follows:

$$\begin{bmatrix} \sigma_b^2 \\ \sigma_m^2 \\ \sigma_s^2 \end{bmatrix} = \begin{bmatrix} \varepsilon_{b,t}^2 \\ \varepsilon_{m,t}^2 \\ \varepsilon_{s,t}^2 \end{bmatrix}$$

and

(4)

$$\begin{bmatrix} \sigma_{bm} \\ \sigma_{bs} \\ \sigma_{ms} \end{bmatrix} = \begin{bmatrix} \varepsilon_{b,t} \varepsilon_{m,t} \\ \varepsilon_{b,t} \varepsilon_{s,t} \\ \varepsilon_{m,t} \varepsilon_{s,t} \end{bmatrix}$$

Optimal weights obtained by solving this matrix are used to determine optimal portfolio return expected by the investor at time t given by;

$$R_{pt} = \mathbf{W} * \mathbf{R}$$

Where $\mathbf{W}$ is a 1×3 vector of optimal weights and $\mathbf{R} = [R_b \ R_m \ R_s]$ is the returns from the respective assets in the portfolio.

3.1.1. Optimized uncovered rate of return parity

Following the well-known forecasting specification as used by Della Corte (2011) Lothian and Wu (2011), the optimized uncovered rate of return parity forecasting regression is expressed as:

$$\Delta e_t = \alpha_0 + \beta_0 (R_{pt-1}^d - R_{pt-1}^f) + u_t \quad (5)$$

Where e is the logarithm of the nominal exchange rate, α and β are constants and u is the error term. According to the optimized uncovered rate of return parity (URRP) equation in equation (5), if the returns from the domestic portfolio are one percentage point above the returns from the foreign portfolio, one would expect, on average, the foreign currency to appreciate by one percent point over the next period.

3.1.2. Un-optimized model

We look at the variables included in the uncovered rate of return parity model in equation (5) above but in this instance, in an un-optimized manner.

$$\Delta e_t = \alpha_0 + \beta_0 (s_{t-1}^d - s_{t-1}^f) + \beta_1 (b_{t-1}^d - b_{t-1}^f) + \beta_2 (tb_{t-1}^d - tb_{t-1}^f) + u_t \quad (6)$$

The un-optimized model looks at the homogeneous differentials between the two countries, one domestic and the other foreign. The model considers the differential of returns from stocks, bonds, and treasury bills between the two countries. Where s , b , and tb in equation (8) denote the returns stocks, returns from bonds, and the returns from treasury bills.

3.1.3. Uncovered Interest Parity

The Uncovered Interest rate parity relationship is a popular relation in the literature of exchange rate predictability. According to the Uncovered Interest rate parity condition, the log of the exchange rate is equal to the interest rate differential for the two countries. Following Clark and West (2006) we specify the Interest rate parity relationship as follows;

$$\Delta e_t = \alpha_0 + \beta_0(i_{t-1}^d - i_{t-1}^f) + u_t \quad (7)$$

Where i^d and i^f is the short-term interest rate for the domestic and foreign country respectively. Since we do not restrict the sign coefficient β_0 , or to $\beta_0=1$, Eq(7) can be consistent with the uncovered interest parity, where a positive interest rate differential is expected to result in forecasts of exchange rate depreciation. An anomaly is also allowed to exist where a positive interest rate differential may result in forecasts of exchange rate appreciation as explained by the forward premium puzzle literature.

3.1.4. The Random walk

We benchmark our forecasting relation using the naïve random walk since it's the standard benchmark in the literature of exchange rate predictability. We specify the random walk with drift model following the specification by Della Corte, Sarno, and Tsiakas (2008) as:

$$\Delta e_t = \alpha_0 + v_t \quad (8)$$

3.1.5. The Autoregressive: AR (1) model

We also look the Autoregressive model which posits that the best predictor of the exchange rate at time $t+1$ is the exchange rate at time t .

$$\Delta e_t = \alpha_0 + \beta_0 \Delta e_{t-1} + v_t \quad (9)$$

4. Data description

We evaluate the optimal portfolio model using data from four advanced countries and then we apply a similar analysis to four emerging countries to see if the performance of the model is consistent. Following Della Corte, Sarno, and Tsiakas (2008) we use monthly data from the Federal Reserve Bank of Saint Louis ranging from January 1990 to December 2014. The reference country used in the study is the United States and the developed countries chosen are: Canada, United Kingdom, Sweden, and Australia. The emerging countries in the study are: South Korea, South Africa, Brazil, and Mexico. All the data set for the developed economies use 2008 as the base year with the sample divided into two periods. Each model is initially estimated using data from January 1990 to December 2008 and the remainder for creating the out-of-sample forecasts.

