Can Survey Data on Exchange Rate Expectations Forecast the Nominal Exchange Rates of CEE Countries?

Anna Naszodi[1]

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 models are fitted on the survey forecasts. Then, the forecasting performances of the fitted forecasts are compared. The long-horizon forecasts estimated from the survey data are proved to be significantly better than the random walk for all the five currencies. The best performing model is the one that assumes an exponential relationship between the forecast and the forecast horizon, and has a time-varying parameter.

JEL: F31, F36, G13.

Keywords: forecasting exchange rates, survey data, time-varying parameter, term-structure of forecasts.

[1]Magyar Nemzeti Bank, Budapest, Hungary.
email: naszodia@mnb.hu, anna.naszodi@gmail.com

The author gratefully acknowledges comments and suggestions from Zsolt Darvas, Zoltan Schepp and participants of the presentation at the Magyar Nemzeti Bank.

The views expressed are those of the author and do not necessarily reflect the official view of the Magyar Nemzeti Bank (National Bank of Hungary).

Can Survey Data on Exchange Rate Expectations Forecast the Nominal Exchange Rates of CEE Countries?

Anna Naszodi

November 14 2009

1 Introduction

This paper examines the forecasting ability of the survey expectations of five Central and Eastern European currencies on different horizons. The currencies are the Czech Koruna, the Hungarian Forint, the Polish Zloty, the Romanian Leu, and the Slovakian Koruna. The forecast horizon ranges from 3 months to 2 years. The paper uses three simple models to estimate the forecasts for those horizons that no survey data are available on. Thereby, we can investigate what are the horizons at which the surveys provide us more accurate forecasts than the random walk model does.

The three models are the linear model, the constant parameter model, and the generalized model. These models have different predictions 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 of the constant parameter model, and the generalized model. What distinguishes the generalized model from the constant parameter model is that its parameter is allowed to be time-varying. The motivation for using such a flexible model are twofold. First, our data are rich enough to identify the time-varying parameter. Second, exchange rate models with time-varying parameter have remarkably good forecasting performance. For instance, the time-varying parameter model by Wolff (1987) enhances the forecasting ability of the structural models. A broader model by Schinasi and Swamy (1989) can even out-perform 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, this paper finds the generalized model to be the most successful in terms of forecasting among the three models investigated here.

Term-structure restrictions, similar to those assumed in these models, are usually violated by the raw survey data as it is documented by Frankel and Froot (1987), and Ito (1990).[1] A likely reason for this finding is that surveys usually report the averages of

[1] In contrast to these studies, Naszodi (2009) finds supporting evidences for the exponential relationship

some heterogeneous individual forecasts. And even if the individual forecasts fulfill the term-structure restriction, the average may not necessarily do so, because of the presence of non-linearities, and heterogeneity. Specifically, the average of different exponential functions is rarely exponential itself. The heterogeneity of the individual forecasts may come from information asymmetry or differences in beliefs. For instance, the forecasters may have noisy information on the current state of the economy, and they may have diverging views on the processes of the state variables.[2] If the heterogeneity comes from private information possessed by the individual forecasters, and these pieces of information are incorporated into their forecasts, then the aggregated survey forecast has a similar role to that of order flow. Both transmit dissipated private information. Since data on order flow have been proved to be helpful at forecasting the exchange rate,[3] we can expect the same for survey data. Whereas if forecasters share the same information, they still can have different beliefs. Since market sentiment is thought to be just as important at determining asset prices as the information on the current state of the economy, the surveys can be useful at forecasting even in the latter case by reporting some aggregates on the diverging views of the market analysts.

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

2 Survey Data on the Expected Exchange Rates

The paper uses survey data of the Consensus Economics on the expected 3 months, 1 year and 2 years ahead exchange rates and the spot exchange rate at the date of the survey.[4] Figure 2 shows the raw survey forecasts together with the spot exchange rate on the survey date. Our survey data are the mean of the forecasts of the individual survey participants.[5] The sample size is determined by the availability of the survey data. Consensus Economics started to publish forecasts on the economies of the Central

between the survey forecast and the forecast horizon for eleven currencies including the major ones on the sample spanned by January 1999 and April 2009.

