SHORT-TERM FORECASTING ROMANIAN GDP GROWTH USING A LIMITED SELECTION OF MONTHLY INDICATORS

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Abstract

We apply a bridge equation model to forecast short-term GDP growth for Romania using a small number of commonly employed indicators with a monthly frequency. The monthly indicators are forecast to the time horizon of interest through an autoregressive process (AR). The data is aggregated to quarterly frequency and each independent variable is paired with the dependent variable (GDP growth). For each pair a distributed lag model is applied, and the forecast is obtained as the average of the forecasts produced by all pairwise models. The idea of using indicators with a higher frequency to forecast quarterly GDP data has been applied to the Euro Area and countries from Western Europe. Despite this, its application to Eastern Europe remains limited. We test our simple model on current quarter (nowcast) and quarter-ahead forecasts under two scenarios. In the first scenario only car-registration data are available for the first month of the current quarter, whereas in the second all data are available for the current quarter. We find that our model produces more accurate forecasts compared to a first-order AR model using only GDP data. As expected, the accuracy of the forecast improves under the second scenario.

Key words: GDP forecasting, nowcasting, dynamic model

JEL Code: C53, C22

Introduction

Having a timely and accurate assessment of the current state of the economy and its near-term prospects is crucial for businesses and policymakers alike. Unfortunately, quarterly GDP data is released weeks after the end of the current quarter. This issue can be partially mitigated by estimating quarterly GDP through monthly indicators. These may be part of the GDP (such as industrial production and retail trade indices) or may represent expectations of consumers or business leaders obtained through surveys. Capital market data, interest rates and other financial data could also be used. All have certain advantages and disadvantages. Macroeconomic data is released with some delay and may be revised, whereas survey and financial data are timelier and generally not subject to revisions. On the other hand macroeconomic data may be more reliable since indicators such as industrial production tend to be strongly correlated with GDP.

We use a limited selection of monthly indicators to forecast quarterly Romanian GDP growth via a bridge equation model. This methodology has been employed in forecasting GDP growth in Western European countries and the Euro area, but its application in Eastern Europe remains limited, although its utility for macroeconomic policy decisions is obvious.

The next section provides a brief overview of the short-term forecasting literature and of the rather timid forecasting research carried out for Romania. The following section describes the model and data used. Results are then presented and discussed. The final section concludes.

1 Literature Review

The bridge equation forecasting methodology involves a number of steps. First the monthly indicators are forecast to the time horizon of interest, typically through a univariate model. The monthly data is then aggregated to quarterly frequency and pairs are formed between each indicator and GDP growth. A bridge equation is estimated via OLS regression for each pair, with GDP growth as the dependent variable. The forecast is obtained as the average of the forecasts produced by each pair. Rünstler & Sédillot (2003) use this methodology for the Euro Area and find that it performs better than an ARIMA forecast. The usefulness of survey data is found to be limited, but the authors point out that such data may be better suited for predicting turning points in the business cycle. Baffigi, Golinelli & Parigi (2004) confirm the superior performance of bridge models for the Euro Area. This is also the case for France (Barhoumi et al., 2012). Nevertheless, their usefulness is found to be limited for new EU members (Lithuania, Hungary and Poland) due to unstable economic relationships and data quality and availability issues (Rünstler et al., 2009).

Bridge equation models usually involve a limited number of monthly variables, but the availability of a large number of indicators can be exploited through factor models. These are similar in principle to bridge equations as both involve "bridging" data with monthly and quarterly frequencies. The main difference comes from the fact that instead of working with the monthly series directly, factor models decompose these into a number of common factors and an idiosyncratic term particular to each series. Factor models may prove more accurate as they have the advantage of exploiting the information content of cross-correlations across series (Angelini et al., 2011). On the other hand, they may be difficult to interpret in practice

(Barhoumi et al., 2012). Arnoštová et al. (2011) apply both types of models for the Czech Republic and find that a principal components factor model performs better than bridge equations, but only on a restricted set of monthly time series, noting that smaller models may be preferable.