The exchange rate data is the monthly average nominal exchange rate. The government 10-year bonds are used as a proxy for the long-term interest rates. Following Flood and Rose (1995), three months Treasury bill returns are used as a measure of short-term interest rates. The exchange rates are also obtained from the Federal Reserve Bank of Saint Louis database. The exchange rate and bond index is transformed by taking logarithms of all the raw data to generate the returns and hence a series for model estimation. The exchange rate and the returns from the bonds are annualized by taking the 12-month differences.

Table 1 presents the descriptive statistics for the logarithm of the nominal exchange rate, the differential between stock prices, treasury bills, and bonds. Within our sample period, the mean of the exchange rate differential is less than one for the United Kingdom, Australia, Canada, and Brazil. It is greater than one for Sweden, South Korea, South Africa, and Mexico. Across all the countries, the standard deviation of both the differential of treasury bills and bonds is less than the standard deviation of the exchange rate differential. This suggests that both the short and long term interest rates are less volatile relative to the exchange rate. However, the standard deviation of the differential between stock prices is seen to be higher than that of the exchange rate for some countries. This suggests that among the three variables, the stock prices might have the biggest contribution to exchange rate volatility. The exchange rate differentials across all countries excluding Sweden, and Mexico exhibit low kurtosis and low skewness.

Table 1: Descriptive statistics

		e	$s_t^d - s_t^f$	$tb_t^d - tb_t^f$	$b_t^d - b_t^f$
UK	Mean	-0.499	0.116	0.017	0.007
	Std Dev	0.091	0.204	0.018	0.009
	Skewness	-0.604	0.179	1.396	1.053
	Kurtosis	2.603	1.567	4.167	3.982
Aus	Mean	0.284	-0.092	0.028	0.016
	Std Dev	0.184	0.148	0.018	0.010
	Skewness	0.131	-0.092	0.547	1.133
	Kurtosis	2.630	2.401	3.351	4.931
Can	Mean	0.216	-0.162	0.011	0.004
	Std Dev	0.147	0.125	0.015	0.008
	Skewness	-0.024	-0.346	1.032	0.841
	Kurtosis	1.764	3.160	4.592	2.707
Swed	Mean	1.992	-0.247	0.015	0.007
	Std Dev	0.148	0.191	0.029	0.016
	Skewness	0.488	-0.664	1.309	1.134
	Kurtosis	3.110	4.356	5.783	3.155
SK	Mean	6.920	-0.280	0.048	0.032
	Std Dev	0.199	0.443	0.042	0.027
	Skewness	-0.196	-0.439	1.048	0.896
	Kurtosis	2.023	2.757	3.138	2.742
SA	Mean	1.769	-0.510	0.075	0.067
	Std Dev	0.428	0.400	0.027	0.020
	Skewness	-0.514	0.220	0.291	0.179
	Kurtosis	2.122	1.773	2.660	2.760
Braz	Mean	0.621	-2.978	0.162	0.052
	Std Dev	0.348	4.840	0.094	0.036
	Skewness	-0.527	-2.195	2.554	2.124
	Kurtosis	2.607	6.321	12.926	7.656
Mex	Mean	2.283	-1.141	0.109	0.095
	Std Dev	0.326	0.821	0.103	0.107
	Skewness	-1.961	0.055	2.342	3.059
	Kurtosis	7.107	1.886	9.948	14.257

5. Out-of-Sample Forecasting methodology

We use test statistics such as the MAE, MAPE, RMSE, and the Clark and West (CW) (2006, 2007) test for equal predictive ability. The statistics are constructed using a recursive regression technique also used by Molodtsova and Papell (2009). The data in each model goes back to January 1990. The sample from January 1990 to December 2008 is used to estimate the coefficients of the model. A predictive recursive regression is then used to forecast one-step-ahead exchange rate starting from January 2009 and then rolling the period forward to estimate over the whole forecasting sample, starting in January 2009 to December 2014. At the end, 72 one-month ahead forecasts are derived and the forecast errors are extracted. The same process is followed to compute three, six, and twelve-steps ahead forecasts.

To compare the out-of-sample forecasting ability of the different models, this study focused on the minimum test statistics (i.e. MAE, MAPE, RMSE) comparison, which became dominant since the study by Meese and Rogoff (1983a, 1983b).

To measure the relative accuracy of the different models against the benchmark models i.e. the naïve random walk and the autoregressive model, we use an alternative test statistic; the Clark and West (CW) statistic.

5.1. The Clark and West (CW) test

The Clark and West (2006, 2007) test shows that the sample difference between the squared errors of two nested models is biased downwards from zero in favor of the random walk. They propose a procedure for adjusting for the difference in the squared errors of the two models.