[2]Bacchetta and van Wincoop (2004) have a model of this type, where the agents have noisy information and they have different views on the auto-regressive parameter of the fundamentals.

[3]See Evans and Lyons (2002).

[4]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, while the forecasts refer to the end-of-month exchange rates. For instance, the survey can be on the 15th of December of a given year and the participants of that survey should forecast the end-of-March, end-of-December exchange rates of the coming year and the end-of-December exchange rate of the year after. See Figure 1 on the variation of the forecast horizons. When estimating the models, I treat the forecast horizons rigorously by using the exact number of days in the calculations. While the above mentioned differences are disregarded throughout the paper.

[5]The reported forecast is the average of the expected exchange rates of the individual forecasters in levels and not the expected log exchange rate of the representative forecaster that we have in the

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 exchange rates of the Polish Zloty, the Romanian Leu and the Slovakian Koruna, the sample is somewhat shorter. Since Slovakia has 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 have 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. The size of the cross-section is 3 as having 3 different forecast horizons for the 5 currencies, and estimations are carried out separately for each exchange rate.

3 The Term-Structure Models of Forecasts

This Section introduces three statistical models on the term-structure of forecasts and explains how their parameters are estimated from survey data. 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.

$$x_{t,T}^{linear} = s_t + (T-t)\mu_t \qquad \forall T > t \quad , \tag{1}$$

where the log exchange rate at time t is denoted by s_t. $T-t$ is the forecast horizon. And μ_t is the time-varying slop parameter in the linear function. It informs us about the expected percentage change in the exchange rate. The $x_{t,T}^{linear}$ is the forecasted log exchange rate at time T that is consistent with the linear model. The forecast is made at time t.

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

$$\min_{\mu_{\underline{\tau}},\dots,\mu_{\overline{\tau}}} \sum_{t=\underline{\tau}}^{\overline{\tau}} \left(\tilde{x}_{t,t+.25Y} - x_{t,t+.25Y}^{linear}\right)^2 + \left(\tilde{x}_{t,t+1Y} - x_{t,t+1Y}^{linear}\right)^2 + \left(\tilde{x}_{t,t+2Y} - x_{t,t+2Y}^{linear}\right)^2 \quad , \tag{2}$$

where $\tilde{x}_{t,t+.25Y}$, $\tilde{x}_{t,t+1Y}$, and $\tilde{x}_{t,t+2Y}$ denote the survey forecasts of the horizons 3 months, 1 year, and 2 years respectively. And the sample period starts at time $\underline{\tau}$, and ends at $\overline{\tau}$. The minimization problem is separable in time: the parameter μ_t of a given time t depends only on the contemporaneous survey forecasts. For each time t, the parameter μ_t is estimated from 3 observations on forecasts with different forecasts horizons.

models. However, the latter can be approximated by the log of the available data. I assume that changes in the exchange rate have Gaussian distribution and it is also thought to be Gaussian by the forecasters, although each individual forecaster may have her own view on the first and second moments of the distribution. Under these assumptions, the approximation error depends on the cross-sectional dispersion of the views of the forecasters on the expected value of the future exchange rate, and also on the average of the individual expectations on the volatility of the exchange rate: $\frac{1}{I}\sum_{i=1}^{I} \mathrm{E}_{t,i}\left[\log(S_T)\right] - \log[\frac{1}{I}\sum_{i=1}^{I} \mathrm{E}_{t,i}(S_T)] = -\frac{1}{2}\left\{\mathrm{Var}_t\left[\log(\mathrm{E}_{t,i}(S_T))\right] + \frac{1}{I}\sum_{i=1}^{I}\mathrm{Var}_{t,i}\left[\log(S_T) - \log(S_t)\right]\right\}$. Where S_T is the exchange rate in level at time T, I denotes the number of forecasters, and index i refers to forecaster i. Since the half variances are negligible, so are the approximation errors.

