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MAGYAR NEMZETI BANK

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Beating the Random Walk in Central and Eastern Europe by Survey Forecasts

(A véletlen bolyongás legyőzése Közép-Európában szakértői előrejelzések segítségével)

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Contents

Abstract

This paper investigates the forecasting ability of survey data on exchange rate expectations with multiple forecast horizons. The survey forecasts are on the exchange rates of five Central and Eastern European currencies: Czech Koruna, Hungarian Forint, Polish Zloty, Romanian Leu and Slovakian Koruna. First, different term-structure models are fitted on the survey forecasts. Then, the forecasting performances of the fitted forecasts are compared. The fitted forecasts for the 5 months horizon and beyond are proved to be significantly better than the random walk on the pooled data of the five currencies. The best performing term-structure model is the one that assumes an exponential relationship between the forecast and the forecast horizon, and has time-varying parameters.

JEL: F31, F36, G13.
Keywords: evaluating forecasts, exchange rate, survey forecast, time-varying parameter, term-structure of forecasts.

Összefoglalás

A tanulmányban a szakértői árfolyam-várakozások különböző horizontú előrejelzési képességét vizsgálom. Az előrejelzések öt Közép-Európai deviza, így a cseh korona, magyar forint, lengyel zlotyi, román lej és a szlovák korona árfolyamára vonatkoznak. Első lépésként különböző lejárati-struktúra modelleket (term-structure model) illesztek az elemzői előrejelzésekre, majd összehasonlítom az illesztett előrejelzések előrejelzési képességét. Ennek eredményeként az illesztett előrejelzések szignifikánsan jobbnak bizonyultak, mint a véletlen bolyongás szerinti előrejelzések (az utóbbi a mindenkori azonnali árfolyammal egyezik meg) az 5 hónapos és annál hosszabb horizontokon a vizsgált öt devizára együttesen (pooled data). A versengő modellek közül pedig az a modell teljesített a legjobban, amelyik exponenciális kapcsolatot feltételez az előrejelzési horizont és az ahhoz tartozó előrejelzés között, és időben-változó paraméterrel rendelkezik.

1 Introduction

There are two disappointing empirical findings of the exchange rate literature. The first one is that exchange rates are difficult to forecast by structural models at short horizons.[1] The other one is that survey expectations also perform poorly in forecasting the exchange rates. It was Meese and Rogoff (1983) who surprised the academic community by the former one, and Frankel and Froot (1987) who documented the latter. The two findings are interrelated. If either the forecast of the econometricians or that of the professional market analysts can systematically outperform a benchmark model, then it is highly probable that the other one can do so as well. This paper presents evidence for the success of the survey data in forecasting some exchange rates at horizons shorter than 2 years. Thereby, it offers hope to academics that a sufficiently sophisticated theoretical model estimated on a broad enough data set, similar to the one available for analysts, can also beat the commonly used benchmark, the random walk model.[2]

The survey forecasts examined in this paper are on the exchange rates of five Central and Eastern European currencies. The exchange rates are the Czech Koruna, the Hungarian Forint, the Polish Zloty, the Romanian Leu, and the Slovakian Koruna against the Euro. The forecast horizons range from 3 months to 2 years. I use three simple models to estimate the forecasts for those horizons that no survey data are available on. Thereby, I can find those horizons at which the survey forecasts are more accurate than the random walk.

The three models are the linear model, the constant parameter model, and the generalized model. These models have different assumptions on the term-structure of forecasts. The functional relationship between the forecast and the forecast horizon is linear in the first model, while it is exponential in both the constant parameter model and the generalized model. What distinguishes the generalized model from the constant parameter model is that its parameters are allowed to change. The motivation for using such a flexible model is twofold. First, the survey data are rich enough to identify the time-varying parameters. Second, exchange rate models with time-varying parameters have remarkably good forecasting performance. For instance, the time-varying parameter model by Wolff (1987) enhances the forecasting ability of some structural models. A broader model by Schinasi and Swamy (1989) can even outperform the random walk in terms of out-of-sample forecasting ability. Another time-varying parameter model by Wu and Chen (2001) is not only able to beat the random walk, but its out-of-sample prediction performance is proved to be significantly better. In line with the literature, I find the generalized model to be the most successful among the three models investigated here.

