Can Trade Partners Help Better FORCEE the Future? Impact of Trade Linkages on Economic Growth Forecasts in Selected CESEE Countries

Tomáš Slačík, Katharina Steiner, Julia Wörz¹ For Central, Eastern and Southeastern European (CESEE) countries, the euro area is the most important export destination. Nevertheless, geographical export patterns differ among individual CESEE countries, and economic growth within the euro area has diverged in the run-up to and since the economic and financial crisis. We therefore examine the effects such heterogeneous developments have had on trade — and thus economic growth — in CESEE. Given the importance of such spillovers for macroeconomic projections, we evaluate the OeNB's macroeconomic forecasting model (FORCEE) for Bulgaria, Croatia, the Czech Republic, Hungary, Poland and Romania. The FORCEE model captures trade spillovers via aggregate demand from the euro area. We challenge this simplification by introducing a more differentiated representation of the regional structure of trading partners. Our results show that such a modification improves the forecasting performance of our structural macro model in particular for the three Southeastern European countries in our sample. However, our tests do not yet account for the additional uncertainty introduced into the model by broadening the set of external assumptions, when we cover external demand from a wider range of partner countries.

IEL codes: C14, C53, E37, F17

Keywords: trade linkages, forecasting; Central, Eastern and Southeastern Europe

Given the importance of economic growth spillovers, euro area GDP growth is a crucial ingredient in the OeNB's macroeconomic forecasting model FORCEE. This time series-based, structural macro model delivers the basis for our semiannual GDP and import projections for six Central, Eastern and Southeastern European (CESEE) countries (Bulgaria, Croatia, the Czech Republic, Hungary, Poland and Romania).² More specifically, for each country's exports, the model captures growth spillovers through the trade channel via external demand from the euro area. To date, we have relied on aggregate euro area demand as a proxy for external demand for each of our six focus countries. However, this simplification might have become questionable in recent years for two related reasons. First, the literature on global value chains suggests a division of supply chains into a European core and a considerably less integrated European periphery. While the core – through trade in tasks – extends to Central and Eastern Europe (CEE), the periphery includes both the Southern European cohesion countries and the Southeastern European (SEE) countries. Second, and presumably related to this, in recent years we have witnessed increasingly divergent economic developments

Oesterreichische Nationalbank, Foreign Research Division, tomas.slacik@oenb.at and julia.woerz@oenb.at, and Financial Stability and Macroprudential Supervision Division, katharina.steiner@oenb.at. We would like to thank Krystian Pawlowski for his research assistance and Peter Backé, Helmut Elsinger, Martin Feldkircher (all OeNB), Achim Zeileis (University of Innsbruck) and an anonymous referee for their valuable comments. All errors remain our own

² In this context, the OeNB additionally cooperates with the BOFIT on the macro forecast for Russia, with the BOFIT responsible for the model-based GDP projections (see the article by Rautava, 2013, in the previous issue).

between euro area members in the core and in the southern periphery. This divergence has been a salient feature in the run-up to the euro area debt crisis, and differences in terms of growth performance have been rather persistent since then. Thus, the euro area aggregate, which serves as our proxy for external demand, does not reflect the current heterogeneity among the individual euro area members. In fact, the aggregate is dominated by developments in Germany and thus mainly representative of the core.

At the same time, the regional trade structures of the six CESEE countries covered in our projections differ greatly. While Germany and other core euro area members are the dominant trading partners for the three CEE countries (the Czech Republic, Hungary and Poland), the three SEE countries (Bulgaria, Croatia and Romania) trade predominantly with partners in the southern euro area periphery. Furthermore, neighboring Eastern European countries are frequently among the five most important individual trading partners for many CESEE countries, a fact which has not been reflected in our projection model so far.

This paper investigates whether a more precise representation of the regional structure of trading partners — by capturing the economic heterogeneity within the euro area — improves the forecasting accuracy of the OeNB's macroeconomic projection model FORCEE. Given the importance of external demand for GDP growth in the six CESEE countries — all of them being small, open economies —, the modeling of external demand is likely to have a noticeable impact on the quality of GDP forecasts. A number of empirical papers also confirm that macro forecasts improve if international linkages are taken into account by including GDP series of a number of related countries as control variables in a VAR or VECM model (e.g. Bańbura, Giannone and Reichlin, 2010; Pesaran, Schuermann and Smith, 2009; Giannone and Reichlin, 2009).

The strong influence of external demand from Western Europe on economic growth in CESEE is also confirmed by recent OeNB research based on global VAR models (Feldkircher, 2013; and Backé, Feldkircher and Slačík, 2013). Feldkircher (2013) develops a global VAR model, which allows for regional differentiation within CESEE and which he uses to simulate four different shock scenarios. His model confirms that the propagation of euro area output shocks to CESEE is substantial in general (a 1% increase in euro area output translates into a permanent rise in CESEE output of approximately 0.6%). But the magnitude of the spillover varies within the region and small, open economies such as Slovenia, Slovakia, Croatia, Romania and Ukraine seem particularly susceptible. Building on the model by Feldkircher (2013), Backé, Feldkircher and Slačík (2013) model trade and financial spillovers simultaneously and find both channels to be of a similarly strong importance for five Central and Eastern European economies (the Czech Republic, Hungary, Poland, Slovakia and Slovenia). Likewise, the IMF (2012) estimates in its Spillover Report a 0.4% decrease in CESEE³ GDP in response to a 1% decrease in Western European GDP through the trade channel alone. Thus, changing economic conditions in the euro area impact considerably on economic growth in the CESEE countries; between one-third and one-half of an output

The IMF's CESEE aggregate covers 22 countries, including e.g. the Eastern European EU Member States, Russia and other CIS countries as well as Turkey.

shock in Western Europe is transmitted to Eastern Europe according to the recent empirical literature. In summary, this effect is not only found to be statistically significant, but also economically meaningful.

