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Abstract

This paper tests of the extent to which available monthly economic indicators help in nowcasting GDP. For this purpose, a factor model is proposed on data relevant for the movement of the domestic GDP (monthly indicator of real economic activity – MRGA) and its results are compared recursively with models for nowcasting from recent related literature and with simple benchmark models. The evaluation of the results of the model indicates that factor models based on the dynamics of a broad group of variables produce better nowcasts than the benchmark models used. Furthermore, different specifications of factor models have similar performance. Another important finding of the analysis is that it is worthwhile to combine the information available in individual models. In addition to nowcasting, monthly series of GDP growth rates for Croatia based on the movement of a large number of available monthly indicators are also constructed in the paper.

JEL:
C53, C55

Keywords:
nowcasting GDP, nowcasting, factor models, Kalman filter

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Contents

1 Introduction and motivation

The Croatian Bureau of Statistics (CBS) releases quarterly GDP data with a substantial lag. For instance, the flash estimate is released only two months after the end of a quarter so that it is difficult accurately to assess the actual state of the economy in real time. In the absence of official (quarterly) data, real activity is thus usually estimated on the basis of available monthly indicators such as industrial production or retail trade. However, in such a way, with the use of a small number of indicators, only a rough approximation of GDP dynamics can be constructed. For this reason, it was necessary to develop a methodology which would enable successful estimation of the actual but unreleased GDP by means of a larger number of relevant indicators available at monthly frequency. This paper presents some models for nowcasting[1] growth rates on the basis of the dynamics of available indicators, most often with monthly frequency. The extent to which these models are successful in nowcasting GDP for the domestic economy will then be tested. In addition to nowcasting of real growth, it will be shown how the models presented can be utilised in the construction of a monthly GDP indicator for Croatia. Monthly indicators of real activity can be interesting to the general public and to economic policy-makers because they clearly link the movement of GDP with the information synthesised from a large number of available monthly indicators. Also, they can be useful in quantitative empirical research in which it is often difficult to find a solid representative of real activity at monthly frequency because of the quarterly compilation of national accounts.

In technical terms, the biggest problem of such a nowcast is designing an appropriate methodological framework which would efficiently relate quarterly GDP to a large number of available economic indicators, most frequently available on a monthly basis. Simple bridge models are usually used for this purpose (see for example Baffigi et al., 2004). The strategy of this approach is simple: monthly indicators are first averaged at a quarterly level, and after that the (quarterly) relationship between GDP and available indicators is estimated, which is finally used in nowcasting still unreleased GDP. Simple OLS specifications, which relate GDP to individual indicators or to a group of indicators simultaneously, are commonly used for this purpose. However, the usefulness of this modelling strategy in which the dynamics of GDP would be explained by a direct inclusion of individual indicators in a regression equation is limited in this context. The shortness of macroeconomic series is the main reason for this, because of which the simultaneous impact of only a few, up to four or five, economic variables on GDP can be estimated. However, the dynamics of GDP is related to the movement of a large number of available variables. Therefore, the possibility of summarising information in economic data using factor analysis[2] has been researched intensively in the literature. It is a fundamental assumption of this methodology that there are only a few common sources of variation in individual series from an overall large group of economic indicators. If these common factors explain the bulk of variation in the variables of interest, then we consider them as acceptable representatives of the entire group. In this case, it is sufficient to observe

1 In this paper, the term *nowcasting* denotes the prediction of GDP in the very recent past, the present and the very near future (Bańbura et al., 2013).

2 See for example Stock and Watson (2002b), Forni et al. (2000) on data for the US and the EU and Kunovac (2007) on domestic data.

the constructed factors exclusively, instead of several dozens or hundreds of available monthly indicators. Finally, if the number of factors representing a group of variables successfully is small enough (usually under five), then the variable of interest, in our context GDP, can be related to a large number of variables represented by means of several factors using a standard regression analysis.

In addition to the construction of common factors that generate the dynamics of a group of economic variables of interest, the problem of consistent aggregation of monthly indicators to a quarterly level also appears in nowcasting GDP. That is, data on individual monthly indicators are released on different dates and are therefore not necessarily available for all three months in the quarter for which the nowcast is computed. For this reason, the question arises of how to treat the problem of an incomplete database in an efficient and a consistent manner. There are several approaches to the problem of infilling missing values in the database. For instance, a special econometric time series model for forecasting missing values can be defined for each series that has unknown values in the past few months. Missing values can also be imputed iteratively using a factor model with the Expectation Maximization (EM) algorithm (see Stock and Watson, 2002a, Schumacher and Breitung, 2008). Finally, missing values can also be treated using the Kalman filter within the state space framework (e.g. Giannone et al., 2008, Matheson, 2010, Rusnak, 2013).