Finally, in order to obtain the forecasts that are consistent with the linear model, we simply fit a linear curve on the survey data of each month. Figure 3 shows the stylized survey forecasts and the fitted linear curve. Formally, the fitted forecasts of the linear model, $\widehat{x}_{t,T}^{linear}$, are obtained by substituting the estimates $\widehat{\mu}_t$ into Equation (1)

$$\widehat{x}_{t,T}^{linear} = s_t + (T-t)\widehat{\mu}_t \qquad T > t \quad . \tag{3}$$

The fitted forecasts $\widehat{x}_{t,T}^{linear}$ are estimated from data available at time t. Therefore, these forecasts can be used even in a real-time forecasting exercise.

The term-structure is assumed to be exponential in the *constant parameter model.*

$$x_{t,T}^{const} = e^{\frac{T-t}{c}}(s_t - v_t) + v_t \qquad \forall T > t \quad , \tag{4}$$

where v_t and c are parameters determining the slope and the curvature of the term-structure. And $x_{t,T}^{const}$ is the forecasted log exchange rate at time T that is consistent with the constant parameter model. The constant parameter model can be rationalized by the conventional asset pricing model,[6] where v_t is the fundamental and c is a parameter capturing the relative importance of the fundamental at determining the exchange rate.

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

$$\min_{c,v_{\underline{\tau}},\dots,v_{\overline{\tau}}} \sum_{t=\underline{\tau}}^{\overline{\tau}} \left(\tilde{x}_{t,t+.25Y} - x_{t,t+.25Y}^{const}\right)^2 + \left(\tilde{x}_{t,t+1Y} - x_{t,t+1Y}^{const}\right)^2 + \left(\tilde{x}_{t,t+2Y} - x_{t,t+2Y}^{const}\right)^2 \quad . \tag{5}$$

Here, I use the entire sample for estimation, not only up to time t. Therefore, the corresponding forecasting exercise is an in-sample one.

The fitted forecasts consistent with the constant parameter model, $\widehat{x}_{t,T}^{const}$, are obtained by substituting the estimates $\widehat{c}$, and $\widehat{v}_t$ into Equation (4)

$$\widehat{x}_{t,T}^{const} = e^{\frac{T-t}{\widehat{c}}}(s_t - \widehat{v}_t) + \widehat{v}_t \qquad T > t \quad . \tag{6}$$

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

$$x_{t,T}^{gener} = e^{\frac{T-t}{c_t}}(s_t - v_t) + v_t \qquad \forall T > t \quad . \tag{7}$$

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

According to the interpretation of parameter c in the conventional asset pricing model, a time-varying c corresponds to the case, when the relative weight of the fundamental in the exchange rate is changing over time. While the parameter restriction $e^{\frac{T-t}{c_t}} = 1$ corresponds to the case, when the fundamental has zero weight in the exchange rate and only the expected future exchange rate is important at determining the exchange rate.

[6]See Engel and West (2005), or Naszodi (2009), for instance.

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

$$\min_{c_{\underline{\tau}},\ldots,c_{\overline{\tau}},v_{\underline{\tau}},\ldots,v_{\overline{\tau}}} \sum_{t=\underline{\tau}}^{\overline{\tau}} \left(\tilde{x}_{t,t+.25Y} - x^{gener}_{t,t+.25Y}\right)^2 + \left(\tilde{x}_{t,t+1Y} - x^{gener}_{t,t+1Y}\right)^2 + \left(\tilde{x}_{t,t+2Y} - x^{gener}_{t,t+2Y}\right)^2 \quad . \tag{8}$$

The minimization is separable in time, just like (2). We can fit the exponential curve on each monthly forecasts with multiple forecast horizons separately. Figure 4 shows the stylized survey forecasts of one cross-section and the fitted exponential curve. The fitted forecasts consistent with the generalized model, $\widehat{x}^{gener}_{t,T}$, are obtained by substituting the estimates $\widehat{c}_t$, and $\widehat{v}_t$ into Equation (7)

$$\widehat{x}^{gener}_{t,T} = e^{\frac{T-t}{\widehat{c}_t}}(s_t - \widehat{v}_t) + \widehat{v}_t \qquad T > t \quad . \tag{9}$$

4 Comparing the Forecasting Abilities

This Section tests whether the forecasting ability of the fitted forecasts obtained by any of the term-structure models is better than that of the random walk model.

