LAJOS TAMÁS SZABÓ

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Forecasting external demand using BVAR models*

(A külső kereslet előrejelzése BVAR modellekkel)

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“Past is the form of present; future is the fragrance of present.”

Sándor Weöres

Contents

Abstract

As the impact of monetary policy decisions manifests itself with a lag, decision-makers also need economic forecasts when they make decisions. In this paper, we present a method that may facilitate the integration of incoming data in the external demand forecast faster than is currently possible. The external demand forecast helps to forecast exports and, through that, developments in GDP. In the current practice, for the imports of Hungary's key trading partners we use the forecasts of international institutions as a starting point. Data received in the meantime can be included in the forecast using expert judgements. With the method described in this paper, we forecast the imports of Hungary's key trading partners – and with the help thereof – their external demand, relying on BVAR models and using monthly time series (confidence indices, industrial production, orders). Based on the literature, we use the Kalman filter to eliminate the differences in the publication lags of the individual time series. The missing variable is then forecast using the other variables. The forecasts thus obtained perform better than the best ARMA models, and the model containing global imports and the oil price. With one exception, the forecast of the imports of the individual countries is more accurate when prepared on the whole sample, rather than on the rolling sample. The forecast of external demand is also more accurate if we use the whole sample. The most accurate BVAR model used to forecast external demand provides an unbiased forecast and also yields a better forecast of turning points than the models used for comparison. Compared to the forecasts of international institutions, the BVAR forecast performs better when actual import data from the respective year are already available. Thus, compared to previous practice, the novelty is represented by the BVAR methodology and the monthly time series, which can be integrated into the forecast in a formalised manner. Looking ahead, it may also be worthwhile to forecast GDP components using this method.

Journal of Economic Literature (JEL) codes: C11, F17, F47
Keywords: BVAR, forecast of external demand

1 Introduction

Forecasts are of key importance in the decision-making of central banks. As Carriero et al. (2015) also note, the impact of monetary policy decisions appears with a lag in the economy, and thus decision-makers must also bear in mind the forecasts for the various economic variables.

According to the MNB's current practice, the quarterly Inflation Report provides a forecast – in addition to other factors – for the import demand of Hungary's export markets, i.e. the average imports of Hungary's key trading partners calculated with Hungarian export weights. The forecast for external demand supports the projection of Hungary's exports, which is an important factor of economic growth in a small open economy.

In current practice, we weight the forecast of three institutions (European Commission, IMF, OECD) for the imports of Hungary's key trading partners together with Hungarian export weights. However, these projections are generally available twice a year.

In this paper, we present a method used in the literature, with which the import growth of Hungary's main trading partners is forecast using short-term indicators. Thereafter, we project external demand on the basis of these forecasts. With the use of these indicators we can only improve our external demand forecast in the short term (1-4 quarters). As far as we know, to date no forecast has been prepared for Hungarian external demand using BVAR models. In the central bank's practice up to now, in the periods between the international forecasts, it was only possible to integrate new information into the external demand forecast through expert judgement. The practice presented in this paper provides a formalised solution for the use of incoming data.

The publication dates of the monthly indicators used do not coincide. In order to eliminate this effect, we use the Kalman filter based on Bańbura – Rünstler (2011) to forecast the individual missing values relying on the available time series.

The forecast is generated using the Bayesian VAR equations. As also noted by Bańbura et al. (2010), VAR models are usual and widely applied analytical and forecasting tools in macroeconomics. When making forecasts relying on BVAR models, it must be decided which priors and time lags are to be used. We choose the model with the smallest Schwartz information criterion on the whole sample for the forecasting of each country and external demand. In accordance with the central bank's practice to date, we prepare a point forecast.

Chapter 2 provides a brief description of the antecedents in the literature on this topic. Chapter 3 presents the MNB's current practice of forecasting external demand. Chapter 4 provides an overview of the data used. Chapter 5 describes the method of selecting the countries to be analysed, briefly presents how the Kalman filter can be used to forecast the missing monthly time series, and reviews the questions arising in respect of the BVAR methodology when used for forecasting external demand. Chapter 6 describes the estimates by countries and evaluates the forecast of external demand. Chapter 7 summarises the results obtained and highlights some potential additional areas of application in Hungary.

2 Literature review

A range of publications have appeared on the topic, and the contents of some of these are described in the following.

Jakab et al. (2000) forecast Hungarian external demand and exports and evaluated the results of the various forecast models. In comparing the forecasts, they considered two criteria: on the one hand, the forecast accuracy, measured by the mean squared error, and on the other hand, the forecast stability, i.e. the time elapsing from the receipt of new data until the change in the forecast. As the measure of stability, they applied – following the mean squared error – the mean square revision. They used the forecast of external demand for the forecast of exports. The authors took the ARIMA model as the starting model and compared their forecasts to this. In addition to forecasting the dynamics of the time series, they also forecast the time series and components broken down in different ways (e.g. HP, BP filter) into trend and cycle. On the whole, they found that – in the case of external demand – the forecast prepared using 3SLS filtered by the Hodrick-Prescott filter performed the best in both approaches. The result of the export forecast was not clear-cut, since there was no forecast which was better according to both criteria.

Golinelli – Parigi (2014) forecast global trade and GDP developments on the basis of monthly data using different approaches. They forecast the quarterly national accounts data by monthly times series. The authors examine two groups of countries: in addition to the developed countries, they also use data for some emerging countries. The countries analysed by the authors account for 70 per cent of global GDP. They take the quarterly average of the monthly figures, thereby bridging the difference in frequencies. Similarly to the practice described in Chapter 5, when one or two months are missing from a quarter, they forecast the monthly time series using supplementary models to obtain data for the whole quarter. The performance of the forecasts improved and the RMSE became smaller when a smaller sample was used for the forecast, since they eliminated structural breaks with higher probability in this way.

In order to forecast the imports of certain countries, we also use confidence indicators. Based on the research to date, the various confidence indicators improve the projection of individual macro variables. In respect of Hungary, it was Vadas (2001) who first examined the correlation of consumption and the GKI confidence indices. He found that the responses to certain sub-questions significantly facilitated the forecast for household consumption expenditures. According to the research of Pula – Reiff (2002), the business activity surveys help forecast manufacturing output in the short run.

Bańbura – Rünstler (2011) came to the conclusion that, due to their quick availability, confidence indicators are particularly useful for forecasting real variables. Hüfner – Schröder (2002) examined several confidence indicators to determine whether they help forecast the performance of the German economy. According to their results, the Ifo, PMI and ZEW indices helped forecast German industrial production. Červená – Schneider (2014) also used confidence indicators for the forecasting of Austrian GDP.