Model 1 is the parsimonious model. Model 2 is the larger model with different parameter that nest model 1-such that, if the parameters of model 2 are set to zero it reduces to model 1. The period t forecasts of $y_{t+\tau}$ from the models are indicated as $\hat{y}_{1t,t+\tau}$ and $\hat{y}_{2t,t+\tau}$ with the corresponding period $t + \tau$ forecast errors $y_{1+\tau} - \hat{y}_{1t,t+\tau}$ and $y_{1+\tau} - \hat{y}_{2t,t+\tau}$. The sample mean squared errors are $\tilde{\alpha}_1^2$ and $\tilde{\alpha}_2^2$ defined as the sample averages of $(y_{1+\tau} - \hat{y}_{1t,t+\tau})^2$ and $(y_{1+\tau} - \hat{y}_{2t,t+\tau})^2$. The term defined as “adj” is the adjustment made and is defined as the sample average of $(\hat{y}_{1t,t+\tau} - \hat{y}_{2t,t+\tau})^2$.

Thus,

$$\tilde{\alpha}_1^2 = P^{-1} \sum (y_{1+\tau} - \hat{y}_{1t,t+\tau})^2, \quad \tilde{\alpha}_2^2 = P^{-1} \sum (y_{1+\tau} - \hat{y}_{2t,t+\tau})^2,$$

$$\tilde{\alpha}_2^2 - adj. = P^{-1} \sum (y_{t+\tau} - \hat{y}_{2t,t+\tau})^2 - P^{-1} \sum (\hat{y}_{1t,t+\tau} - \hat{y}_{2t,t+\tau})^2.$$

Under the null hypothesis, there is no difference in the predictive power of the two models. The alternative is that model 2 has lower squared errors than model 1. Clark and West (2006, 2007) propose that this hypothesis be tested by examining not $\tilde{\alpha}_1^2 - \tilde{\alpha}_2^2$ but $\tilde{\alpha}_1^2 - (\tilde{\alpha}_2^2 - adj.)$, rejecting the null if the difference is sufficiently positive.

6. Results

We commence our model analysis by estimating the fundamental formulation based on the optimized uncovered rate of return parity using a simple OLS method. The estimation results for the model and the benchmark model are reported in table 2. From the table, we focus on the sizes and the signs of the coefficients since they capture the effect of the independent variable on the depended variable. From table 2, the R^2 for the optimized uncovered rate of return parity model appear to be moderately low across all the countries, both developed and emerging countries. Looking at the un-optimized model, there seems to be an improvement in the R^2 , with the highest reported for South Korea at 0.50. This suggests that the un-optimized model provides a better explanation of the fundamental level of the exchange rate compared to the optimized uncovered rate of return parity model.

The results reported in table 2 also suggest that the mean variance portfolio return made up of stocks, treasury bills, and bonds is very significant in exchange rate determination. The F-probabilities are also moderately high which suggests strong goodness of fit for the model. We estimated the parameters for the models in table using time-varying variance co-variance matrices from section 3. It is clear from table 2 that accounting for the time varying effects is relevant in modelling exchange rates as seen from the p-values of the beta coefficient. Therefore, the prompt conclusion from table 2 is that the inclusion of the three market variables and accounting for the time varying effects play an important role in model precision and dependability.

The parameter of the coefficient for equation (5), β_0 is expected to be negative which would suggest that when the return of the domestic portfolio increases, investors choose to re-diversify their investment portfolio towards the domestic market leading to an appreciation of the domestic currency. However, from table 2 the coefficient is seen to be positive across all the countries in the study. Perhaps this is an anomaly which can be best explained by the famous forward premium puzzle since the Uncovered rate of return parity model (5) follows a similar specification to that of the Uncovered interest parity model, but considering the return differential of two portfolios. A similar anomaly is observed with the coefficient for equation (7), the uncovered interest parity model as it also provides variation in results with a negative coefficient reported for the United Kingdom, Australia, Sweden and a positive coefficient for the other five countries.