In recent years, the literature has presented a series of models which deal with growth rate nowcasting based on the dynamics of a large number of available indicators, most often with a monthly or even daily frequency. Giannone et al. (2008) is the starting point of the literature. In that paper, the authors propose an algorithm that estimates common factors from the group of monthly indicators in two steps in the form of a state space model. Estimated monthly factors summarize the information contained in a large number of available monthly indicators. To be utilised for the purpose of estimating current GDP, they should be aggregated to a quarterly level. Then, by means of the OLS relation between these quarterly factors and GDP, it is easy to compute the projection of current GDP. In this way, Giannone et al. (2008) estimate the model on the US data iteratively and conclude that their model is more successful in the estimation of growth in the current quarter than the estimations based on the random walk naive model or the estimations from the Survey of Professional Forecasters (SPF). Also, it has been shown that apart from the nowcast, on average neither the factor model nor forecasts of professional forecasters can predict the growth of GDP better than the naive model, which for the future growth rates forecasts that they are equal to the latest actual rate. The asymptotic properties of the estimators used in Giannone et al. (2008) are given in Doz et al. (2011). Bańbura and Modugno (2010) estimate a similar model, but now with the EM algorithm, and enable the treatment of an arbitrary missing data pattern. The asymptotics for this estimator is given in Doz et al. (2012). A detailed overview of related literature can be found in Bańbura et al. (2013).

Factors do not necessarily have to be computed by means of the state space representation. Unlike Giannone et al. (2008), Stock and Watson (2002a) and Schumacher and Breitung (2008) impute missing values with the EM algorithm, instead of using the Kalman filter, so that factors are estimated on the basis of PCA[3]. Schumacher and Breitung (2008) estimate monthly GDP rates on German data using the EM algorithm. When monthly indicators are available for the last quarter in a sample, and quarterly GDP is not yet available, the authors use a factor model to estimate corresponding monthly GDP rates. Aggregated to a quarterly level, the estimated monthly rates represent the nowcast of the quarterly growth rate.

In accordance with the previously published literature, an alternative version of the factor model is proposed in this paper. In the first step, following the example of Schumacher and Breitung (2008), by using PCA on available monthly data, a few common factors are estimated, which summarise the information of a large number of available monthly indicators. Then, as suggested by Giannone et al. (2008), the growth rate nowcast is computed with a special OLS projection of GDP on the factors estimated. Missing values are imputed either with the EM algorithm, as suggested in Schumacher and Breitung (2008), or using simple time series methods. The advantage of the proposed model is in a simpler implementation than that provided by Giannone et al. (2008) as the state space representation for the estimation of factors is not used. The use of a

3 Principal Component Analysis (PCA)

special OLS relation between factors and GDP also enables additional flexibility when compared to the model by Schumacher and Breitung (2008). The simple implementation of the model facilitates the evaluation of the performance of different methods of treating missing values. Also, the implementation of PCA simplifies the estimation of factors for different groups of monthly variables (e.g. for domestic or foreign variables), which ensures higher flexibility in modelling and facilitates the interpretation of results.

The primary goal of this paper is to test a series of relevant models for nowcasting domestic GDP on a monthly basis. The models developed by Giannone et al. (2008), Schumacher and Breitung (2008) and the factor model presented in this paper (MRGA)[4] are tested. These models differ in the manner in which they treat missing values and in the manner in which factors are estimated as well as in the strategy by which they relate quarterly values of GDP to monthly factors. Furthermore, the aim is to compare the performances of different specifications of factor models. The key results of the analysis performed indicate that factor models outperform the benchmark naive random walk model substantially, which confirms the assumption that the monthly indicators used can help in nowcasting GDP. In addition, factor models also outperform bridge regressions, which include only the dynamics of retail trade and industrial production. This is an important result, and it demonstrates that it is possible to use the informative character of a large number of series within the factor analysis framework successfully. With regard to the performance of forecasts of different specifications of factor models, it appears that their performances are very similar. The nowcasting model (MRGA) suggested in this paper, although simpler to implement, does not yield poorer results when compared with more complex specifications based on the Kalman filter. Finally, an important result of the analysis is that the results of individual models are worth averaging in this case. The average of individual models has yielded better results than individual models on all observed samples.

Although the focus of this paper is on the nowcasting of domestic real activity, the methodology implemented can be used directly for other purposes[5] as well. In this paper, the estimates of GDP growth at monthly frequency are thus constructed on the basis of the two presented factor models[6]. The constructed monthly rates of domestic GDP reflect the dynamics of the monthly indicators applied and are therefore more volatile than the quarterly ones. Since monthly rates are under the strong impact of short-term fluctuations, they are probably useful to a limited extent in the analysis of real activity in the medium and long-run. Despite this, since they relate the dynamics of used indicators to GDP directly, they provide a detailed insight into the sources of volatility of the official statistics of national accounts.

Although the domestic literature has not addressed the issue of nowcasting the GDP growth rate so far, we mention the paper by Rašić-Bakarić, Tkalec and Vizek (2013) in which the authors use dynamic factors to synthesize the dynamics of a larger number of monthly variables. However, the explicit estimation of GDP in the current quarter and the accompanying problem of the treatment of monthly missing values are not the focus of that paper, for its primary concern is the construction of a monthly coincident indicator of real activity, which is more on the path of the CFNAI index released by the Chicago Fed or the Eurocoin indicator under the CEPR and the Italian central bank. In contrast to Rašić-Bakarić, Tkalec and Vizek (2013), in this paper, GDP and the dynamics of a large number of monthly indicators are related directly using a factor model.

The remainder of the paper is organised as follows. The second chapter presents nowcasting models. The third chapter presents the evaluation of the models implemented. In the fourth chapter, monthly rates of domestic GDP are constructed. The fifth chapter concludes.