3 Current practice

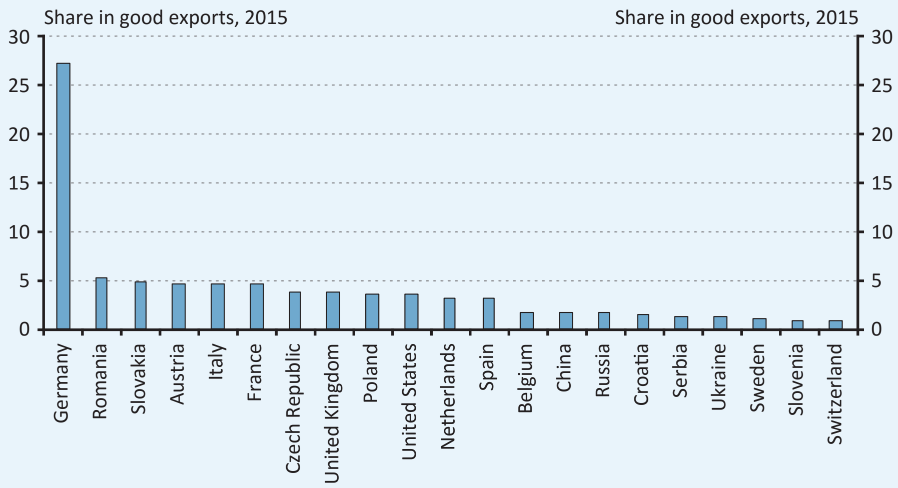
In its quarterly Inflation Report, the MNB also publishes a forecast for the size of Hungary's export market (external demand). In this forecast, we weight the import volume of Hungary's 21 largest trading partners in accordance with their weight in Hungarian exports. The growth forecast for Hungary's export markets facilitates the projection of Hungarian exports (in addition to external demand, growth in exports is also influenced by other factors, such as export market share, real exchange rate).

In the external demand forecast, we use the country forecasts of three institutions (European Commission, IMF, OECD). Not all institutions provide a forecast for all individual countries, and thus the weighted values are not fully comparable. In addition, the publication of these forecasts does not coincide with the information base of the Inflation Report, and thus the gap between the forecast used and the information base of the Inflation Report may be as much as one and a half months. Hence, it makes sense to also use the monthly data published in the meantime. Until now, this took place in the form of expert adjustment; however, formal use of the data has not yet been resolved. The practice presented in this paper also represents a step forward, in addition to the approach used.

4 Data used

In calculating the external demand of the actual period, we weight the import volume of Hungary's 21 largest trading partners (Chart 1) based on their weight in Hungarian goods exports (the weights may change from year to year).

Chart 1
Weight of individual countries in Hungarian goods exports
(2015)



Source: HCSO.

In order to forecast the imports of the individual countries, we use the ESI indicators, the industrial production of the individual countries, the industrial orders and – in the case of euro area countries – the EABCI (euro area business confidence indicator). In addition to the aforementioned, the forecast is supported with the ZEW and IFO indicators in the case of Germany, and the OECD CLI indicators in the case of Russia.

For all of the countries, the dependent variable is the seasonally adjusted import volume, in the form of 2000=100 per cent.

The ESI data are available for the EU Member States and for candidate countries. The ESI confidence indices in the EU Member and candidate countries are prepared by different research institutions delegated by the European Commission. One of the key objectives of the ESI indices is to provide a view of economic agents' (households, corporations) judgement and to identify changes occurring in the business cycle. Publication of the ESI indices precedes the regularly published statistical figures, and hence it shows the potential changes and reversals earlier. The ESI indices also have the advantage that they use standard methodology and their time series are long; consequently, they can be compared both in time and in cross section.

In addition to the ESI main index, we also use the sector (industry, services, construction, retail trade) and the consumer confidence indices. The sub-indices of the main sectors (e.g. industry, construction, services) are compiled based on questions related to, among others, production prospects, orders, inventories, factors limiting production and capacity utilisation. In addition, households also have their own questionnaire, containing questions on the financial situation, consumer prices, general economic situation and savings. In the individual cases, the number of respondent corporations and households is typically between 500 and 5,000, varying by country. For details on the methodology, see EC (2016).

During the forecast, we attempted to use a time series as independent variables that are available with a relatively small lag. The various confidence indicators are already available in the reporting month (e.g. ESI, EABCI) or in the first weeks after the reporting month. Another advantage they offer is that they are not revised.

In the case of Russia, we also used monthly OECD CLI data. In contrast to the ESI indices, these indicators are prepared from regularly published statistical series rather than from questionnaire-based surveys. Their purpose is to identify turning points in economic activity and business cycles (for more details, see Gyomai – Guidetti (2012)). Compared to the ESI data, their disadvantage is that they are not available so swiftly.

The other type of time series is related to industrial production (level of industrial output, orders). We chose these times series, because in the past decade one half of Hungarian exports consisted of industrial commodities and capital goods. Consequently, the evolution of industrial production in Hungary's external markets has a substantial impact on Hungary's export opportunities.

The order data for the individual countries are also available in more detail (domestic orders, export orders, total orders). In this case, similarly to the ESI indices, we choose the series with the best forecast capability (for more details, see the description of the individual countries). Table 1 shows the data available by country.

Table 1
Time series used in the forecast

	AT	DE	FR	IT	RO	RU	SK	UKR
ESI	X	X	X	X	X		X	
Industrial production	X	X	X	X	X	X	X	X
Orders	X	X		X				
EABCI	X	X	X	X			X	
Other		ZEW, IFO				OECD CLI		

In order to generate proper estimates, we would need the import data available at the time of the estimation (vintage data) since these are revised in the meantime. However, these are not available, and thus we carry out the estimation without these data.

5 Methodology

5.1 SELECTING THE COUNTRIES

In respect of the countries selected for the forecast of external demand, the volume and "usefulness" of the used data should be assessed. In respect of the small-weight countries, the forecast prepared for the given country does not significantly improve the external demand forecast. We use two selection approaches. One of them simply considers the weight of the given countries in Hungarian external trade, while the other one considers the weighted variance of the countries' imports.

Based on the weights, countries whose share exceeds 4 per cent are included in the forecast. Based on this criterion, we selected 6 countries (Germany, Romania, Slovakia, Austria, Italy and France), which covered 50-60 per cent of Hungarian exports in the past 10 years.

As the goal is to forecast the change in external demand as accurately as possible, it is also worth examining which countries' import variance makes the largest contribution to the variance of external demand. To this end, we need to break down the variance of the change in external demand to the weighted sum of the individual countries' variance (and covariance).

External demand is obtained on the basis of equation (1).

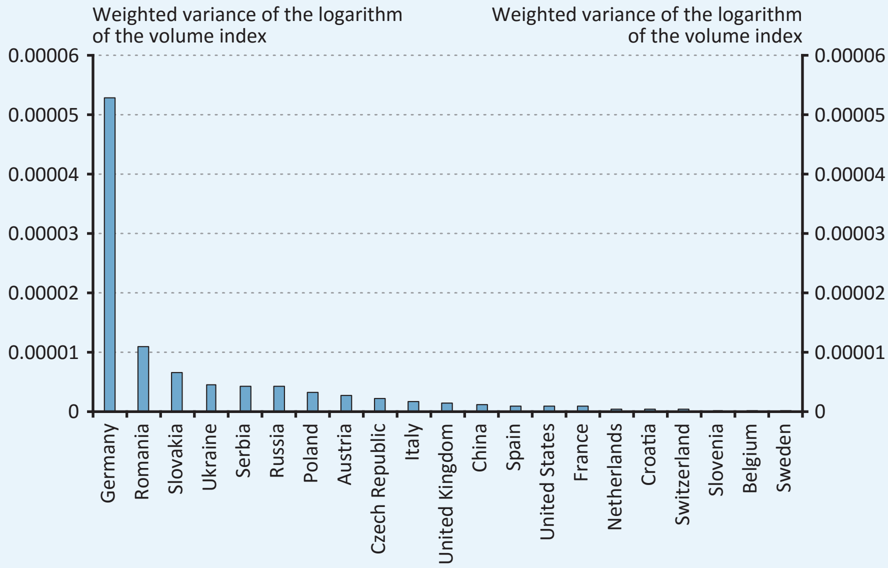
$$extD_t = \sum_{i=1}^{21} w_{it} imp_{it} \tag{1}$$

where t denotes the quarters and i denotes the countries. It follows from the foregoing that:

$$var\left(dlog\left(extD_t\right)\right) = \sum_{i=1}^{21} w_i^2 var\left(dlog\left(imp_{it}\right)\right) + \sum_{i \neq j} w_i w_j cov\left(dlog\left(imp_{it}\right), dlog\left(imp_{jt}\right)\right) \tag{2}$$