Such large spillover effects seem plausible given the strong trade linkages between Western and Eastern Europe. These linkages are likely to gain further strength in view of the increasing integration of CESEE countries into Europewide supply chains. Recent empirical research on the importance of global value chains highlights the formation of three major regional supply chains in the world. For example, Baldwin and López González (2013) identify the "factory Europe," with Germany as the headquarter economy that arranges European production networks and CESEE countries as the major "factory economies" that provide labor in this production network. A recent IMF staff report deals more specifically with the "German-Central European Supply Chain" which has evolved since the 1990s and which has led to a rapid expansion of bilateral trade links between Germany, the Czech Republic, Hungary, Poland and Slovakia (IMF, 2013). Both studies reveal that CEE economies are integrated into European production chains most strongly, while the more peripheral SEE economies seem to be far less affected by changes in demand originating from the Germany-dominated European supply chain. Hence, the region shows a considerable amount of heterogeneity in this respect. Unfortunately, such peripheral European supply chains are by far less well researched. However, a simple comparison of regional trade patterns already reveals the smaller importance of Germany for these countries. As a consequence, economic shocks affecting the euro area's core should impact primarily on the CEE countries, while SEE economies are likely to be more susceptible to economic developments in their main trading partners.

The paper is structured as follows: Section 1 describes the regional patterns of trade linkages for the six CESEE countries under examination, section 2 gives a brief description of the economic and econometric properties of the FORCEE model, section 3 describes the approach we use for assessing and comparing the forecasting accuracy of both models, and section 4 describes our results. Finally, section 5 concludes.

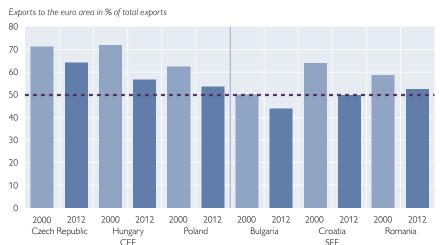
1 Regional Differentiation and Changes in CESEE Export Patterns

At least since the trade liberalization in the 1990s, Western European countries have been among the top export destinations for CESEE producers. Between 1995 and 2012, more than 50% of total exports from the Czech Republic, Croatia, Hungary, Poland and Romania on average went to euro area countries. However, trade patterns vary across countries and time. The euro area was by far the most important trade partner for the Czech Republic, with 64% of Czech exports destined for this market in 2012. In contrast, the SEE countries are less involved in euro area trade, as evidenced by their 2012 export shares of 50% (Croatia) and 44% (Bulgaria, see chart 1). The SEE countries also focus on export destinations outside the European Union, but tend to trade mostly with EU countries. Croatian exports were largely oriented toward the Western Balkan countries given Croatia's

⁴ The share of total exports to the EU-27 on average amounted to more than 70%.

Chart 1

Share of Euro Area Exports Is Downtrending, but Still Largely above 50%



Source: IMF DOTS, authors' calculations.

Note: CEE = Central and Eastern European countries; SEE = Southeastern European countries

membership in the Central European Free Trade Agreement (CEFTA)⁵. When it joined the European Union in July 2013, Croatia had to resign from CEFTA, and the Croatian industry might further redirect its exports in the future.

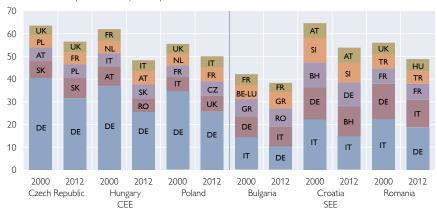
Between 2000 and 2012, the importance of the euro area as an export destination declined somewhat for all countries in our sample. The greatest amount of export reorientation — away from the euro area toward partners in CESEE, including Turkey and the CIS — was observed for Hungary and Croatia.

The regional trade structures of the six CESEE countries covered in our projections show a great deal of differentiation (chart 2). While Germany and other core euro area members are the dominant trading partners for the CEE countries, the SEE countries trade predominantly with partners in the southern euro area periphery. In 2012, the share of exports to Germany and Italy was almost equal for both Bulgaria and Romania. However, this had not always been the case. In 2000, Italy used to be the main export destination within the EU for Bulgaria and Romania. In part due to declining import demand from Italy in the wake of the economic and financial crisis in 2008, Germany emerged as the leading export destination. On the other hand, Germany had continuously lost importance as an export destination for the CEE countries and Croatia, at least since the end of the 1990s. Another common characteristic besides the dominance of Germany and Italy is that at least one neighboring CESEE EU country featured among the five most important trade partners for all six countries in our sample in 2012.

⁵ CEFTA is a trade agreement between Southeastern European countries, namely Albania, Bosnia and Herzegovina, the former Yugoslav Republic of Macedonia, Moldova, Montenegro, Serbia and Kosovo (as at November 2013).

Regional Trade Patterns Differ among Central, Eastern and Southeastern European Countries

Five main EU trade partners in % of total exports



Source: IMF DOTS, authors' calculations

Note: CEE = Central and Eastern European countries; SEE = Southeastern European countries.

To sum up, the euro area as an aggregate remained the most important export destination for five of the six CESEE countries under review between 2000 and 2012, although its share in the total exports of these countries declined somewhat. We observe, however, that exporters react rather swiftly to changes in import demand by redirecting their exports toward more promising markets. As long as the euro area as a whole remains the major export destination, the composition of exports will not greatly impact the performance of the forecasting model as such. Yet, the different export destination patterns might well matter for the forecasting accuracy of the model at a time when the speed of economic growth between countries in the euro area's core and in the South is diverging and there are differences in the regional trade structure between the CESEE countries. Furthermore, the rising importance of neighboring Eastern European EU countries as trading partners for many CESEE countries has not yet been reflected in our projection model. These aspects would favor a modified approach to proxying external demand in the forecasting model via import demand from the respective major trading partners. The following sections will shed more light on these issues.

2 The OeNB's FORCEE Forecasting Model

The FORCEE model is a country-specific structural error correction model used by the OeNB's Foreign Research Division to forecast GDP and imports of non-euro area CESEE EU members. The model output underpins the expert-based projections which are published semiannually in the Focus on European Economic Integration (in every second and fourth issue per year). The core part of the econometric model consists of six structural cointegration relationships, linking private consumption, gross fixed capital formation, exports, imports, interest rates and exchange rates with the remaining variables in the model. This demand side-oriented model follows closely the aggregate demand-aggregate supply model in Merlevede, Plasmans and Van Aarle (2003) and is described in more detail in Crespo Cuaresma et al. (2009).