4 The MRGA (Monthly Indicator of Real Economic Activity) model has been used for nowcasting GDP since 2009 for the internal needs of the Croatian National Bank, and has proved to be a robust alternative to bridge models.

5 Angelini and Marcellino (2011) use similar models in backdating GDP when constructing German macroseries for the period before unification. Such imputation based on the dynamics of factors can be particularly useful to young economies facing the problem of shortness of macroeconomic series. In addition, Angelini et al. (2010) define a model which integrates the dynamics of a large number of monthly indicators and monthly GDP and its main components, with exact national accounts identities. In other words, the model is suitable for the estimation of consistent monthly national accounts. Finally, in the recent period, the indicators of real activity have been defined at very high frequencies, weekly or even daily (e.g. Modugno et al., 2012).

6 Schumacher and Breitung (2008) and MRGA.

2 Models for nowcasting GDP growth rates

In this chapter, we briefly describe the three models recursively tested on the example of nowcasting domestic GDP. The key features of the models by Giannone et al. (2008) and Schumacher and Breitung (2008) are illustrated, and the MRGA model is introduced. Special attention is paid to the methods by which missing values are imputed. A detailed exposition of the first two models is presented in the respective papers.

2.1 Schumacher and Breitung (2008)

According to this model, the nowcasting of GDP is performed based on a large factor model which is adapted so that it uses the dynamics of both monthly and quarterly variables simultaneously. The quarterly variables are first represented through their (unobserved!) monthly growth rates. After that, the missing data are estimated with the EM algorithm (Stock and Watson, 2002a) as part of an iterative procedure. In this case, estimation is performed for missing monthly variables at the end of the sample and (non-existent) monthly GDP growth rates. The factors on which the EM algorithm is based are estimated by the principal components analysis (PCA). Bearing in mind that monthly GDP growth rates are the main output of the algorithm, it is easy to construct a nowcast, namely the estimation of the actual, but not yet released quarterly GDP rate. In more detail, these steps can be written in the following way.

Summarising a large number of indicators to factors – principal components analysis. In the model, we assume that each of the N monthly indicators (their respective stationary transformations), $X_i=(x_{i1},\dots,x_{iT})$, for $i=1,\dots,N$ can be represented as a linear combination of a small number $(r<<N)$ of factors given in the $T\times r$ matrix F:

$$X_i=F\Lambda_i+e_i$$

where Λ_i is the r-dimensional vector of factor loadings, and where e_i are idiosyncratic errors. Factors F (and the associated weights Λ_i) can be estimated consistently under certain conditions by employing the principal components method (PCA) if N and T go to infinity (asymptotic properties are analysed in Bai, 2004 and in Stock and Watson, 2002b). Although formal procedures for the selection of the number of factors in the model have been developed (see Bai and Ng, 2002), this number has been selected *ad hoc* in the analysis.

Estimation of missing values in the database. Missing values are estimated iteratively with the EM algorithm. For this purpose, it is useful to introduce a notation first by which available data are related to the (unobserved) data to be imputed using the model. In general, the literature differentiates between several important cases in the treatment of missing values. The most important ones refer to the missing value of monthly indicators on the edges of the analysed sample (ragged edge data) and to the use of quarterly data at monthly frequency. For simplicity, we will illustrate the methodology in a case in which only the latest value of the monthly indicator X_i is missing. It is then easy to generalise this simple example. $\tilde{X}_i$ is the $T–1$ dimensional shortened vector obtained by excluding the last (missing) observation from X_i. Furthermore, matrix A_i is the matrix connecting the original vector X_i and the shortened $\tilde{X}_i$, as follows:

$$\tilde{X}_i = A_i X_i .$$

In this case the $(T–1)\times T$ transformation matrix is obviously of the following form:

$$A_i = \begin{bmatrix} 1 & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & 1 & 0 \end{bmatrix}.$$

The general case (more than one missing observation) is analogously treated by removing the necessary number of rows and adding the necessary number of null columns to the transformation matrix A_i.

Quarterly GDP as a monthly variable. Effectively, this methodology is employed to construct monthly GDP growth rates, and it is therefore necessary to establish a relation between the monthly and quarterly GDP rates. The idea is to express quarterly GDP as the sum of monthly values:

$$Y_t^q = Y_t^m + Y_{t-1}^m + Y_{t-2}^m,$$

where t denotes the months. The expression above is thus valid for t=3,6,9,... If geometric mean is used as an approximation to arithmetic mean (Mariano and Murasawa, 2003), the expression above becomes:

$$Y_t^q = Y_t^m + Y_{t-1}^m + Y_{t-2}^m \approx 3(Y_t^m Y_{t-1}^m Y_{t-2}^m)^{\frac{1}{3}}.$$

Since the difference of logarithms of GDP approximates the rate of change, the following is valid:

$$\begin{aligned}\Delta^q y_t^q &= \log(Y_t^q) - \log(Y_{t-3}^q) = \\ &= \frac{1}{3}(\Delta\log(Y_t^m) + 2\Delta\log(Y_{t-1}^m) + 3\Delta\log(Y_{t-2}^m) + 2\Delta\log(Y_{t-3}^m) + \Delta\log(Y_{t-4}^m)) \\ &= \frac{1}{3}(\Delta y_t^m + 2\Delta y_{t-1}^m + 3\Delta y_{t-2}^m + 2\Delta y_{t-3}^m + \Delta y_{t-4}^m).\end{aligned} \tag{1}$$