The paper is structured as follows. Section 2 describes the survey data. Section 3 introduces the models and explains how they are estimated. Section 4 compares the forecasting abilities of the fitted forecasts with that of the random walk model. Finally, Section 5 concludes.

---

[1] Although there is some encouraging empirical evidence in the recent literature that support the predictability of the exchange rates, most of the results remain quantitatively moderate or fail to be robust. See Cheung et al. (2005) for an overview.

[2] There is indirect evidence for the improvement of the forecasting ability of the traditional structural models when survey data on market expectation are used. For instance, Engel et al. (2009) show that the risk premium calculated from survey forecasts exhibit strong stationarity. Moreover, stationary fundamentals of the monetary and Taylor rule models, such as the risk premium, contribute to these models long-horizon predictability of exchange rate.

2 Data

I use the Consensus Economics survey data. It consists of the spot exchange rate on the date of the survey, and the mean of the exchange rate forecasts of the individual survey participants. The forecasts refer to the 3 months, 1 year, and 2 years ahead end-of-month exchange rates.[3]

The sample size is determined by the availability of the survey data. Consensus Economics started to publish forecasts on the economies of the Central and Eastern European countries in January 2003. Consequently, the sample is spanned by January 2003 and February 2009 for the Czech Koruna and the Hungarian Forint. For the currencies of the Polish Zloty, the Romanian Leu and the Slovakian Koruna, the sample is somewhat shorter. Since Slovakia joined the Euro-area in 2009, its sample ends in December 2008. The sample starts in January 2007 for the Polish Zloty, and March 2006 for the Romanian Leu, because the previous surveys reported the forecasted exchange rates against the US Dollar and not the Euro. The frequency of the data is bi-monthly until May 2007, afterwards it is monthly.

I use not only the survey data, but also the end-of-month exchange rate data in order to evaluate the forecasts. The source of these data is the European Central Bank. The time series of the exchange rates starts in March 2003 and ends in March 2009.

[3] The forecast horizons usually differ from 3 months, 1 year, and 2 years by a few days, because the surveys do not take place exactly at the end of each month. The variation in the survey date within the month is substantial: for instance, it makes the 3-month horizon vary between 70 and 108 days. Disregarding this variation in the forecast horizons biases some of the fitted forecasts by an economically significant magnitude. Therefore, I treat the forecast horizons rigorously by using the exact number of days when estimating the models.

3 The Term-Structure Models of Forecasts

This Section introduces three statistical models on the term-structure of forecasts and explains how they are estimated. The models are the linear model, the constant parameter model, and the generalized model.

The *linear model* assumes a linear relationship between the forecasted log exchange rate and the forecast horizon.

$$x^{linear}_{t,t+\theta} = s_t + \theta\mu_t \qquad \text{for all } \theta > 0\,, \tag{1}$$

where the log exchange rate at time t is denoted by s_t. And μ_t is the time-varying slope parameter that informs us about the expected percentage change in the exchange rate. The forecast horizon is denoted by θ. The $x^{linear}_{t,t+\theta}$ is the forecasted log exchange rate at time t.

The only parameter of the linear model, μ_t, is estimated by the least squares:

$$\min_{\mu_t}\left[\left(\tilde{x}_{t,t+.25Y} - x^{linear}_{t,t+.25Y}\right)^2 + \left(\tilde{x}_{t,t+1Y} - x^{linear}_{t,t+1Y}\right)^2 + \left(\tilde{x}_{t,t+2Y} - x^{linear}_{t,t+2Y}\right)^2\right]\,, \tag{2}$$

where $\tilde{x}_{t,t+.25Y}$, $\tilde{x}_{t,t+1Y}$, and $\tilde{x}_{t,t+2Y}$ denote the log survey forecasts of the horizons at 3 months, 1 year, and 2 years respectively.[4] The fitted forecasts of the linear model are obtained by substituting the estimates of μ_t into Equation (1). The fitted forecasts can be used even in a real-time forecasting exercise, because the estimates of μ_t of a given time t depends only on the contemporaneous survey forecasts.

