# Exchange Rate Forecasting: Evidence from the Emerging Central and Eastern European Economies

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# Exchange Rate Forecasting: Evidence from the Emerging Central and Eastern European Economies*

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**Abstract**

There is a vast literature on exchange rate forecasting focusing on developed economies. Since the early 1990s, many developing economies have liberalized their financial accounts, and become an integral part of the international financial system. A series of financial crises experienced by these emerging market economies ed them to switch to some form of a flexible exchange rate regime, coupled with inflation targeting. These developments, in turn, accentuate the need for exchange rate forecasting in such economies. This paper is a first attempt to compile data from the emerging Central and Eastern European (CEE) economies, to evaluate the performance of versions of the monetary model of exchange rate determination, and time series models for forecasting exchange rates. Forecast performance of these models at various horizons are evaluated against that of a random walk, which, overwhelmingly, was found to be the best exchange rate predictor for developed economies in the previous literature. Following Clark and West (2006, 2007) for forecast performance analysis, we report that in short horizons, structural models and time series models outperform the random walk for the six CEE countries in the data set.

Key Words: Exchange rate forecasting; Out-of-sample forecast performance.
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# 1 Introduction

Contrary to the then popular belief in the academic circles, in their seminal paper, Meese and Rogoff (1983) conclude that the monetary models of exchange rate determination, and univariate and multivariate time series models have poor out-of-sample forecast performance when compared to the simple random walk model. Since then, attempts have been made to show that forecasts from a variety of models of exchange rate determination outperform those from the random walk model, which essentially implies no-change in the exchange rate. Indeed, a vast literature on exchange rate forecasting has emerged, particularly due to the increased adoption of some form of flexible exchange rate regimes in the developed world, as uncertainty about future exchange rates is inherent in such regimes.[1]

Especially since the mid-1990s, the empirical evidence reported by this literature for the predictability of exchange rates have become slightly more encouraging. For example, Mark (1995), and Chinn and Meese (1995) find that monetary fundamentals outperform the random walk at longer horizons, both using similar sets of currencies against the U.S. dollar. Also, Mark and Sul (2001), for a panel of 19 currencies, report significant forecasting power of fundamentals-based models.

However, a different strand of literature stands to be more pessimistic in this regard. Specifically, Groen (1999), Kilian (1999), Berkowitz and Giorgianni (2001), and Faust *et al.* (2003) show that long-horizon exchange rate predictability as put forth by the abovementioned studies depend on the econometric techniques and the sample period used. In addition, Cheung *et al.* (2005) document that the reported favorable results for the forecast performance of the structural exchange rate models are not robust to different combinations of models, specifications and currencies. This divide in the empirical literature is further emphasized by Engel and West (2005), who show analytically that exchange rates may indeed be unpredictable. Within an asset pricing framework, when the discount factor is close to one, and the underlying fundamentals are integrated of order one, Engel and West demonstrate that an asset price, here, the exchange rate, will be a near-random walk process.

It is also important to mention, at this point, that the empirical methodology used in forecasting has undergone many changes since Meese and Rogoff (1983). In the earlier literature, evaluations of forecasts of various models are based on absolute comparisons of certain forecast error criteria, such as root mean squared error (RMSE), mean squared prediction error (MSPE), mean absolute error (MAE), etc., and the model that yields the smallest error is perceived to be the one that produces the best out-of-sample forecasts. Following Diebold and Mariano (1995) and West (1996), the standard practice emerges in the form of conducting hypothesis tests that these error values from competing models do not differ significantly. This type of test is referred to as the "DMW test" hereafter. Specifically, in the context of exchange rate forecasting, the DMW test compares forecasts from the random walk to those from any other model of exchange rate determination in which the random walk is nested. Clark and West (2006, 2007) show that the DMW test statistic is biased downward under the null hypothesis, so that one tends to fail to reject the null and ends up favoring the random walk. Clark and West propose an adjustment to the DMW statistic to correct for this bias. This type of test is referred to as the "CW" test hereafter.

Regarding these developments in forecast evaluation methodology, a new strand of literature employs the CW test in the context of exchange rate forecasting . This emerging literature is composed of Clark and West (2006), Alquist and Chinn (2007), Gourinchas and Rey (2007), Engel *et al.* (2007), and Molodtsova and Papell (2008). The common themes in all of these

[1]See Neely and Sarno (2002) for a summary of this literature and empirical evidence.

studies are that they use data from a number of developed economies, they utilize various structural models of exchange rate determination, and they report better forecast performance by different structural models against the random walk at different horizons.