First, the forecast errors are calculated for each model.

$$e_{t,T} = s_T - \widehat{x}_{t,T} \quad , \tag{10}$$

where s_T is the log of the realized exchange rate at time T. And $\widehat{x}_{t,T}$ is the fitted forecast given either by Equation (3), or (6), or (9).

The forecast errors of the random walk model are given by

$$e^{RW}_{t,T} = s_T - s_t \quad . \tag{11}$$

We can calculate the forecast errors for the raw survey data the same way. These forecast errors are available only for a limited number of forecast horizons, for 3 months, 1 year, and 2 years. Whereas the forecast errors of the models can be calculated for any horizon.

Figure 5 shows the forecast errors under different model specifications for the 3 months, 1 year, and 2 years horizons for each of the exchange rates. It suggests that the forecast errors obtained by using the generalized model, the constant parameter model, and the linear model deviate only slightly from the forecast errors of the raw survey data. Or, in other words, the raw survey data do not violate substantially any of the term-structure restrictions of (1), (4), and (7). In contrast, the forecast errors of the random walk model do not move so closely together with the others especial for the longer horizons. Therefore, we can expect the following. First, no matter how exactly the forecasting performance is measured, there will be no significant difference among the forecast accuracies of the survey-based forecasts, *i.e.*, the raw survey data, and the fitted forecasts consistent with the linear model, the constant parameter model, and the generalized model. Second, the forecasting ability of the random walk model is likely to be different from those of the other models and the difference varies across forecast horizons.

We check the above conjectures drawn from the time-series of forecast errors in a formal way. We measure the forecast accuracy by the root mean square forecast error

(RMSE), and the mean absolute forecast error (MAE).

$$\text{RMSE} = \sqrt{P^{-1} \sum_{t=\underline{\tau}}^{\min(\overline{\tau},\text{T})} (e_{t,T})^2} \quad , \tag{12}$$

$$\text{MAE} = P^{-1} \sum_{t=\underline{\tau}}^{\min(\overline{\tau},\text{T})} |e_{t,T}| \quad , \tag{13}$$

where P denotes the length of the time series of the forecast errors.

In order to test the hypotheses that the forecasting performance of the random walk model is the same as that of its alternatives, we use the Diebold-Mariano test.[7] In case of the RMSE,[8] 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:

$$H_0 : E\left[(e_{t,t+\theta}^{RW})^2\right] - E\left[(e_{t,t+\theta})^2\right] = 0 \qquad \forall t \quad . \tag{14}$$

The forecast error of the random walk model is denoted by $e_{t,t+\theta}^{RW}$, while that of the alternative model is $e_{t,t+\theta}$.

Under the null

$$\bar{g} \left(\frac{\widehat{V}}{P} \right)^{-\frac{1}{2}} \sim_A N(0,1) \quad , \tag{15}$$

where $g_t = (e_{t,t+\theta}^{RW})^2 - (e_{t,t+\theta})^2$ is the difference between the squared errors at time t, and $\bar{g} = P^{-1} \sum_t g_t$ is the average of the differences between the squared 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, or the generalized model. Furthermore, bootstrapping the errors is not feasible either, because of the very small size of the cross-sections. 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.

Table 1, 2, and 3 report the statistics of the model comparisons for each of the horizons separately. These results are in line with our previous findings. First, the forecasting performance of the generalized model, the constant parameter model, the linear model, and the raw survey forecasts are very close to each other. Moreover, they are neither statistically, nor economically different from that of the random walk forecast for most of

[7]See Diebold and Mariano (1995).

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

the exchange rates for the 3 months horizon. However, they tend to be better than the random walk as the forecast horizon gets longer.[9]

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 likely to be useful for the Hungarian Forint. Although their MAE is somewhat smaller than that of the random walk model, the difference is not significant even at 10%. And their RMSE is somewhat higher than that of the random walk model, but the random walk model does not perform significantly better than any of its alternatives even for the 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 the 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 2-year 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 size is too small to take the estimates seriously. For the Hungarian Forint, the survey-based forecasts have smaller MAE and RMSE than the random walk model for the 2 years horizon. And 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 forecast is beaten by the survey-based forecasts also on the pooled data.