Furthermore, if we define the matrix:

$$A_q = \begin{bmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \dots & 3 & 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \dots & 0 & 1 & 2 & 3 & 2 & 1 & 0 & 0 & 0 \\ \dots & 0 & 0 & 0 & 0 & 1 & 2 & 3 & 2 & 1 \end{bmatrix}$$

then it is easy to establish link (1) between the vector of quarterly and monthly GDP rates: $\Delta^q Y^q = A_q \Delta Y^m$, where $\Delta^q Y^q = (\dots, \Delta^q y_{T-6}^q \Delta^q y_{T-3}^q, \Delta^q y_T^q)'$ correspond to quarterly and $\Delta Y^m = (\dots, \Delta y_{T-2}^m, \Delta y_{T-1}^m, \Delta y_T^m)'$ to monthly growth rates. Finally, by combining the treatment of missing values and the representations of quarterly variables at monthly frequency, combined cases can also be taken into account, for instance the treatment of quarterly variables when we have data only for one or two months for the current quarter.

EM algorithm. The applied EM algorithm iterates two basic steps, the E-step and the M-step. Before this, missing values are initialised arbitrarily, e.g. with the average value of a given stationary series. The E-step estimates the factors of the model using the principal components method (PCA).

E-step. In step k, for the given estimate of factors $\hat{F}^{(k-1)}$ and weights $\hat{\Lambda}_i^{(k-1)}$ from the previous step of the algorithm, we estimate the expectation of the missing value with regard to the existing factor model:

$$\begin{aligned}\hat{X}_i^{(k)} &= E\left(X \mid \hat{F}^{(k-1)}, \hat{\Lambda}_i^{(k-1)}, \tilde{X}_i\right) = \\ &= \hat{F}^{(k-1)}\hat{\Lambda}_i^{(k-1)} + A_i^\tau (A_i A_i^\tau)^{-1} (\tilde{X}_i - A_i \hat{F}^{(k-1)} \hat{\Lambda}_i^{(k-1)}),\end{aligned}$$

where matrix A_i corresponds to the transformation associated to variable i. In other words, this matrix relates quarterly series to their unobserved monthly counterparts, while missing values at the end of the sample are treated as described earlier.

M-step. By using the imputed data from the E-step of the algorithm, factors $\hat{F}^{(k)}$ and weights $\hat{\Lambda}_i^{(k)}$ are now re-estimated in step $k+1$ and the E-step is iterated. The procedure is iterated as long as the difference between imputed values from two successive steps in the algorithm exceeds a sufficiently small number ε. A detailed description of the EM algorithm can be found in Watson and Engle (1983).

2.2 Giannone et al. (2008)

The model assumes that the available monthly data, namely their stationary and standardised transformation $X_t=(x_{1t},\ldots,x_{nt})'$, for $i=1,\ldots,N$ and $t=1,\ldots,T$ can be presented by the dynamic factor model in a satisfactory manner:

$$X_t = \Lambda F_t + \xi_t \tag{2}$$

where $F_t=(f_{1t},\ldots,f_{rt})'$ are common factors which describe the bulk of the common variation of variables in X_t, Λ is the $n\times r$ matrix of factor loadings and $\xi_t=(\xi_{1t},\ldots,\xi_{nt})'$ is the idiosyncratic component of individual variables. The covariance matrix of the idiosyncratic component is given by:

$$\begin{aligned} E(\xi_t\xi_t') &= \psi_t = diag(\tilde{\psi}_{1t},\ldots,\tilde{\psi}_{nt}) \\ E(\xi_t\xi'_{t-s}) &= 0, \text{ for } s > 0. \end{aligned}$$

Furthermore, it is assumed that the dynamics of factors is regulated by the standard VAR model:

$$F_t = AF_{t-1} + Bu_t \tag{3}$$

where A is an $r\times r$ matrix of parameters of the model and B is an $r\times q$ matrix of rank q, where q is the number of common shocks that affect the economy. The covariance matrix of shocks is given by: $Q=E(Bu_t(Bu_t)')$. Equations (2) and (3) define the state space representation of the model.

Since the parameters of the model are estimated in the case when some of the values of vector X at the end of the sample are unknown, the variance associated to the missing values is defined as infinite:

$$\tilde{\Psi}_{it} = \begin{cases} \Psi_i \text{, if } x_{it} \text{ is avaliable} \\ \infty \text{, if } x_{it} \text{ is not avaliable.} \end{cases}$$

The reason for such a definition of the variance lies in the algorithm of the Kalman filter according to which new information is taken into account in the estimation of factors together with the weight which is inversely proportional to its variance. In this way, the algorithm takes missing values into account infinitely little, i.e. it ignores them.

The parameters of the model (Λ, A, B, Ψ) are estimated in two steps. In the first step, factors and factor loadings are estimated on a maximum sample on which there are no missing values using PCA and OLS. The estimation of the VAR model on the estimated factors produces estimates of matrices A and B. In the second step, factors are re-estimated using the Kalman filter and the Kalman smoother, but now missing data in X are taken into account and the variance is defined appropriately, as already shown. Doz et al. (2011) show the asymptotic properties of this estimator.