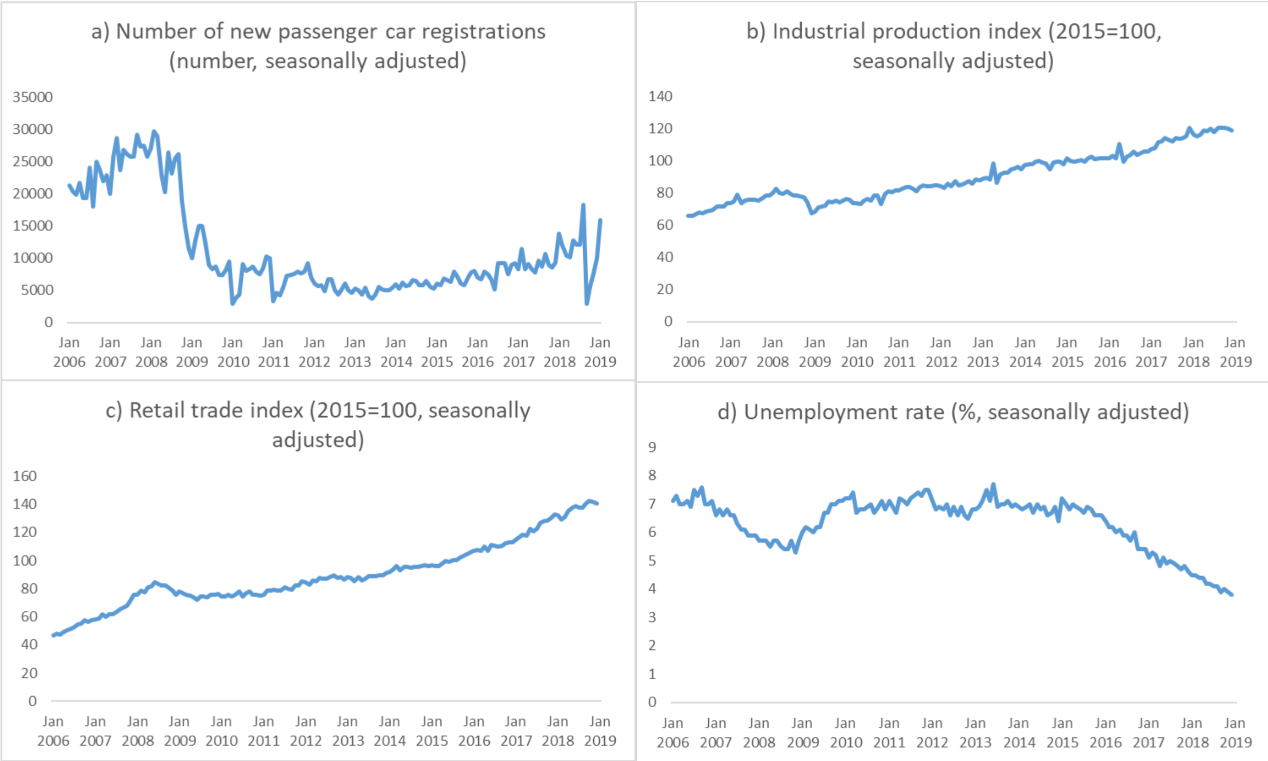
One of the main limitations of models involving monthly series comes from the difficulty in evaluating their performance. This evaluation is carried out in a pseudo real-time context meaning that researchers try to mimic the release schedule of the data used, but employ the final version of the data. The results can be misleading as, in practice, the data is often preliminary and subject to revisions – macroeconomic series in particular. Despite this issue, errors from revisions are found to be relatively small and may be partially mitigated by the use of survey and financial data (Diron, 2008).

The short-term macroeconomic forecasting literature is scarce in the case of Romania, a state which motivates the present paper. Short-term GDP forecasts have been carried out through Bayesian Vector Autoregressive models (Caraiani, 2010). Saman (2011) used neural networks to model GDP based on financial data (investments and real interest rates). Regardless of the method used in forecasting Romanian macroeconomic indicators, the issue of short time series and their low reliability constitute a significant hindrance (Armeanu et al., 2015).

2 Data and Methodology

We use a set of monthly indicators commonly employed in the literature due to their strong correlation with the GDP. These are new passenger car registrations, unemployment, and industrial production and retail trade indices. All are plotted in Fig. 1. Data come from Eurostat with the exception of car registrations and GDP growth rates which come from the European Central Bank. All indicators are seasonally adjusted and used in logarithm form. The difference between each month and the corresponding month in the previous quarter is then computed, rendering the series stationary. Outliers, defined as values more than three scaled median absolute deviations away from the median, have been replaced through linear interpolation.