Table 2
Regression coefficient estimates

Coeff	UK	Aus	Can	Swed	SK	SA	Braz	Mex
$\Delta e_t = \alpha_0 + \beta_0(R_{pt-1}^d - R_{pt-1}^f) + u_t$								
α_0	-0.006 (0.420)	-0.002 (0.005)	-0.011 (0.009)	-0.001 (0.890)	0.012 (0.310)	0.009 (0.431)	0.008 (0.662)	0.015 (0.048)
β_0	0.041 (0.076)	0.470 (0.000)	0.540 (0.000)	0.370 (0.003)	0.490 (0.002)	0.740 (0.000)	0.880 (0.000)	0.380 (0.000)
R ²	0.0042	0.046	0.18	0.031	0.045	0.12	0.15	0.11
F-stat	0.093	13.18	58.29	8.72	9.43	34.24	28.55	21.91
DW-stat	0.13	0.14	0.19	0.12	0.15	0.21	0.41	0.27
$\Delta e_t = \alpha_0 + \beta_0(s_{t-1}^d - s_{t-1}^f) + \beta_1(b_{t-1}^d - b_{t-1}^f) + \beta_2(tb_{t-1}^d - tb_{t-1}^f) + u_t$								
α_0	0.023 (0.007)	0.035 (0.003)	-0.009 (0.110)	-0.006 (0.511)	-0.016 (0.213)	-0.019 (0.611)	-0.065 (0.160)	-0.010 (0.531)
β_0	0.600 (0.000)	0.011 (0.870)	-0.042 (0.311)	0.170 (0.000)	-0.140 (0.000)	0.230 (0.000)	-0.270 (0.000)	0.019 (0.711)
β_1	-0.088 (0.911)	-5.040 (0.000)	0.790 (0.381)	-1.880 (0.005)	3.190 (0.000)	1.820 (0.011)	-0.240 (0.621)	0.591 (0.001)
β_2	-0.630 (0.032)	-1.941 (0.000)	0.170 (0.582)	0.301 (0.274)	1.140 (0.000)	0.771 (0.075)	0.940 (0.000)	0.642 (0.000)
R ²	0.18	0.22	0.013	0.099	0.5	0.083	0.27	0.18
F-stat	15.98	24.93	1.23	9.98	67.66	7.46	20.44	12.74
DW-stat	0.22	0.157	0.11	0.11	0.23	0.11	0.15	0.2
$\Delta e_t = \alpha_0 + \beta_0(i_{t-1}^d - i_{t-1}^f) + u_t$								
α_0	0.010 (0.271)	0.048 (0.000)	-0.011 (0.034)	0.007 (0.390)	-0.074 (0.000)	0.009 (0.752)	-0.170 (0.000)	-0.009 (0.411)
β_0	-0.740 (0.016)	-2.140 (0.000)	0.380 (0.181)	-0.330 (0.193)	2.360 (0.000)	0.501 (0.161)	1.391 (0.000)	0.531 (0.000)
R ²	0.026	0.11	0.0067	0.0063	0.27	0.0079	0.21	0.12
F-stat	5.92	34.56	1.84	1.72	77	1.99	43.4	23.43
DW-stat	0.14	0.13	0.11	0.1	0.17	0.098	0.16	0.18
$\Delta e_t = \alpha_0 + v_t$								
α_0	-0.006 (0.293)	-0.003 (0.630)	-0.006 (0.203)	0.001 (0.917)	0.027 (0.040)	0.060 (0.000)	0.043 (0.004)	0.077 (0.000)
R ²	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DW-stat	0.14	0.11	0.11	0.10	0.12	0.09	0.10	0.11
$\Delta e_t = \alpha_0 + \beta_0\Delta e_{t-1} + v_t$								
α_0	0.00041 (0.851)	-0.00110 (0.653)	-0.00042 (0.771)	-0.00014 (0.951)	0.00110 (0.782)	0.00160 (0.614)	-0.00021 (0.970)	0.00280 (0.313)
β_0	0.952 (0.000)	0.940 (0.000)	0.940 (0.000)	0.951 (0.000)	0.941 (0.0001)	0.953 (0.001)	0.960 (0.000)	0.932 (0.000)
R ²	0.86	0.89	0.89	0.9	0.88	0.91	0.89	0.86
F-stat	1450.25	2237.84	2257.94	2489.99	297.63	2386.17	1422.27	1071
DW-stat	1.22	1.27	1.42	1.09	1	1.24	1.02	1.34

Notes: The numbers inside the parentheses report the p-values of each coefficient estimate in the regression.

We continue our analysis by performing an out of sample analysis to test the significance and predictive power of the model specifications presented in section 3 in comparison to the famous benchmark model, the naïve random walk. We use data over the period January 1990 to December 2008 for the estimation and then reserve the data from January 2009 to December 2014 for the out-of-sample forecasting. To evaluate the out-of-sample performance of the models, we estimate them by a recursive OLS rolling regression also used by Molodtsova and Papell (2009).

We construct test statistics such as MAE, MAPE, RMSE, and the CW statistic for model comparison. The models are first estimated using data from 1990 to 2008 and then a one month, three months, six months, and twelve months ahead forecast is constructed. We then extract the forecasting errors given by the difference between the actual and the fitted values resulting from the different models over the forecasting period. We use these errors to compute the different statistics, first the MAE, then the MAPE, and lastly the RMSE for the model evaluation as also used by Mark (1995).

Table 3 presents the out-of-sample evaluation statistics for the optimized uncovered rate of return parity forecasting model (5), the un-optimized model (6), uncovered interest parity model (7). Table 4 shows the statistics for the naïve random walk benchmark model (8), and the autoregressive benchmark model (9). Using these statistical methods, the most accurate forecasting model is said to be that with the lowest MAE, lowest RMSE, lowest MAPE according to Somanath (1986). Table 3 and table 4 present the forecasting ability of the models across all horizons for the four developed countries and the four emerging countries. The uncovered rate of return model appears to perform better than the naïve random walk benchmark at one-month ahead forecasting horizon for both the developed countries and the emerging countries. A similar pattern is observed with the un-optimized model, with strong evidence of superior performance appearing across all forecasting horizon.