In the *constant parameter model*, the term-structure is assumed to be exponential.

$$x^{const}_{t,t+\theta} = e^{\frac{\theta}{c}}(s_t - v_t) + v_t \qquad \text{for all } \theta > 0\,, \tag{3}$$

where v_t and c are parameters determining the slope and the curvature of the term-structure. And $x^{const}_{t,t+\theta}$ is the forecasted log exchange rate that is consistent with the constant parameter model. The constant parameter model can be rationalized by the conventional asset pricing model,[5] where v_t is the fundamental and c is a parameter capturing the relative importance of the fundamental at determining the exchange rate. Obviously, parameter c depends on the discount factor.

The parameters v_t and c are estimated by the non-linear least squares.

$$\min_{c,v_{\underline{\tau}},\ldots,v_{\overline{\tau}}}\sum_{t=\underline{\tau}}^{\overline{\tau}}\left(\tilde{x}_{t,t+.25Y} - x^{const}_{t,t+.25Y}\right)^2 + \left(\tilde{x}_{t,t+1Y} - x^{const}_{t,t+1Y}\right)^2 + \left(\tilde{x}_{t,t+2Y} - x^{const}_{t,t+2Y}\right)^2\,. \tag{4}$$

The sample of the survey forecasts starts at time $\underline{\tau}$, and ends at $\overline{\tau}$. Here, I use the entire sample for estimation, not only up to time t. Therefore, the corresponding forecasting exercise is an in-sample one.

Similarly to the constant parameter model, the *generalized model* assumes an exponential relationship between the forecast and the forecast horizon.

$$x^{gener}_{t,t+\theta} = e^{\frac{\theta}{c_t}}(s_t - v_t) + v_t \qquad \text{for all } \theta > 0\,. \tag{5}$$

[4] The survey forecast is the average of the expected exchange rates of the individual forecasters in *level* and not the expected *log* exchange rate of the representative forecaster that we have in the model. I proxy the latter by the log of the reported expected exchange rate in all calculations and estimations.

[5] See Engel and West (2005), for instance.

The generalized model encompasses both the constant parameter model and the random walk model. If its parameter c_t were constant, then the generalized model would reduce to the constant parameter model. Whereas under the condition of $e^{\frac{\theta}{c_t}} = 1$, the forecasts for all horizons would be equal to the spot exchange rate, like in the random walk model.

The parameters of the generalized model v_t and c_t are estimated by solving the following minimization problem:

$$\min_{c_t, v_t} \left[\left(\tilde{x}_{t,t+.25Y} - x^{gener}_{t,t+.25Y} \right)^2 + \left(\tilde{x}_{t,t+1Y} - x^{gener}_{t,t+1Y} \right)^2 + \left(\tilde{x}_{t,t+2Y} - x^{gener}_{t,t+2Y} \right)^2 \right] . \tag{6}$$

Equations (5) and (6) suggest that the estimation of the generalized model is equivalent to fitting exponential curves on each monthly forecasts with multiple forecast horizons separately. The fitted forecasts are obtained by substituting the estimates of c_t, and v_t into Equation (5). Similarly to the fitted forecasts of the linear model, the fitted forecasts of the generalized model can be used in a real-time, out-of-sample forecasting exercise.

4 Comparing the Forecasting Abilities

In this Section, I test whether the forecasting ability of any of the survey-based forecasts is better than that of the random walk model. The survey-based forecasts are the fitted forecasts obtained by the term-structure models and the raw survey forecasts. I measure the forecast accuracy by the root mean square forecast error RMSE, and the mean absolute forecast error MAE. In order to test the hypothesis that the forecasting performance of the random walk model is the same as that of its alternative, I use the Diebold-Mariano test.[6] In case of the RMSE,[7] the hypothesis to be tested is that the expected values of the squared forecast errors are the same for the competing models for the forecast horizon θ:

$$H_0 : E\left[\left(e^{RW}_{t,t+\theta}\right)^2\right] - E\left[e^2_{t,t+\theta}\right] = 0 \qquad \text{for all } \ t\,, \tag{7}$$

where $e^{RW}_{t,t+\theta}$ is the forecast error of the random walk model defined as $e^{RW}_{t,t+\theta} = s_{t+\theta} - s_t$. And $e_{t,t+\theta}$ denotes the forecast error of any of the alternatives.

