Could Markets Have Helped Predict the Puzzling Exchange Rate Path in CESEE Countries during the Current Crisis?

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In the present paper we examine whether financial markets could have helped predict exchange rates in selected Central, Eastern and Southeastern European (CESEE) economies, namely the Czech Republic, Hungary and Poland, during the current financial crisis. To this end, we derive risk-neutral densities from the implied volatilities of FX options, which approximate market expectations about exchange rate developments. Based on these risk-neutral density estimates, we then assess the out-of-sample predictive power of indicators. The forecasting results suggest that models based on FX options are inferior to the random walk in terms of the forecasting error, confirming a stylized fact about the short-term forecasting of exchange rates. Yet, we also find that, for the Czech Republic and Poland, risk-neutral densities contain useful information on the direction of change of the exchange rate.

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1 Introduction

The current financial and economic crisis has had a rather unexpected impact on the foreign exchange markets in Central, Eastern and Southeastern European (CESEE) non-euro area countries with flexible exchange rate regimes. This study focuses on the Czech Republic, Hungary and Poland (in the following referred to as CESEE-3), whose currencies – the forint, the Czech koruna and the złoty – appreciated heavily vis-à-vis the euro during the first phase of the global credit crunch, i.e. between the summer of 2007 and the fall of the U.S. investment bank Lehman Brothers in September 2008. This was quite surprising given that already in this first phase of the global credit crisis, financial markets were severely hit by widespread distrust and reduced risk appetite. In the subsequent period until early March 2009, the negative liquidity shock affecting financial markets following the Lehman Brothers collapse impacted dramatically on investors' perceptions. Suddenly market attention shifted to the external positions of the CESEE-3 and the deteriorating real economy. As a consequence, the forint, Czech koruna and złoty came under heavy pressure. In March 2009, market sentiment turned around and the CESEE-3 currencies have since recovered significantly.

Were these exchange rate developments and summersaults that unexpected or could they – to some extent – have been predicted? Despite the seminal paper by Meese and Rogoff (1983), which shows that in the short run the predictive quality of the random walk model is superior to that of the most relevant economic models for the exchange rate, various approaches have emerged in the literature that

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[2] *A major part of this joint paper was written when Jesús Crespo Cuaresma and Tomáš Slačík visited Česká národní banka (ČNB) in September 2008 and Adam Geršl paid a brief visit to the OeNB (Foreign Research Division) in July 2009. These visits were part of the regular cooperation between the ČNB and the OeNB.*

have tried to challenge this stylized fact. For the very short run, one approach suggests using the volatility implied by FX options, which, according to some authors, contains information on future exchange rate developments as it reflects market sentiment and beliefs.[3] The use of such a market-based indicator is in line with Crespo Cuaresma and Slačík (2009), who review standard early warning indicators for currency crises in the framework of model uncertainty and conclude that indicators which mirror market sentiment (unlike fundamental variables) have some predictive power with respect to recent dramatic exchange rate moves.

The objective of the present paper is to explore whether the implied volatility of FX options vis-à-vis the euro in the CESEE-3 contains information on future exchange rates and, hence, whether such information could have been used to predict the exchange rate during the crisis. Since information on market sentiment and beliefs can be expressed in terms of the probability distribution over the expected exchange rate, we employ a method developed by Malz (1997) to extract an estimate of such a density from observed option prices at each point in time.

From the densities obtained we compute various statistics, such as the moments or the probability of a depreciation/appreciation exceeding a certain threshold. In the next step, we assess the out-of-sample forecasting ability of these density-based statistics along with other financial market variables, such as stock indices or short- and long-term interest rates within the framework of vector autoregressive (VAR) models. The fact that there is no finite, well-specified set of explanatory variables (and lags thereof) to be included in the VAR model gives rise to a serious problem of model uncertainty. We address this issue by employing Bayesian model averaging techniques. Besides the model averaged forecasts, we present predictions of the "best" model in the Bayesian sense, i.e. the model with the highest posterior probability, and predictions based on simple bivariate models including the exchange rate and a constructed financial sentiment indicator.

Our results are mixed. On the one hand, they indicate that none of the models employed improves forecasts over the random walk model in terms of the root mean square forecasting error. This outcome thus confirms the above-mentioned stylized fact about the short-term forecasting of exchange rates made well known by the contribution of Meese and Rogoff (1983). On the other hand, risk-neutral densities seem to provide some information on the direction of change of the exchange rate, particularly in the case of the Czech Republic.

The paper is structured as follows. In the next descriptive section, we analyze exchange rate developments in the Czech Republic, Hungary and Poland since these countries' EU entry, with a particular focus on the current financial crisis. Section 3 explains the method we used to extract risk-neutral probability distributions from quoted option prices and describes the data as well as some basic features of FX option markets in the CESEE-3. In section 4, we shed some light on how we address the problem of model uncertainty and conduct the forecasting exercise. Section 5 concludes.

[3] *See e.g. Cincibuch and Bouc (2004) for a discussion.*

2 Exchange Rates of the CESEE-3 Currencies during the Crisis – A Puzzle

The evolution of exchange rates in the CESEE-3 during the global financial crisis between 2007 and 2009 has been sort of a puzzle.[4] The three panels of chart 1 depict the development of the forint, Czech koruna and złoty (the blue line in each panel) against the development of the one-month at-the-money (ATM)[5] implied volatility (magenta line) in the period from 2004 to June 2009. In terms of the exchange rate development, the whole period can be tentatively divided into four subperiods. The first period, ranging from the entry of these economies into the EU in 2004 until the outbreak of the global credit crisis in summer 2007, was marked by trend appreciation due to productivity increases as well as prevailing risk appetite. The only exception to the appreciation trend is Hungary, with a more volatile exchange rate, which was at least in part associated with high fiscal deficits during this period: After consolidation had finally started in 2006, it weighed on the country's growth performance.