While exchange rate forecasting literature progresses in such a way as outlined above, these studies utilize data from developed economies where flexible exchange rate regime is almost like a norm, and foreign exchange markets as well as other financial markets are well-developed and deep. As the history of financial liberalization and flexible exchange rates in developing economies is quite recent, it became possible to collect a sufficiently long time series data set on such countries only lately. In this respect, a recent study by Alper and Ardic (2006) utilizes data from Turkey during the post-2001 flexible exchange rate regime period and estimates a number of structural and time series models. Based on absolute comparisons of RMSE values of alternative models, they report that while the random walk is better in short horizons, there is evidence of exchange rate predictability in longer horizons. Another study with developing country data is by Crespo Cuaresma and Hlouskova (2005). They use pre-2000 data from the Central and Eastern European (CEE) countries and a variety of multivariate time series models. Comparing the forecast performance of models via the DMW test, they report short horizon predictability of exchange rates.

A few important points are lacking in the previous two articles: (*i*) Crespo Cuaresma and Hlouskova (2005) use data from the CEE countries for a period in which those countries are in the process of transition, and thus may have thin foreign exchange markets, (*ii*) Crespo Cuaresma and Hlouskova (2005) use multivariate time series models only, as alternatives to random walk, and (*iii*) neither Crespo Cuaresma and Hlouskova (2005), nor Alper and Ardic (2006) employ the CW test.

In this paper, we address these three points by using post-2000 data from six emerging CEE countries (Croatia, Czech Republic, Hungary, Poland, Romania, and Turkey) that use some form of a flexible exchange rate regime; structural as well as univariate and multivariate time series models; and the CW test to stress the importance of exchange rate forecasting for developing economies as the world financial markets become more and more integrated. Hence, the paper contributes to the existing literature in two aspects: (*i*) it is one of the few papers that adopt the adjustment by Clark and West (2006, 2007) in the context of exchange rate forecasting, and (*ii*) it is one of the first attempts to conduct a systematic analysis of exchange rates forecasting in the context of developing economies.

The findings of this paper indicate that, in the short horizon (one-month), the out-of-sample forecasts of the interest differential and monetary fundamentals as well as univariate and multivariate time series models outperform the random walk for almost all of the countries in the sample. However, we are unable to document the predictability of exchange rates for longer horizons. These results are in line with Clark and West (2006) and Molodtsova and Papell (2008) who also report short-horizon predictability only.

The rest of the paper is organized as follows. Section 2 presents the models of exchange rate determination used in this study. The data set is described and the results of the empirical analyses are reported in Section 3. Section 4 concludes.

## 2 Methodology

We use a variety of models to forecast the exchange rate for different horizons. Both structural and time series models are used in order to assess whether any of these models has advantages in terms of out-of-sample forecast performance over the random walk. In addition, each model is estimated for different horizons to investigate if the forecast performance depends on horizon.

The next subsection presents the structural models used while subsection 2.2 gives information on the time series models. Forecast evaluation method is described in subsection 2.3.

### 2.1 Structural Models

This subsection outlines the structural models used in this paper, as well as many other papers in the literature, to forecast exchange rates. These are the interest rate differential, which is simply the uncovered interest parity (UIP) condition, and two versions of the monetary model, both of which also utilize the UIP condition.

The basic uncovered interest parity (UIP) condition expresses the expected depreciation as a function of the interest differential as

$$s^e_{t+k} - s_t = i_t - i^*_t \tag{1}$$

where $s_t$ denotes the natural logarithm of the nominal exchange rate expressed as the amount of domestic currency per unit of foreign currency, the superscript $e$ denotes expectations, $k$ is the investment horizon, and $i_t$ and $i^*_t$ are $k$-period domestic and foreign interest rates, respectively. Under the assumptions that the foreign exchange market participants are risk neutral, and the underlying alternative domestic and foreign assets are perfect substitutes, i.e. the political risk of underlying assets are comparable, equation (1) states that the expected depreciation of the domestic currency against the foreign currency over $k$ periods is equal to the premium of the return on the domestic asset over that on the foreign asset, both with time to maturity of $k$ periods. Once $\epsilon_t$ is taken as the rational expectations forecast error, equation (1) becomes