Under the null

$$\bar{g}\left(\frac{\widehat{V}}{P}\right)^{-\frac{1}{2}} \sim_A N(0,1)\,, \tag{8}$$

where $g_t = \left(e^{RW}_{t,t+\theta}\right)^2 - e^2_{t,t+\theta}$ is the difference between the squared errors at time t, $\bar{g} = P^{-1}\sum_t g_t$ is the average of the differences between the squared errors, and P is the number of forecast errors. Finally, $\widehat{V}$ is the estimated variance of g_t. If the forecast horizon θ is γ number of months, then the number of overlapping months for two consecutive monthly forecasts is $\gamma - 1$. The forecast errors follow moving average processes of order $\gamma - 1$, therefore, the autocorrelation consistent variance is estimated by $\widehat{V} = \sum_{k=-\gamma+1}^{\gamma-1} \widehat{\Gamma}_k$, where $\widehat{\Gamma}_k = P^{-1}\sum_{t>|k|}(g_t - \bar{g})(g_{t-|k|} - \bar{g})$.

As it is pointed out by Clark and West (2006), the Diebold-Mariano test has the disadvantage of being undersized in case of nested models, *i.e.*, the null hypothesis is rejected too rarely. Unfortunately, there is no easy way to correct the test statistics for non-linear models, like the constant parameter model, and the generalized model. But, as we will see, H_0 is rejected for most of the exchange rates and forecast horizons. In these cases a properly sized test would reject the null as well. Therefore, we should not worry much about this drawback of the test.

Tables 1, 2, and 3 report the statistics of the model comparisons for each of the horizons separately. We can learn the following from the Tables. First, the forecasting performances of the generalized model, the constant parameter model, the linear model, and the raw survey forecasts are very close to each other. Or, in other words, the raw survey data do not violate substantially any of the term-structure restrictions of (1), (3), and (5). This finding is interesting, because term-structure restrictions, similar to those assumed in this paper, are usually violated by the survey data as it is documented by Frankel and Froot (1987), and Ito (1990).

Second, the performance of the survey-based forecasts are neither statistically, nor economically different from that of the random walk forecast for most of the exchange rates at the *3 months horizon*. However, they tend to be better than the random walk as the forecast horizon gets longer.[8]

[6] See Diebold and Mariano (1995).

[7] In case of the MAE, the hypothesis and test statistics can be obtained analogously.

[8] As the forecast horizon gets longer, the time series of the forecast errors get shorter. This may contribute artificially to the finding that the forecast accuracy is increasing in the horizon. By comparing the forecasting accuracies on the synchronized samples, our finding proves to be robust.

The *1 year survey-based forecasts* are significantly better at 1% than the random walk for the Czech Koruna and the Slovakian Koruna. For the Polish Zloty, and the Romanian Leu, the 1-year forecasts of the raw survey data have smaller MAE and RMSE than the random walk model, but the difference between the forecast errors are less significant than for the Czech Koruna, and the Slovakian Koruna. The survey-based 1-year forecasts are the least useful for the Hungarian Forint.

In order to compare the models on an even larger sample, I calculate also the aggregated MAE, and RMSE by pooling the forecast errors for all five exchange rates. The survey-based 1-year forecasts are significantly better than the random walk forecast for this larger sample. The H_0 of equal forecasting ability can be rejected at 1% for the MAE, and 5% for the RMSE.

The results for the *2-years horizon* are the following. The survey forecasts are significantly better at 1% than the random walk for the Czech Koruna, and the Slovakian Koruna. For the Polish Zloty and the Romanian Leu, the sample is too small to take the test seriously. For the Hungarian Forint, the H_0 of equal forecasting ability can be rejected for both measures of forecast accuracy and for each of the survey-based forecasts at 5%. The random walk is beaten by the survey-based forecasts also on the pooled data.

We have seen that the survey-based forecasts can systematically and significantly outperform the random walk model at the 2 years horizon, but not at the 3 months horizon. Whereas for the pooled data, the survey-based forecasts start to beat the random walk between 3 months and 1 year. It is interesting to find the shortest horizon where the survey-based forecasts are already better than the random walk. For this purpose, I use the fitted forecasts that are available for any forecast horizon. I compare the forecasting ability of the fitted forecasts with that of the random walk forecast on the pooled data. Table 4 shows that the survey-based forecasts start to be significantly better than the random walk already from the 5th month. The cut-off horizon, however, varies across currencies as it is reported by Table 5.