For the purpose of our analysis, the first terms of equation (2) are important, i.e. the squared weighted terms of the individual countries' variance. Since the weights appear as squared terms, the countries with decreasing weight must have increasing variance to be in the front of the line. Based on the weighted variance, the first three countries are already among the selected countries. Germany's weighted variance exceeds the sum of the weighted variance of all other countries, and thus its inclusion is justified based on both analyses (Chart 2). Based on the ranking, we also included Ukraine and Russia in the forecast, since in the past years their average weight exceeded 2 per cent. Had we included the covariance, the modelling of external demand would rely on a completely different model (e.g. global VAR, factor model), and thus we do not use it in this paper.

Chart 2
Squared weighted variance of the individual countries' imports
(2000-2015)



Source: Own calculation based on HCSO.

5.2 KALMAN FILTER

We use monthly time series for the forecast of quarterly import data. However, these data are not published simultaneously and are not necessarily available for the same horizon. Thus, based on Bańbura – Rünstler (2011), with the help of the individual monthly time series we forecast the time series which is unavailable. In the case of Germany, the confidence indices help forecast industrial production (simultaneous equation system 1).

Estimation using the Kalman filter is performed with the state-space model, which contains two types of equations. The connection between the observable and non-observable variables describes the observation equation. The status equations describe the non-observed variables. The volatility of the non-observed variables may be influenced by the error terms' variance relative to each other. However, in relation to the estimation of the non-accelerating inflation rate of unemployment (NAIRU), Driver et al. (2006) and Ball – Mankiw (2002) write that there is no generally accepted rule as to the basis that can be used for selecting the proper ratio. For the detailed methodology of the Kalman filter, see Hamilton (1994b).

$$
\begin{gathered}
esi = esit \\
ifo = ifot \\
ip = ipt \\
esit = \beta_1 esit_{-1} + \beta_2 ifo_{-1} + \beta_3 ip_{-1} + \beta_4 + \varepsilon_1 \\
ifot = \beta_5 esit_{-1} + \beta_6 ifo_{-1} + \beta_7 ip_{-1} + \beta_8 + \varepsilon_2 \\
ipt = \beta_9 esit_{-1} + \beta_{10} ifo_{-1} + \beta_{11} ip_{-1} + \beta_{12} + \varepsilon_3
\end{gathered}
$$

The first three equations are the observation ones, which are identities, while the second three equations are state equations, which explain the non-observed variables (in our case, actually, only industrial production). In fact, the stated scheme is a VAR, estimated by Kalman filter. In this estimation, in the economic sense we cannot talk about the estimation of a non-observed variable, such as in the case of estimating the output gap or NAIRU; there is a difference only in the availability of certain variables (dates of publication).

5.3 BVAR

Based on Hunyadi (2005), the variable to be estimated under Bayesian econometrics, is not a predefined value, but rather a probability variable. In addition, one significant departure of the Bayesian estimate from the traditional approach is that it uses not only the information available in the sample, but also the economist's prior assumption and opinion on the given variable and distribution, thereby permitting the use of subjective probability.

BVAR estimates are widely used for forecasting macro variables (e.g. Caraiani (2010), Ciccarelli (2003), Demeshev (2015)). To the best of our knowledge, to date no forecast has been prepared using BVAR for Hungarian external demand. For details on the BVAR estimation methodology, see e.g. Hamilton (1994a) or Koop (2003).

We project the time series, extended by the Kalman filter based on Bańbura – Rünstler (2011) on a quarterly basis, and then relying on these we estimate BVAR for the individual countries and make a forecast for 4 quarters. Of the models by countries, based on the Schwartz information criterion, we select the one, the forecast of which will be used for the forecast of external demand. The import forecast for the examined countries is included in the BVAR equation for external demand, which is also used for forecasting.

For the BVAR estimation, the type of the priors must be selected. In the technical literature, the Minnesota (Litterman) prior is quite commonly used; however, Carriero et al. (2015) and Bańbura et al. (2010) use the Normal-Wishart prior, since in a structural analytical framework it must be take into consideration that there may be a correlation between the residuals of the different variables. The prior was selected based on Diebold (2015), relying on the Schwartz information criterion. The estimates were prepared by four types of priors, namely: Litterman (or Minnesota), Normal-Wishart prior, Sims-Zha Normal-Wishart prior, Sims-Zha normal-flat prior (for the details of the priors, see Litterman (1986), Sims – Zha (1998)).

The literature is divided as to whether or not it is necessary to differentiate under the VAR estimation to reach stationarity. Some believe (e.g. Bańbura et al (2010)) that it is not, because the unit root process can be managed by different priors. On the other hand, several other economists (Clements – Hendry (1996), Diebold- Kilian (2000)) demonstrated that differentiation enhances forecast performance, and thus in the case of the time series (e.g. import volume, industrial production, orders) where this is necessary, we log differentiate the variables to achieve the stationarity.

Under the BVAR estimation, as much time lag was added to a given specification that achieved the lowest Akaike information criterion. We performed the test to 1-4 time lags; typically, the information criterion was the lowest in the case of 4 time lags. A higher number of time lags would substantially reduce the sample size, and thus, as the data are quarterly data, we examined the AIC criterion up to 4 time lags.[1]

For the forecast of external demand, we used the import forecast of 8 countries, also within the framework of BVAR estimation.

[1] In the subsection presenting the estimations we showed the variables in the equations only up to 1 time lag, but in each case we selected the maximum number of time lags based on the AIC criterion.

6 Results

In this chapter, we present the models that performed the best in the case of the individual countries, and – relying on the obtained individual import forecasts – forecast the external demand trends and evaluate the results.

In the case of the individual countries, the estimation start date may vary depending on the available data. During the individual estimations, we expanded the sample by odd observations. For the purpose of sample selection, we evaluated the forecasts in two ways. On the one hand, we did not change the available start date, i.e. we used all information that was available in the past. In this case, we estimate the model on the whole available sample and based on the Schwartz information criterion select the one, the forecast of which is used for the external demand forecast.

On the other hand, we also performed the estimation and forecast on a rolling sample, choosing a 5-year time window for this. This was necessary to ensure that the potential structural breaks have no impact on the forecast. Several papers have warned (e.g. Constantinescu et al. (2015), IMF (2016)) that the structure and growth rate of world trade changed after the crisis; hence it is advisable to perform the estimation on a rolling sample as well.

When selecting the priors, a sample of sufficient length was available for half of the countries under review (Austria, Germany, France and Italy). In the case of these countries, we estimated the models between the start date of the sample and 2000, and forecast four quarters. Based on these, the Normal-Wishart prior had the lowest forecast error in the case of all four countries. Accordingly, we also applied this prior to the other four countries, and used it to select the one with the highest forecast power from the different types of variables. The selection of the prior is supported by the fact that in the case of the whole sample estimation, the value of the Schwartz criterion was the lowest for all countries in the case of the Normal-Wishart prior.