Finally, after factors are estimated, and possibly forecast at an arbitrary horizon in the future, they are transformed to quarterly frequency, which gives $\hat{F}_T^q$. The nowcasting/forecasting of GDP is then performed as a simple projection on the constructed quarterly factors:

$$E(y_T^Q \,|\, \text{available monthly information at the time of nowcasting}) = \hat{\alpha} + \hat{\beta}\hat{F}_T^q.$$

Note that the OLS specification above actually reduces this model to a standard bridge model. However, unlike the standard bridge models in which GDP is related directly to only a handful of variables, here the relationship is established between GDP and a potentially large number of available indicators represented by dynamic factors.

2.3 MRGA

This model has been used at the Croatian National Bank since 2009 for in-house nowcasting of the quarterly GDP growth rate and it has proved to be a robust alternative to standard bridge models. In terms of structure, the model is a combination of the two described models. More precisely, following the example of Schumacher and Breitung (2008), missing values at the end of the sample are imputed with the EM algorithm[7] and common factors are estimated using principal components analysis (PCA), while, analogously to Giannone et al. (2008), the nowcast is constructed by a direct projection on the estimated factors. Unlike the previous models, specific factors from the subgroups of monthly variables can be estimated – domestic variables, foreign variables and credits, which are then aggregated to a quarterly level.

Let us assume that nowcasting is based on the dynamics of N monthly indicators $X_i=(x_{i1},\dots,x_{iT})$, for $i=1,\dots,N$, whose missing values are first imputed according to the described EM algorithm, ARIMA models, or similar. After that, monthly factors f_{it} are estimated from monthly indicators using PCA, which are aggregated to a quarterly level and quarterly factors f_{it}^{Q} are thus obtained. Due to the fact that GDP data are released with a lag relative to the information available from monthly indicators, that is, factors are available for periods $1,\dots,T^q$, and GDP for one period less – $1,\dots,T^q–1$, the following "bridge equation" is used for computing the forecast/nowcast of the GDP growth rate:

$$y_t^Q = \alpha + \beta_i f_{it}^Q + \varepsilon_i^Q .$$

The parameters of regression are estimated to $1,\dots,(T^q–1)$, while the nowcast, or GDP in T^q is constructed as:

$$E(y_{T^q}^Q \mid \Omega_{T^q}) = \hat{\alpha} + \hat{\beta}_i f_{iT^q}^Q . \qquad (4)$$

2.4 Benchmark models (random walk model and bridge model)

The quality of the forecasts of the models presented is compared with the forecasts of two benchmark models. The first model is the random walk model for the rates of change of GDP, and it assumes:

$$y_t^Q = y_{t-1}^Q + \varepsilon_i^Q$$

which also means that it is optimal to construct the forecast of the current rate of GDP as the last observed growth rate:

$$E(y_{T^q}^Q \mid \Omega_{T^q}) = y_{T^q-1}^Q .$$

As well as the random walk model, a simple bridge model is also used as a benchmark, in which the GDP rate is explained by the dynamics of the volume of industrial production, retail trade and past GDP[8] values. The missing monthly values of industry and trade at the end of the quarter are updated in different ways, by using special ARIMA models or by assuming a zero monthly growth of the series.

7 Missing values can also be imputed with alternative methods, for instance with ARIMA models etc.

8 Within this model, specifications which include the dynamics of loans and external indicators (e.g. trends in EUROCOIN and external trade indicators) have also been tested. Since it was only occasionally that these indicators explained the dynamics of GDP substantially, they were not incorporated in the final specification. On the other hand, industry and trade are important for the movement of GDP on the entire observed sample.

3 Evaluation of nowcasting models

In this chapter, the quality of forecasts obtained on the basis of the presented nowcasting models is tested. For the calculation of factors, 41 time series are taken into account, which represent movements in trade, domestic industry and construction, credit activity, financial sector, labour market, price indices, foreign trade indicators, nominal exchange rate and indicators of economic activity for main trading partners, or the foreign sector. The list of indicators, the sources of data and transformations by which they are reduced to stationarity are given in the Appendix. The series are seasonally adjusted using the X12 procedure.

Final revised data for the period from 2000 to the second quarter of 2013 are used in the analysis. The sample, from 2000 to the first quarter of 2006, is used exclusively for the estimation of factors and other parameters of the model and, subsequently, nowcasts are constructed for the period from the first quarter of 2006 to the second quarter of 2013 by successive addition of new monthly data and the re-estimation of the model. In order to take account of the fact that the recent recession has had a considerable impact on relations between the indicators considered and overall real activity, the results are shown on three samples, first on the entire sample from 2006 to the second quarter of 2013, then also for two characteristic periods – before and after the beginning of the 2008 recession.