The predictability of the exchange rates of some transition economies is not a new finding in the literature. Cuaresma and Hlouskova (2005) also study whether there is any better forecast for the exchange rates of some Central and Eastern European currencies than the spot exchange rate. They sample ranges from January 1993 to January 2000. They consider a number of structural, and non-structural models as competitors of the random walk model. They find that their models tend to outperform the random walk for the 6 months horizon and beyond. However, neither of their models could outperform the random walk at the 5% level of significance in terms of MAE and RMSE simultaneously for shorter than 1 year horizon for any of the exchange rates. In this respect our survey-based forecasts perform remarkably better. This conjecture can be explained as follows. Either professional forecasters use more sophisticated models than the ones considered by Cuaresma and Hlouskova (2005). Or they use a broader set of information than what is available for the econometricians. For instance, they can be better informed about the magnitude of risk premium that is not observable directly. Or the exchange rates in Central and Eastern Europe became more predictable after the millennium when our sample starts.

In comparison to the exchange rates of the transition economies, the major exchange rates are more difficult to forecast. Neither structural models, nor statistical models, nor survey data are able to significantly outperform the random walk model in forecasting the major exchange rates on such a short horizon as 5 months. The cut-off horizon is found to be over two years by Meese and Rogoff (1983) for some structural models. This horizon is substantially shorter for models with time-varying parameter, but it is still longer than 5 months. For instance, Wu and Chen (2001) find that the forecast horizon for which their non-linear error correction model is significantly better than the random walk, is 3 quarters. Regarding the survey forecasts, both the consensus expectations and the expectations of individual forecasters perform poorly for the major exchange rates as it is documented by Frankel and Froot (1987), and Macdonald and Marsh (1996), respectively.

Interestingly, if the forecasting performance is measured by the ability of predicting the direction of changes in the exchange rate, then survey forecasts are not as bad as if we also required them to forecast the magnitude of changes accurately. Predicting the sign of changes correctly is sufficient for those who base their trading strategy on survey forecast.[9] Whereas for some others, it is essential to have an accurate exchange rate prediction. For instance, these users of survey forecasts are potentially the central bankers in Central and Eastern Europe, who wish to forecast the inflation rate precisely in their small and open countries with high exchange rate pass-through.

[9] The survey-based trading strategy is found to be profitable by Elliott and Ito (1999), and Macdonald and Marsh (1996).

From a practical point of view, it is also important to know which of the models perform best among the linear model, the constant parameter model, and the generalized model. As we have seen, there are no substantial differences between the fitted forecasts and the raw survey forecasts for those horizons that we have survey data on. Therefore, one can simply use the raw survey data for the 3-months, 1-year, and 2-years forecasts. Whereas for some other horizons, it is unavoidable to estimate the forecasts. Table 4 shows that from 5 months on, the generalized model has the smallest MAE and RMSE out of the three models on the pooled data. Therefore, I recommend to apply this exponential model with time-varying parameters to estimate the forecasts for horizons that we do not have direct observation on.

It is worth to remark that the generalized model outperforms the others not simply because of being the broadest. Thus, extending a model by some extra parameters that are zero under the null reduces the out-of-sample performance of the model. This finding is proved analytically by Clark and West (2006). The intuitive explanation for the finding is that the broader model is flexible enough to learn sample specific regularities that are disadvantageous in the out-of-sample prediction.[10] It is important to note also that the generalized model performs slightly better than the constant parameter model on the pooled data despite of the fact that the latter is given the advantage of being estimated from the entire sample. This finding can be interpreted as a weak evidence for parameter instability, or more specifically, as evidence for changes in the discount factor.

[10] This finding can be somewhat surprising, since exactly the opposite holds for the in-sample fit, *i.e.*, the broader model cannot perform worse than the restricted one.

5 Conclusion

This paper investigates whether survey-based exchange rate forecasts are useful for forecasting the nominal exchange rates of five Central and Eastern European currencies on a sample spanned by January 2003 and February 2009. The most important finding is that the survey offers significantly better forecast at some horizons than the naive model predicting no change in the exchange rate. This finding is most likely explained as follows. The Czech Koruna, the Polish Zloty, and the Slovakian Koruna have a clear appreciating trend in the major part of our sample period, while the exchange rates of the Hungarian Forint and the Romanian Leu can be characterized by mean-reversion. We cannot rule out that the participants of the surveys have learnt the above statistical properties of the series, or they have known the fundamental reasons behind these characteristics,[11] or the exchange rates have been driven partly by bubbles and the surveys have reflected the market's view about the dynamics of the bubbles.[12] Any of these explanations may contribute to the survey data to beat the random walk model.

