NATIONAL BANK OF POLAND
WORKING PAPER
No. 127

Can we beat the random walk in forecasting CEE exchange rates?

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Warsaw 2012

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Design:

Oliwka s.c.

Layout and print:

NBP Printshop

Published by:

National Bank of Poland
Education and Publishing Department
00-919 Warszawa, 11/21 Świętokrzyska Street
phone: +48 22 653 23 35, fax +48 22 653 13 21

ISSN 2084–624X

http://www.nbp.pl

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Abstract

It is commonly known that various econometric techniques fail to consistently outperform a simple random walk model in forecasting exchange rates. The aim of this study is to analyse whether this also holds for selected currencies of the CEE region as the literature relating to the ability of forecasting these exchange rates is scarce. We tackle this issue by comparing the random walk based out-of-sample forecast errors of the Polish zloty, the Czech koruna and the Hungarian forint exchange rates against the euro with the corresponding errors generated by various single- and multi-equation models of these exchange rates. The results confirm that it is very difficult to outperform a simple random walk model in our CEE currencies forecasting contest.

Keywords: CEE currencies, exchange rate forecasting, random walk, VAR, BVAR.

JEL: C22, C32, C53, F31, G17.

1 Introduction

As shown in the economic literature proper forecasting of the exchange rates is a challenging task. Nearly 30 years ago Meese and Rogoff (1983) showed that monetary models cannot outperform a naive random walk in out-of-sample exchange rate forecasting. Since that seminal article many authors investigated whether it is possible to forecast the future movements of the exchange rates at all by analysing various currencies, time samples and data frequencies by means of various econometric techniques. All in all the relevant literature can be divided arbitrarily into two lines of research, where the classification depends on whether the emphasis was put on the underlying economic theory or econometric techniques applied in the analysis.

In the first part of the literature the theoretical frameworks are used to generate the prediction about exchange rates. Virtually all of these papers attempt to take advantage of macroeconomic information to produce the forecasts which are more accurate than the naive ones. Mark (1995), Chinn and Meese (1995) show that monetary fundamental models could outperform simple random walk forecasts only at long horizon. However the approach proposed by Mark (1995) was questioned by e.g. Berkowitz and Giorgianni (1996) who undermine the assumption about the cointegration relationship between main macroeconomic fundamentals and exchange rate and Kilian (1999) who pointed out the lack of robustness check among countries and time sample.

The second strand of literature focuses on accuracy of generated forecast by different econometric techniques, especially more advanced ones. The latest and actual review of these studies is described by Rubaszek et al. (2010).

The literature related to forecasting the Central and Eastern European (CEE) exchange rates is still scarce. According to authors best knowledge there are only three papers related to the topic. Cuaresma and Hlouskova (2005) tackle with variety of multiple time series models (VAR, restricted VAR,BVAR, VEC, BVECM) for CEE[1] and they conclude that analysed models tend to outperform random walk only at horizons no shorter than 6 months. Ardic, Ergin, and Senol (2008) show that structural models and

[1] They use bilateral exchange rate of the Czech koruna, Hungarian forint, Slovak koruna, Slovenian tolar and the Polish zloty against the euro and the US dollar.

time series models outperform the random walk model in six CEE countries (Croatia, Czech Republic, Hungary, Poland, Romania and Turkey). Rubaszek, Skrzypczyński, and Koloch (2010) try forecasting Polish Zloty with nonlinear models and the main conclusion of their work is the fact that predictive ability of random walk is unbeaten by more advanced univariate time series models.

Our study aims to fill this gap and mainly builds upon the research presented in the article by Rubaszek et al. (2010). The goal of this study is to analyse whether it is possible to outperform a simple random walk model in forecasting the exchange rates of the CEE region. We tackle this issue by comparing the random walk based out-of-sample forecast errors of the Polish zloty (PLN), the Czech koruna (CZK) and the Hungarian forint (HUF) exchange rates against the euro with the corresponding errors generated by various single- and multi-equation models of these exchange rates. In particular, we analyse the set of competing models consisting of a random walk, fractional random walk and several vector autoregression type models.