A second period can be recognized between the beginning of the crisis in summer 2007 and the fall of the U.S. investment bank Lehman Brothers in September 2008. During this time the appreciation trend sped up in the Czech Republic and in Poland, and the forint started to appreciate heavily vis-à-vis the euro area. In light of the widespread distrust and reduced risk appetite, which characterized financial markets at that time, this development may seem surprising. Two main causes are cited as an explanation for this development: the unwinding of carry trades and the "safe haven" hypothesis.

The very low short-term interest rates on the CESEE-3 currencies, especially the Czech koruna, predestined them as financing currencies for carry trades. As the risk appetite diminished in markets when the U.S. subprime problems hit a number of global financial institutions via structured instruments, these institutions started to unwind carry trades given their nature as a risky and speculative investment strategy. Evidence for the Czech koruna, as described in the Financial Stability Report 2007 of Česká národní banka (ČNB, 2008), suggests that this development might have been important in the first two or three months after the beginning of the global crisis, but can hardly explain the appreciation trend over a longer horizon.

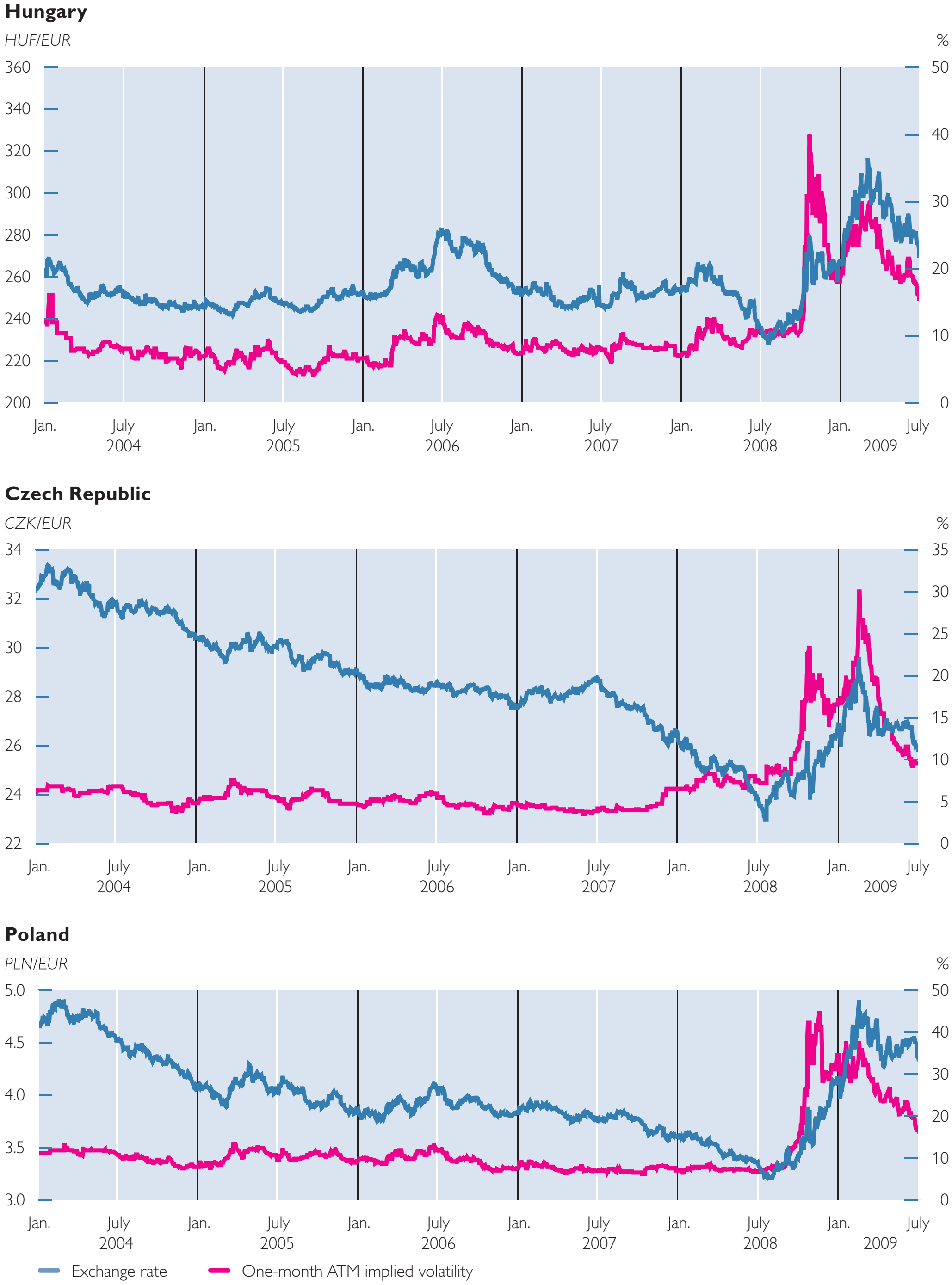
The "safe haven" hypothesis (see ČNB, 2009) is a more comprehensive, albeit also questionable, explanation for the appreciation of the CESEE-3 currencies in the crisis period. This hypothesis is based on the observed fact that the global financial crisis first spread only across advanced countries, where banks were holding toxic assets linked to subprime mortgages. In contrast, emerging countries in Europe were not directly hit, as banks in the region – many of them foreign owned – concentrated on more traditional banking activities, such as deposit collection and lending, given the yet unsaturated markets in these countries. The direct holding of subprime securities was negligible in the CESEE-3 banking sectors, which led many market participants to believe that, instead of the U.S. dollar or Western European currencies, the CESEE-3 currencies would take on the role of

[4] *For a detailed discussion on financial market developments in Central, Eastern and Southeastern Europe during the crisis, see box 1 in the OeNB's Focus on European Economic Integration Q2/09 and Q4/09.*

[5] *For an explanation of moneyness, see section 3.1.*

Chart 1

Development of Exchange Rates and One-Month ATM Implied Volatilities



Source: Bloomberg.