$$s_{t+k} - s_t = \beta_0 + \beta_1(i_t - i^*_t) + \epsilon_{t+k} \tag{2}$$

Equation (2) can then be used to test the validity of the UIP condition as well as to forecast the $k$-period-ahead nominal exchange rate. The monetary model takes equation (2) as basis and uses the determinants of the interest rates to eliminate the interest rate differential on the right hand side of equation (2). Generally, the model assumes a money demand function of the form

$$m_t - p_t = \theta y_t - \lambda i_t \tag{3}$$

for the domestic economy, and similarly, for the foreign economy as

$$m^*_t - p^*_t = \theta y^*_t - \lambda i^*_t \tag{4}$$

where $m_t$, $y_t$, and $p_t$ denote the domestic monetary aggregate, domestic real income, and domestic price level. The letters with stars as superscripts denote the same variables for the foreign economy. The major underlying assumption of equations (3) and (4) is that the functional form of the money demand in both the domestic and the foreign economy are identical as well as their parameters. One can derive the domestic interest rate as a function of domestic monetary aggregate, price level and real income, and the foreign interest rate as a function of respective foreign economic variables. Substituting these for the interest differential in equation (2) yields

$$s_{t+k} - s_t = \beta_0 + \beta_1[(m_t - m^*_t) - \theta(y_t - y^*_t) - (p_t - p^*_t)] + \epsilon_{t+k} \tag{5}$$

In addition, one can also put the purchasing power parity (PPP) relation in the picture. The PPP in the form of "law of one price" suggests

$$s_t = p_t - p^*_t \tag{6}$$

Thus, substituting (6) in (5) yields

$$\begin{aligned} s_{t+k} - s_t &= \beta_0 + \beta_1[(m_t - m^*_t) - \theta(y_t - y^*_t) - s_t] + \epsilon_{t+k} \\ &= \beta_0 + \beta_1(f_t - s_t) + \epsilon_{t+k} \end{aligned} \tag{7}$$

where $f_t$ denotes "fundamentals." Exchange rate forecasting is done through the estimation of equations (2), (5) and (7). Note that when one uses overlapping observations, an MA($k$-1) process for the error terms are introduced.[2] See Hansen and Hodrick (1980), Taylor (1995), and Mark (2001) for details.

### 2.2 Time Series Models

Other than employing the structural models, one may also adopt univariate and multivariate time series techniques to model the exchange rate series. Univariate modeling is done through Box-Jenkins type ARIMA modeling where lag selection is done via information criteria and ensuring there is no pattern left in the residuals. Exchange rate depreciation, that is the first difference of the natural logarithm of the exchange rate, is modeled by the equation

$$\Delta s_t = \phi_0 + \phi_1 \Delta s_{t-1} + \phi_2 \Delta s_{t-2} + \ldots + \epsilon_t \tag{8}$$

where $\Delta s_t$ shows the first difference of the natural logarithm of the exchange rate at time $t$, and $\epsilon_t$ is a white noise error term. In addition, multivariate time series modeling is applied through an unconstrained VAR as

$$X_t = \Phi_0 + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \ldots + E_t \tag{9}$$

where $X_t$ is an $n \times 1$ vector of endogenous variables which may include the domestic interest rate (and some other monetary fundamentals) as well as the exchange rate, and $E_t$ is a vector of white noise error terms. The reason for estimating such a VAR is to see how the dynamics of the interest rate as well as the exchange rate itself might have an impact on the exchange rate and hence might have an added value for forecasting the future values of the exchange rate.

Note that as the data frequency is monthly, there is no ARCH effect in the data and hence volatility modeling is not done. However, for higher frequency data, volatility modeling might be necessary.

### 2.3 Forecast Evaluation

Our analyses are based on three different forecast horizons: monthly (one-step-ahead), quarterly (three-step-ahead), and semiannually (six-step-ahead). The procedure we follow is similar to that by Meese and Rogoff (1983) except for the evaluation criteria.