We have seen that the survey-based forecasts can significantly out-perform the random walk model at the 2-years horizon, but not at the 3 months horizon. While 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 at which the survey-based forecasts are already better than the random walk. For this purpose, we can use the fitted forecasts that are available for any forecast horizon. The forecasting ability of the fitted forecasts are compared 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 months. Therefore, we can recommend to use the survey-based forecasts instead of the random walk forecast for horizons longer than 5 months. The cut-off horizon, however, varies across currencies as it is reported by Table 5.

From a practical point of view, it is also important to know which of the models performs the 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

[9]As the forecast horizon gets longer, the samples of the realized exchange rate and the forecast errors get shorter. This may contribute artificially to the finding that the forecast accuracy is increasing in the horizon. I.e., theoretically, if the short and long horizon forecasts perform equally well on average on an infinitely long sample, but in a finite sample the exchange rate is less predictable at the beginning of the sample than in the rest, then our test can find falsely the short horizon forecasts to perform worse than the long one. By comparing the forecasting accuracies on the synchronized samples, our finding proves to be robust.

and the raw survey forecasts for those horizons that we have survey data on. Therefore, one can use simply the raw survey data for the 3-months, 1-year, and 2-years forecasts. While 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. Therefore, we can recommend to apply this exponential model with time-varying parameter to estimate the forecasts for horizons that we do not have direct observation on.

It is worth to remark that the generalized model dominates 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 better than the constant parameter model despite of the fact that the latter has been given the advantage of being estimated from the entire sample.

5 Conclusion

This paper has investigated whether survey-based exchange rate forecasts are useful by any means at forecasting the nominal exchange rates in five Central and Eastern European countries on a sample spanned by January 2003 and February 2009. Our most important finding is that the survey offers better forecast at the longer horizons than the naive model predicting no change in the exchange rate. This finding is likely to be attributable to the following. First, the Czech Koruna, the Polish Zloty, and the Slovakian Koruna had a clear appreciating trend in the major part of our sample period. While the other studied exchange rates, the Hungarian Forint and the Romanian Leu, can be characterized mostly by mean-reverting processes. We can not 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 coordinated the market's view about the dynamics of the bubbles.[12] Any of these explanations might have contributed to the survey data to beat

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

[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. The appreciation of the Hungarian Forint has been limited by the target zone abandoned in February 2008. Slovakia has applied a flexible managed float until November 2005, when it entered the ERM II system. 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

the random walk model at forecasting.

Although it is a well known robust finding that exchange rates are more predictable at long horizons (see Meese and Rogoff (1983), Mark (1995), Engel et al. (2007)), this paper is the first at documenting the long-run predictability of the exchange rates of some Central and Eastern European countries. Darvas and Schepp (2007a) obtain the opposite result for the Czech Koruna, Hungarian Forint, and Polish Zloty on the sample period between 1999 and 2007 by estimating error correction models in which the long maturity forward rate is assumed to be stationary.[13] They estimate several different error correction models, where the exchange rate is assumed to revert to the stationary forward rate. As it is pointed out by the authors, the poor forecasting ability of their error correction models is most likely to be due to the lack of stability of the forward rates of these foreign exchanges. In contrast, for the major exchange rates the hypothesis that the long maturity forward rates follow unit root processes can be rejected and therefore, the error correction models perform remarkable well at forecasting these exchange rates. See Darvas and Schepp (2007b).

It has been investigated also whether the fitted forecasts consistent with the models are better than the raw survey data at forecasting. We have found that it is not worth adjusting the survey data by any of the exchange rate models we have considered. However, for those horizons, where survey forecasts are not available, we need to estimate the forecast anyway by applying one or another estimation or interpolation technique. The best forecasts are obtained by using the estimated 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. This model nests the conventional asset pricing model with constant parameter, and the random walk model as well.