For the forecast of external demand by country we use the import forecast of the model that has the lowest Schwartz criterion value for the whole sample.

For the evaluation of the external demand forecast, we also examined the stability based on Jakab et al. (2000). Here we tested the degree of the change in the forecast compared to the previous ones upon preparing additional forecasts. In addition, based on BoE (2015), we also tested to what degree it is unbiased, i.e. whether the BVAR estimation regularly underestimates or overestimates external demand. We also examined how the BVAR performs in terms of identifying the turning points.

6.1 AUSTRIA

In terms of goods exports in 2015, Austria was Hungary's fourth largest trading partner.

The available data cover the period 1996 Q1 to 2015 Q4. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of Austrian imports, in addition to the EABCI and ESI indicators, we used the industrial production data and orders. We performed 6×4 estimations on each sample based on equation (3).[2]

[2] In Chapter 5, we indicated those variables in bold in the equations; several sub-indices and types of these were included in the estimates. In these cases, only one type of the given variable was included in the equation; the intention was to identify the index or sub-index that performs the best in the forecast.

$$dlog(imp_{AT,t}) = \beta_1 \mathbf{ESI_{t-1}} + \beta_2 dlog(ip_{t-1}) + \beta_2 dlog(ord_{t-1}) + \\ + \beta_4 EABCI_{t-1} + \beta_5 dlog(imp_{AT,t-1}) + \beta_6 + \varepsilon \quad (3)$$

In the case of Austria, the best performing estimate on the rolling sample included the construction ESI indicator. Based on the whole sample, the value of the Schwartz criterion was the lowest in the equation that used the ESI confidence index. Of the two sample selections, the value of RMSE was the lowest in the case of the whole sample, and thus we use the import forecasts of this estimate for the external demand forecast.

6.2 GERMANY

Germany has been one of Hungary's most important trading partners in recent decades; in 2015 it accounted a share of over 27 per cent in Hungarian goods exports. With this ratio, it significantly exceeds the rest of Hungary's trading partners.

In the case of Germany, the available data cover the period 1996 Q1 to 2015 Q4. The whole sample estimate covers the period 1996 Q1 to 2015 Q3. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

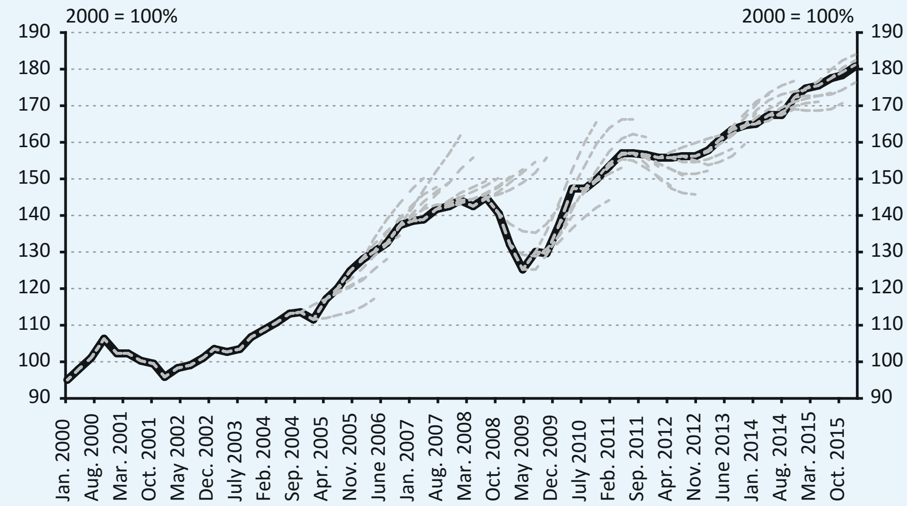
During the estimation, each of the ESI, IFO and ZEW indicators was included in the estimate, in addition to the manufacturing orders and EABCI. Six variables (industry, services, construction, commerce, consumer and whole ESI) of the ESI indicator, five of the IFO and two of the ZEW (*Economic Sentiment, Economic Situation*) were included in the estimate. For each sample, we estimated 6×5×2, i.e. 60 equations with a given prior, based on equation (4). In BVAR, we selected the number of time lags based on the Akaike information criterion.

We prepared four-quarter forecasts for each estimate.

$$dlog(imp_{DE,t}) = \beta_1 \mathbf{ESI_{t-1}} + \beta_2 \mathbf{IFO_{t-1}} + \beta_3 \mathbf{ZEW_{t-1}} + \beta_4 dlog(ip_{t-1}) + \\ + \beta_5 dlog(ord_{t-1}) + \beta_6 EABCI_{t-1} + \beta_7 dlog(imp_{DE,t-1}) + \beta_8 + \varepsilon \quad (4)$$

On the rolling sample, the best performing model includes the ZEW1 (ZEW Indicator of Economic Sentiment), the services ESI sub-index and the IFO business expectations.

Chart 3
Forecast of German imports with the model providing the smallest Schwartz criterion



Source: Own calculation based on Eurostat and other data.

In the estimations performed on the whole sample, the value of the Schwartz criterion was the smallest for the model that used the ZEW2 (Economic Situation Germany) indicator, the industrial ESI confidence index and the IFO business climate (Chart 3). Based on the sample selection, the forecasts that used the whole sample proved to be more accurate.

6.3 FRANCE

In terms of goods exports in 2015, France was Hungary's sixth largest trading partner. In the past years, its weight in Hungarian exports consistently exceeded 4 per cent.

The available data cover the period 1996 Q1 to 2015 Q4. The whole sample estimate covers the period 1996 Q1 to 2015 Q3. On the rolling sample the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of French imports, we used the EABCI and ESI indicators, as well as the industrial production data. We performed 6×4 estimations on each sample based on equation (5).

$$dlog(imp_{FR,t}) = \beta_1 \boldsymbol{ESI_{t-1}} + \beta_2 dlog(ip_{t-1}) + \beta_3 EABCI_{t-1} + \beta_4 dlog(imp_{FR,t-1}) + \beta_5 + \varepsilon \tag{5}$$

On the rolling sample, the estimate containing the industrial ESI resulted in the most accurate forecast. On the whole sample, the equation containing the industrial ESI had the smallest Schwartz information criterion. Similarly to the previous two countries, the more accurate forecast was prepared with the use of the whole sample in the case of France as well.

6.4 ITALY

The weight of Italy in Hungarian goods exports was above 5 per cent after the turn of the millennium and has been around 5 per cent since 2010, making it Hungary's fifth largest trading partner.

In the case of Italy, the data used cover the period 2000 Q1 to 2015 Q4. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of Italian imports, we used the EABCI and ESI indicators, as well as the industrial production data and the orders. In addition to overall Italian orders, the domestic and export orders are also available. We performed 6×3×4, i.e. 72 estimations on each sample based on equation (6).

$$\begin{gathered} dlog(imp_{IT,t}) = \beta_1 \boldsymbol{ESI_{t-1}} + \beta_2 dlog(ip_{t-1}) + \beta_3 \boldsymbol{ord}_{t-1} + \\ + \beta_4 EABCI_{t-1} + \beta_5 (imp_{IT,t-1}) + \beta_6 + \varepsilon \end{gathered} \tag{6}$$

In the case of Italy, the model containing domestic orders and the general ESI confidence index performed the best on the rolling sample. On the whole sample, the model containing overall orders and the industrial ESI had the smallest Schwartz information criterion. In the case of all equations, the RMSE was smaller on the total sample than on the rolling sample.