The models are parameterised so that specifications with a varied number of factors were first tested on a presample, after which models which describe the dynamics of GDP in a satisfactory manner were selected. The specification by Giannone et al. (2008) is thus based on three dynamic factors and three orthogonal shocks in the respective VAR model. In a separate equation, GDP is then related to the indicators used with only one factor. The specification by Schumacher and Breitung (2008) is defined with the use of three factors (principal components). The MRGA model allows different specifications and for this reason it has been tested in two versions. The first version estimates one factor from the subgroups of domestic or foreign variables, which it then relates to GDP[9]. The second version is based on the extraction of one common factor from the group of all available indicators. The model in which specific factors are constructed for the individual group of variables (for instance, domestic, foreign variables, credits, etc.) also provides forecasters with a storytelling device, while it enables the users of forecasts to identify the principal generators of the dynamics of forecasts. Despite this, it is unclear whether the estimation of specific factors leads to improvement in the nowcast accuracy, which is to be tested. Finally, models are defined for each of the two versions by three ways to treat missing values – with the EM algorithm, ARIMA models and the random walk model. The bridge model implemented is based on the dynamics of trade and industrial production. In models which relate GDP to monthly indicators (Giannone et al., 2008 and MRGA) using a particular OLS specification, we allow a distinctive constant (dummy variable) to be added for the period of recession, or after the third quarter of 2008. Finally, in addition to the individual models, the quality of forecasts of the average of the individual models was also tested. The literature often mentions that simple combinations of forecasts of individual models, in this case the arithmetic mean, can provide more accurate forecasts than the majority, or sometimes all of the models[10] used.

In Table 1, the results of nowcasting of the models used are evaluated, with the assumption that we have all monthly indicators for all three months for the quarter for which the nowcast is constructed. RMSE (Root Mean Squared Error) is the statistics with which the accuracy of the individual models is measured, which is presented in relation to the naive random walk model. If the relative RMSE of a model was less than one on a given sample, this model gave better forecasts than the benchmark model. The results in the table indicate the

9 In the past, apart from factors from the group of domestic and foreign variables, factors describing loan dynamics were also used for nowcasting GDP, in an endeavour to emphasize the importance credit growth had for broader economic activity at the time. With regard to the decline in the correlation of credits and GDP, a more robust version has been tested in this paper, which also takes into account the dynamics of credits, however, in such a way that credits are incorporated in the domestic factor only as one of the series from which this factor is constructed.

10 See, for example, Timmermann (2006), Stock and Watson (2004), Clemen (1989) and Marcellino (2002) on possible reasons for good results of a combination of forecasts.

following basic conclusions. First of all, factor models are much more successful than the naive benchmark random walk model on all subsamples, which confirms the assumption that the information contained in the monthly indicators used helps in the estimation of GDP. Then, in almost all cases, factor models outperform bridge regressions, that include the dynamics of retail trade and industrial production. This is an important result, which shows that it is possible to utilize the informativeness of a large number of series successfully within the factor analysis framework. As to the performance of forecasts of the specifications of individual factor models, their performances appear to be very similar. However, small differences still exist. Thus the model based on the Kalman filter (Giannone et al., 2008) gives marginally better nowcasts than the two remaining models in the recession period, while the MRGA model gives the best projections in the period before recession. Furthermore, it seems that the estimation of specific factors from the subgroups of indicators used does not improve the nowcast accuracy. Finally, an important result of the analysis is that it is worth averaging the results of the individual models in this case. The average of the individual models gave results on all subsamples observed, which were more accurate than the results of all individual models.

Table 1 Evaluation of GDP nowcasts (complete dataset)

Model	2006 – Q2 2013	2006 – Q2 2008	Q3 2008 – Q2 2013
MRGA (1)	0.74	0.63	0.78
MRGA (2)	0.70	0.62	0.73
BM	0.84	1.05	0.75
Giannone et al.	0.68	0.67	0.68
Schumacher-Breitung	0.82	0.78	0.84
Average	0.66	0.60	0.68

Note: Relative RMSE statistics of the models tested are shown compared to the benchmark random walk model for the entire sample and for the periods before and after the third quarter of 2008 (which marks the beginning of the recession). MRGA (1) denotes the model in which domestic and foreign factors are constructed from the associated groups of variables, while MRGA (2) is based on factors computed from the group of all analysed variables. BM stands for bridge model.
Source: Authors' computation.

When a database is not complete missing values are treated in some of the ways already presented in the text. To illustrate the performances of nowcasting models in this case, a recursive nowcasting procedure is simulated for a characteristic case from application. In every quarter, it is assumed that all data for the first month in the quarter and in part for the second month of the quarter are known. Such data availability is typical at the end of the quarter for which the nowcast is being constructed (see the table and release patterns for the data used in the Annex). Giannone et al. (2008) impute missing values within the state space methodology, while Schumacher and Breitung (2008) use the EM algorithm. On the other hand, in the MRGA model, alternative approaches in imputing missing values are allowed. Since, in principle, it is not clear how and to what extent alternative methods of infilling missing values affect the result, three approaches have been tested in this respect: with ARIMA models for each indicator, with the random walk model for each series and, finally, using the EM algorithm. The results are shown in Table 2.

Table 2 Evaluation of GDP nowcasts (incomplete dataset)

Model	Treatment of missing values	2006 – Q2 2013	2006 – Q2 2008	Q3 2008 – Q2 2013
MRGA (1)	Random Walk	0.80	0.77	0.81
MRGA (2)	Random Walk	0.79	0.74	0.81
MRGA (1)	ARIMA	0.78	0.68	0.81
MRGA (2)	ARIMA	0.77	0.65	0.81
MRGA (1)	EM algorithm	0.81	0.75	0.83
MRGA (2)	EM algorithm	0.81	0.72	0.84
BM	ARIMA	0.87	1.06	0.79
Giannone et al.	Kalman filter	0.76	0.69	0.78
Schumacher-Breitung	EM algorithm	0.81	0.93	0.77
Average		0.73	0.67	0.75

Note: Relative RMSE statistics of the models tested are shown compared to the benchmark random walk model for the entire sample and for the periods before and after the third quarter of 2008 (which marks the beginning of the recession). MRGA (1) denotes the model in which domestic and foreign factors are constructed from the associated groups of variables, while MRGA (2) is based on factors computed from the group of all analysed variables. BM stands for bridge model.
Source: Authors' computation.