The long-run equilibrium relationships in the model are predominantly Keynesian with stable consumption, investment, import and export ratios, but also include some neoclassical features, such as the dependence of private consumption on interest rates. The short-term interest rate is estimated by an augmented Taylor rule, and the formation of exchange rates is based on the flexible price monetary approach, thus resting on the purchasing power parity condition in its weak form. The core structure of the model is given by the structural equations (1) to (6) below:

$$c_priv = \alpha_1 * gdp + \alpha_2 * (ir - \Delta cpi) + \alpha_3 * wage$$
 (1)

$$inv = \beta_1 * gdp + \beta_2 * (ir - \Delta ppi) + \beta_3 * priv_credit$$
 (2)

$$exp = \gamma_1 * ip + \gamma_2 * (er * \frac{cpi - ea}{cpi}) + \gamma_3 * gdp - ea + \gamma_4 * exp - ea$$
 (3)

$$imp = \delta_1 * gdp + \delta_2 * (er * \frac{cpi - ea}{cpi})$$

$$\tag{4}$$

$$ir = \phi_1 * ppi + \phi_2 * \Delta gdp + \phi_3 * er + \phi_4 * ir_ea$$
 (5)

$$er = \kappa_1 * (m3 - m3 ea) + \kappa_2 * (gdp - gdp ea)$$
(6)

GDP is calculated as the sum of its components. The remaining GDP components (public consumption and stock changes) as well as all other exogenous variables entering the model are assumed to follow simple AR(1) processes, which is least costly in terms of degrees of freedom loss.⁶

While referring the interested reader to Crespo Cuaresma et al. (2009) for a more detailed discussion of the model, let us go briefly through the economic intuition behind the equilibrium relationships above: Private consumption (c priv) is determined by the consumption-to-GDP ratio and nominal interest rates (ir) deflated by consumer prices (cpi). Furthermore, labor market variables (wages in this case) are included to capture households' and companies' cyclical positions. In the same vein, the investment equation is modeled as a function of GDP (gpd) and the interest rate (ir) deflated by producer prices (ppi) plus a variable capturing financial conditions. In times when credit to the private sector (priv_credit) is high, firms and households are likely to use this liquidity for investments. Exports depend primarily on supply capacity as given by industrial production (ip) and the real exchange rate (er*cpi ea/cpi) as an indicator of price competitiveness. It is here that we include external demand via euro area GDP (gdp ea). Moreover, euro area exports (exp_ea) are included as a proxy for global trade volume and reflect trends in world trade which are common to all countries.⁷ The import equation is again characterized by a constant import-to-GDP ratio, where GDP approximates

⁶ In most cases the optimal lag length proved to be 1, therefore the results do not change significantly if the optimal lag length of each AR process is chosen according to standard information criteria.

⁷ In the initial version of the model, we used EU exports, which capture a slightly larger share of world exports. The switch to euro area exports improved the quality of the external assumptions as we are now able to use the confidential quarterly export forecast from the ECB's macroeconomic projection exercise.

domestic demand⁸ and the real exchange rate covers price effects. The short-term interest rate is following an augmented Taylor rule determined by inflation (cpi), nominal interest rates in the euro area (ir_-ea) and the output gap (proxied very roughly by the first difference of GDP, Δgdp), as well as the nominal exchange rate (er).⁹ Finally, exchange rates are determined by differences in money supply and activity between the respective country and the euro area.¹⁰ As the majority of foreign trade in our sample is denominated in euro, we consider this specification to be appropriate for modeling the exchange rate.

The core model is modified to respond to country-specific characteristics. To this end, we drop highly insignificant variables and include additional or differentiated variables (e.g. we use the unemployment rate instead of wages in equation (1) for some countries) to obtain a good fit to the data. A major deviation from the standard model is implemented for Bulgaria due to the currency board arrangement: here the exchange rate is kept constant and interest rates are modeled as a markup over euro area interest rates.

The whole system of six structural equations and roughly ten AR processes is estimated by means of seemingly unrelated regressions to account for correlations between the model components through the unobserved correlation in the error terms. The model contains also purely exogenous variables, such as euro area GDP, euro area exports, euro area inflation rates and euro area interest rates. These variables are taken from the most recent ECB forecast. Furthermore, an identity equation for GDP, which is simply the sum of its components, is included. 1- to 8-step ahead dynamic forecasts are then derived from the structural parameters of the model.

In what follows, we scrutinize the role of external demand for the forecast accuracy of our model. In equation (3) above, external demand is captured by aggregate demand from the euro area. As we have shown above, the euro area is the most important trading partner for all the six CESEE countries. However, within the euro area, different Member States emerge as the most important destinations for goods exports. This — coupled with the increased (and to date persistent) heterogeneity in economic growth within the euro area — may result in a poor forecasting performance. Therefore, we modify the model, introducing external demand in a more differentiated way into our model, to reflect the intra-euro area heterogeneity. We include the GDP of each country's five main trading partners separately. This alternative specification takes into account different growth prospects of individual trading partners as well as the fact that non-euro area members (in particular neighboring CESEE EU countries) are among the most important individual trading partners for some countries.

We experimented with a more detailed specification of domestic demand, using only the respective components of GDP (private and public consumption, gross fixed capital formation). However, this introduced strong feedback loops between the respective equations and resulted in great volatility in out-of-sample predictions. Furthermore, all CESEE countries are characterized by a strong export-import nexus in line with their integration into global supply chains. Thus, aggregate GDP can be considered to be a good proxy for import demand.

⁹ In this specification we differ from Merlevede, Plasmans and Van Aarle (2003).

According to economic theory, the interest rate differential would also determine exchange rate formation. We decided to exclude this variable, however, as it caused overly strong feedback loops with the previous equation in the model, which would result in high volatility in out-of-sample predictions.

Thus, we modify the FORCEE model by replacing equation (3) with equation (3a):

$$exp = \gamma_1 * ip + \gamma_2 * (er * \frac{cpi - ea}{cpi}) + \sum_{i=1}^{5} \varphi_i * gdp_i + \gamma_4 * exp_ea$$
 (3a)

where euro area GDP is replaced by the GDP of the five most important trading partners for each country. The five most important trading partners are defined as those with the largest share in each country's exports calculated as the average over the entire period. There is a clear tradeoff between the two specifications: the modified model captures heterogeneous economic developments among a country's most important trading partners, while the benchmark model captures a larger fraction of external demand. If the modified model (which captures only a lower share of external demand) produces more accurate forecasts than the benchmark model, we may safely conclude that more weight should be given to heterogeneity among trading partners.