6.5 RUSSIA

Russia's weight in Hungarian exports rose substantially in the first half of the 2000s to reach 3.5 per cent before the crisis; however, it has significantly decreased in recent years, mostly due to the sanctions against Russia and Russia's countermeasures. In 2015, Russia's weight within Hungarian goods exports was around 1.5 per cent.

The Russian data used cover the period 2000 Q1 to 2015 Q4. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of Russian imports, we used three OECD indicators applicable to the Russian economy, as well as the Russian industrial production data.

$$dlog\left(imp_{RU,t}\right)=\beta_1\boldsymbol{OECD_{t-1}}+\beta_2 dlog\left(ip_{t-1}\right)+\beta_3 dlog\left(imp_{RU,t-1}\right)+\beta_4+\varepsilon \tag{7}$$

On the rolling sample, the estimation containing the Normalised Business Confidence index (NCLI) proved to be the best. On the whole sample, the smallest Schwartz value was returned by the estimate that contained the NCLI. It should be noted that of all estimates performed, the forecast prepared for Russian imports contained the highest forecast error, which was roughly twice as high as that of the other countries, but relative to the individual countries, differences of one magnitude were also observed. This is presumably attributable to the sanctions in recent years that these models are unable to handle.

6.6 ROMANIA

The weight of Romania in Hungarian goods exports increased dynamically after the turn of the millennium, reaching 6 per cent in 2012, while it was above 5 per cent in 2015, thus making it the second largest trading partner of Hungary after Germany.

In the case of Romania, most of the data used cover the period 2000 Q1 to 2015 Q4. However, the consumer sub-index and the service sub-index of ESI is available from 2001 Q2 and 2002 Q2, respectively. The two shorter time series are included in the estimate with the same delay as the delay of their start. The whole sample estimate covers the period 2000 Q1 to 2015 Q3. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of Romanian imports, we used the ESI indicators and the industrial production data. We performed 6×4 estimations on each sample based on equation (8).

$$dlog\left(imp_{RO,t}\right)=\beta_1\boldsymbol{ESI_{t-1}}+\beta_2 dlog\left(ip_{t-1}\right)+\beta_3 dlog\left(imp_{RO,t-1}\right)+\beta_4+\varepsilon \tag{8}$$

On the rolling sample, the equation containing the general ESI confidence index performed the best. On the whole sample, the value of the Schwartz information criterion was the smallest in the case of the model containing the industrial ESI confidence index.

6.7 SLOVAKIA

Hungary's trade in goods with Slovakia has increased substantially since the turn of the millennium. In terms of goods exports in 2015, Slovakia was Hungary's third largest trading partner. Its weight in Hungarian exports was around 5 per cent in 2015.

The data used cover the period 2000 Q1 to 2015 Q3, with the exception of the ESI services sub-index, which is available from 2002 Q1. On the rolling sample, the first estimate and last estimate cover the periods 2000 Q1 to 2004 Q4 and 2011 Q3 to 2015 Q3, respectively.

For the estimation of Slovakian imports, we used the EABCI and ESI indicators, as well as the industrial production data. We performed 6×4 estimations on each sample based on equation (9).

$$dlog\left(imp_{SK,t}\right)=\beta_1\boldsymbol{ESI_{t-1}}+\beta_2 dlog\left(ip_{t-1}\right)+\beta_3 EACBI_{t-1}+\beta_4 dlog\left(imp_{SK,t-1}\right)+\beta_5+\varepsilon \tag{9}$$

In the case of Slovakia, the estimate that performed the best on the rolling sample contained the ESI services sub-index. In the case of the whole sample, the estimate using the general ESI confidence index returned the smallest Schwartz criterion. The whole sample estimate had higher forecast error.

6.8 UKRAINE

The weight of Hungarian goods exports to Ukraine within Hungarian exports rose substantially until 2013, but then dropped off significantly in 2014-2015. In 2015 it was already less than 1.5 per cent.

The data used cover the period 2006 Q1 to 2015 Q4. On the rolling sample, the first estimate and last estimate cover the periods 2006 Q1 to 2008 Q4 and 2010 Q4 to 2015 Q3, respectively. For the forecasting of Ukrainian imports, we used the industrial production of Ukraine. Thus, the individual estimates were differentiated by the used prior, apart from the sample element number. The estimates were performed on the basis of equation (10).

$$dlog\left(imp_{UKR,t}\right)=\beta_1 dlog\left(ip_{t-1}\right)+\beta_2 dlog\left(imp_{UKR,t-1}\right)+\beta_3+\varepsilon \tag{10}$$

In the case of Ukraine, the rolling sample-based forecast has a smaller forecast error than the one based on the whole sample. The Schwartz information criterion on the whole sample was the smallest in the case of the Normal-Wishart prior.

When comparing the RMSE of the forecasts belonging to the Schwartz criteria, it is clear that the forecast error is typically low in the case of those countries where the equation contains several variables (Table 2). The only exception to this is Slovakia. In the case of Russia, it is not only the small number of independent variables that may explain the high forecast error, but also the economic sanctions introduced in recent years.

Table 2
Average four-quarter forecast error (RMSE) of forecasts prepared by the best models

Country	RMSE belonging to the smallest Schwartz criterion	Number of independent variables used in the equation
AT	5.4	4
DE	11.1	6
FR	4.5	3
IT	5.3	4
RO	31.2	2
RU	60.3	2
SK	21.9	3
UKR	26.7	1

6.9 FORECAST AND EVALUATION OF EXTERNAL DEMAND

The indicators which performed best in the case of the individual countries are summarised in Table 3 (industrial production was included in the estimate for all countries). In the case of four countries, it was certain sub-indices of the ESI, rather than the general ESI, that performed the best. This may be attributable to the fact that the EABCI already contains the information that is included in ESI, while some of the specific sub-indices of ESI may provide extra information in the forecast.

Table 3
Best performing time series based on the Schwartz criterion

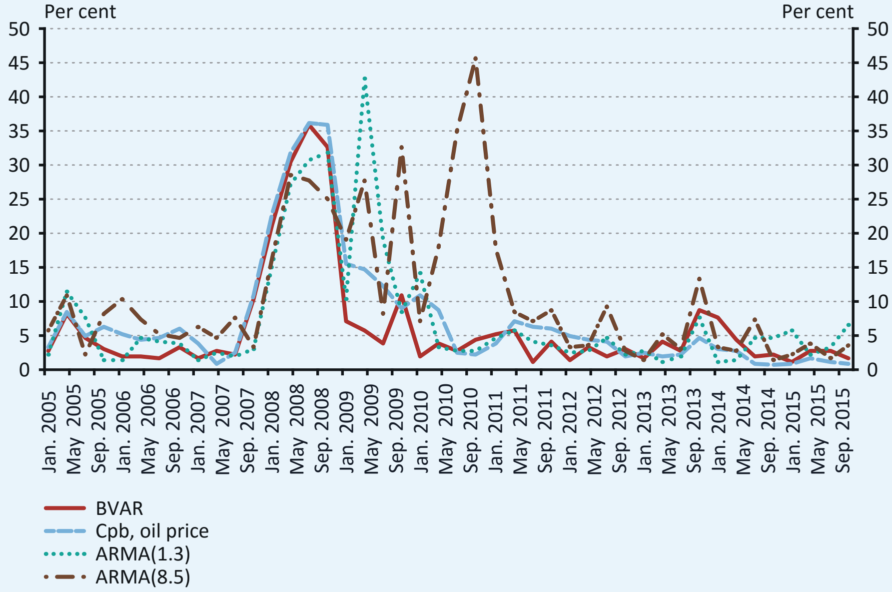
	AT	DE	FR	IT	RO	RU	SK	UKR
ESI	ESI	industry	industry	industry	industry	-	ESI	-
Other	-	ZEW Economic Situation, IFO business expectations	-	domestic orders	-	NCLI	-	-