The sample is split into two parts: estimation sample and forecast evaluation sample. We use a rolling window estimation method: first, a fixed window of $n$ observations is used for the estimation of a model, and second, the one-step-, three-step-, and six-step-ahead forecasts are calculated. Then the sample is rolled forward by one observation, and the two-stage procedure is repeated. This gives us a sequence of $T - n$ forecasts, where $T$ is the size of the entire sample. These forecasts are then compared to the actual values in the forecast evaluation sample by forming a series of forecast errors. This procedure is repeated for each model under consideration, and the models are then compared based on their out-of-sample forecast accuracy.

Meese and Rogoff (1983) take the random walk model as the benchmark, where the best predictor of the exchange rates in the future is the last known value. They calculate the RMSE of the random walk model, the structural models, and the time series models using the sequence of forecasts from each model and the actual values in the forecast evaluation sample. Next, they

[2] The use of overlapping observations implies the following. For example, the data are collected every month, so that the frequency of the data set is monthly, and 3-month ahead forecasts are made. Then, once the 3-month forecast is made, information updating is possible in the next two periods. This causes an MA(2) process in the error term.

choose the model that has the lowest RMSE as the model that yields the best out-of-sample forecasts. In their analysis, as mentioned earlier, Meese and Rogoff find that the best exchange rate predictor is the random walk.

Diebold and Mariano (1995), West (1996), and later Clark and West (2006, 2007) improve upon the absolute comparison of the RMSE criterion used by Meese and Rogoff (1983). The improved procedure is based on two main ideas. First, the forecasts from a larger (less parsimonious) model are compared to the forecasts from a model that is nested (more parsimonious) in the larger model. For instance, in this case, the benchmark model is the random walk, and it is nested in all the structural and time series models that we are using. Thus, pairwise comparisons of each structural and time series model with the random walk can be made. Second, it is not sufficient to find that a particular model has a lower RMSE than the random walk. One needs to make sure that the RMSE of that particular model is lower than that of the random walk at a certain significance level. That is, we need to have a formal hypothesis testing procedure rather than an absolute comparison of RMSEs of two models.

In the analysis that follows, rather than RMSE, MSPE (which is simply the square of RMSE) is used. Note that it is possible to use other criteria such as RMSE itself, or MAE, etc. as well with the procedure put forth by Diebold and Mariano (1995), West (1996), and Clark and West (2006, 2007). We chose to use the MSPE as it has been commonly used in the recent literature.

The procedure is as follows. Once the forecasts from the random walk are constructed, the MSPE of the random walk model is calculated. In addition, the forecasts of other models are used to calculate their respective MSPE values. The MSPE of a model is calculated as:

$$MSPE = \sigma^2 = P^{-1}\Sigma(y_{t+i} - \hat{y}_{t+i})^2 \tag{10}$$

where $y_{t+i}$ is actual value at time $t+i$, $\hat{y}_{t+i}$ is the forecast for time $t+i$, and $P$ is the number of forecasts, which is equal to $T-n$ for one-step-ahead forecasts. We have:

$$y_t = s_t - s_{t-1} \tag{11}$$

and, the MSPE for the random walk will be:

$$\sigma_1^2 = P^{-1}\Sigma(y_{t+i})^2 \tag{12}$$

where $i$ runs from $n+1$ to $T$ for one-step ahead forecasts. Similarly, the MSPE from the other model that is to be compared with the random walk is given by:

$$\sigma_2^2 = P^{-1}\Sigma(y_{t+i} - \hat{y}_{t+i})^2 \tag{13}$$

Note that $y_{t+i}$ and $(y_{t+i} - \hat{y}_{t+i})$ are the sample forecast errors from random walk and the larger model, respectively.

As Diebold and Mariano(1995), and West (1996) point out, it is reasonable to examine whether our larger model performs better than the parsimonious model (here, the random walk) significantly by using sample MSPEs to make a $t$ test. Hence, we test the null hypothesis that the two prediction errors are equal against the alternative hypothesis that parsimonious model's prediction error is larger. If the null hypothesis is rejected, then the larger model is better than the random walk. Thus, we have:

$$\begin{aligned} H_0 &: \sigma_1^2 - \sigma_2^2 = 0 \\ H_1 &: \sigma_1^2 - \sigma_2^2 > 0 \end{aligned} \tag{14}$$

The $DMW$ test statistic (for Diebold-Mariano and West) is then given by:

$$DMW = \frac{\bar{f}}{\sqrt{P^{-1}V}} \tag{15}$$

where $f = y_{t+i} - (y_{t+i} - \hat{y}_{t+i})$ and $\bar{f} = P^{-1} \sum f$. Note that $V = P^{-1} \sum (f)^2$ is the corresponding variance term. Diebold and Mariano (1995), and West (2006) propose a standard $t$ test for the null hypothesis given by equation (14).