Although it is not our focus here to analyze in detail where improvements in forecasting accuracy arise from, we would like to mention that the design of a theoretically sound comparison is far from trivial. Such a comparison should differentiate between a change in the number of trading partners and the role of heterogeneous developments within the euro area¹² and could involve two steps: First, we would replace euro area GDP in equation (3) by individual GDP series for all euro area members and compare the results. Second, we would augment this new specification by adding GDP series of the major non-euro area trading partners (mostly neighboring CESEE countries) and assess the magnitude of additional gains. This comes at the cost of using up a large number of additional degrees of freedom, though.¹³ Given the short time series for CESEE countries, such statistical considerations play a nonnegligible role and would render a meaningful estimation impossible.¹⁴ Alternatively, one could work with trade-weighted averages of trading partner blocs (euro area versus non-euro area). While such an approach would save degrees of freedom, the assignment of trade weights over the projection horizon is highly problematic. Hence, we opt for a simple comparison between two practically feasible model specifications without trying to split the gains in forecasting accuracy between considering additional trading partners versus respecting heterogeneity among trading partners.

Naturally, this set of five most important trading partners would need to be revised regularly as regional trade patterns are constantly changing.

 $^{^{12}}$ We thank the referee for making this point.

A further limitation to the number of trading partners included arises from the practical use of the model in semiannual forecasting rounds: external demand is purely exogenous, hence the GDP forecasts for trading partners are not generated by the model itself but have to be taken from other sources. This can become a tedious and possibly insurmountable task if a large range of non-euro area countries is included in the specification. Generating GDP forecasts for trading partners through AR processes within each model would not be feasible either as this violates a common set of exogenous assumptions for all countries.

Alternatively, we could have included a trade-weighted GDP aggregate of the most important trading partners. However, we feel that our current specification allows for more flexibility with respect to changing weights. In our current specification, trade weights are implicitly captured in the estimation coefficient and will thus be adjusted in each forecasting round. Otherwise we would need to make an assumption on future weights.

Each country model is estimated based on quarterly data from Eurostat ranging from the first quarter of 1995 to the fourth quarter of 2012.¹⁵ The country models for Bulgaria and Romania are estimated on a slightly shorter time period: suitable time series for Bulgaria start in the first quarter of 1997, and, given the lack of quarterly GDP series for Greece, one of Bulgaria's main trading partners, our sample ends with the first quarter of 2011. Data for Romania start in the first quarter of 2000, thus we exclude the recession years in the late 1990s. All data are seasonally and working day adjusted and deflated by using chained linked values.

In view of the regional export patterns, we expect the results to differ most in the forecasts for Bulgaria and Romania. For these two countries, the most important trade partners were Italy and Germany — in other words, two countries that have shown markedly different economic developments, especially in recent years, and are thus likely to show dissimilar developments in import demand.

3 Validation of the Predictive Power of Competing Models

To evaluate the forecasting power of the FORCEE model with respect to precision and its ability to correctly capture a variable's direction of change, we produce ex post out-of-sample forecasts by using a rolling window approach in the following way: We cut out a window of eight quarters at the beginning of the sample and use the remaining data to simultaneously estimate the parameter values for our modified, i.e. five main trading partner, model on the one hand and the benchmark model on the other. Using these parameter estimates, we produce an out-of-sample forecast with both models — the modified model and the benchmark model — for 1 to 8 quarters for the eight-quarter window previously cut out. The forecasting errors are computed by comparing both sets of forecasts with actual realizations. This eight-quarter window is subsequently moved one quarter ahead, the models are reestimated and new out-of-sample forecasts are obtained for the new eight-quarter window. This procedure is repeated until the window reaches the end of the sample, and all available observations are used to estimate the model parameters. ¹⁶

For each of the eight forecasting horizons, we compute three quality indicators to evaluate the forecasting ability of our models: the root mean squared error (RMSE), the Diebold-Mariano test and the hit rate. The RMSE is a measure of forecasting accuracy and is defined as

$$RMSE_{h} = \sqrt{\frac{\sum_{n=1}^{N_{h}} (\hat{g}_{n} - g_{n})^{2}}{N_{h}}},$$

where N_h is the number of h-steps ahead forecasts computed, g_n is the actual value of the respective variable and \hat{g}_n is the corresponding forecast. The Diebold-

We extrapolated time series at the beginning of our sample with monthly data from the Vienna Institute for International Economic Studies and from national sources in cases where the Eurostat time series did not go back to 1995.

¹⁶ In a few cases, the rolling procedure of the forecast window has to be adjusted given data peculiarities caused by the economic transition at the beginning of the sample and the outbreak of the crisis. For certain (very few) forecasting windows, the constellation of the remaining data used for parameter estimation resulted in a nearsingular covariance matrix for the coefficient estimates and thus made the model crash. Hence, such periods were skipped and the forecasting window simply moved one step ahead.

Mariano test (Diebold and Mariano, 1995) is based on the null hypothesis stating that the forecasting ability of the modified model and of the benchmark model is equal. In our case we apply a one-sided test of the null hypothesis that the RMSE of the benchmark model is smaller than or equal to the RMSE of the modified model. If we can reject the null hypothesis, we may conclude that the modified model beats the benchmark model in terms of forecast accuracy.

The hit rate computes, for a given horizon, the percentage of cases in which the forecast movement direction of a variable relative to its previous level coincides with the direction of change of the realized data. In other words, it gives the percentage of cases where the model correctly predicts the sign of the quarter-on-quarter growth rate. Formally, the hit rate for a horizon h (HR_h) is defined as follows:

$$HR_h = I \text{ if } \{(g_{t+h} - g_t) > 0 \text{ and } (\hat{g}_{t+h} - g_t) > 0\} \text{ or if } \{(g_{t+h} - g_t) < 0 \text{ and } (\hat{g}_{t+h} - g_t) < 0\}$$

and
 $HR_h = 0 \text{ else.}$

 g_{t+h} denotes the actual value of the respective variable h steps ahead from time t while \hat{g}_{t+h} is again the corresponding forecast. We then test for the difference between the hit rate of the modified model and the hit rate of the benchmark model, using a binomial test for paired samples.¹⁷

4 Results

Tables 1 to 6 report the results of the Diebold-Mariano test and the binomial test on differences in hit rates between the modified and the benchmark model for each country. GDP and imports are the most important variables as projections for these two variables are published semiannually. In the tables below, we also report the results for exports (as this variable is directly affected by the modification) and for gross fixed capital formation (GFCF). Tables 1 to 3 give the results for the three CEE countries and tables 4 to 6 for the three SEE countries. Details on the actual hit rates and the root mean squared errors are given in the annex (see tables A1 to A6). Overall, the results do not only show country differences, but also differences according to variables.