By applying the generalized model, we have calculated the fitted forecasts for various horizons. These estimated forecasts have been used to study at what horizon does the survey-based forecast start to perform significantly better than the random walk. The answer to the question varies across currencies. It is estimated to be relatively short for the trending exchange rates: 7 months for the Czech Koruna, 5 months for the Slovakian Koruna, and 6 months for the Polish Zloty. While the cut-off horizon is around 13 months for the Romanian Leu, and close to 17 months for the Hungarian Forint.

fundamentals, are beyond the scope of this paper.

[13]The results of Darvas and Schepp (2007a) are not directly comparable with the ones in this paper, because they do not use survey data.

References

[1] Bacchetta, P., van Wincoop, E., 2004. A Scapegoat Model of Exchange-Rate Fluctuations. American Economic Review, 94 (2), 114–118.

[2] Clark, T. E., West, K. D., 2006. Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. Journal of Econometrics, vol 135, 155–186.

[3] Darvas, Zs., and Schepp Z., 2007a. Forecasting the exchange rates of three Central-Eastern European currencies with forward exchange rates. Hungarian Economic Review (Közgazdasági Szemle), 54, 501–528.

[4] Darvas, Zs., and Schepp Z., 2007b. Forecasting Exchange Rates of Major Currencies with Long Maturity Forward Rates. Working Papers 2007/5, Department of Mathematical Economics and Economic Analysis, Corvinus University of Budapest.

[5] Diebold, F. X., Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253–263.

[6] Engel, C., West, K. D., 2005. Exchange Rates and Fundamentals. Journal of Political Economy 113 (3), 485–517.

[7] Engel, C., Mark, N. C., West, K. D., 2007. Exchange Rate Models Are Not As Bad As You Think. NBER Macro Annual 2007.

[8] Evans, M., Lyons, R., 2002. Order Flow and Exchange Rate Dynamics. Journal of Political Economy, 110, 170–180.

[9] Frankel, J. A., Froot, K. A., 1987. Using survey data to test standard propositions regarding exchange rate expectations. American Economic Review 77, 133–153.

[10] Ito, T., 1990. Foreign Exchange Rate Expectations: Micro Survey Data. American Economic Review, 80, 434–449.

[11] Mark, N., C., 1995. Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability. American Economic Review, 85, 201–218.

[12] Meese, R. A., Rogoff K., 1983. The Out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification, in Jacob A. Frenkel (eds). Exchange Rates and International Macroeconomics (NBER).

[13] Naszodi, A. 2009. The Asset Pricing Model of Exchange Rates and its Test on Survey Data, ECB WP, forthcoming.

[14] Schinasi, G.J., Swamy, P.A.V.B., 1989. The out-of-sample forecast in performance of exchange rate models when coefficients are allowed to change. Journal of International Money and Finance 8 (3), 375–390.

[15] Wolff, C.C.P., 1987. Time-varying parameters and the out-of-sample forecasting performance of structural exchange rate models. Journal of Business and Economic Statistics 5 (1), 87–97.

[16] Wu, J., Chen, S., 2001. Nominal exchange-rate prediction: evidence from nonlinear approach. Journal of International Money and Finance 20, 521–532.

Tables and Figures

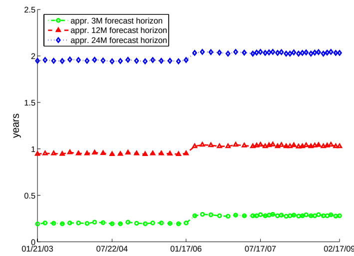
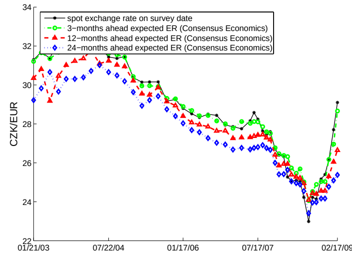
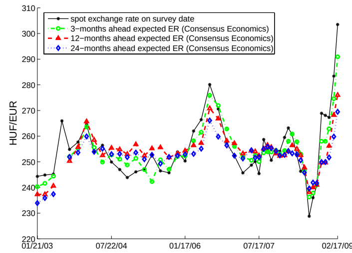


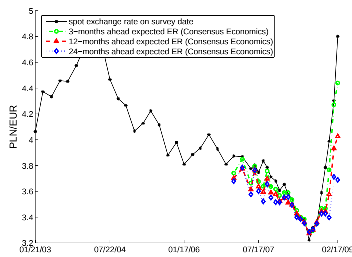
Figure 1: The forecast horizons of the surveys.