Note: Cutoff date: July 10, 2009.

a safe haven. Investors shed assets denominated in U.S. dollar or euro and started investing in CESEE-3 assets.

We can discern a third period starting with the Lehman Brothers collapse in mid-September 2008 and lasting until early March 2009. The liquidity shock in global financial markets caused by Lehman's fall led investors to focus on the dependence of CESEE economies on external funding. Suddenly, the negative external positions of the banking sectors of some economies in this region, such as Hungary and the Baltic countries – which international investors had up to then considered to be within an acceptable range – played an important role in increasing risk aversion toward the CESEE region as a whole. In chart 1, this abrupt change in market sentiment is pictured by the magenta line, which clearly portrays the unprecedented rise of the implied volatility in the CESEE-3 during this period of increased uncertainty. Given the liquidity shock triggered by the Lehman failure, it was feared that these countries would not be able to roll over their external (mainly short-term) debt. Moreover, real economic developments in the CESEE-3 started to give signs of weakness, driven by these countries' dependence on the macroeconomic development in the euro area, which deteriorated significantly as a consequence of the financial crisis. The depreciation pressures that emerged also put the extent of foreign currency lending in most CESEE countries into the spotlight, except for the Czech Republic, where foreign currency lending had been less pronounced. Fears that depreciation would further increase the problems of the indebted private sector, already hit by the lack of external demand, accelerated the depreciating path, especially in the first two months of 2009.

While all CESEE economies were hit by the increased risk aversion toward the region, the three economies analyzed presented different characteristics in this respect. The risk aversion drivers mentioned above were mostly valid only for Hungary, given its large external funding needs, widespread foreign currency lending and particularly high dependence on external demand. When the domestic bond market dried up completely in early October 2008, Hungarian authorities asked for IMF assistance. In contrast, the Czech Republic launched a strong communication campaign emphasizing the positive external position of its banking sector[6] (thus implying virtually no need for external funding) and the absence of foreign currency lending to households (and relatively low foreign currency lending levels vis-à-vis the corporate sector). Given the high openness of the Czech economy and the important role of the manufacturing sector, the impact on the real economy was nevertheless large. Poland – also due to its size – was less dependent on external demand and is one of the few countries where the impact of the crisis on domestic economic activity was relatively subdued.

Finally, a fourth period starting in March 2009 is characterized by a certain recovery of the CESEE-3 currencies from the low levels recorded in February/ March 2009. When global financial markets stabilized and IFI/EU assistance to CESEE countries in need was stepped up, CESEE countries experienced a slow return of optimism in the financial markets – mainly stock but also exchange rate

[6] *At the end of 2008, the Czech banking system had a positive external position of around 6% of GDP, mainly due to a very high deposit-to-loan ratio (130%). The Polish banking system had a negative external position of –7% of GDP (with a deposit-to-loan ratio of 92%), and the Hungarian banking system's external position was negative as well, at –18% of GDP (with a deposit-to-loan ratio of only 71%). For a comparison with other EU countries, see ČNB (2009, pp. 49–50).*

markets – patently documented for the CESEE-3 in chart 1 by the gradual decline of both the exchange rate and the implied volatility.

3 Would Markets Have Been Able to Predict the Exchange Rate Path?

Against this backdrop, we raise the question whether financial markets were caught by surprise by the exchange rate path described above. Put differently, we wonder whether markets could have had some predictive power with respect to the future exchange rate even though Meese and Rogoff (1983) showed that in the short run exchange rates follow the random walk. Crespo Cuaresma and Slačík (2009), who review standard early warning indicators for currency crises under the aspect of model uncertainty, conclude that only indicators which mirror the market sentiment (unlike fundamental variables) have some predictive power with respect to recent dramatic exchange rate moves. In the same vein, several studies[7] have shown that the implied volatility of FX options, which reflects market sentiment and beliefs, contains information on future exchange rate performance.

Using these findings, we hence proceed to explore whether observed FX option prices provide some information not yet incorporated into the price of the underlying spot exchange rate. Since information on market beliefs can be neatly expressed in terms of a probability distribution, the task is to estimate the density function based on FX options in order to draw inference on it and test its predictive ability.

3.1 Extracting Risk-Neutral Density from Option Prices

A European option provides the holder with the right (not obligation) to buy (in the case of a call option) or sell (put option) an asset on a certain expiration date at a certain price, the so-called strike or exercise price. At maturity T, a European call option with a strike price X thus yields either the difference between the spot asset price (S_T) and the strike price if the option is exercised, or 0 otherwise. The price $c(t, X, T)$ of a European call option at time t thus corresponds to the discounted value of the option's expected payoff at T:

$$\begin{aligned} c(S_t, t, X, T, r) &= e^{-r\tau} E[\max(S_T - X, 0)] \\ &= e^{-r\tau} \int_X^{\infty} (S_T - X)\pi(S_T)\, dS_T \end{aligned} \tag{1}$$

where $\tau \equiv T - t$ is the time to maturity, r stands for the appropriate risk-free domestic interest rate and $\pi(.)$ denotes the risk-neutral probability density function (RND) of the asset price S_T.