However, Clark and West (2006 and 2007) show that the difference between two sample MSPEs is biased downward from zero. The larger model introduces a noise into forecasts by trying to estimate parameters having zero population values under the null hypothesis. Thus, the MSPE from the larger model is expected to be greater than the parsimonious model, i.e. $\hat{\sigma_1^2} - \hat{\sigma_2^2}$ tends to be negative. Clark and West propose an adjustment to the larger model's MSPE to correct for the bias:

$$\sigma^2_{2_{adj}} = P^{-1}\Sigma(y_{t+i} - \hat{y}_{t+i})^2 - P^{-1}\Sigma(\hat{y}_{t+i})^2 \tag{16}$$

where $\sigma^2_{2_{adj}}$ is the adjusted MSPE of larger model and $P^{-1}\Sigma(\hat{y}_{t+i})^2$ is the adjustment term. The adjusted $DMW$ statistic, namely, the $CW$ statistic (for Clark and West), is given by:

$$CW = \frac{\bar{f}_{adj}}{\sqrt{P^{-1}V}} \tag{17}$$

where $\bar{f}_{adj} = \sigma_1^2 - \sigma^2_{2_{adj}}$. Then, the $CW$ statistic can be compared to the appropriate critical value from the $t$ distribution.

Note that for longer horizon forecasts serial correlations should be accounted for, i.e. in equation (15) or (17) a HAC variance estimator such as in Newey and West (1994) or West (1996) should be used.

# 3 Data and Empirical Analysis

## 3.1 The Data Set

Monthly observations for the six emerging CEE economies that do not follow some form of fixed exchange rate regime are used for the analysis. These are Croatia, Czech Republic, Hungary, Poland, Romania, and Turkey. The data sources are the International Financial Statistics (IFS) Database of the IMF, Eurostat, the Federal Reserve Bank of St. Louis, Croatian National Bank, Czech National Bank, the Central Bank of Hungary, the Central Statistical Office of Poland, the National Bank of Poland, the National Bank of Romania, and the Central Bank of the Republic of Turkey.

Except for Croatia and Turkey, the samples for each country consist of 84 monthly observations for the period between January 2000 - December 2006. The Turkish sample has 69 monthly observations for the period between April 2001 - December 2006, which is arranged according to the start of the floating exchange rate regime. The Croatian sample has 60 monthly observations for the period between January 2002 - December 2006 due to data availability.

Exchange rates are defined as the local currency per an equally weighted basket of USD and Euro. The money supply indicator used to construct the fundamental values in Croatia, Hungary, Poland, Romania and Turkey regressions is M1 while the "money" series from the IFS is used for the Czech Republic. Interest rates are: short-term deposit rate for Croatia, Lombard rate for Czech Republic and Poland, effective rate for Hungary, BUBID for Romania, and overnight interest Rate for Turkey. In order to calculate the interest differential, the average of Eonia for Europe and effective Federal Funds rate for the U.S. are used as the foreign interest rate. CPI series are used for all six countries as the price variable.

Real GDP values are used as the income measure in the structural models. As real GDP for the sample period is not available for Romania, nominal GDP series is deflated by the

PPI. Since real GDP values are released quarterly, Friedman's Interpolation Method (Friedman, 1962) is used to convert quarterly real GDP data into monthly series for all countries. Industrial Production Index is used in the interpolation process. This is done to increase the sample size as well as to be able to construct one-month-ahead forecasts.

Except for interest rates, all variables are expressed in natural logarithms.

The fixed window size for the estimation sample is 36 for all countries for one-step-, three-step-, and six-step-ahead forecasts.

### 3.2 Results

Table 1 summarizes our empirical findings. As can be observed from the table, with the exception of one-step-ahead forecasts for Turkey and Romania, both univariate and multivariate time series models perform better than the random walk based on an absolute comparison of the MSPE of each model and the MSPE of the random walk. However, it is not possible to come to similar conclusions for the structural models. Based on the same criterion, the forecasts from structural models beat those of the random walk only for one-step-ahead forecasts for all countries except Romania where the MSPEs of the structural models and the random walk are almost the same. Thus, if one were to base the forecast evaluations on an absolute pairwise comparison of the MSPEs of time series models and structural models with the MSPEs of the random walk, it would seem that the time series models have a better forecast performance than the structural models against the random walk.