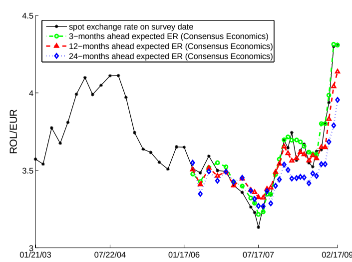
(a) Czech Koruna



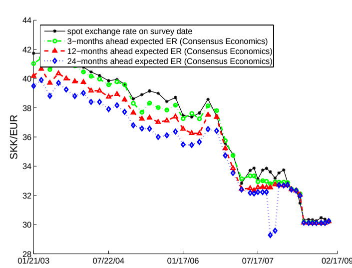
(b) Hungarian Forint



(c) Polish Zloty



(d) Romanian Leu



(e) Slovakian Koruna

Figure 2: The spot exchange rate and the survey data.

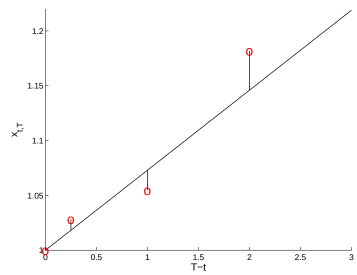


Figure 3: The stylized linear term-structure of the forecasts.

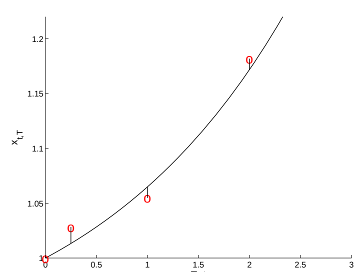
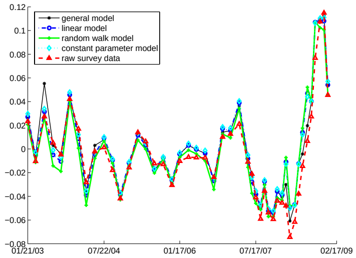
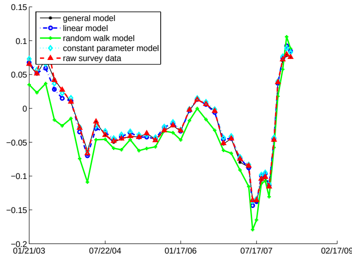


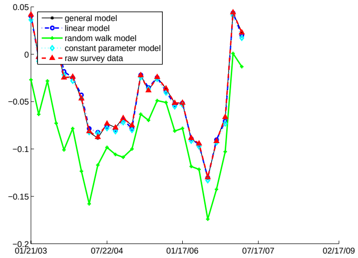
Figure 4: The stylized exponential term-structure of the forecasts.