To extract the RND from a European call option price, we can use the result derived by Breeden and Litzenberger (1978), according to which the RND is proportional to the second derivative of the call price with respect to the strike price:

$$\pi(S_T) = e^{r\tau} \frac{\partial^2 c(t, X, T)}{\delta X^2}. \tag{2}$$

Option prices, determined by the demand-supply relationship in the market, are typically transformed to the implied volatility in units called vols that are used to quote option "prices." Hence, option prices expressed in currency units are not

[7] *See e.g. Cincibuch and Bouc (2004) for a discussion.*

directly observable and the derivative of the call price cannot be obtained in a straightforward manner. For this transformation, practitioners employ the extension of the Black-Scholes formula[8] to FX options by Garman and Kohlhagen (1983), according to which the value of a currency call option is given in accordance with equation (1) by

$$c^{fx}(S_t,\tau,X,\sigma,r,r^*) = e^{-r^*\tau}S_t\varphi\left[\frac{\ln(\frac{S_t}{X})+(r-r^*+\frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}}\right] - e^{-r\tau}X\varphi\left[\frac{\ln(\frac{S_t}{X})+(r-r^*-\frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}}\right] \quad (3)$$

where r and r^* represent the domestic and foreign risk-free domestic interest rate, $\varphi(.)$ is the standard cumulative normal distribution function and σ the volatility parameter. Hence, according to the Black-Scholes model, there is one-to-one mapping between the option price and the volatility parameter or, in other words, each option price determined in the market implies a unique volatility parameter σ. Therefore, in order to derive the RND, we first transform observed data on implied volatilities at time t into option prices as a function of the strike price.

First of all, we need to define the concept of moneyness. An option is said to be at the money if the strike price equals the price of the underlying asset. In contrast, a call (put) option is in the money if $S_t>X$ ($S_t<X$) or out of the money if $S_t<X$ ($S_t>X$). However, rather than in terms of the spot and the strike price the moneyness of an option is usually expressed by the option's delta. Delta is defined as the rate of change (first derivative) of the Black-Scholes option price with respect to the spot exchange rate:

$$\Delta(S_t,\tau,X,\sigma,r,r^*) = \frac{\partial c^{fx}(S_t,\tau,X,\sigma,r,r^*)}{\partial S_t} \quad (4)$$

Delta is thus a measure for the extent to which an option is exposed to changes in the price of the underlying asset and ranges between 0 and 1 in absolute value terms (negative for puts and positive for calls). An at-the-money option has a delta of approximately 0.5 in absolute value. The more an option is in the money, the closer its delta to 1; the more it is out of the money, the smaller its delta (in absolute values).

Although the Black-Scholes model assumes that irrespective of moneyness or time to maturity all options on the same currency have an identical implied volatility, in practice it is often observed that out-of-the money options have higher implied volatilities than at-the-money options. This phenomenon, often referred to as the volatility smile, suggests that the distribution of exchange rates has fatter tails (i.e. higher kurtosis) than the normal distribution.

Against this backdrop, in the first step we need to construct a continuous volatility smile from observable data. We do this in the spirit of Malz (1997) by inter-

[8] *While the Black-Scholes model, developed by Black and Scholes (1973) for pricing stock options, has facilitated the exponential growth of derivatives and is widely used, it is certainly not undisputed as it is based on several simplifying (arguably simplistic) assumptions. For example, one of the shortcomings of the Black-Scholes model is the mixing of discrete-in-time and continuous-in-price space. Problematic is also the fact that the model abstracts from important market elements (e.g. the role of liquidity) or real market features, particularly volatility smiles. (See below a brief discussion on the latter and e.g. Chorafas (2008) for a detailed discussion on the shortcomings of the Black-Scholes model).*

polating at each point in time a particular functional form through the prices of three commonly traded option products: (1) At-the-money forwards, for which the strike price corresponds to the forward price, (2) risk reversals and (3) strangles. The latter two are different combinations of out-of-the money call and put options. The interpolation function proposed by Malz (1997) is linear in the at-the-money volatility, the risk reversal price and the deviation of delta from 0.5, and quadratic in the strangle price and the deviation of delta from 0.5. Hence, we obtain a functional form for the volatility as a function of delta ($\sigma_t(\delta)$), which can be interpreted as a Taylor approximation to $\sigma_t(\delta)$ at $\delta=0.5$.[9]

As we eventually want to estimate the RND by second-differentiating equation (3) with respect to the strike price in accordance with equation (2), the thus far derived volatility smile in the delta-volatility space has to be translated in the next step into the strike price-volatility space. This can be easily done by substituting delta with the derivative of the Black-Scholes formula with respect to the strike price in the interpolated volatility smile function, so that we get $\sigma_t(\delta(S_t,\tau,X,\sigma,r,r^*)) = \sigma_t(X)$. Unfortunately, as this function cannot be inverted, we cannot solve for X analytically. However, we can use an iterative grid search procedure to find for each value of σ the corresponding value of X. We thus transform the interpolated volatility smile in the delta-sigma space into a continuous function in the strike price-volatility space.

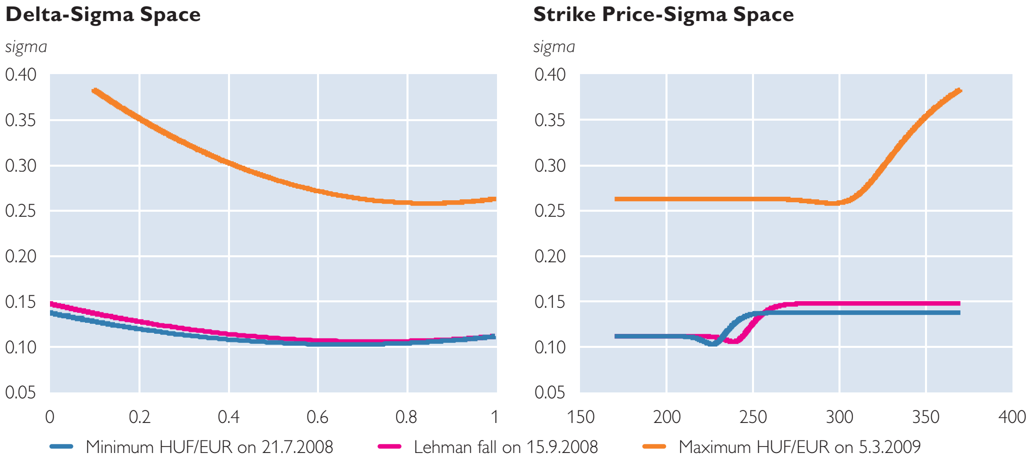
For the sake of illustration, the two panels of chart 2 show – for Hungary – the volatility smile for the option combination described above in the delta-sigma space and in the strike price-sigma space at three different points in time:

(1) On a representative day in tranquil times prior to the outbreak of the crisis,
(2) on the day of the Lehman Brothers collapse and
(3) on the day when the forint reached the trough vis-à-vis the euro.