The comparison of the results in Tables 1 and 2 leads to the basic conclusion that forecasts based on all three months in the quarter (Table 1) are somewhat better than those based on a more narrow information set (Table 2). Furthermore, the strategy of updating missing values applied for the MRGA model has not affected the quality of the forecast significantly. ARIMA models gave only marginally better results than the remaining strategies. In terms of quality, other results are identical to those when a full database is used (Table 1). It has been proved again that it is worthwhile averaging the results of the individual models when nowcasting.

4 Monthly indicator of real economic activity

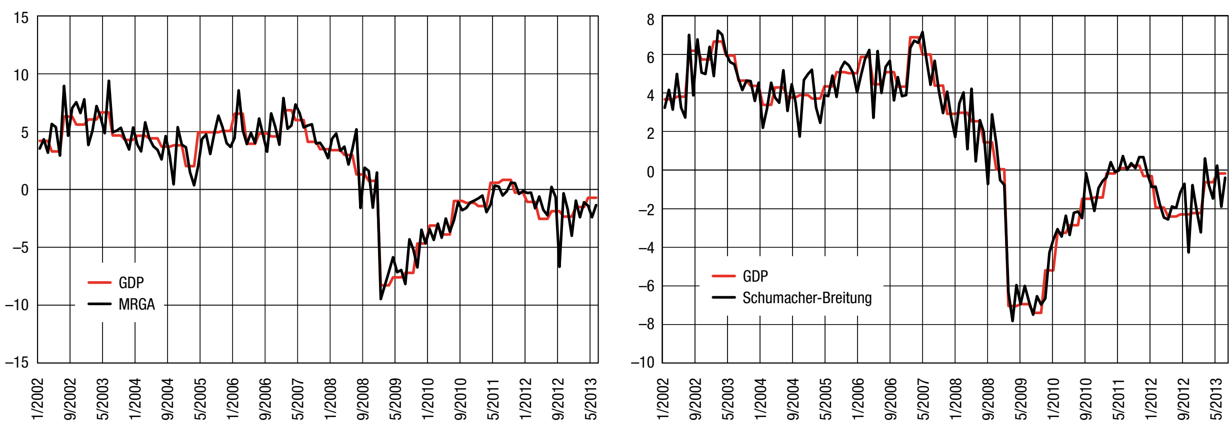
The focus of this paper is on the problem of nowcasting real activity using a larger number of monthly indicators. However, this chapter indicates that the methodology implemented can also be used for other purposes, including computing the dynamics of GDP at a monthly level.

Some of the models presented here enable a direct estimation of GDP at monthly frequency. For instance, the (standardised) monthly GDP rate is a useful direct result of the model by Schumacher and Breitung (2008). On the other hand, the structure of the MRGA model on the basis of the dynamics of a large number of indicators enables the computation of the monthly GDP rate as compared to the same month of the previous year[11]. For comparison, monthly GDP growth rates as compared to the same month of the previous year are constructed by means of the two methodologies mentioned.

The MRGA model relates the dynamics of a large number of indicators to GDP with a simple bridge equation on quarterly data, whose parameters α and β are estimated with the OLS method. Note first that the incorporation of monthly factors f_{it} into the bridge equation will construct an approximate monthly GDP growth rate as compared to the same month of the previous year:

$$\hat{y}_t^m = \hat{\alpha} + \hat{\beta}_i \hat{f}_{it}.$$

Figure 1 Model-based monthly GDP rates



Note: The figures show the annual GDP growth rates (at a monthly level) computed using MRGA and Schumacher-Breitung models and actual growth of quarterly GDP. Actual GDP is shown at a monthly level so that actual annual growth for that quarter is shown for each month in a quarter.
Source: Authors' computation.

11 Unlike the two previous analyses, Gianonne et al. (2008) aggregate monthly data to a quarterly level so that it is not possible to read the monthly dynamics of growth of GDP directly. Monthly series are transformed so that they reflect growth in the current quarter as compared to the previous one. In this way, the last month of the quarter reflects the quarterly growth of a series. However, the monthly dynamics of GDP can also be computed by an alternative transformation of indicators from which dynamic factors are computed.

A good property of the constructed series is that its average within each quarter equals the (estimated) quarterly GDP rate computed on the basis of projection (4). This construction is based on the assumption that monthly factors are aggregated to a quarterly level by averaging their values within each quarter.