As an important observation, we find that the modified model performs at least as well as, and in many cases outperforms, the benchmark model. Thus, controlling for heterogeneity in the economic developments of major trading partners does not worsen the forecasting performance of the model. Let us focus on forecasting accuracy first: The Diebold-Mariano test performed on the difference between the root mean squared errors of both model specifications should give a significant and negative test statistic if the model incorporating five main trading partners beats the standard model (with the euro area as the proxy for external demand). Since we are only interested in whether our modification lowers the

To respect the fact that the two samples — the forecasts under the modified and the benchmark model — are paired is important, since the probability of hitting the correct sign is not time invariant. The hit rate depends on the realization and differs between turbulent (crisis) times and stable growth periods. Moreover, it has to be noted that due to the small number of observations, we are not likely to obtain a statistically significant result even when we observe an economically highly relevant difference. Please refer to the tables A1 to A6 in the annex for the fraction of hit rates in each model specification.

root mean squared forecasting error, we perform a one-sided test and, hence, any t-value lower than -1.645 reported in the tables 1 to 6 below can be interpreted as showing the modified model to be more precise. In the Czech Republic, the modified model gives better results than the benchmark model for imports and exports for all forecasting horizons, yet the forecasting accuracy of GDP and GFCF is not improved. For Hungary, the results are sketchy, with the forecasting accuracy according to the Diebold-Mariano test only higher for imports, GFCF and GDP for some forecasting horizons, mostly the nearer-term forecasts. In contrast, for Poland, there are many cases where the modified model delivers a more accurate forecast than the benchmark model. Especially exports are predicted with higher precision at all horizons, and the same is true for the remaining three variables at longer-term horizons (i.e. 4 to 8 quarters ahead).

For the SEE countries, forecasting accuracy is significantly higher in all three countries for 4- to 8-step ahead GDP forecasts. In Bulgaria and Croatia, gross fixed capital formation is predicted with higher accuracy, and Croatia shows some improvements in import forecasts. Finally, we obtain better GDP and import forecasts for Romania at (almost) all horizons and also better near-term export forecasts.

While the results are somewhat mixed with respect to forecasting accuracy, the modified model clearly produces the correct direction of the predicted variable more often than the benchmark model. Analyzing quarter-on-quarter changes, we assess which model specification is better able to capture cyclical movements. This difference is not always statistically significant, with the three CEE countries a case in point. For the three SEE countries, however, the modified model clearly shows better hit rates in a number of cases. We also obtain better results for Hungary for many variables, especially for exports. In contrast, the differentiation in trading partners does not improve the hit rate for Poland and the Czech Republic meaningfully. These results stand in contrast to the previous results, where the modified model for Poland yielded the strongest improvements in terms of forecasting accuracy, followed by the modified models for Romania and Croatia.

Table 1

Comparison of Forecast Accuracy for the Czech Republic

GDP			Imports		Exports		GFCF	GFCF	
Horizon	Diebold- Mariano	Difference in hit rates							
1	1.08	0.55	-2.46	0.06	-2.17	0.04	-3.19	1.00	
2	-0.13	0.13	-2.00	0.07	-1.99	0.13	-1.63	0.22	
3	0.25	0.22	-1.97	1.00	-2.24	1.00	-1.38	0.25	
4	0.53	1.00	-2.06		-2.48	1.00	-1.24	0.69	
5	0.49	1.00	-2.15	1.00	-2.47	1.00	-0.86	0.63	
6	0.44	0.38	-2.12	1.00	-2.41	0.50	-0.39	0.13	
7	0.19	0.63	-2.07	0.50	-2.42	0.50	-0.03	1.00	
8	-0.25	1.00	-2.14	0.50	-2.53	0.13	-0.23	1.00	

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Table 2

Comparison of Forecast Accuracy for Hungary

	GDP		Imports		Exports		GFCF	
Horizon	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates
1	-2.08	0.23	-1.84	0.50	-1.54	0.25	-1.85	0.06
2	-1.79	0.39	-1.46	1.00	-1.54	0.13	-2.51	0.02
3	-1.40	0.07	-1.59	0.25	-1.45	0.03	-2.64	0.01
4	-1.27	0.29	-1.66	0.06	-1.34	0.02	-2.79	0.73
5	-1.25	0.04	-1.73	0.03	-1.31	0.01	-1.02	1.00
6	-1.26	0.04	-1.68	0.06	-1.29	0.00	0.07	1.00
7	-1.26	0.02	-1.55	0.25	-1.28	0.00	0.43	1.00
8	-1.26	0.13	-1.43	0.38	-1.26	0.02	0.58	1.00

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Table 3

Comparison of Forecast Accuracy for Poland

	GDP		Imports		Exports		GFCF	
Horizon	Diebold- Mariano	Difference in hit rates						
1	-0.89	0.55	-0.24	0.75	-4.68	0.02	0.00	0.69
2	-1.71	0.69	-0.01	1.00	-2.81	0.04	-0.64	0.38
3	-1.99	0.38	-1.27	0.63	-2.20	0.22	-1.16	0.38
4	-2.20	1.00	-1.41	1.00	-2.27	0.25	-1.64	0.38
5	-2.26	1.00	-1.66	1.00	-2.36	1.00	-2.01	1.00
6	-2.41	1.00	-2.09	1.00	-2.49	0.50	-2.37	1.00
7	-2.63	1.00	-2.46	1.00	-2.61	0.50	-2.70	1.00
8	-2.92	1.00	-2.92	1.00	-2.87	1.00	-2.88	0.69

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Table 4

Comparison of Forecast Accuracy for Bulgaria

	GDP		Imports		Exports		GFCF	
Horizon	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates
1	2.32	0.63	-1.55	0.45	-1.44	0.55	-2.82	0.01
2	0.55	0.18	-1.19	1.00	-2.04	0.01	-1.97	0.04
3	0.46	0.58	-1.46	0.79	-2.01	0.00	-2.52	0.01
4	-1.36	0.29	-1.55	0.04	-1.21	0.00	-2.24	0.00
5	-2.35	0.15	-1.61	0.07	-0.74	0.00	-2.35	0.00
6	-2.97	0.00	-1.37	0.04	-0.39	0.01	-2.49	0.00
7	-2.90	0.00	-1.55	0.07	-0.02	0.30	-2.71	0.00
8	-3.80	0.00	-1.34	0.04	0.21	0.21	-2.97	0.00