The message to be taken out of chart 2 is twofold. On the one hand, it is evident that the implied volatility is higher in the out-of-the-money area (lower delta

Chart 2

Example of Volatility Smile: Hungary



Source: Authors' calculations.

[9] *See Malz (1997) for a detailed discussion.*

and higher strike price) of the combined option product. On the other hand, on the day of the fall of Lehman Brothers, the implied volatility of a particular delta/strike price did not rise significantly, but at the peak of the crisis, it was several times higher than in normal times.

Substituting in the next step the strike price-volatility combinations derived through the grid search into equation (3), we obtain a continuum of expressions for c_t^{fx}. The (numerical) second differentiation of the latter multiplied by $e^{r\tau}$ in accordance with equation (2) yields the risk-neutral probability density function. We can summarize the characteristics of the RND, using moments or other statistics derived from the estimated distributions. In our case, we calculate the standard deviation, skewness, kurtosis as well as the probability that the exchange rate will appreciate/depreciate by 3% or more, which we use in the forecasting exercise below.

3.2 Data and Some Basic Features of FX Option Markets in the CESEE-3

For the analysis in this paper, we use data on FX options for all of the CESEE-3 currencies. The FX markets in the CESEE-3 are structured as typical over-the-counter (OTC) markets, where most transactions take place in the interbank market, often with nonresident (London-based) banks or even between nonresident banks. Given the high relevance of the euro, euro options dominate the market.[10] Among nonfinancial institutions, export-oriented companies very often use option markets (via local banks) to hedge their FX risk. Their demand triggers further contracts as local banks hedge their option positions immediately with nonresident banks, usually their parent banks (ČNB, 2009).

Given the OTC nature of the FX option market and the fact that a number of FX option contracts are closed between nonresident institutions, it is difficult to get comparable and timely data on the size and liquidity of this market. One of the most reliable sources of comparable data is the Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity conducted by the BIS, of which the most recent run was organized in April 2007. According to these data, of the CESEE-3 currencies, the Polish złoty records the biggest FX option market in absolute terms, with an estimated daily average volume of USD 940 million. This contrasts with USD 269 million for the Hungarian forint option market and USD 226 million for the Czech koruna option market.[11] By way of comparison, the average daily turnover in the Swedish krona option market was USD 2,885 million.

The data are sourced from UBS and the exchange rate is quoted as domestic currency per euro. Given that UBS is not present locally in the CESEE-3 countries and serves as a typical nonresident counterparty in the option market, the data are representative of both the local (local interbank) and the nonresident (global interbank) market.

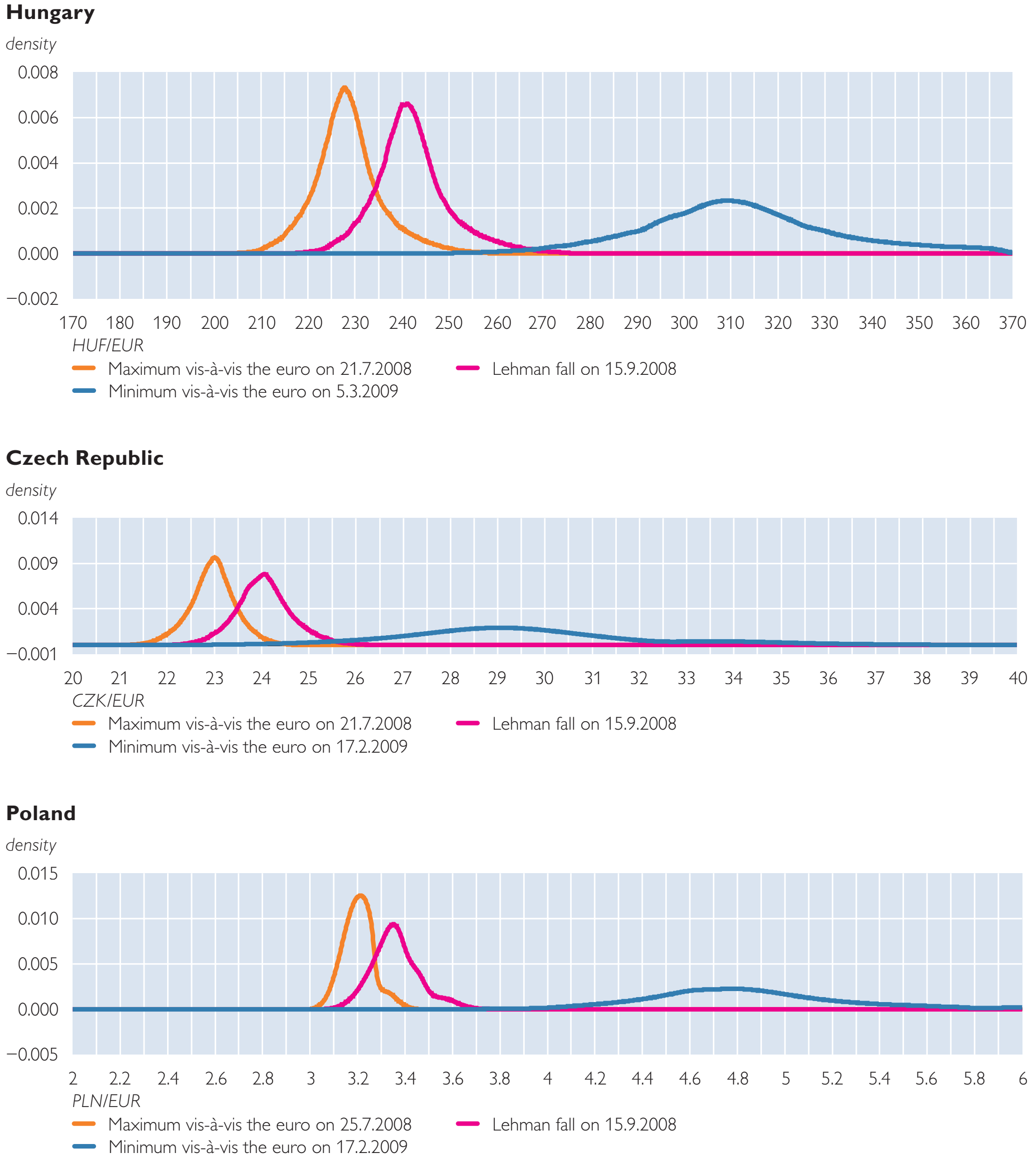
For our computations we use daily FX option data from the Czech Republic, Hungary and Poland for the period from April 1, 2003, to July 10, 2009. We make use of quoted one-month 25 delta put and 25 delta call option implied vola-