It is also examined whether the fitted forecasts consistent with some term-structure models are better than the raw survey data in forecasting. I find that one does not gain much by adjusting the survey data by any of the models considered in this paper. However, for those horizons, where survey forecasts are not available, one needs to estimate the forecast anyway by applying one or another estimation or interpolation technique. The best forecasts are obtained by using the fitted forecast consistent with the generalized model. This model is the most flexible one. It is a time-varying parameter model, where the forecast is an exponential function of the forecast horizon.

By applying the generalized model, I calculate the fitted forecasts for various horizons. These estimated forecasts are used to study at what horizon the survey-based forecast starts to perform significantly better than the random walk. The answer to the question varies across currencies. It is found to be relatively short for the trending exchange rates: 5 months for the Slovakian Koruna, 6 months for the Polish Zloty, and 7 months for the Czech Koruna, while the cut-off horizon is around 13 months for the Romanian Leu, and close to 17 months for the Hungarian Forint. In comparison with the major exchange rates, these cut-off horizons are surprisingly short.

[11] One potential fundamental reason for these characteristics is the real appreciation of the currencies predicted by the Balassa-Samuelson effect. In some of the countries, the real appreciation has been achieved mainly by the nominal appreciation of the domestic currency, while in some other countries, it has been caused by having higher inflation rate. An alternative, although not independent, fundamental reason for these characteristics is the exchange rate regime. The Czech Koruna and the Polish Zloty have freely floated during the sample period with no limit on their appreciation. Slovakia has applied a flexible managed float until November 2005, when it entered the ERM II system. The appreciation of the Hungarian Forint has been limited by the target zone abandoned in February 2008. Finally, Romania has introduced a managed float from November 2004 on.

[12] Whether market expectations are typically formed by the logic of chartists, or fundamentalists; and also whether expectations are partly exogenous and self-fulfilling, or they are pinned down by the fundamentals, are beyond the scope of this paper.

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Appendix A Tables

Table 1
Forecasting performance of the models and the survey data on the 3 months horizon

Exchange rate	Num. obs.	RW	gener	const c	linear	survey data
		Model				
		Mean absolute error (MAE)				
CZK/EUR	46	0.0305	0.0297	0.029	0.0293	0.0304
(test stat)			(0.5351)	$(1.4036)^{*}$	$(1.4335)^{*}$	(0.0249)
HUF/EUR	45	0.0435	0.0459	0.0448	0.0435	0.0462
(test stat)			(-0.7084)	(-0.4555)	(0.0068)	(-0.8733)
PLN/EUR	22	0.0728	0.0729	0.0719	0.0723	0.0747
(test stat)			(-0.0189)	(0.1457)	(0.1548)	(-0.2044)
ROL/EUR	27	0.0477	0.0462	0.0482	0.0483	0.0476
(test stat)			(0.7882)	(-0.4332)	(-0.4268)	(0.035)
SKK/EUR	43	0.0208	0.021	0.0201	0.02	0.0214
(test stat)			(-0.1384)	(0.9773)	$(1.4035)^{*}$	(-0.3077)
Pooled	183	0.039	0.0393	0.0388	0.0386	0.04
(test stat)			(-0.1594)	(0.2473)	(0.838)	(-0.5861)
		Root mean square error (RMSE)				
CZK/EUR	46	0.0399	0.0404	0.0396	0.0395	0.0401
(test stat)			(-0.316)	(0.189)	(0.2947)	(-0.0727)
HUF/EUR	45	0.058	0.0628	0.0611	0.0587	0.0625
(test stat)			(-0.749)	(-0.5958)	(-0.3812)	(-0.9194)
PLN/EUR	22	0.1003	0.1142	0.1077	0.1036	0.116
(test stat)			(-0.8539)	(-0.7861)	(-0.7326)	(-0.9261)
ROL/EUR	27	0.0606	0.0607	0.0618	0.062	0.0575
(test stat)			(-0.0697)	(-0.8479)	(-0.8455)	(0.6393)
SKK/EUR	43	0.0306	0.0299	0.0292	0.0293	0.0308
(test stat)			(0.5321)	$(2.0372)^{**}$	$(2.3545)^{***}$	(-0.187)
Pooled	183	0.0566	0.0608	0.0589	0.0574	0.0608
(test stat)			(-1.0561)	(-0.9474)	(-0.776)	(-1.0003)