For forecasting external demand, we set out from equation (11).

$$dlog(extD_t) = \sum_{i=1}^{8} \beta_i dlog(imp_{i,t}) + \beta_9 extD_{t-1} + \beta_{10} + \varepsilon \tag{11}$$

We projected the change in external demand by forecasting the imports of the 8 countries under review and by the time lag of external demand (Chart 5).

Chart 4
RMSE of the individual models



Source: Own calculation based on Eurostat and other data.

Similarly to the equations for the individual countries, we selected the BVAR time lags based on the AIC criterion. Of the priors, the forecast prepared with the Litterman prior returned the smallest Schwartz criterion for the whole sample.

Similarly to Jakab et al. (2000), we also compared the forecasts obtained to the best ARMA forecasts. Estimated between 1996 and 2012, the ARMA (8,5) specification was the best, both with the Akaike and the Schwartz information criterion. Estimated on the sample for 2000-2012 the ARMA (1,3) proved to be the best. We determined the best ARMA specification not on the whole sample, in order to avoid overfitting. Having compared the ARMA forecasts with the BVAR forecast, the BVAR forecasts were clearly the best. It can be observed with all three models that forecast accuracy deteriorates as a result of the crisis, but the RMSE becomes larger with the ARMA models (Chart 4).

In addition to the ARMA models, we compared the BVAR forecast to another model specification as well. In addition to the world import data, which are published monthly by the Netherlands Bureau of Policy Analysis (Centraal Planbureau, CPB), this estimate also contained oil prices (see equation (12)).

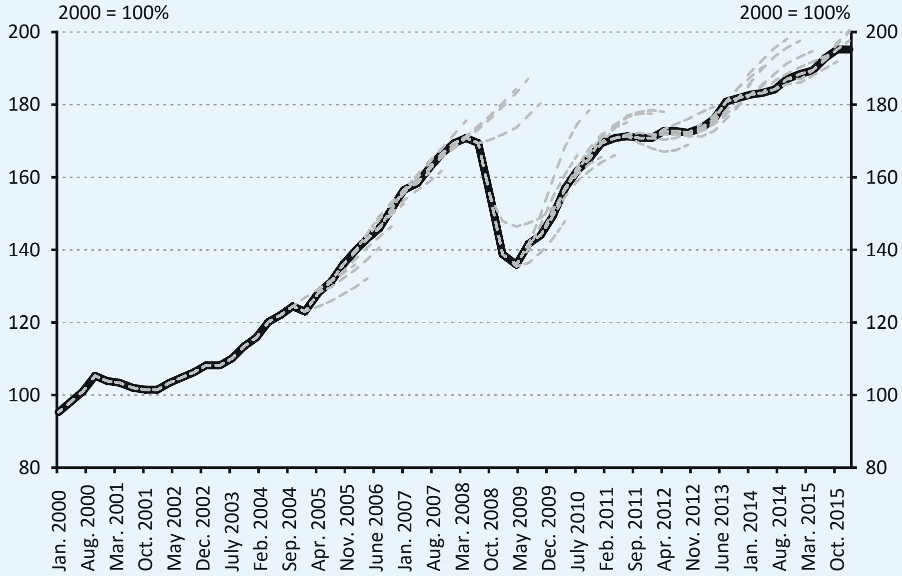
$$dlog(extD_t) = \beta_1 extD_{t-1} + \beta_2 cpb_{t-1} + \beta_3 oil_{t-1} + \beta_4 + \varepsilon \tag{12}$$

The estimate containing the CPB and oil price data proved to be better than the ARMA estimates, but its forecast error exceeded that of the BVAR estimate which we prepared. We can draw a similar conclusion, if we forecast with equation 12 only after 2010, i.e. the sequence specified on the basis of the forecast accuracy of ARIMA, BVAR and equation (12) has not changed in the post-crisis period (Table 4).

Table 4
Average, four-quarter forecast error of forecasts calculated with whole sample estimates

RMSE	BVAR	CPB, oil	ARMA(1, 3)
2005-2015	6.2	7.4	7.4
2010-2015	3.3	3.6	4.0

Chart 5
Forecast of external demand with the BVAR model providing the smallest Schwartz value



Source: Own calculation based on Eurostat and other data.

We also compared the forecast of the best BVAR and the best ARMA models in terms of stability, based on Jakab et al. (2000, p. 28). This criterion tests the degree of the change in the forecast as a result of new incoming data. The smaller the change (revision) of the forecast after the receipt of a new data point, the more reliably the forecast of economic time series can assist monetary policy decision-making.

We compared BVAR and ARMA forecasts by comparing the difference between the actual data and the forecast. In our case the loss function was the square of the differences. Subtracting the loss functions of the two forecasts from each other, we obtain the loss difference time series. We tested the loss difference time series based on Jakab et al. (2000, p. 28) and Diebold – Mariano (1995), to determine whether or not it differed significantly from 0. If not, the errors of the two forecasts are identical in statistical terms. We grouped the loss difference time series by quarters, i.e. one time series belonged to each of the one-quarter, two-quarter, etc. forecast. Thus, we obtained four loss difference time series in total, on which we performed the DM test (for the results see the appendix), and we found that the null hypothesis, i.e. that the loss difference time series is 0, can be dropped in all cases. Thus, the two forecasts also differ from each other in terms of stability.

In addition, based on BoE (2015), using a simple test, we examined whether the external demand forecast prepared by the BVAR model is biased, i.e. whether it can be proven that it tendentiously over or underestimates external demand. For this purpose, we calculated the forecast error.

$$e_t^{t-h} = extD_t - extD_t^{t-h}, \quad \mathrm{h}=1,\dots,4 \tag{13}$$

For testing the level of bias, we performed the following estimate with the obtained four time series based on BoE (2015, p. 19):

$$e_t^{t-h} = \beta_0 + \varepsilon_t, \quad \mathrm{h}=1,\dots,4 \tag{14}$$

where ε_t is an error term. When it is unbiased β_0=0. We performed the OLS estimate by heteroscedastic and autocovariance consistent standard errors. In the estimate, we ignored the two crisis years (2008-2009). Based on the results, no bias can be found even at significance level of 10 per cent (for the detailed results see the appendix).