Our motivation to test multiple time series models in forecasting CEE exchange rates is caused by two reasons. Firstly, we combine exchange rates of the economies that have such common characteristics as the same level of economic development, GDP growth. Moreover we choose the currencies which have floating regime.[2]. Secondly, we want to test multi-equation models which behave well in forecasting exercises concerning macroeconomic variables (Lütkepohl, 2006; Carriero, Kapetanios, and Marcellino, 2009).

The structure of the paper is following. In section 2 we discuss the econometric methods used in forecasting the exchange rates, including the benchmark random walk model. Section 3 describes the data set used in our study. In section 4 we evaluate the out-of-sample forecast errors by conducting the unbiasedness and equal forecast accuracy tests and we discuss the obtained results. Section 5 concludes.

[2]The floating regime condition was not satisfied by the Bulgarian lev, Latvian lat, Lithuanian litas and the Romanian leu.

2 Forecasting methods

In this section we sketch out the tools used in our forecasting challenge for the CEE's currencies.

2.1 Random walk

As a benchmark we use the random walk (RW). It is assumed that the exchange rate is generated by the unit root process:

$$y_{t+1} = y_t + \varepsilon_{t+1} \tag{1}$$

where $\varepsilon_{t+1} \sim NID(0, \sigma^2)$ is white noise. In the sample of length T, the h steps ahead forecast of RW $y^{\tau}_{T+h}$is equal to the last available observation y_T:

$$y^{\tau}_{T+h} = y_T. \tag{2}$$

In our research y_t refers to the logarithm of the exchange rate.

2.2 Fractional random walk

We check the prediction ability of fractional random walk model (FRW) due to high accuracy of forecast provided by this tool in recent works Rubaszek et al. (2010). In this model univariate time series y_t is generated by fractionally integrated process which could be written in the following way:

$$(1 - L)^d y_t = \varepsilon_t \tag{3}$$

where d is a differencing operator, L is a lag operator and ε_t is a white noise. Note that the process y_t is covariance stationary for $d \in (0, 0.5)$ and still mean reverting if $d \in [0.5, 1)$. Moreover, in these cases y_t is recognized as long-memory or long-range between observations process. When differencing operator is equal to 1 then y_t is simply RW (described in part 2.1).

We use the Haslett and Raftery (1989) algorithm to estimate d and Hyndman and Khandakar (2008) procedure to specify moving average part. Finally, estimation of MA coefficients of fractional random walk model allows us to forecast log of the exchange rate y_t.

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2.3 VAR

Vector autoregression (VAR) is a multivariate time series model which is very useful in macroeconomic forecasting (Lütkepohl, 2006). Generally, the VAR model can be described as below:

$$\mathbf{y_t} = \mathbf{A_0} + \mathbf{A_1}\mathbf{y_{t-1}} + \cdots + \mathbf{A_p}\mathbf{y_{t-p}} + \varepsilon_\mathbf{t} \tag{4}$$

where $\mathbf{y_t}$ is a vector of variables observed at time t, $\mathbf{A_0}$ is a vector of constants and $\varepsilon_\mathbf{t}$ is a vector of residuals. The parameters of the vector $\mathbf{A_0}$ and matrices $\mathbf{A_1} \cdots \mathbf{A_p}$ are estimated using OLS. In the section 4 we present the results for VAR's specification assuming first lag order[3], for which the h-step forecast is computed in the following way:

$$\mathbf{y}^{\tau}_{\mathbf{T+h}} = (\mathbf{I} + \hat{\mathbf{A}}_\mathbf{1} + \cdots + \hat{\mathbf{A}}_\mathbf{1}^{h-1})^{-1}\hat{\mathbf{A}}_\mathbf{0} + \hat{\mathbf{A}}_\mathbf{1}^{h}\mathbf{y_T}. \tag{5}$$

We analyse two versions of VAR. In the first one , the vector $\mathbf{y_t}$ is represented by the logarithm of exchange rates (denoted as **VAR**) and in the second one $\mathbf{y_t}$ refers to the first differences of logarithms (denoted as **dVAR**) of exchange rates.