The Diebold-Mariano test statistics in parentheses compares the forecasting ability of the random walk model (RW) with that of its alternatives. The alternatives are the generalized model (gener), the constant parameter model (const c), the linear model (linear), and the raw survey data.
$*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

Table 2
Forecasting performance of the models and the survey data on the 1 year horizon

Exchange rate	Num. obs.	RW	Model gener	const *c*	linear	survey data
		Mean absolute error (MAE)				
CZK/EUR	37	0.0625	0.0531	0.0517	0.0526	0.054
(test stat)			(4.746)***	(4.7581)***	(6.8491)***	(2.5378)***
HUF/EUR	36	0.056	0.0549	0.0549	0.0545	0.0554
(test stat)			(0.1921)	(0.1835)	(0.3317)	(0.0875)
PLN/EUR	13	0.1347	0.1211	0.1215	0.1247	0.1224
(test stat)			(1.5407)*	(1.5665)*	(1.6249)*	(1.4465)*
ROL/EUR	18	0.095	0.0874	0.0934	0.0931	0.0849
(test stat)			(1.584)*	(0.4272)	(0.4707)	(1.8732)**
SKK/EUR	34	0.0612	0.0386	0.0373	0.0388	0.0387
(test stat)			(9.9233)***	(8.1499)***	(11.255)***	(10.675)***
Pooled	138	0.0715	0.0609	0.061	0.0618	0.0611
(test stat)			(3.385)***	(2.9314)***	(3.0377)***	(3.1773)***
		Root mean square error (RMSE)				
CZK/EUR	37	0.075	0.0631	0.0617	0.0631	0.0643
(test stat)			(4.177)***	(6.589)***	(19.0993)***	(2.4396)***
HUF/EUR	36	0.0693	0.0715	0.0716	0.07	0.0718
(test stat)			(-0.2782)	(-0.2758)	(-0.1268)	(-0.2952)
PLN/EUR	13	0.1547	0.1511	0.1511	0.1512	0.1533
(test stat)			(0.5541)	(0.573)	(0.743)	(0.1959)
ROL/EUR	18	0.1018	0.0971	0.1028	0.1028	0.0955
(test stat)			(0.8284)	(-0.2046)	(-0.1865)	(1.0159)
SKK/EUR	34	0.0724	0.0511	0.0496	0.0516	0.0512
(test stat)			(2.5715)***	(2.576)***	(2.6751)***	(2.6615)***
Pooled	138	0.0875	0.0801	0.0806	0.0808	0.0806
(test stat)			(2.4833)***	(2.0247)**	(2.3021)**	(2.2425)**

The Diebold-Mariano test statistics in parentheses compares the forecasting ability of the random walk model (RW) with that of its alternatives. The alternatives are the generalized model (gener), the constant parameter model (const c), the linear model (linear), and the raw survey data.
$*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

Table 3
Forecasting performance of the models and the survey data on the 2 years horizon

Exchange rate	Num. obs.	Model				survey data
		RW	gener	const *c*	linear	
		Mean absolute error (MAE)				
CZK/EUR (test stat)	26	0.0865	0.0534 (6.2393)***	0.0552 (6.0624)***	0.0538 (6.0053)***	0.0531 (6.2973)***
HUF/EUR (test stat)	25	0.0575	0.0487 (1.9263)**	0.049 (2.0171)**	0.0481 (1.8414)**	0.0487 (2.0155)**
PLN/EUR (test stat)	2	0.1668	0.2051 (−4.9998)	0.2079 (−3.5855)	0.2117 (−3.6386)	0.2036 (−3.5058)
ROL/EUR (test stat)	7	0.1029	0.1022 (0.0948)	0.1037 (-0.0902)	0.1036 (-0.0808)	0.1031 (-0.0234)
SKK/EUR (test stat)	24	0.1137	0.0645 (36.6969)***	0.0632 (15.3942)***	0.0619 (15.188)***	0.0638 (70.5021)***
Polled (test stat)	84	0.0889	0.0629 (2.3899)***	0.0633 (2.21)**	0.0623 (2.2902)**	0.0626 (2.3196)**
		Root mean square error (RMSE)				
CZK/EUR (test stat)	26	0.0962	0.062 (6.0123)***	0.0636 (5.8597)***	0.062 (5.8393)***	0.0618 (6.0119)***
HUF/EUR (test stat)	25	0.0847	0.0705 (2.5297)***	0.0711 (2.6224)***	0.0695 (2.4462)***	0.0721 (2.3519)***
PLN/EUR (test stat)	2	0.1688	0.2056 (−7.8513)	0.2081 (−4.5202)	0.2118 (−4.5544)	0.2039 (−4.4448)
ROL/EUR (test stat)	7	0.13	0.1251 (0.6949)	0.1244 (0.6598)	0.1243 (0.6675)	0.1252 (0.6468)
SKK/EUR (test stat)	24	0.126	0.0831 (7.6348)***	0.0831 (7.4742)***	0.0818 (7.4388)***	0.0827 (7.6621)***
Pooled (test stat)	84	0.1078	0.0834 (2.8771)***	0.084 (2.6625)***	0.083 (2.8298)***	0.0835 (2.626)***