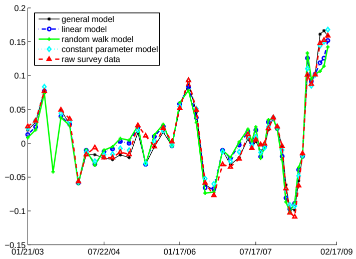
(a) Czech Koruna 3-months



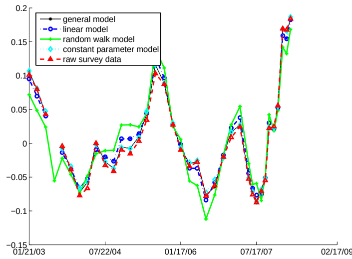
(b) Czech Koruna 1-year



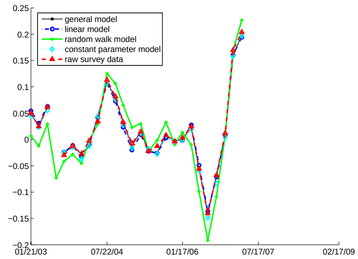
(c) Czech Koruna 2-years



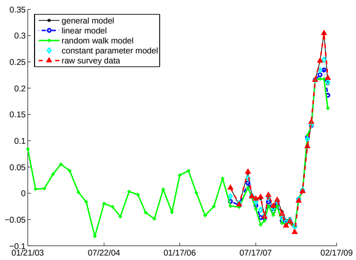
(d) Hungarian Forint 3-months



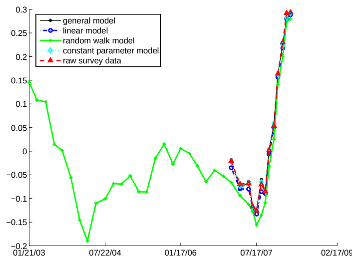
(e) Hungarian Forint 1-year



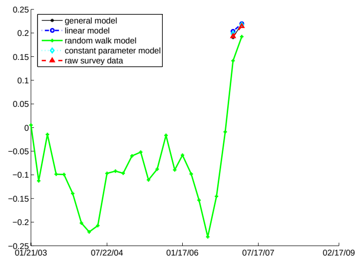
(f) Hungarian Forint 2-years



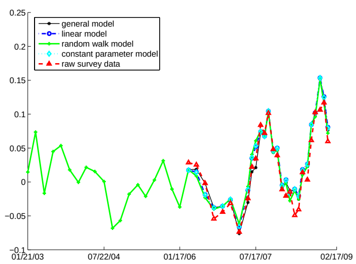
(g) Polish Zloty 3-months



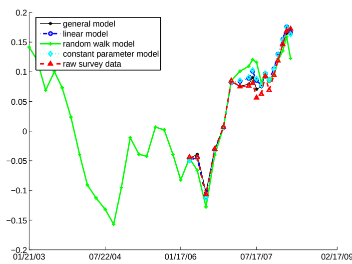
(h) Polish Zloty 1-year



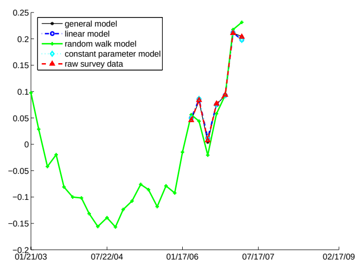
(i) Polish Zloty 2-years



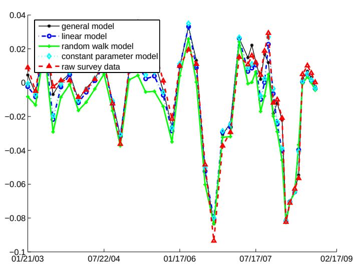
(j) Romanian Leu 3-months



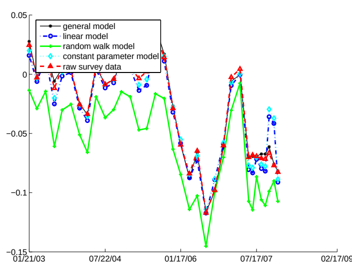
(k) Romanian Leu 1-year



(l) Romanian Leu 2-years



(m) Slovakian Koruna 3-ms



(n) Slovakian Koruna 1-year

(o) Slovakian Koruna 2-years

Figure 5: The forecast errors under different model specifications.

Exchange rate	Num. obs.	Model: RW	gener	const c	linear	survey data
		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)

Table 1: Forecasting performance of the models on the 3 months horizon. $*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

Exchange rate	Num. obs.	Model: RW	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)**

Table 2: Forecasting performance of the models on the 1 year horizon. $*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

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

Table 3: Forecasting performance of the models on the 2 years horizon. $*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

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)***

Table 4: Forecasting performance of the models for different forecast horizons. (Pooled forecast errors) $*$: significant at 10%, $**$: significant at 5%, $***$: significant at 1%.

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

Table 5: The horizon at which the survey-based forecasts start to be significantly better than the random walk model at 5%.