[10] *This was not always the case: As shown by Cincibuch and Bouc (2004), U.S. dollar options were as relevant as Deutsche mark options in the Czech Republic in 1997.*

[11] *The figure for the Czech Republic is comparable to the estimate of the average daily turnover in 2004 of around EUR 100 million given in Cincibuch and Bouc (2004).*

Chart 3

Risk-Neutral Probability Distribution Derived from the Implied Volatility



Source: Authors' calculations.

tilities as well as one-month ATM implied volatility. The reference exchange rate is domestic currency against the euro. As mentioned above, broader coverage of different delta put and call options would be preferable for estimating risk-neutral density, but such data are not available for all currencies and all times. Therefore, we transformed quoted implied volatilities into implied volatilities of risk reversal (25 delta call minus 25 delta put) and strangle (average of implied volatilities of 25 delta put and 25 delta call options minus ATM volatility) contracts.

The Malz (1997) method described above produces a risk-neutral density for each day for which option prices are available. Chart 3 illustrates RNDs for all three analyzed currencies on three specific dates during the crisis period:

(1) The peak (strongest value of the respective currency) in the safe haven period (July 2008),
(2) the Lehman Brothers fall on September 15, 2008, and
(3) the day on which the respective currencies were weakest vis-à-vis the euro in the risk aversion period (February or early March 2009).

Chart 3 shows that after the fall of Lehman Brothers a systematic move toward a weaker exchange rate took place (the mean of the distribution moved to the right in all three cases), but the uncertainty surrounding the average expected level increased only slightly (the bell shape is only slightly squeezed compared with the one before the crisis). In contrast, at the peak of the risk aversion period the currencies were expected to stay at a depreciated level and also the uncertainty was substantially higher.

4 Out-of-Sample Properties of Risk-Neutral Densities

4.1 Evaluating the Out-of-Sample Predictive Ability

In this section, we assess the out-of-sample forecasting ability of exchange rate models containing statistics based on the estimated densities described in the previous sections. We limit ourselves to the evaluation of the predictive power within the class of vector autoregressive (VAR) models, specified as

$$Y_t = A_0 + \sum_{j=1}^{p} A_j Y_{t-j} + \varepsilon_t \qquad (5)$$

where Y_t is a k-dimensional vector composed by the change in the (log) exchange rate and k–1 other variables, which are assumed to potentially contain information about future developments of the exchange rate. The vector of intercept terms is given by A_0, A_j, *for* $j=1 \ldots p$, which are assumed to be $k \times k$ matrices, and ε_t is a multivariate Gaussian error term with zero mean and a variance-covariance matrix Σ. In principle, several statistics obtained from the risk-neutral densities, as well as other explanatory variables, could be included in the VAR model given by (5), which gives rise to the extra problem of model uncertainty. Table 1 presents the variables we consider potential elements of the vector Y_t in our study. They include statistics from the estimated densities as well as other financial market variables, such as stock indices and short- and long-term interest rates.

The first issue is how to choose the set of variables which should be included in the forecasting model. We approach this issue of model uncertainty by using Bayesian model averaging techniques.[12] In concrete terms, the method we apply is an example of Bayesian Averaging of Classical Estimates (BACE) as presented by Sala-i-Martin, Doppelhofer and Miller (2004) and used in the framework of forecasting with VAR models by Crespo Cuaresma (2007). The intuition is to form weighted averaged predictions from all possible specifications in the model space. The weights are proportional to the explanatory power of the respective models for the exchange rate, once the inclusion of a large number of parameters was penalized. We build the weights, using the Bayesian Information Criterion (BIC) (Schwarz 1978),[13] whose use has been put forward in the literature as an instru-

[12] *See Doppelhofer (2008) for a survey on the issue.*

[13] *See Raftery (1995) for a discussion on the use of the BIC in model averaging.*

ment to obtain approximation of posterior model probabilities in the framework of Bayesian model averaging (Raftery, 1995, and Clyde, 2000).

Building weights for the predictions computed from the individual models presents an extra complication, which emanates from the large number of models in the space of possible specifications. Fixing the exchange rate as a variable in the vector Y_t and assuming that there are K potential variables to form VAR models such as (5) implies that there are $p2^K - (p-1)$ possible models to evaluate. For large values of K and if we allow for specifications with long lag lengths, this figure becomes intractable. Markov Chain Monte Carlo Model Composite (MC^3) methods have been proposed in the literature to deal with such large model spaces (Madigan and York, 1995). In our application, we make use of the MC^3 method to reduce the number of models that need to be evaluated.