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Table 5

Comparison of Forecast Accuracy for Croatia

	GDP		Imports		Exports GFCF			
Horizon	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates	Diebold- Mariano	Difference in hit rates
1	-1.10	0.39	-2.02	0.02	-2.18	0.12	-2.03	0.45
2	-1.20	0.04	-1.82	0.04	-1.36	0.58	-1.97	0.04
3	-1.32	0.18	-1.87	0.02	-1.16	0.17	-2.23	0.11
4	-1.38	0.73	-1.63	0.00	-1.32	0.00	-2.11	0.09
5	-1.65	0.73	-1.64	0.06	-1.37	0.01	-2.20	0.04
6	-2.15	1.00	-1.72	0.00	-1.47	0.15	-2.26	0.00
7	-2.01	0.29	-2.10	0.02	-1.56	0.73	-2.21	0.00
8	-2.16	0.22	-1.94	0.01	-1.56	0.07	-2.15	0.00

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Table 6

Comparison of Forecast Accuracy for Romania

	GDP		Imports		Exports		GFCF	
Horizon	Diebold- Mariano	Difference in hit rates						
1	-0.52	0.38	-1.73	0.03	-3.57	0.27	-1.55	0.25
2	-1.70	0.38	-1.68	0.03	-3.39	0.30	-1.50	0.13
3	-1.83	0.13	-1.68	0.02	-2.91	0.55	-1.45	0.01
4	-1.83	0.22	-1.67	0.01	-2.66	0.18	-1.46	0.01
5	-1.88	0.02	-1.70	0.07	-2.04	0.51	-1.47	0.01
6	-1.89	0.45	-1.71	0.02	-1.23	0.39	-1.47	0.00
7	-2.01	0.07	-1.67	0.45	-0.94	0.04	-1.47	0.01
8	-2.04	0.02	-1.65	0.45	-0.70	0.04	-1.47	0.00

Source: Authors' calculations.

Note: "Diebold-Mariano" shows the t-value of the one-sided Diebold-Mariano test on the difference between the modified and the benchmark model, with statistically significant values at the 5% level marked in bold. "Difference in hit rates" gives the p-value of a binomial test on the differences between the hit rates of either model specification, with statistically significant values at the 10% level marked in bold.

Thus, our initial expectation was met by the results. We expected to see stronger improvements in the forecasting ability of our structural macro model for the SEE economies, given the marked differentiation in the geographical structure of external demand between SEE and CEE countries. Interestingly, our initial specification of external demand is more in accordance with the CEE countries' actual export structure. Poland represents a positive exception to this, showing a significant improvement in forecasting accuracy.

5 Summary and Conclusions

The OeNB produces semiannual forecasts for six Central, Eastern and South-eastern European countries with its macroeconomic forecasting model FORCEE, using aggregate euro area GDP growth as a proxy for external demand. Yet, there are two factors that call for a differentiated approach to modeling external demand in the OeNB's model. First, these six CESEE countries show different regional

structures in terms of their main trading partners. Also, the growth paths within the euro area are likewise diverging. Given recent developments, the question arises whether the model's forecasting performance would benefit from capturing these differing geographical trade patterns. We therefore modified the FORCEE model to capture external demand in each of the six country models by including the individual GDP growth rates of each country's main trading partners.

This modification of the model entails practical and statistical issues and does not come at zero cost. From a statistical point of view, we lose degrees of freedom in an error-correction model, where a large number of endogenous variables is estimated on a relatively short time series. Furthermore, by splitting a single variable for external demand into a number of different time series, we introduce additional volatility into the model. In particular, we generate feedback loops between individual country models that had previously been estimated separately and had been connected only by the common set of external assumptions, most prominently by the assumption about the future development of external demand from the euro area. Hence, from a practical point of view, implementing the modification implies a strong dependence of each model's predictions on reliable estimates of future developments in individual trading partners. In other words, the modified model should significantly improve forecasting ability to justify the extra costs and additional amount of uncertainty associated with the modification.

We tested for the difference in forecasting performance between the two model specifications by comparing ex post out-of-sample forecasts over the entire sample period, using a rolling window approach. We based our assessment on root mean squared errors, the Diebold-Mariano test (which compares root mean squared errors of both model specifications) and a hit rate comparison (i.e. we compared the fraction of cases where each model predicts a quarter-on-quarter movement in the same direction as the respective realization of a variable). Our results showed that the modified model performs at least as well as, and in many cases significantly better than, the benchmark model. In particular, both forecasting accuracy and the hit rate are statistically significantly better for the three Southeastern European countries, especially for Romania and Croatia. Given this evidence, it might well be worthwhile to implement a modification to the model structure in order to better capture differences in external demand – if not for all, at least for some – of the countries in question.

However, the results were not always clear cut: While forecasting accuracy often improved in the Polish model, the hit rate did not significantly improve in statistical terms and the absolute difference in hit rates exceeded 5 percentage points in only 5 of the 32 cases we investigated (32 predictions for four time series and eight different forecasting horizons). While our hit rate for the Southeastern European countries (Bulgaria, Croatia and Romania) often improved significantly – especially when forecasting imports and gross fixed capital formation as well as GDP in the longer run –, the root mean squared error improved significantly only in less than half of all possible cases. By contrast, for the 1-step ahead GDP forecast for Bulgaria, the outcome was significantly worse, but this was the only incidence where forecasting accuracy had deteriorated as a result of the model modification.

Furthermore, these results do not represent the full degree of uncertainty underlying out-of-sample forecasts. In future forecasting rounds, the actual improvement in terms of forecasting accuracy will to a large extent also depend on the quality of the estimates of GDP growth in the main trading partners. It is not possible to account for this additional uncertainty about external assumptions in our empirical test.