2.4 BVAR

We adopt also the bayesian technique of VAR's estimation.The general specification is almost the same as in equation 5, but the method of estimating matrices $\mathbf{A_0}$, $\mathbf{A_1}$ is different. We use the standard Minnesota prior proposed by Litterman (1986) so in the first order VAR process following restrictions are imposed: $\mathbf{A_0} = \mathbf{0}$ and $\mathbf{A_1} = \mathbf{I}$. First restriction means the absence of drift and second one allows us to assume that the *prior* reflects a random walk process for all variables because autoregressive coefficients are equal to 1 and other parameters are zero.

In our BVAR specification $\mathbf{y_T}$ denotes a vector of the logarithm of the CEE exchange rates. We follow by Waggoner and Zha (1999) procedure of unconditional forecasting bayesian VAR. Finally, as a point forecast we use median of foretasted density which are estimated as the posterior sample for the BVAR model.

[3] Firstly, this specification was pointed out by information criteria. Secondly, VAR(1) provides the most accurate forecasts.

3 Data

We test the models introduced in the previous section on the basis of weekly, end-of-period data for the nominal exchange rate of the Polish zloty, the Czech koruna and the Hungarian forint against the euro. Using bilateral exchange rate against the euro is caused by the fact that this currency is the most important one for the analyzed economies. The models are estimated and used for forecasting on the set of the recursive samples, each starting in the first week of 2000 (2000:w1) and ending in one of the weeks from the period 2004:w53-2012:w22. For instance, the first set of models is estimated with the use of the time series covering the period 2000:w1-2004:w53 (261 weekly observations) and used for out-of-sample forecasting for 52 weeks starting in the first week of 2005. The second sample for estimation covered one weekly observation more (262 weekly observations). Subsequently, the last recursive sample used covered the period 2000:w1-2012:w22 (648 weekly observations). As a result, each model for each of the three analyzed exchange rates is estimated and used for forecasting 388 times. The results of the recursive forecasts for the log of the EUR/PLN, the EUR/CZK and the EUR/HUF are presented in Figures 1, 2 and 3, respectively.

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4 Out-of-sample forecasts comparison

In this section we evaluate the out-of-sample forecast errors of the exchange rates from the models described in section two. The main focus of this analysis is to establish whether the forecasts from these models are more accurate than those coming from a simple random walk model. To achieve this goal we compare two standard measures of forecast accuracy. Namely, the mean forecast errors (MFEs) and the root mean squared forecast errors (RMSFEs). In order to establish statistical significance of these measures we test the null of forecast unbiasedness and the null of equal forecast accuracy of a given model and a random walk. To test the null of forecast unbiasedness we use the p-value of the coefficient of the forecast errors regression on a constant. In other words, we test whether the MFE is significantly different from zero. To correct for heteroskedasticity and autocorrelation we use the HAC covariance matrix estimates obtained via the modified Bartlett kernel in line with Newey and West (1987), where the truncation lag is set automatically as proposed by Newey and West (1994). In order to test the null of equal forecast accuracy we use the Harvey-Leybourne-Newbold (1997) modification of the Diebold-Mariano (1995) test, with the long-run variance estimated via the modified Bartlett kernel, where the truncation lag is set to $h-1$, where h is the forecast horizon. The forecasting horizon ranges from one to 52 weeks, and in particular the presentation of the results focuses on horizons of 1, 4, 8, 12, 26 and 52 weeks.

The forecasts are evaluated with the recursive data from the period 2005:w1-2012:w23. For one-week ahead forecasts we use all 388 weekly observations from that period. Generally, in the case of h-step ahead forecasts, the evaluation sample is truncated of the first $h-1$ observations, for which forecasts are not available. This means that 52-weeks ahead forecasts are compared with 337 observations from the period 2005:w52-2012:w23.

In Table 1 we report the results of the unbiasedness test. The main conclusion which builds upon these results is that most of the obtained forecasts are unbiased, with little exceptions relating to long-run forecasts of the EUR/HUF form all considered models and to the EUR/CZK random walk long-run forecasts. In case of the EUR/CZK the VAR forecasts tend to outperform others as the absolute values of the MFEs for this method are minimal regardless the forecast horizon. In case of the EUR/HUF the same is true but for the fractional random walk model, while in the case of the EUR/PLN for the simple random walk model.