Using the autoregressive model as the benchmark, table 3 and table 4 show that the proposed optimized uncovered rate of return parity model performs better than the autoregressive model for South Korea at a one-month ahead forecasting horizon. At three-months ahead forecasting the proposed model performs better than the autoregressive model for Canada, Sweden, South Korea, and Mexico. The un-optimized model also shows evidence of short term predictability as it performs better than the autoregressive model for South Korea and Brazil at one-month forecasting

horizon. The evidence of predictability improves with longer forecasting horizons, with the model performing better for the United Kingdom, Canada, South Korea, Brazil, and Mexico at three-months ahead forecasting horizon.

Since Clark and West (2006) show that using the RMSE as a measure for forecast comparison may have disadvantages as it might be biased downward from zero in favor of the random walk. We therefore use the CW statistic to test if there is a significant difference between the reported RMSE values. Using the CW statistic as a measure of statistical difference follows from studies such as Alquist and Chinn (2008), Clark and West (2006, 2007), Molodtsova and Papell (2009) where the following hypothesis is set up:

$$H_0 : \text{Squared error}_{\text{benchmark model}} - (\text{Squared error}_{\text{proposed model}} - \text{adjustment}) = 0$$

$$H_1 : \text{Squared error}_{\text{benchmark model}} - (\text{Squared error}_{\text{proposed model}} - \text{adjustment}) > 0$$

The hypothesis test is set up such that the null stipulates that there is no evidence of superior predictive power of the benchmark model against that of the proposed model. The alternative stipulated that the proposed model has superior predictive power over the benchmark model in the forecasting of exchange rates.

The CW statistic is computed by regressing the difference between the squared errors of the benchmark and the squared errors of the proposed model with an adjustment against a constant. We report the t-statistic from the regression; we reject the null of no difference in predictive power of the benchmark model against the proposed model when the t-statistic is greater than 1,282 at 10 percent level using a one-sided test. The procedure followed is thus in line with studies by Clark and West (2006) Alquist and Chinn (2008) and Molodtsova and Papell (2009).

Table 5 and table 6 report the out-of-sample forecasting evaluation between the proposed forecasting models (5), model (6), and the benchmark model (8). We also look at model (7) which is the uncovered interest parity model, a famous relation in finance. In the developed countries, the proposed optimized uncovered rate of return parity model (5) performs better than the naïve random walk in forecasting one and three-months ahead for all the countries. At a six-months ahead forecasting horizon, the model performs better than the benchmark for Brazil and South Africa. For the other six countries, there is no significant difference in performance. At twelve

months forecasting horizon, the model outperforms the benchmark model for 6 out of the 8 countries, with the exceptions being South Korea and the United Kingdom.

We also look at the performance of model (6) and model (7) against the naïve random walk. For both developed and emerging countries, the un-optimized model (6) performs better than the random walk in forecasting one, three, six, and twelve-months ahead for all the countries except for United Kingdom at six-months forecasting horizon. The uncovered interest parity model (7), on the other hand does not shows strong evidence of better performance against the naïve random at one-month ahead forecasting horizon. The uncovered interest parity outperforms the naïve random walk for 3 out of the 8 countries at one-month ahead forecasting horizon. This is aligned with the studies by Lothian and Wu (2011) which suggests that the uncovered interest parity relationship works better at long forecasting horizons.

We also look at how these models perform against a more stringent measure, the autoregressive model (9). The results are shown in table 6 for the three models. The optimized uncovered rate of return model shows evidence of superior performance against the autoregressive for 2 out of the 8 countries, i.e. Brazil and South Africa at one-month ahead forecasting horizon. The autoregressive model shows superior performance for Australia at one-month forecasting horizon, with the remainder of the countries showing no significant difference in performance. The optimized uncovered rate of return parity model also shows evidence of better performance at three, six, and twelve-months ahead forecasting horizon. The un-optimized model shows evidence of superior performance at one-month head forecasting horizon for 3 out of the 8 countries, i.e. South Korea, Mexico, and Brazil. Strong evidence of the un-optimized model is seen at three, six and twelve months forecasting horizons. The uncovered interest parity model shows no evidence of superior performance at one-month ahead forecasting horizon. Evidence is only seen at longer forecasting horizon, at six and twelve months.