[Insert Table 1 about here.]

As explained above in section 2.3, rather than an absolute pairwise MSPE comparison, formal hypothesis testing should be done to evaluate the forecast performance of competing models. In this respect, the test proposed by Diebold and Mariano (1995), and West (1996) is where one constructs a $t$ test for the difference between the MSPEs of two competing models as in (14). Table 1 also reports the DMW test statistic for each model against the random walk for different horizons. This test does not provide as good a picture for the forecast performance of the time series models as does the absolute comparison of MSPEs. It is not possible to reject the null hypothesis that the MSPE from the random walk and the MSPE from VAR do not differ at any conventional significance level. Furthermore, the univariate time series model performs better than the random walk only for one-step-ahead forecasts for the Czech Republic, Hungary, and Poland.

Based on the DMW test results, among the structural models, the UIP relation, given by equation (2), is found to perform better than the random walk for one-step-ahead forecasts in the Czech Republic, Hungary, and Poland at 10% level of significance. Monetary Model I, given by equation (5), does not outperform the random walk for any country at any horizon at any conventional significance level, while Monetary Model II, given by equation (7), has a better forecast performance than the random walk only for the Czech Republic for one-step-ahead forecasts at 10% level of significance.

As the DMW test statistic is biased downward, i.e. it favors the random walk, we correct for this bias using the method proposed by Clark and West (2006, 2007). Table 1 presents the modified test statistic, CW. Based on our findings tabulated in Table 1, the CW test provides more favorable results for the structural and time series models against the random walk than the DMW test as it corrects for the downward bias of the DMW test. It is possible to reject the null hypothesis that the MSPE from the random walk is not different from the MSPE of any of the structural models under consideration against the alternative that the structural model outperforms the random walk for Croatia, Czech Republic, Hungary, and Poland for one-step-ahead forecasts. In addition, Monetary Model II (equation 7) also outperforms the random walk for one-step-ahead forecasts in Romania. The univariate time series models show better forecast performance than the random walk for all countries under investigation for one-step-ahead forecasts, while VARs seem to be better for the Czech Republic, Hungary, and Poland at one-month forecast horizon. Note that while none of the structural models have a better forecast performance for the Turkish data, only the univariate time series model improves upon the forecasts from a random walk for one-month forecasts.

To sum up, although absolute comparisons of MSPEs from alternative models seem to be a good way of evaluating the forecast performance of alternative models, formal hypothesis testing allows us to put a confidence level on our evaluations. The data from the six emerging CEE economies investigated here suggest that, at least for short horizons, structural and time series models outperform the random walk up to a certain confidence level. In addition, it is possible to observe that once the bias in the DMW statistic is corrected for, the results for the exchange rate models as well as the time series models become more favorable.

# 4 Concluding Remarks

The use of flexible exchange rate regime necessarily creates uncertainty about the future exchange rates, which in turn brings the need to forecasting exchange rates. Using post-Bretton Woods data from developed economies, the seminal paper by Meese and Rogoff (1983) documents that the forecasting ability of both structural and time series models of exchange rates is very weak. Since then, a vast literature has been developed which focuses on developed economies. In the meanwhile, new methods of forecast evaluation are developed and implemented in this area. Recently, a few studies utilizing such forecast evaluation methods (Clark and West, 2006; Alquist and Chinn, 2007; Gourinchas and Rey, 2007; Engel *et al.*, 2007; Molodtsova and Papell, 2008) find evidence for exchange rate predictability for developed economies for different horizons, using different models.

This paper uses data from six emerging economies in the CEE region that use some form of a flexible exchange rate regime and documents that it is possible to use certain structural and time series models to forecast exchange rates for short horizons in these countries. An obvious extension of this paper would be to conduct similar analyses for other emerging market economies for which data is available, and also to extend the variety of the structural models of exchange rate determination used in the analysis as far as data availability.

# References


[1] Alper, C.E. and O.P. Ardic (2006). "Exchange Rate Forecasting: An Application to Turkey During the Floating Regime Period," *International Economics and Trade Policy*, 1(1): 49-67 (In Turkish).