Table 2 reports the results of the equal forecast accuracy test. The general conclusion here is that the random walk forecasts are a hard to beat benchmark as in most cases we are not able to reject the null of equal forecast accuracy. In fact the only cases where we are able to reject the null in favour of the competing method are those relating to the short-run dVAR forecasts of all considered currencies. However, there are also cases where the null is rejected but in favour of the simple random walk model. For example in the case of the EUR/HUF forecasts from the BVAR model this holds for all forecast horizons at 10% significance level.

5 Conclusions

In this paper we have shown that the random walk model turns out to be a hard to beat benchmark in forecasting the CEE exchange rates. We used fractionally integrated random walk and several VAR-type models in our forecasting excersise for the EUR/CZK, the EUR/HUF and the EUR/PLN exchange rates. Our results lead to the conclusion that none of the analysed models was able to consistently outperform the naive forecast. In turn our empirical results are in line with the general findings from the literature on the exchange rates forecasting.

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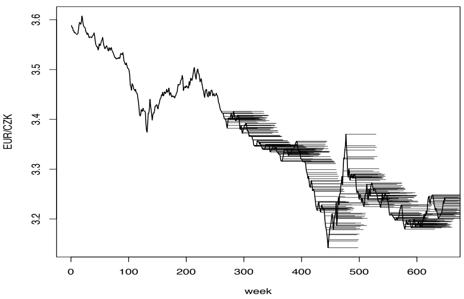
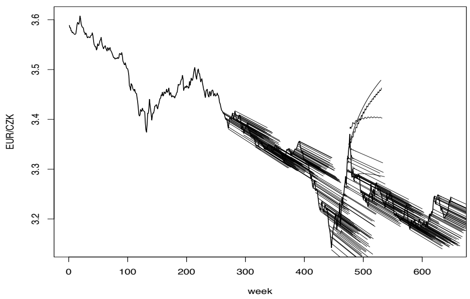
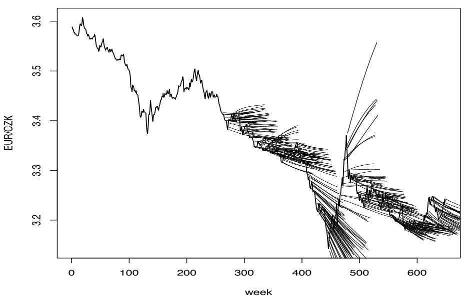
Figure 1: Forecasts for CZK