Table 3
Out-of-sample forecast valuation

Horizon	Statistic	UK	Aus	Can	Swed	SK	SA	Braz	Mex
$\Delta e_t = \alpha_0 + \beta_0(R_{pt-1}^d - R_{pt-1}^f) + u_t$									
1	RMSE	0.061	0.103	0.044	0.072	0.027	0.072	0.109	0.051
	MAE	0.046	0.078	0.030	0.057	0.023	0.057	0.088	0.043
	MAPE	256	175	81	2016	241	69	113	538
3	RMSE	0.061	0.124	0.057	0.085	0.041	0.144	0.104	0.061
	MAE	0.041	0.073	0.033	0.058	0.031	0.118	0.089	0.048
	MAPE	230	60	100	486	297	154	127	440
6	RMSE	0.062	0.113	0.068	0.092	0.043	0.144	0.112	0.071
	MAE	0.001	0.091	0.054	0.073	0.033	0.133	0.013	0.058
	MAPE	251	237	219	974	272	181	19	498
12	RMSE	0.043	0.080	0.044	0.069	0.044	0.126	0.096	0.058
	MAE	0.029	0.055	0.031	0.050	0.033	0.111	0.073	0.047
	MAPE	207	44	37	172	266	111	78	947
$\Delta e_t = \alpha_0 + \beta_0(s_{t-1}^d - s_{t-1}^f) + \beta_1(b_{t-1}^d - b_{t-1}^f) + \beta_2(tb_{t-1}^d - tb_{t-1}^f) + u_t$									
1	RMSE	0.044	0.089	0.074	0.127	0.026	0.104	0.034	0.040
	MAE	0.034	0.070	0.059	0.100	0.023	0.079	0.029	0.035
	MAPE	179	141	129	3015	148	97	37	432
3	RMSE	0.041	0.126	0.058	0.110	0.038	0.124	0.055	0.049
	MAE	0.028	0.082	0.042	0.068	0.030	0.103	0.045	0.038
	MAPE	154	67	73	324	311	129	54	359
6	RMSE	0.058	0.085	0.037	0.071	0.036	0.111	0.084	0.047
	MAE	0.048	0.068	0.001	0.049	0.029	0.088	0.007	0.037
	MAPE	297	110	0	523	264	110	9	262
12	RMSE	0.034	0.064	0.006	0.051	0.026	0.055	0.059	0.032
	MAE	0.026	0.044	0.000	0.035	0.021	0.042	0.047	0.025
	MAPE	191	39	0	106	220	47	60	649
$\Delta e_t = \alpha_0 + \beta_0(i_{t-1}^d - i_{t-1}^f) + u_t$									
1	RMSE	0.103	0.101	0.087	0.134	0.049	0.150	0.083	0.064
	MAE	0.074	0.101	0.065	0.104	0.036	0.128	0.064	0.051
	MAPE	136	139	95	578	203	114	83	277
3	RMSE	0.078	0.125	0.061	0.114	0.047	0.140	0.085	0.066
	MAE	0.056	0.078	0.041	0.075	0.034	0.119	0.069	0.051
	MAPE	160	65	57	484	321	137	79	275
6	RMSE	0.058	0.115	0.044	0.087	0.039	0.125	0.108	0.064
	MAE	0.001	0.091	0.037	0.066	0.031	0.100	0.012	0.051
	MAPE	299	268	112	967	262	142	13	277
12	RMSE	0.043	0.088	0.055	0.057	0.041	0.058	0.107	0.034
	MAE	0.032	0.053	0.031	0.042	0.034	0.046	0.085	0.030
	MAPE	212	38	73	298	306	51	83	758

Table 4

Out-of-sample forecast valuation for the random walk and autoregressive model

Horizon	Statistic	UK	Aus	Can	Swed	SK	SA	Braz	Mex
$\Delta e_t = \alpha_0 + v_t$									
1	RMSE	0.112	0.048	0.100	0.141	0.051	0.104	0.141	0.064
	MAE	0.080	0.034	0.076	0.107	0.039	0.079	0.119	0.052
	MAPE	276	139	123	414	202	97	148	340
3	RMSE	0.083	0.128	0.077	0.114	0.051	0.124	0.124	0.069
	MAE	0.054	0.081	0.051	0.075	0.039	0.103	0.108	0.056
	MAPE	105	153	174	469	423	129	151	380
6	RMSE	0.062	0.116	0.068	0.093	0.046	0.111	0.123	0.072
	MAE	0.048	0.090	0.053	0.072	0.035	0.088	0.015	0.058
	MAPE	251	249	218	1052	376	110	211	473
12	RMSE	0.045	0.088	0.057	0.076	0.044	0.055	0.107	0.034
	MAE	0.032	0.058	0.051	0.054	0.033	0.042	0.085	0.060
	MAPE	215	296	111	337	277	47	82	361
$\Delta e_t = \alpha_0 + \beta_0 \Delta e_{t-1} + v_t$									
1	RMSE	0.034	0.053	0.032	0.046	0.036	0.053	0.039	0.032
	MAE	0.024	0.037	0.022	0.037	0.029	0.039	0.031	0.025
	MAPE	132	0	68	267	159	52	36	165
3	RMSE	0.060	0.105	0.065	0.092	0.049	0.110	0.073	0.064
	MAE	0.037	0.061	0.036	0.061	0.039	0.082	0.058	0.053
	MAPE	159	52	102	338	415	122	75	668
6	RMSE	0.061	0.116	0.068	0.093	0.046	0.141	0.099	0.071
	MAE	0.049	0.090	0.051	0.072	0.035	0.112	0.010	0.057
	MAPE	258	249	214	1045	379	179	13	376
12	RMSE	0.045	0.081	0.047	0.075	0.037	0.140	0.100	0.072
	MAE	0.032	0.056	0.033	0.055	0.031	0.123	0.076	0.059
	MAPE	192	42	39	198	216	136	74	373