[2] Alquist, R. and M. Chinn (2008). "Conventional and Unconventional Approaches to Exchange Rate Modeling and Assessment," *International Journal of Finance and Economics*, Forthcoming.

[3] Berkowitz, J. and L. Giorgianni (2001). "Long-Horizon Exchange Rate Predictability?" *Review of Economics and Statistics*, 83(1): 81-91.

[4] Cheung, Y-W., M.D. Chinn, and A.G. Pascual (2005). "Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?" *Journal of International Money and Finance*, 24: 1150-1175.

[5] Chinn, M.D. and R.A. Meese (1995). "Banking on Currency Forecasts: How Predictable Is Change in Money?" *Journal of International Economics*, 38: 161-178.

[6] Clark, T. and K. West (2006). "Using Out-of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis", *Journal of Econometrics*, 135(1-2):155-186.

[7] Clark, T. and K. West (2007). "Approximately Normal Tests For Equal Predictive Accuracy in Nested Models" *Journal of Econometrics*, 138(1): 291-311.

[8] Crespo Cuaresma, J. and J. Hlouskova (2005). "Beating the Random Walk in Central and Eastern Europe," *Journal of Forecasting*, 24: 189-201.

[9] Diebold, F. and R. Mariano (1995). "Comparing Predictive Accuracy", *Journal of Business and Economic Statistics*, 13(3): 253-263.

[10] Engel, C., N.C. Mark, and K. West (2007). "Exchange Rate Models Are Not as Bad as You Think," *NBER Macroeconomics Annual 2007*, Forthcoming.

[11] Engel, C. and K. West (2005). "Exchange Rates and Fundamentals," *Journal of Political Economy*, 113(3): 485-517.

[12] Faust, J.R., J. Rogers, and J.H. Wright (2003). "Exchange Rate Forecasting: The Errors We've Really Made," *Journal of International Economics*, 60: 35-59.

[13] Friedman, M. (1962). "The Interpolation of Time Series by Related Series," *Journal of the American Statistical Association*, 57(300): 729-757.

[14] Gourinchas, P. and H. Rey (2007). "International Financial Adjustment," *Journal of Political Economy*, 115(4): 665-703.

[15] Hansen, L.P. and R.J. Hodrick (1980). " Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis", *Journal of Political Economy*, 88(5): 829-853.

[16] Kilian, L. (1999). "Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions," *Journal of Applied Econometrics*, 14(5): 491-510.

[17] Mark, N.(1995). "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability", *American Economic Review*, 85(1): 201-218.

[18] Mark, N. (2001). *International Macroeconomics and Finance: Theory and Empirical Methods*, Blackwell Publishers.

[19] Mark, N. and D. Sul (2001). "Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post-Bretton Woods Panel," *Journal of International Economics*, 53: 29-52.

[20] Meese, R.A. and K. Rogoff (1983). "Empirical Exchange rate Models of Seventies: Do They Fit Out of Sample?", *Journal of International Economics*, 14(February): 3-24.

[21] Molodtsova, T. and D. Papell (2008), "Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals", Mimeo, University of Houston.

[22] Neely, C. and L. Sarno (2002). "How Well Do Monetary Fundamentals Forecast Exchange Rates?" *The Federal Reserve Bank of St. Louis Review*, 84: 51-74.

[23] Newey, W. and K. West (1987). "A Simple, Positive Semidefinite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3): 703-708.

[24] Taylor, M. (1995). "The Economics of Exchange Rates," *Journal of Economic Literature*, 33: 13-47.

[25] West, K. (1996). "Asymptotic Inference about Predictive Ability", *Econometrica*, 64(5): 1067-1084.