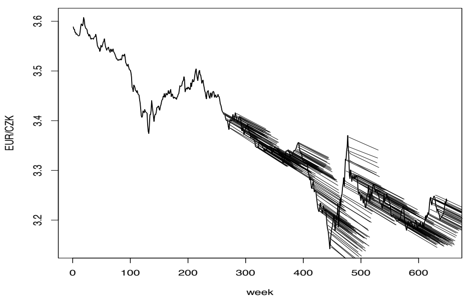
(a) RW



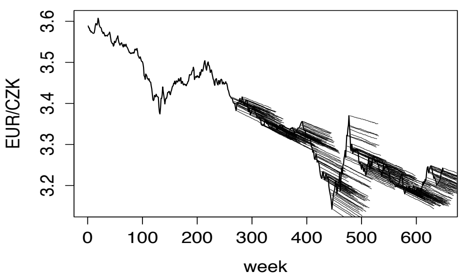
(b) FRW



(c) VAR

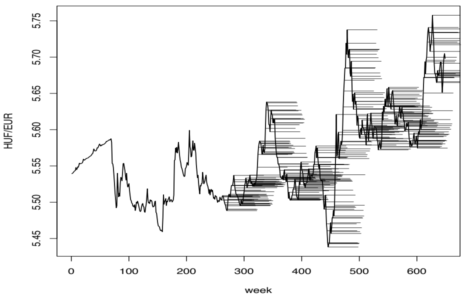


(d) dVAR

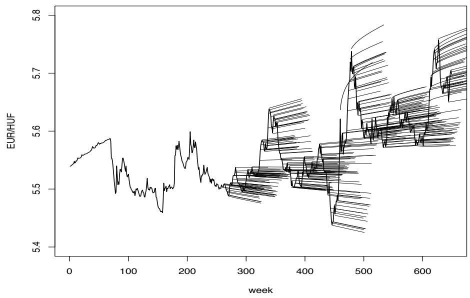


(e) BVAR

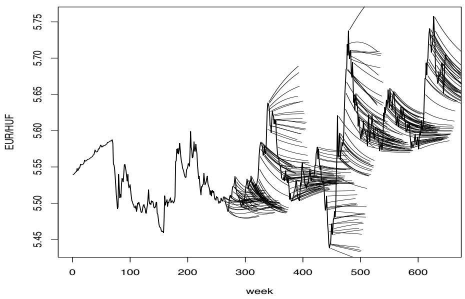
Figure 2: Forecasts for HUF



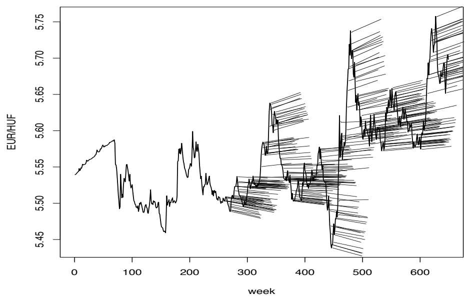
(a) RW



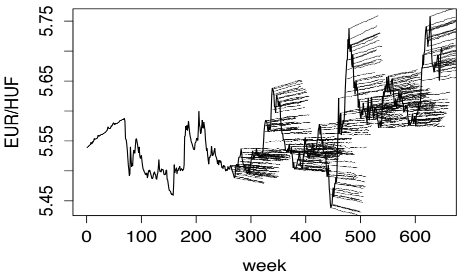
(b) FRW



(c) VAR

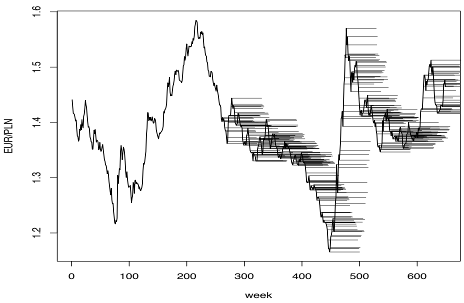


(d) dVAR

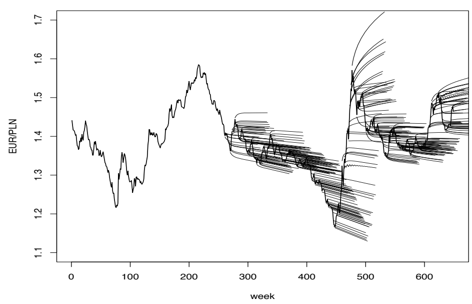


(e) BVAR

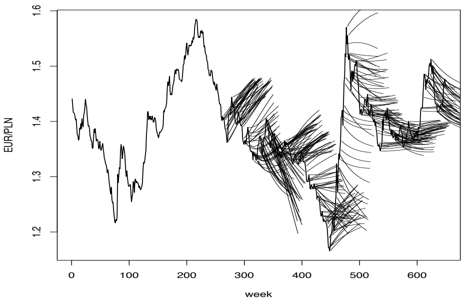
Figure 3: Forecasts for PLN



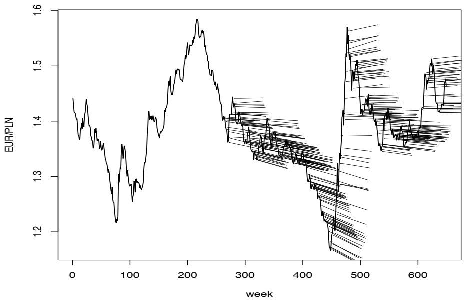
(a) RW



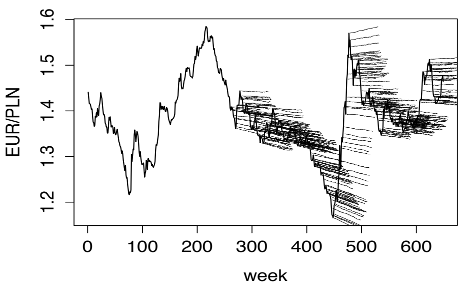
(b) FRW



(c) VAR



(d) dVAR



(e) BVAR

Table 1: MFEs and the forecast unbiasedness test

h	RW	FRW	VAR	dVAR	BVAR
EUR/CZK					
1	0.000	0.000	**0.000**	0.000	0.000
4	0.002	0.001	**-0.001**	0.001	0.002
8	-0.004	0.002	**-0.001**	0.002	0.001
12	-0.006	0.002	**-0.003**	0.002	0.002
26	-0.013**	0.005	**-0.003**	0.005	0.004
52	-0.028***	0.008	-0.008	0.008	**0.005**
EUR/HUF					
1	0.001	**0.000**	0.001	0.000	0.000
4	0.002	**0.001**	0.004	0.002	0.002
8	0.004	**0.003**	0.008*	0.003	0.003
12	0.006	**0.005**	0.011*	0.005	0.005
26	0.013	**0.011**	0.022**	0.011	0.012
52	0.025***	**0.021****	0.035***	0.022**	0.022**
EUR/PLN					
1	**0.000**	0.000	0.000	0.000	0.000
4	**0.001**	0.001	0.002	0.001	0.001
8	**0.001**	0.002	0.003	0.002	0.002
12	**0.002**	0.003	0.004	0.003	0.004
26	**0.003**	0.006	0.005	0.007	0.008
52	0.008	0.016	**0.006**	0.016	0.018