Figure 1 shows the monthly series of GDP growth as compared to the same month of the previous year obtained by the models[12] described. These series are shown together with actual annual GDP growth rates. The figure shows that constructed series follow the dynamics of quarterly GDP closely. However, they are subject to short-term fluctuations that are not necessarily essential for the dynamics of the business cycle, or for the frequencies of the series that determine movements in the medium and long run. Unlike this, the EUROCOIN indicator, for instance, is constructed so that it isolates the signal from GDP which is important only for the medium and long term movement, while it ignores short-term volatile movements to a large extent. Despite this, the dynamics of GDP on a monthly basis directly relates the movements of the indicators used to GDP, and as such provides a detailed insight into the sources of volatility of the official statistics of national accounts. Apart from this, the constructed series can serve as a good representative of real activity at monthly frequency in quantitative analyses.

5 Conclusion

This paper tests the extent to which available monthly economic indicators help in the process of nowcasting GDP. For this purpose, nowcasts based on factor models, presented in Giannone et al. (2008) and Schumacher and Breitung (2008) as well as on the MRGA model introduced in this paper, were constructed recursively on data relevant for the movement of domestic GDP. The implemented models differ primarily in the way in which they treat the missing values of the monthly indicators used, not all of which are available because of different release patterns. The evaluation of the results of the models indicates the following basic conclusions. Factor models based on the dynamics of a broad group of variables, in terms of mean squared error, give better nowcasts than those based on the naive random walk model, or nowcasts based exclusively on the dynamics of retail trade and industrial production. In other words, factor models seem to be a good methodological framework by which the information available in a large number of available indicators can be synthesised. Differences among individual factor models do exist, but they are not of crucial importance.

It is an important finding of the analysis that it is worth combining the information available in individual models in the case of nowcasting. The average of the results of individual models regularly resulted in more accurate nowcasts than those obtained on the basis of individual models. This result is probably the consequence of the fact that the averaging of the results of individual models decreases the effect of significant errors while nowcasting. Besides, if an unambiguous selection of a single best model in terms of RMSE is difficult, it is a good decision to compute the average of the several models.

The methodological framework used also enables the computing of the GDP growth rate at a monthly level. In this paper, the monthly series of the GDP growth rate for Croatia based on the movement of a large number of available monthly indicators are constructed and shown. The monthly dynamics of real GDP can be useful to economic policy-makers, general public and in empirical research as a representative of real activity at monthly frequency.

Building on related literature, this paper also shows that information available in a large number of available economic indicators can be related to the official statistics of national accounts under the methodological framework of factor models. Although this paper focuses on two applications of the methodology – nowcasting GDP and computing the monthly GDP growth rates, the methodology also allows for a broader implementation.

12 The two figures are not comparable directly because the first figure was computed on the basis of the model on original GDP and the other one on seasonally adjusted GDP.

Appendix

Monthly indicators and corresponding transformations

Series	Source of data	Release (No. of weeks after expiry of the month)	log	diff
CROBEX average value	ZSE	0 weeks	x	x
Monthly average of HRK/EUR exchange rate	CNB	0 weeks	x	x
Monthly average of HRK/USD exchange rate	CNB	0 weeks	x	x
EURIBOR 12 months	http://www.euribor-rates.eu/	0 weeks		x
EURIBOR 3 months	http://www.euribor-rates.eu/	0 weeks		x
Average monthly CDS price for Croatia	Bloomberg	0 weeks	x	x
Eurocoin indicator	CEPR, Banca D'Italia	0 weeks		x
Economic sentiment indicator (European Union)	Eurostat	0 weeks	x	x
Consumer economic sentiment indicator (eurozone)	Eurostat	0 weeks		x
Total credits	CNB	1 week	x	x
Consumer price index – total	CBS	2 weeks	x	x
PPI index – industry	CBS	2 weeks	x	x
Registered unemployment	CBS	~ 3 weeks	x	x
Industrial production index – total	CBS	4 weeks	x	x
Industrial production index – energy	CBS	4 weeks	x	x
Industrial production index – intermediate goods	CBS	4 weeks	x	x
Industrial production index – capital goods	CBS	4 weeks	x	x
Industrial production index – durable goods	CBS	4 weeks	x	x
Industrial production index – non-durable goods	CBS	4 weeks	x	x
Industrial production index – mining and quarrying	CBS	4 weeks	x	x
Industrial production index – manufacturing	CBS	4 weeks	x	x
Industrial production index – electricity supply	CBS	4 weeks	x	x
Tourism – arrivals	CBS	4 weeks (first results)	x	x
Tourism – overnight stays	CBS	4 weeks (first results)	x	x
Total employment	CBS	4 weeks (first results)	x	x
Number of employees in legal entities – financial activities	CBS	4 weeks	x	x
Number of employees in legal entities – service activities	CBS	4 weeks	x	x
Value added tax	MoF	4 weeks	x	x
Retail trade turnover index	CBS	5 weeks (first results)	x	x
Imports	CBS	6 weeks (first results)	x	x
Exports	CBS	6 weeks (first results)	x	x
Imports (excluding ships and oil)	CBS	6 weeks	x	x
Exports (excluding ships and oil)	CBS	6 weeks	x	x
Industrial production index – Austria	Eurostat	6 weeks	x	x
Industrial production index – Germany	Eurostat	6 weeks	x	x
Industrial production index – Hungary	Eurostat	6 weeks	x	x
Industrial production index – Italy	Eurostat	6 weeks	x	x
Industrial production index – Slovenia	Eurostat	6 weeks	x	x
Volume index of construction works	CBS	8 weeks	x	x
Average real gross wage	CBS	8 weeks	x	x

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