Thus, the jury is still out and will probably be influenced to a large extent by future developments within the euro area: If economic developments inside the euro area become more homogenous as a result of diminishing imbalances, it will be less important to model external demand in a differentiated way. On the other hand, if CESEE countries increasingly reorient their trade from partners inside toward partners outside the euro area, then a differentiated approach should be implemented to capture economic developments in such new and increasingly important trading partners.

References

- **Backé, P., M. Feldkircher and T. Slačík. 2013.** Economic Spillovers from the Euro Area to the CESEE Region via the Financial Channel: A GVAR Approach. In: Focus on European Economic Integration Q4/13. 50–64.
- **Baldwin, R. and J. López González. 2013.** Supply-Chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses. CEPR Working Paper 9421 and NBER Working Paper 18957.
- **Bańbura, M., E. Giannone and L. Reichlin. 2010.** Large Bayesian vector auto regressions. In: Journal of Applied Econometrics 25. 71–92.
- Crespo Cuaresma, J., M. Feldkircher, T. Slačík and J. Wörz. 2009. Simple but Effective: The OeNB's Forecasting Model for Selected CESEE Countries. In: Focus on European Economic Integration Q4/09. 84–95.
- **Diebold, F. X. and R. S. Mariano. 1995.** Comparing Predictive Accuracy. In: Journal of Business and Economic Statistics 13. 253–263.
- Feldkircher, M. 2013. A Global Macro Model for Emerging Europe. OeNB Working Paper 185.
- **Giannone, D. and L. Reichlin. 2009.** Comments on "Forecasting economic and financial variables with global VARs." In: International Journal of Forecasting 25. 684–686.
- IMF. 2012. Spillover Report. IMF Policy Papers. http://www.imf.org/external/np/pp/eng/2012/070912.pdf (retrieved on November 14, 2013).
- **IMF. 2013.** German-Central European Supply Chain Cluster report. IMF Multi-Country Report 13/263.
- **Merlevede, B., J. Plasmans and B. Van Aarle. 2003.** A Small Macroeconomic Model of the EU-Accession Countries. In: Open Economies Review 14. 221–250.
- **Pesaran, M. H., T. Schuermann and L. V. Smith. 2009.** Forecasting economic and financial variables with global VARs. In: International Journal of Forecasting 25. 642–675.
- **Rautava, J. 2013.** Oil Prices, Excess Uncertainty and Trend Growth A Forecasting Model for Russia's Economy. In: Focus on European Economic Integration Q4/13. 77–87.

Annex

Table A1

RMSE and **Direction** of **Change – Czech Republic**

	GDP				Imports				
	RMSE		Hit rates RMSE Hit r				Hit rates	lit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	8,975	7,812	0.77	0.82	15,552	17,724	0.79	0.70	
2	13,267	13,478	0.80	0.88	18,608	24,580	0.88	0.77	
3	16,506	15,926	0.86	0.93	21,641	31,262	0.91	0.91	
4	18,882	17,050	0.91	0.91	24,272	37,084	0.96	0.96	
5	20,705	18,700	0.93	0.95	26,110	42,001	0.96	0.95	
6	21,777	19,764	0.89	0.95	26,927	45,558	0.96	0.95	
7	22,531	21,656	0.91	0.95	26,648	48,040	0.96	0.93	
8	23,149	24,145	0.91	0.93	28,068	50,923	0.93	0.89	

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

Table A1 continued

RMSE and Direction of Change – Czech Republic

	Exports				GFCF			
	RMSE		Hit rates		RMSE		Hit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
1	11,985	17,354	0.82	0.70	6,455	7,396	0.73	0.71
2	15,216	27,153	0.91	0.82	9,235	10,595	0.75	0.68
3	15,706	33,192	0.93	0.91	10,497	12,538	0.75	0.70
4	17,525	39,151	0.98	0.96	11,494	13,031	0.75	0.71
5	18,076	44,576	0.98	0.96	12,201	13,113	0.79	0.75
6	17,662	49,180	0.96	0.93	12,609	13,025	0.88	0.80
7	18,186	53,174	0.96	0.93	12,620	12,649	0.86	0.84
8	18,747	56,373	0.98	0.91	12,598	12,830	0.84	0.86

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, \ normalized \ between \ 0 \ and \ 1.$

RMSE and Direction of Change – Hungary

	GDP				Imports			
	RMSE		Hit rates		RMSE		Hit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
1	66,129	108,376	0.66	0.53	133,000	150,737	0.82	0.76
2	123,692	226,958	0.58	0.47	210,210	261,028	0.82	0.79
3	229,170	464,146	0.53	0.37	329,716	424,377	0.87	0.79
4	406,761	914,726	0.47	0.37	479,295	623,373	0.89	0.76
5	636,223	1,530,206	0.42	0.24	656,794	873,023	0.84	0.68
6	922,177	2,401,554	0.45	0.26	855,143	1,172,942	0.82	0.68
7	1,264,124	3,593,996	0.39	0.21	1,102,806	1,587,632	0.71	0.63
8	1,672,037	5,234,758	0.32	0.21	1,414,624	2,172,965	0.66	0.58

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

Table A2 continued

RMSE and Direction of Change – Hungary

	Exports				GFCF			
	RMSE		Hit rates		RMSE		Hit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
1	109,401	167,465	0.82	0.74	24,888	31,354	0.84	0.71
2	218,187	368,417	0.84	0.74	37,649	50,591	0.76	0.58
3	405,458	723,010	0.76	0.61	50,958	66,241	0.79	0.58
4	671,366	1,290,432	0.79	0.61	66,249	81,658	0.68	0.63
5	993,085	2,061,676	0.71	0.50	87,724	97,590	0.71	0.68
6	1,386,588	3,135,056	0.66	0.42	116,052	114,363	0.66	0.66
7	1,862,773	4,622,790	0.66	0.42	150,911	134,068	0.66	0.66
8	2,445,706	6,702,508	0.55	0.37	191,251	157,657	0.63	0.63

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, normalized \ between \ 0 \ and \ 1.$

RMSE and Direction of Change – Poland

	GDP				Imports			
	RMSE		Hit rates		RMSE		Hit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
1	2,766	3,435	0.85	0.78	5,166	5,241	0.54	0.49
2	3,080	4,310	0.88	0.93	6,872	6,877	0.76	0.73
3	3,273	6,698	0.88	0.95	8,563	9,298	0.78	0.73
4	4,169	7,872	0.98	0.95	9,705	10,860	0.85	0.85
5	5,121	10,022	0.98	0.95	10,426	11,831	0.88	0.90
6	6,330	10,778	1.00	0.98	10,624	13,041	0.85	0.85
7	7,362	12,494	1.00	0.98	10,861	13,607	0.80	0.83
8	8,346	13,103	1.00	0.98	11,119	14,768	0.78	0.76