Table 5

CW statistics to evaluate model performance (naïve random walk used as benchmark)

Horizon	SK	Mex	Braz	SA	Swed	Can	Aus	UK
$\Delta e_t = \alpha_0 + \beta_0(R_{pt-1}^d - R_{pt-1}^f) + u_t$								
1	3.967** (0.000)	3.139** (0.003)	4.765** (0.001)	5.080** (0.000)	4.297** (0.000)	4.227** (0.000)	3.973** (0.000)	3.967** (0.000)
3	3.173** (0.003)	3.186** (0.003)	3.476** (0.001)	1.282 (0.206)	3.448** (0.001)	3.425** (0.001)	1.995** (0.050)	3.174** (0.003)
6	0.078 (0.903)	0.625 (0.536)	2.808** (0.008)	1.763* (0.084)	0.630 (0.531)	0.556 (0.580)	1.185 (0.241)	0.078 (0.938)
12	1.276 (0.208)	3.792** (0.001)	2.243** (0.031)	1.980** (0.050)	2.302** (0.026)	2.472** (0.017)	2.308** (0.025)	1.276 (0.208)
$\Delta e_t = \alpha_0 + \beta_0(s_{t-1}^d - s_{t-1}^f) + \beta_1(b_{t-1}^d - b_{t-1}^f) + \beta_2(tb_{t-1}^d - tb_{t-1}^f) + u_t$								
1	4.281** (0.000)	4.302** (0.000)	5.480** (0.000)	4.616** (0.000)	2.781** (0.003)	3.361** (0.001)	4.407** (0.000)	4.281** (0.000)
3	3.122** (0.003)	4.777** (0.000)	5.932** (0.000)	4.573** (0.000)	2.831** (0.007)	3.453** (0.001)	2.074** (0.044)	3.122** (0.003)
6	1.459* (0.101)	4.052** (0.000)	6.552** (0.000)	5.057** (0.000)	4.784** (0.000)	4.816** (0.000)	4.926** (0.000)	1.459 (0.151)
12	3.125** (0.003)	4.280** (0.000)	4.771** (0.000)	4.520** (0.000)	3.932** (0.000)	4.136** (0.000)	4.659** (0.000)	3.126** (0.003)
$\Delta e_t = \alpha_0 + \beta_0(i_{t-1}^d - i_{t-1}^f) + u_t$								
1	4.268** (0.001)	1.411 (0.167)	1.265 (0.250)	1.362 (0.222)	1.051 (0.146)	2.720** (0.009)	0.427 (0.200)	4.268** (0.000)
3	1.231 (0.224)	1.693* (0.099)	6.319** (0.000)	2.199** (0.033)	0.204 (0.839)	3.666** (0.000)	1.616 (0.113)	1.231 (0.224)
6	1.298 (0.201)	4.590** (0.000)	5.012** (0.000)	5.159** (0.000)	2.946** (0.005)	3.804** (0.000)	0.958 (0.343)	1.298 (0.201)
12	1.336 (0.187)	4.591** (0.000)	2.141* (0.056)	4.210** (0.000)	4.073** (0.000)	3.934** (0.000)	0.606 (0.548)	1.336 (0.188)

Notes: (1) Column 1 shows CW statistics for South Korea, 2 Mexico, 3 Brazil, 4 South Africa, 5 Sweden, 6 Canada, 7 Australia, and 8 the United Kingdom. (2) **denotes test statistics significant at the 5 percent level according to both standard normal and Clark and McCracken's (2005) asymptotic critical values: *denotes a test statistic significant at the 10 percent level according to Clark and McCracken (2001, 2005)

Table 6

CW statistics to evaluate model performance (autoregressive model used as benchmark)