| | | Random Walk | UIP (Equation 2) | | | Monetary Model I (Equation 5) | | | Monetary Model II (Equation 7) | | | ARIMA(2,1,0) | | | VAR(2) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | $k$ | MSPE $\times 10^{-5}$ | MSPE $\times 10^{-5}$ | DMW | CW | MSPE $\times 10^{-5}$ | DMW | CW | MSPE $\times 10^{-5}$ | DMW | CW | MSPE $\times 10^{-5}$ | DMW | CW | MSPE $\times 10^{-5}$ | DMW | CW |
| | 1 | 15 | 12 | 0.98 | 1.65* | 12 | 0.98 | 1.67* | 11 | 1.25 | 2.04** | 11 | 1.14 | 1.92* | 14 | 0.31 | 1.06 |
| Croatia | 3 | 20 | 55 | -0.45 | 0.12 | 61 | -0.46 | 0.08 | 32 | -0.26 | 0.24 | 11 | 0.36 | 0.41 | 13 | 0.24 | 0.34 |
| | 6 | 20 | 38 | -0.43 | 0.20 | 33 | -0.29 | 0.15 | 35 | -0.41 | 0.23 | 11 | 0.56 | 0.62 | 9 | 0.59 | 0.65 |
| | 1 | 36 | 24 | 1.94* | 2.13** | 25 | 1.84 | 2.28** | 25 | 1.74* | 1.95* | 24 | 1.95* | 2.76*** | 29 | 1.09 | 2.02** |
| Czech Rep. | 3 | 56 | 103 | -0.27 | 0.29 | 82 | -0.19 | 0.39 | 65 | -0.08 | 0.42 | 24 | 0.42 | 0.47 | 28 | 0.32 | 0.41 |
| | 6 | 46 | 82 | -0.22 | 0.17 | 51 | -0.06 | 0.27 | 54 | -0.09 | 0.23 | 23 | 0.45 | 0.50 | 22 | 0.45 | 0.51 |
| | 1 | 64 | 42 | 1.66* | 2.25** | 42 | 1.75 | 1.94* | 45 | 1.48 | 1.83* | 42 | 2.60*** | 3.29*** | 47 | 1.60 | 2.10** |
| Hungary | 3 | 76 | 147 | -0.27 | 0.16 | 131 | -0.25 | 0.17 | 117 | -0.18 | 0.16 | 41 | 0.35 | 0.37 | 44 | 0.32 | 0.36 |
| | 6 | 70 | 119 | -0.25 | 0.20 | 118 | -0.28 | 0.20 | 99 | -0.16 | 0.16 | 41 | 0.34 | 0.36 | 42 | 0.34 | 0.36 |
| | 1 | 70 | 48 | 1.79* | 1.95* | 49 | 1.80 | 2.20** | 53 | 1.28 | 2.04** | 43 | 2.48** | 3.71*** | 61 | 0.82 | 1.79* |
| Poland | 3 | 61 | 133 | -0.37 | 0.02 | 132 | -0.38 | 0.09 | 139 | -0.36 | 0.01 | 44 | 0.30 | 0.31 | 55 | 0.15 | 0.21 |
| | 6 | 83 | 179 | -0.4 | 0.08 | 167 | -0.36 | 0.15 | 166 | -0.31 | 0.10 | 44 | 0.38 | 0.39 | 41 | 0.41 | 0.45 |
| | 1 | 37 | 37 | 0.08 | 1.00 | 32 | 0.01 | 1.61 | 37 | 0.00 | 1.93** | 33 | 0.86 | 2.51** | 38 | -0.08 | 1.28 |
| Romania | 3 | 59 | 263 | -0.53 | 0.01 | 266 | -0.56 | 0.06 | 270 | -0.58 | 0.06 | 35 | 0.37 | 0.49 | 36 | 0.37 | 0.51 |
| | 6 | 67 | 215 | -0.42 | -0.02 | 188 | -0.49 | 0.11 | 160 | -0.41 | 0.17 | 35 | 0.31 | 0.40 | 35 | 0.32 | 0.41 |
| | 1 | 183 | 135 | 0.61 | 0.65 | 140 | 0.59 | 0.87 | 133 | 0.66 | 0.79 | 121 | 1.05 | 1.70* | 198 | -0.21 | 0.34 |
| Turkey | 3 | 282 | 395 | -0.16 | 0.19 | 479 | -0.22 | 0.14 | 548 | -0.35 | 0.17 | 161 | 0.38 | 0.41 | 189 | 0.31 | 0.35 |
| | 6 | 254 | 515 | -0.28 | 0.05 | 542 | -0.26 | 0.07 | 591 | -0.34 | 0.06 | 134 | 0.29 | 0.29 | 124 | 0.30 | 0.34 |

Table 1: Diebold & Mariano (1995) and West (1996) (DMW), and Clark & West (2007) (CW) statistics for the null hypothesis that the MSPE values for the forecasts of the model in the column is different from the MSPE values for the forecasts of the random walk. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. Note: ARIMA(0,1,2) was used for Poland.