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, \ normalized \ between \ 0 \ and \ 1.$

Table A3 continued

RMSE and **Direction** of Change – Poland

	Exports				GFCF			
	RMSE		Hit rates		RMSE		Hit rates	
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark
1	2,656	4,834	0.88	0.68	1.059	1.059	0.73	0.78
2	3,610	7,492	0.88	0.71	1,712	1,775	0.78	0.85
3	4,610	9,475	0.95	0.85	2,260	2,497	0.78	0.85
4	5,922	11,198	0.85	0.78	2,814	3,421	0.73	0.80
5	7,084	12,533	0.88	0.85	3,383	4,515	0.73	0.76
6	7,869	13,151	0.85	0.80	4,050	5,902	0.73	0.73
7	7,892	12,961	0.93	0.88	4,774	7,535	0.68	0.71
8	8,281	12,636	0.93	0.90	5,607	9,420	0.66	0.61

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

RMSE and Direction of Change - Bulgaria

	GDP				Imports				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	352	201	0.68	0.76	609	669	0.56	0.65	
2	427	388	0.68	0.82	716	860	0.62	0.62	
3	494	458	0.85	0.76	887	1,213	0.71	0.65	
4	552	742	0.88	0.76	1,004	1,399	0.79	0.56	
5	566	844	0.85	0.68	1,042	1,736	0.79	0.59	
6	684	1,147	0.85	0.50	1,255	1,821	0.79	0.56	
7	721	1,204	0.91	0.56	1,290	2,166	0.79	0.59	
8	770	1,473	0.88	0.47	1,411	2,106	0.82	0.59	

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

Table A4 continued

RMSE and Direction of Change - Bulgaria

	Exports				GFCF				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	348	500	0.74	0.65	126	165	0.65	0.41	
2	439	746	0.82	0.56	216	274	0.79	0.59	
3	537	941	0.85	0.47	311	408	0.88	0.59	
4	754	1,090	0.91	0.50	383	550	0.88	0.56	
5	970	1,226	0.94	0.47	469	700	0.91	0.56	
6	1,202	1,344	0.79	0.44	529	826	0.97	0.56	
7	1,372	1,379	0.68	0.53	586	962	0.88	0.47	
8	1,515	1,442	0.71	0.53	649	1,055	0.91	0.50	

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, normalized \ between \ 0 \ and \ 1.$

RMSE and Direction of Change - Croatia

	GDP				Imports				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	1,018	1,454	0.67	0.56	1,171	1,439	0.79	0.59	
2	1,571	2,146	0.79	0.59	1,522	2,472	0.82	0.62	
3	2,231	3,093	0.74	0.62	1,878	3,051	0.72	0.49	
4	3,006	3,887	0.67	0.62	2,249	4,187	0.74	0.38	
5	3,692	4,660	0.54	0.59	2,761	4,716	0.69	0.49	
6	4,396	5,405	0.56	0.56	3,297	5,412	0.72	0.44	
7	5,243	6,226	0.59	0.49	3,752	5,893	0.59	0.36	
8	6,054	6,988	0.56	0.46	4,251	6,601	0.59	0.36	

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, \ normalized \ between \ 0 \ and \ 1.$

Table A5 continued

RMSE and **Direction** of Change – Croatia

	Exports				GFCF				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	685	1,175	0.69	0.51	742	884	0.74	0.67	
2	1,033	1,640	0.77	0.69	1,052	1,390	0.82	0.62	
3	1,381	2,286	0.72	0.54	1,186	1,750	0.79	0.64	
4	1,778	3,146	0.77	0.49	1,509	2,249	0.82	0.64	
5	2,180	3,533	0.77	0.54	1,843	2,790	0.82	0.59	
6	2,667	3,877	0.62	0.46	2,104	3,305	0.85	0.51	
7	3,262	4,313	0.44	0.38	2,328	3,785	0.85	0.51	
8	3,801	4,631	0.46	0.31	2,522	4,241	0.90	0.49	

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

RMSE and Direction of Change - Romania

	GDP				Imports				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	1,014	1,074	0.81	0.73	1,795	2,344	0.86	0.70	
2	1,168	1,560	0.95	0.86	3,256	4,399	0.92	0.76	
3	1,366	2,537	0.95	0.84	4,206	6,594	0.95	0.76	
4	1,763	3,900	0.95	0.84	5,021	8,783	1.00	0.78	
5	2,147	5,106	0.95	0.76	5,660	11,461	0.92	0.76	
6	2,419	6,667	0.86	0.78	5,966	13,660	0.92	0.73	
7	2,616	7,888	0.92	0.76	6,188	16,472	0.81	0.73	
8	2,767	9,294	0.95	0.76	6,468	19,438	0.78	0.70	

Source: Authors' calculations.

Note: "RMSE" values are given in million local currency; "Hit rates" are given as a percentage, normalized between 0 and 1.

Table A6 continued

RMSE and Direction of Change – Romania

	Exports				GFCF				
	RMSE		Hit rates		RMSE		Hit rates		
Horizon	Model	Benchmark	Model	Benchmark	Model	Benchmark	Model	Benchmark	
1	734	1,068	0.81	0.68	804	1,125	0.86	0.78	
2	1,010	1,637	0.78	0.65	1,589	2,537	0.92	0.81	
3	1,385	2,035	0.78	0.70	2,382	4,215	0.97	0.76	
4	1,927	2,582	0.84	0.70	3,095	6,140	0.97	0.76	
5	2,579	3,200	0.81	0.73	3,622	8,169	0.97	0.76	
6	3,157	3,719	0.78	0.68	4,038	10,374	0.97	0.70	
7	3,711	4,312	0.84	0.62	4,330	12,712	0.95	0.70	
8	4,376	4,987	0.86	0.65	4,542	15,284	0.95	0.65	

Source: Authors' calculations.

 $Note: "RMSE" \ values \ are \ given \ in \ million \ local \ currency; "Hit \ rates" \ are \ given \ as \ a \ percentage, normalized \ between \ 0 \ and \ 1.$