In addition to the aforementioned criteria, we also tested how well the individual models forecast turning points. We determined the turning points based on the following criterion. We defined as a turning point that observation t of the time series that satisfies the following criterion:

$$\frac{extD(t)-extD(t-i)}{extD(t+1)-extD(t)}<0, \qquad i=1;2;3;4. \tag{15}$$

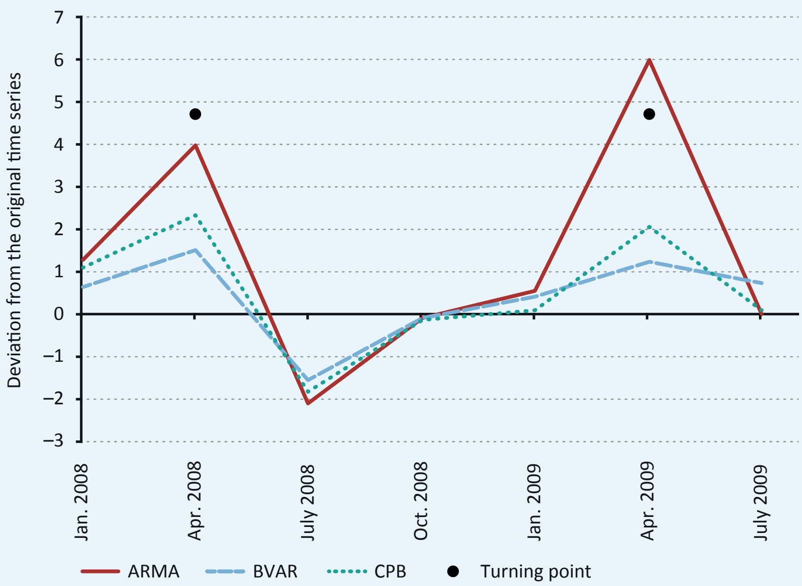
That is, the criterion was that the steepness of the external demand's time series should change in the longer run (through 4 quarters), persistently. With this we can avoid identifying minor volatilities as a turning point. Based on the aforementioned considerations, there were two turning points between 2005 and 2015: 2008 Q2 and 2009 Q2. Since the turning points were very close to each other, we expanded the sample by one quarter (2008 Q4), and thus the sample covers the entire crisis period.

We compared the difference in the steepness of the forecasts and the original time series for the individual models, as follows:

$$\frac{extD\_fc(t-1)-extD\_fc(t-2)}{extD(t-1)-extD(t-2)}=difference^{3} \tag{16}$$

If the above value is positive, the forecast properly projected the direction of the change in external demand, while if it is negative it projected a change in a different direction. The closer the above value is to 1, the more accurate the forecast is. For the comparison we used the more accurate ARMA model and the model that contained the CPB and the oil price data. In the period under review, BVAR came closest to 1 five times, while the other two models once each. Hence, BVAR was the most efficient model examined in terms of forecasting turning points as well (Chart 6).

Chart 6
Deviation of the forecast by the individual models from the external demand close to the turning points

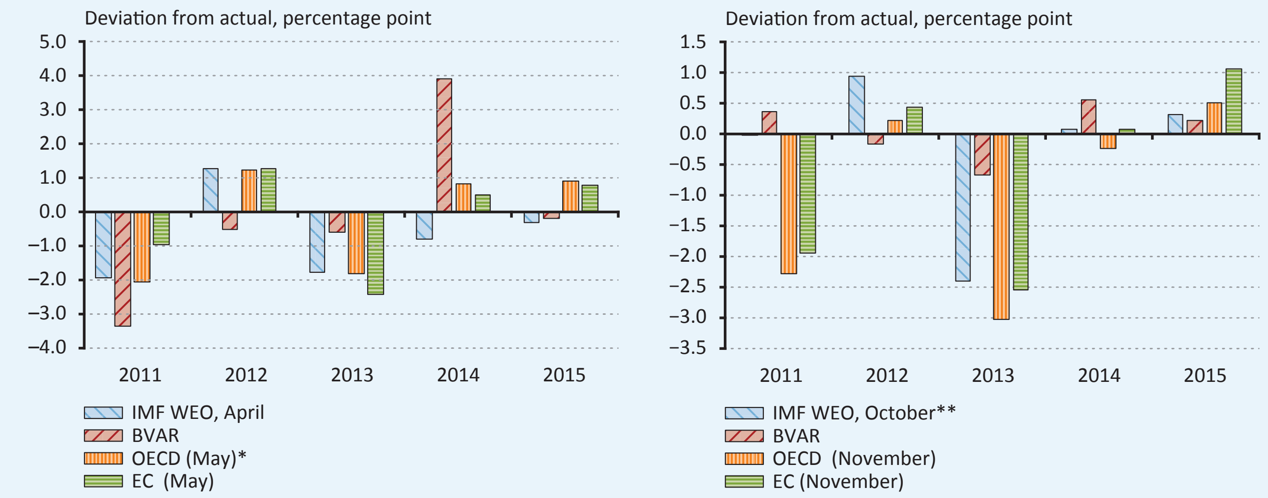


Source: Own calculation based on Eurostat and other data.

[3] t=the turning point and the two adjacent quarters

Since the objective is to improve the current forecasting practice, it is worth comparing the BVAR forecasts with the forecast of the three institutions (European Commission, IMF and OECD). However, it should be emphasised that it should not be expected that we obtain a better forecast than the forecast of the institutions in all cases, as the information used in the BVAR models is limited to a few indicators. To illustrate this, we compared forecasts prepared at two dates. In the first case, we compared the spring forecasts of the individual institutions with the corresponding BVAR forecast. In this case, no actual data are available in respect of the import data for the forecast related to the given year (in April only the previous year's detailed GDP data are available). In the second case, we compared the autumn forecasts of the institutions with the BVAR forecast (Chart 7). At this time, we already had actual import data for two quarters. In the period under review, in the case of both the spring and autumn forecasts, BVAR performed better in 3 out of 5 years. At the autumn forecasts, the BVAR forecast errors are obviously smaller. This result is not surprising, as the forecasts of the indicator variables perform better in the short run.

Chart 7
Comparison of the BVAR forecast with the institutional forecasts



*Note: *June in 2015, **September in 2011.*

At the same time, this practice also highlights the limits of the forecast. In the longer run (especially, when no actual data are available for the respective year), the weighted average prepared from the institutions' forecasts performs better than the BVAR forecast.

7 Conclusion

In this paper, we described the MNB's current practice for forecasting external demand. At present, we weight together the forecasts of three international institutions for the import of Hungary's main trading partners with the Hungarian export weights. This practice has two constraints. On the one hand, the publication of the forecasts does not coincide with the closing of the Inflation Report's information base, i.e. the data may already be outdated. The other constraint is that until now new information could only be integrated through expert judgement, and there was no formal tool to update the forecasts.

In this paper, we presented a tool for the short-term forecasting of the imports of Hungary's key trading partners using monthly indicators. In the forecast of imports, we used not only "hard" data, but also confidence indices as well. According to the technical literature, the information inherent in the latter helps forecast the various economic variables. The forecast may be performed relying on BVAR both in the case of the individual countries and external demand. The BVAR forecast proved to be better than the best ARMA forecasts, and it also returned a more accurate forecast than the models using the world imports and the oil price developments. In addition, the BVAR model also forecast the turning points more accurately. Ignoring the two crisis years, the BVAR forecast is unbiased.

Comparing it with the forecast of the international institutions, reviewing the data of the last 5 years, for the forecasts prepared at the beginning of the year and at half-year, the BVAR performed better in 3 out of 5 cases compared to the forecasts of the international institutions. The BVAR errors were smaller when we already had actual data from the respective years. Based on this, the presented tool is suitable for forecasting external demand only in the short term (1-4 quarters).