Horizon	SK	Mex	Braz	SA	Swed	Can	Aus	UK
$\Delta e_t = \alpha_0 + \beta_0(R_{pt-1}^d - R_{pt-1}^f) + u_t$								
1	-0.065 (0.948)	0.027 (0.707)	1.521* (0.100)	2.489** (0.016)	0.151 (0.881)	-0.472 (0.639)	-1.821 (0.074)	-0.065 (0.948)
3	2.833** (0.007)	2.008** (0.050)	0.618 (0.541)	1.097 (0.278)	2.935** (0.005)	2.380** (0.021)	1.468** (0.019)	2.833** (0.007)
6	0.068 (0.946)	0.659 (0.514)	0.547 (0.588)	1.988** (0.050)	0.638 (0.525)	0.566 (0.574)	1.188 (0.241)	0.068 (0.946)
12	1.253 (0.217)	4.668** (0.000)	3.322** (0.007)	1.954* (0.057)	2.415** (0.020)	3.012** (0.000)	2.520** (0.015)	1.253 (0.217)
$\Delta e_t = \alpha_0 + \beta_0(s_{t-1}^d - s_{t-1}^f) + \beta_1(b_{t-1}^d - b_{t-1}^f) + \beta_2(tb_{t-1}^d - tb_{t-1}^f) + u_t$								
1	2.168* (0.068)	1.364* (0.100)	2.646** (0.012)	0.818 (0.417)	0.511 (0.612)	0.507 (0.614)	0.412 (0.682)	0.168 (0.868)
3	3.416** (0.001)	4.340** (0.000)	4.990** (0.000)	1.590* (0.100)	1.136 (0.262)	2.878** (0.006)	0.511 (0.611)	3.416** (0.001)
6	1.678* (0.100)	3.791** (0.001)	8.275** (0.000)	4.203** (0.000)	4.752** (0.000)	4.534** (0.000)	4.957** (0.000)	1.678* (0.100)
12	3.092** (0.003)	4.195** (0.000)	3.166** (0.009)	4.312** (0.000)	3.724** (0.001)	4.889** (0.000)	4.995** (0.000)	3.092** (0.003)
$\Delta e_t = \alpha_0 + \beta_0(i_{t-1}^d - i_{t-1}^f) + u_t$								
1	0.248 (0.805)	0.112 (0.911)	1.082 (0.285)	0.126 (0.900)	-0.311 (0.757)	1.020 (0.312)	-1.001 (0.321)	0.249 (0.805)
3	1.087 (0.283)	1.401 (0.170)	1.625 (0.114)	1.597 (0.117)	-0.006 (0.995)	2.864** (0.006)	-0.554 (0.582)	1.087 (0.283)
6	1.475 (0.147)	4.687** (0.000)	0.160 (0.874)	3.949** (0.000)	2.873** (0.006)	3.697** (0.001)	0.971 (0.336)	1.475 (0.147)
12	1.275 (0.209)	4.469** (0.000)	-3.756 (0.004)	4.029** (0.000)	3.943** (0.000)	2.001* (0.051)	-0.202 (0.840)	1.275 (0.209)

Notes: (1) Column 1 shows CW statistics for South Korea, 2 Mexico, 3 Brazil, 4 South Africa, 5 Sweden, 6 Canada, 7 Australia, and 8 the United Kingdom. (2) **denotes test statistics significant at the 5 percent level according to both standard normal and Clark and McCracken's (2005) asymptotic critical values: *denotes a test statistic significant at the 10 percent level according to Clark and McCracken (2001, 2005)

7. Conclusion

Research on exchange rate predictability has evolved starting with the works of Meese and Rogoff (1983) with no evidence of predictability at any horizon, to predictability at long horizon with no predictability at short horizons, from studies such as Mark (1995), Cheung, Chinn and Pascual (2005), Molodtsova, and Papell (2008).

In this paper, we develop the optimized uncovered rate of return parity model using the minimum variance portfolio theory developed by Markowitz (1952) in the forecasting of exchange rate. We also test an alternative model which is not optimized. The models use returns from the money market, stock market and the bonds as the main variables. Time varying effects of exchange rate are controlled by estimating a model with time varying weights derived on the asset returns. We benchmark the estimation and forecasting ability of our models with that of the naïve random walk and an autoregressive model. According to the test statistics computed to evaluate the performance of the models, the optimized uncovered rate of return model developed in this paper appears to show evidence of superior performance at a one-month forecasting horizon against the naïve random walk. The model outperforms the naïve random walk in all the 8 countries in the study. Looking at a three months forecasting horizon, the model still shows superior performance against the random walk for 7 out of the 8 countries, except for South Africa.

The out-of-sample forecasting statistics suggest that the un-optimized model shows better performance as compared to the optimized uncovered rate of return parity model. The un-optimized model, on average outperforms the naïve random walk at all forecasting horizons in all the countries in the study, except for the United Kingdom at a six months forecasting horizon. Our findings suggest that the outstanding forecasting ability of the existing models of exchange rate is possibly due to the omission of key market variable which play a crucial role in the volatility of exchange rates. This follows from the fact that stock prices, bond prices, and the money market show strong significance in most of the countries in study.

The optimized uncovered rate of return parity also shows evidence of superior performance when benchmarked with the autoregressive model. Although the evidence is not as strong as the evidence seen when the model is benchmarked with the naïve random walk. The model outperforms the autoregressive model at a one month ahead forecast for 2 out of the 8 countries (i.e. Brazil and

South Africa). The un-optimized model also shows evidence of superior performance for 3 out of the 8 countries at a one month ahead forecasting horizon.

The other underlying assumption which was made when developing the model is that investors follow rational approach in deciding whether to invest their capital domestically or in the United States. A rational approach would suggest that investors reallocate their funds between the domestic country and the United States to minimize risk with a given return in an optimized manner. However, it is possible that at times investors might chase returns without putting a lot of emphasis on the assumed risk, or on other occasions minimizing risk without a great regard for returns.

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