The prediction exercise is carried out as follows. We use daily data on the variables listed in table 1 for the period from April 1, 2003, to July 10, 2009, and divide them into an in-sample period (April 1, 2003, to July 31, 2007) and an out-of-sample period (August 1, 2007, to July 10, 2009). We compute model averaged forecasts by obtaining h-steps ahead forecasts from the models employed and by expanding the in-sample period recursively. The model weights are obtained in each case by using the information criteria corresponding to the exchange rate equation in (5) and are interpreted as the posterior probability assigned to each particular specification. We also obtain the predictions of the single specification which has the highest posterior model probability, which we use as a benchmark for comparison.

An important statistic that can be obtained within the model averaging framework is the posterior inclusion probability of a given variable, which is defined as the sum of the posterior probability of the models containing this covariate. This statistic can be interpreted as the probability that a variable belongs to the true model. Using the posterior inclusion probabilities, we also compute an early warning indicator, which we call the financial sentiment indicator (FSI). The FSI summarizes the dynamics of the variables which contain information about future changes in the exchange rate according to the results of our analysis. The index is constructed as follows:

$$FSI_t = \sum_{j=1}^{K} \left[\left(\frac{y_{jt} - \overline{y_j}}{\sigma_{y_j}} \right) \frac{P(y_{jt} \mid D)}{\sum_{l=1}^{K} P(y_{lt} \mid D)} \right], \tag{6}$$

where y_{jt} is variable j, $j=1, ..., K$, and σ_{y_j} and $P(y_{jt} \mid D)$ are its standard deviation and posterior inclusion probability given data D, respectively.

In addition to the model averaged forecasts and the predictions of the model with the highest posterior probability (= "best" model), we also obtain predictions based on simple bivariate models including the exchange rate and the FSI (= index model).[14] We consider VAR models which include the exchange rate together with any subset of the variables in table 1, and up to five lags for all variables in the

[14] *Our depreciation and appreciation probabilities refer to a threshold of 3%. Results for a threshold of 5% were also obtained, which were qualitatively similar to those using 3%. The results using the 5% threshold are available from the authors upon request.*

Table 1

Variables Used in the Forecasting Exercise

Variable
Implied probability of an appreciation larger than 3%
Implied probability of a depreciation larger than 3%
Standard deviation of the risk-neutral density estimate
Skewness of the risk-neutral density estimate
Kurtosis of the risk-neutral density estimate
Stock returns (domestic economy)
S&P GSCI returns
EMBI returns
Stock returns (EUR)
Change in short-term interest rate differential with the euro area
Change in long-term interest rate differential with the euro area
EUR/USD exchange rate returns
Difference between implied appreciation and depreciation probabilities

Source: Compiled by authors, UBS.

model. This implies that our model space is composed of around 41,000 models. We use Markov Chain Monte Carlo (MCMC) methods to identify the most promising models in the model space. Starting with an estimated model M_j for a given in-sample period, we propose randomly, and then estimate, an alternative model from its neighborhood, defined as a model with one variable more or less and any number of lags. Let this model be denoted M_k. We move from M_j to this new model with a probability which is proportional to the exponent of the difference in the BIC for the exchange rate equation between M_j and M_k (see Raftery, 1995, or Clyde, 2000). This implies that we visit models which explain the data relatively well after accounting for the large number of parameters they include. Instead of computing and averaging predictions over the whole model space, we only average over the models visited by the chain. This procedure is repeated a large number of times and the models visited are recorded. In particular, we obtain out-of-sample predictions from each visited model, which we average in order to compute model averaged forecasts. We also identify the single model with the strongest data support (the model with the lowest BIC, which can be interpreted in Bayesian model averaging as the model with the highest posterior probability) and compute predictions based on this "best" model.

4.2 Out-of-Sample Forecasting Results

The results for each country are presented in table 2. We report the root mean square prediction error (RMSE), defined as $RMSE = \sqrt{\frac{\sum_{t=1}^{N}(S_t - \tilde{S}_t)^2}{N}}$, where S_t, $t=1, \ldots, N$ are the (log) exchange rate observations in the out-of-sample period (of size N) and $\tilde{S}_t$ is the corresponding prediction of the model. And we also report the direction of change (DOC) statistic, which measures the proportion of forecasts where the change in the exchange rate was correctly predicted. Since we use data on options with a maturity of one month, we compute the forecasts at a 22 days-ahead horizon, which is the natural predictive horizon of the computed risk-neutral densities. As a benchmark for comparisons, we also include the results corresponding to the random walk model, which predicts the exchange rate in 22

Table 2

Out-of-Sample Predictive Ability Results

Czech Republic	RMSE	DOC
Averaged forecasts	2.994	0.561
Best model	3.009	0.563
Index model	3.015	0.699
Random walk	2.938	–
Hungary	RMSE	DOC
Averaged forecasts	12.787	0.427
Best model	18.005	0.419
Index model	4.002	0.472
Random walk	2.938	–
Poland	RMSE	DOC
Averaged forecasts	4.604	0.528
Best model	4.680	0.514
Index model	4.139	0.465
Random walk	2.938	–

Source: Authors' calculations.

Note: The root mean square prediction error (RMSE) is the square root of the average forecasting error, while the direction of change (DOC) statistic measures the proportion of forecasts where the change in the exchange rate was correctly predicted. The benchmark DOC of the random walk model is assumed to be 0.5.

days to be equal to the exchange rate level today. The results indicate that none of the models entertained improves forecasts over the random walk model in terms of RMSE, which ties in with the above-mentioned stylized fact on the short-term forecasting of exchange rates (Meese and Rogoff, 1983).

In spite of the discouraging results based on RMSE, we found in our analysis of the CESEE-3 that risk-neutral densities nevertheless seem to provide some useful information on the direction of change of the exchange rate. In particular, the results for the Czech Republic indicate very large improvements in the direction of change statistic for all possible prediction strategies (averaged forecasts, best model and bivariate model based on the artificial financial sentiment index). A slight improvement is also obtained in the case of Poland, albeit only marginally over the 0.5 DOC statistic implied by the random walk model.