Notes: bold figures indicate minimal absolute value of the MFE for a given forecast horizon. A positive MFE indicates that on average forecasts are below the actual values. Symbols ***, ** and * indicate the rejection of the null that the MFE is equal to zero at 1%, 5% and 10% significance levels, respectively.

Table 2: RMSFEs and equal forecast accuracy test

EUR/CZK					
h	RW	FRW	VAR	dVAR	BVAR
1	0.0083	1.00	1.01	**0.85*****	1.00
4	0.0176	1.02	1.04	**0.96****	1.00
8	0.0260	1.02	1.07	**0.98**	1.00
12	0.0318	1.03	1.08	**0.98**	**0.99**
26	0.0489	1.03	1.19	**0.98**	**0.99**
52	0.0638	**0.99**	1.31	**0.95**	**0.95**
EUR/HUF					
h	RW	FRW	VAR	dVAR	BVAR
1	0.0122	1.01	1.01*	**0.89*****	1.00*
4	0.0259	1.01	1.02*	**0.98*****	1.00*
8	0.0384	1.01	1.03	1.00	1.01**
12	0.0487	1.02**	1.03	1.00	1.01**
26	0.0723	1.03**	1.03	1.02*	1.02**
52	0.0763	1.05*	1.04**	1.04*	1.04*
EUR/PLN					
h	RW	FRW	VAR	dVAR	BVAR
1	0.0123	1.01	1.01**	**0.83*****	1.00
4	0.0273	1.00	1.03*	**0.96*****	1.01
8	0.0425	1.03	1.03	**0.98****	1.01
12	0.0540	1.04*	1.02	**0.99**	1.01
26	0.0723	1.06	1.02	1.02	1.02
52	0.1110	1.09	1.10	1.05	1.05

Notes: a RW model RMSFEs are reported in levels while other presented figures are ratios of RMSFE from a given model to the corresponding RMSFE from a RW model. A ratio below unity indicates that the RMSFE for a given model is lower than the corresponding one from a RW model (boldfigures). Symbols ***, ** and * indicate the rejection of the null of the HLN-DM test, stating that the given RMSFE is not significantly different from the corresponding RMSFE from a RW model, at 1%, 5% and 10% significance levels, respectively.