The Diebold-Mariano test statistics in parentheses compares the forecasting ability of the random walk model (RW) with that of its alternatives. The alternatives are the generalized model (gener), the constant parameter model (const c), the linear model (linear), and the raw survey data.
$*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

Table 4
Forecasting performance of the models for different forecast horizons on the pooled data

Forecast horizon	Num. obs.	Model			
		RW	gener	const c	linear
		Mean absolute error (MAE)			
4-months	181	0.044	0.043	0.0426	0.0427
(test stat)			(0.7227)	(1.5073)*	(2.2999)**
5-months	176	0.0503	0.0472	0.0473	0.0478
(test stat)			(2.1857)**	(2.3754)***	(3.0243)***
6-months	171	0.0577	0.0524	0.0525	0.0539
(test stat)			(3.2214)***	(3.2182)***	(3.5573)***
7-months	166	0.0589	0.0529	0.0532	0.0545
(test stat)			(3.4494)***	(3.2489)***	(3.5246)***
8-months	161	0.0611	0.0529	0.0535	0.055
(test stat)			(4.1911)***	(3.6755)***	(3.7684)***
9-months	156	0.0646	0.0561	0.0562	0.0575
(test stat)			(3.7354)***	(3.2283)***	(3.4391)***
		Root mean square error (RMSE)			
4-months	181	0.0642	0.0663	0.0647	0.0641
(test stat)			(-0.7086)	(-0.3356)	(0.1502)
5-months	176	0.0732	0.0712	0.0714	0.0718
(test stat)			(1.7762)**	(1.8447)**	(2.5462)***
6-months	171	0.0843	0.0793	0.0803	0.0817
(test stat)			(3.224)***	(2.78)***	(3.2767)***
7-months	166	0.084	0.0778	0.0788	0.0804
(test stat)			(3.3204)***	(2.9698)***	(3.3435)***
8-months	161	0.0838	0.0766	0.0778	0.0793
(test stat)			(3.8226)***	(3.2083)***	(3.1653)***
9-months	156	0.0854	0.0789	0.0796	0.0807
(test stat)			(3.8725)***	(2.8955)***	(2.8726)***

The pooled data consists of the forecast errors of all the five exchange rates. The Diebold-Mariano test statistics in parentheses compares the forecasting ability of the random walk model (RW) with that of its alternatives. The alternatives are the generalized model (gener), the constant parameter model (const c), and the linear model (linear).
$*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

Table 5
The horizon at which the survey-based forecasts of the generalized model (gener), the constant parameter model (const *c*), and the linear model (linear) start to be significantly better than the random walk model at 5%

Exchange rate	Model: gener	const *c*	linear
	Cut-off horizon for mean absolute error (MAE) (in months)		
CZK/EUR	7	7	7
HUF/EUR	18	18	16
PLN/EUR	6	6	6
ROL/EUR	13	14	14
SKK/EUR	5	2	2
Pooled	5	5	4
	Cut-off horizon for root mean square error (RMSE) (in months)		
CZK/EUR	7	5	5
HUF/EUR	17	17	16
PLN/EUR	6	6	6
ROL/EUR	13	17	17
SKK/EUR	5	2	2
Pooled	5	5	5

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