In table 3 we identify the variables that are chosen by our MCMC search as the most robust in-sample determinants of the exchange rate. In our application, the method tends to visit only few models after the burn-in phase, which implies that there are single specifications that explain exchange rate dynamics in our samples much better than the rest. This manifests itself in the relatively small differences in the predictive ability between averaged results and those implied by the best model in table 2. The variables chosen in the best model, which systematically coincide with those receiving large weights in the averaging technique and in the construction of the FSI, include in all cases variables related to market sentiment as measured by the risk-neutral densities. As the posterior model probability is concentrated in very few specifications, the FSI is practically an unweighted average of the indicators identified in table 3.

Overall, our results thus suggest that in the Czech Republic and in Poland most of the available information has been incorporated into the currency price. Some additional information can, however, be extracted from the markets, which is relevant enough to somewhat improve the ability to forecast exchange rates in the CESEE-3 compared with naïve forecasting models. In Hungary, in contrast, option prices do not seem to contain information that would substantially help forecast exchange rate movements. Our analysis does not allow for any conclusions on whether these differences stem from a different degree of market efficiency, the market structure and liquidity or the rather specific macroeconomic fundamentals and very volatile environment in Hungary.

While our results, which attest to a rather limited predictive power of FX options, may to a large extent contrast with the findings in the existing literature (see e.g. Cincibuch and Bouc, 2004), it should be borne in mind that we tested the

Table 3

Components of the Financial Sentiment Index by Country

Variable	Czech Republic	Hungary	Poland
Change in long-term interest rate differential with the euro area			
Change in short-term interest rate differential with the euro area		×	×
Difference between implied appreciation and depreciation probabilities	×	×	×
EMBI returns			
EUR/USD exchange rate returns			
S&P GSCI returns			
Implied probability of a depreciation larger than 3%	×	×	×
Implied probability of an appreciation larger than 3%	×	×	×
Kurtosis of the risk-neutral density estimate	×	×	×
Skewness of the risk-neutral density estimate		×	
Standard deviation of the risk-neutral density estimate	×	×	×
Stock returns (domestic economy)			
Stock returns (EUR)			

Source: Authors' calculations.

markets' predictive power in a substantially different environment. For instance, the paper by Cincibuch and Bouc (2004) analyzes the predictive power of FX options prior to the currency crisis in the Czech Republic in 1997, which was preceded by massive structural problems and disequilibria. The outbreak of this "homemade" crisis of the first generation type was basically only a matter of time, endogenously determined by the markets themselves. The authors thus conclude that high option prices might have revealed speculators' positioning before their attacking the Czech koruna.

However, the current financial and economic crisis was imported to the countries under study from outside and had little in common with the idiosyncratic fundamental development. The CESEE-3 were affected by the general decline in risk appetite traceable to a crisis triggered in mature economies. In this context, the current crisis is more of the second generation type, with the countries shifting from a sustainable to an unsustainable equilibrium as a consequence of an exogenous shock, a sun spot. Small wonder that such a sun spot was not anticipated by the markets. Hence, further research is certainly needed to identify the causes of these differences found across countries and time.

5 Summary and Conclusions

Given the rather unexpected and puzzling exchange rate development in some Central, Eastern and Southeastern European countries during the current financial crisis, we examine whether financial markets could have helped predict exchange rate changes in this period. In particular, we derive from the implied volatilities of FX options risk-neutral densities, which approximate market perceptions and expectations of future exchange rate developments. We employ a method developed by Malz (1997), which is based on the Black-Scholes option pricing formula and which entails interpolating a particular functional form through the prices of commonly traded option products at each point in time. Based on the thus derived risk-neutral densities, we compute various indicators which are supposed to exploit all the information contained in the distribution and therefore precisely describe market expectations about the exchange rate. Besides the moments of the distribution, we also calculate the probability that the exchange rate will appreciate/depreciate by 3% or more. Subsequently, we test the predictive power of these indicators and other financial sector variables in a VAR framework. We control for the high level of model uncertainty by employing Bayesian model averaging techniques.

We obtain mixed results on the predictive ability of market expectations as measured by the characteristics of the risk-neutral densities. Predictions based on models which include this information are inferior to those of the random walk in terms of the mean square forecasting error. Yet, risk-neutral densities seem to provide some useful information on the direction of change of the exchange rate for the Czech Republic and Poland. In contrast, option prices in Hungary do not seem to contain information on future exchange rate changes. In general, our results suggest a lower predictive power of FX options than the existing literature. Future research should thus focus on where the differences along the country and time dimensions come from, whether they have anything to do with different degrees of market efficiency and/or crisis generation and how the predictive power of financial markets changes in normal tranquil times. Our results indicate that the financial market information embodied in risk-neutral densities may contain interesting clues about exchange rate dynamics. RNDs may thus be a useful instrument for monetary authorities to learn about the expected exchange rate development.

Further research may shed light on the reasons for the differing results for the group of countries under study in this contribution. In particular, enlarging the set of models used to predict the exchange rate (by potentially including nonlinear models and specifications that explicitly account for the high frequency of the data) could improve the ability of risk-neutral densities to forecast exchange rates. On the methodological side, linking countries in the framework of a Global VAR (GVAR) model should prove to be a fruitful path of further research. In this case, the uncertainty concerning the choice of the weight variable linking countries together in the GVAR may also be modeled using Bayesian methods, such as those recently proposed by Crespo Cuaresma and Feldkircher (2009) for spatially correlated data. A generalization in this direction of the method put forward in this contribution would allow us to gain useful insights into contagion processes during financial crises. The model space may also be enlarged by including univariate or multivariate nonlinear time series specifications (e.g. Markov switching, threshold models, smooth transition models, to name the most popular ones), which would shed light on parameter heterogeneity and structural breaks in the data.

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