The forecast presented has a number of novelties compared to the practice pursued to date. On the one hand, it uses BVAR for forecasting external demand, which – as far as we know – so far has not been performed on Hungarian data. On the other hand, it is able to formally integrate the information inherent in the monthly data in the forecasts, which was not previously possible in the case of external demand, and could be performed only through expert judgement.

As part of enhancing the external demand forecast, it may be worthwhile to estimate the imports of the individual countries systematically, e.g. with a global VAR model. Thus, the impacts of the interactions between the countries may also be included in the forecast, which presumably will further improve the forecast accuracy.

It may also be useful to employ this methodology to forecast the production and expenditure components of GDP. With the expenditure components, it would be also useful to examine to what extent the presented external demand forecast helps forecast exports.

References

Ball, Laurence – Mankiw, N. Gregory (2002): The NAIRU in Theory and Practice, Journal of Economic Perspectives, Volume 16, Number 4, pp. 115-136

Bańbura, Marta – Giannone, Domenico – Reichlin, Lucrezia (2010): Large Bayesian Vector Autoregressions, Journal of Applied Econometrics 25, pp. 71–92

Bańbura, Marta – Rünstler, Gerhard (2011): A look into the factor model black box: Publication lags and the role of hard and soft data in forecasting GDP, International Journal of Forecasting 27, pp. 333–346

Bank of England (2015): Evaluating forecast performance, November 2015

Carriero, Andrea – Clark, Todd – Marcellino, Massimiliano (2015): Bayesian VARS: Specification Choices and Forecast Accuracy, Journal of Applied Econometrics 30, pp. 46-73

Caraiani, Petre (2010): Forecasting Romanian GDP Using a BVAR Model, Romanian Journal of Economic Forecasting, pp. 76-87, 4/2010

Červená, Marianna – Schneider, Martin (2014): Short-term forecasting of GDP with a DSGE model augmented by monthly indicators, International Journal of Forecasting 30 (2014) pp. 498–516

Ciccarelli, Matteo – Rebucci, Alessandro (2003): Bayesian VARs: A Survey of the Recent Literature with an Application to the European Monetary System, IMF Working Paper, WP/03/102

Clements, Michael P. – Hendry, David F. (1996): Intercept Corrections and Structural Change, Journal of Applied Econometrics 11. pp. 475–494

Constantinescu, Cristina – Mattoo, Aaditya – Ruta, Michele (2015): The Global Trade Slowdown: Cyclical or Structural?, IMF Working Paper, WP/15/6

Demeshev, Boris B. – Malakhovskaya, Oxana A. (2015): Forecasting Russian Macroeconomic Indicators with BVAR, WP BRP 105/EC/2015

Diebold, Francis X. – Kilian, Lutz (2000): Unit Root Tests are Useful for Selecting Forecasting Models, Journal of Business and Economic Statistics 18, pp. 265–273

Diebold, Francis X. (2015): Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold-Mariano Tests, Journal of Business and Economic Statistics, 33, pp. 1-24

Driver, Rebecca L. – Greenslade, Jennifer V. – Pierse, Richard G. (2006): Whatever Happened to Goldilocks? The Role of Expectations in Estimates of the NAIRU in the US and the UK, Oxford Bulletin of Economics and Statistics, Vol. 68. No. 1., pp. 45-79

European Commission (2016): The Joint Harmonised EU Programme of Business and Consumer Surveys, European Commission, Directorate-General for Economic and Financial Affairs

Giannone, Domenico – Lenza, Michele – Primiceri, Giorgio E. (2015): Prior Selection for Vector Autoregressions, The Review of Economics and Statistics, May 2015, 97(2): 436-451

Golinelli, Roberto – Parigi, Giuseppe (2014): Tracking world trade and GDP in real time, International Journal of Forecasting 30 (2014), pp. 847–862

Gyomai, Gy. – Guidetti, E. (2012): OECD System of Composite Leading Indicators, OECD Publishing, April 2012

Hamilton, James D. (1994a): Time Series Analysis, Princeton University Press, pp. 351-371

Hamilton, James D. (1994b): State-Space Models, in Handbook of Econometrics, Volume IV, Edited by R.F. Engle and D.L. McFadden, Elsevier, pp. 3041-3062

Hunyadi, L. (2005): Theory of statistical inference for economist, HCSO (Statisztikai következtetéselmélet közgazdászoknak, KSH)

Hüfner, Felix P. – Schröder, Michael (2002): Forecasting Economic Activity in Germany – How Useful are Sentiment Indicators?, ZEW Discussion Paper No. 02-56

IMF (2016): World Economic Outlook (WEO), Global Trade: What's behind the Slowdown? Chapter 2, October 2016

Jakab, M.Z. – Kovács, M.A. – Lőrincz, Sz. (2000): Forecasting exports by econometric methods MNB Working Papers 2000/4, (Az export előrejelzése ökonometriai módszerekkel, MNB Füzetek, 2000/4)

Koop, G. (2003): Bayesian Econometrics, Wiley

Litterman, Robert B. (1986): Forecasting With Bayesian vector autoregressions: five years of experience, Journal of Business and Economic Statistics 4, pp. 25–38

Pula, G. – Reiff, Á. (2002): Role of domestic business surveys in the short-term forecast of manufacturing output MNB Occasional Papers 2002/3. (A hazai konjunktúra-felmérések szerepe a feldolgozóipari termelés rövid távú előrejlzésében)

Sims, Christopher A. – Zha, Tao (1998): Bayesian methods for dynamic multivariate models. International Economic Review 39 (4): pp. 949–968

Vadas, G. (2001): Beyond Macro Variables: Consumer Confidence Index and Household Expenditure in Hungary, MNB Background Studies, 2001/2. (Túl a makrováltozókon: Lakossági bizalmi index és a magyar háztartások fogyasztási kiadása)

Appendix

Used data and their starting date								
	AT	DE	FR	IT	RO	RU	SK	UKR
Imports	Jan 1996	Jan 1995	Jan 1996	Jan 1996	Jan 2000	Jan 2000	Jan 2000	Jan 2000
ESI	Jan 1996	Jan 1995[1]	Jan 1996	Jan 1995	Jan 2000[2]		Jan 2000[3]	
Industrial production	Jan 1996	Jan 1995	Jan 1996	Jan 1995	Jan 2000	Jan 2000	Jan 2000	Jan 2006
Orders	Jan 1996	Jan 1995	Jan 1996	Jan 2000	Jan 2000		Jan 2000	
EABCI	Jan 1996	Jan 1995	Jan 1996	Jan 2000	Jan 2000		Jan 2000	
ZEW		Jan 1995						
IFO		Jan 1995						
OECD CLI						Jan 2000		

[1] Services only from April 1995.

[2] Consumer only from May 2001, services only from June 2002.

[3] Services only from January 2002.

Data sources: Eurostat, European Commission, CESifo Group Munich, ZEW, Istat.

Results of the Diebold-Mariano test		
	DM statistics	p-value
1 quarter	5.21	0.0000
2 quarters	3.90	0.0001
3 quarters	4.65	0.0000
4 quarters	5.14	0.0000

Bias test		
	Coefficient	p-value
1 quarter	-0.89	0.1402
2 quarters	-2.07	0.1242
3 quarters	-3.36	0.1188
4 quarters	-4.51	0.1240

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