Fig. 1: Monthly indicators



Source: European Central Bank for new passenger car registrations, Eurostat for the rest

We follow the methodology outlined in the previous section as follows. Monthly indicators are forecast individually to the period six months ahead of the latest quarter with GDP data available, through an AR (p_k) model (Equation 1). Where p_k is the lag length selected for each k series based on the Schwarz information criterion and X_k^M is the monthly indicator to be forecast. We use superscripts M and Q to denote monthly and quarterly frequencies respectively throughout the paper. t and k represent the time and indicator indexes respectively. α_k, $\beta_{k,i}$, and $\varepsilon_{k,t}$ are the constant, parameter for each lagged value of the monthly indicator, and error term, respectively.

$$X_{k,t}^M = \alpha_k + \sum_{i=1}^{p_k} \beta_{k,i} X_{k,t-i}^M + \varepsilon_{k,t} \qquad (1)$$

Each X_k^M monthly indicator is aggregated to quarterly frequency by simple averaging, and pairs are created between each indicator and GDP growth. For each pair a distributed lag model (Equation 2) is estimated by OLS, with the lag length q_k again determined based on the Schwarz information criterion. X_k^Q denotes the monthly indicator aggregated to quarterly frequency. t and k represent the time and indicator indexes respectively. μ_k, $\varphi_{k,s}$, and $\delta_{k,t}$ are the constant, parameter for each lagged value of the quarterly indicator, and error term, respectively.

$$GDP_t^Q = \mu_k + \sum_{s=0}^{q_k} \varphi_{k,s} X_{k,t-s}^Q + \delta_{k,t} \qquad (2)$$

The forecast is obtained as the simple arithmetical average of the forecasts produced by all pairwise models.

3 Results and Discussion

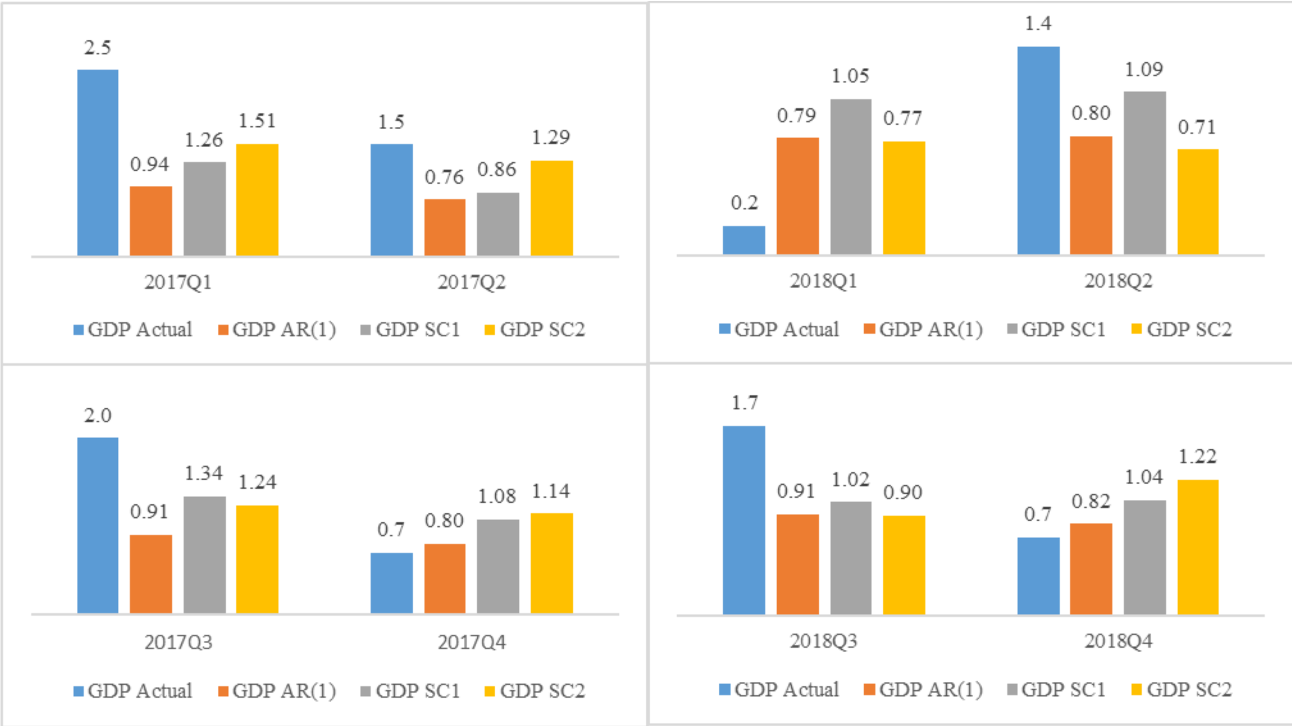
We test our simple model on current quarter (nowcast) and quarter-ahead forecasts for the 8-quarter period up to the end of 2018, under two scenarios. In the first scenario (SC1) only car-registration data are assumed to be available for the first month of the current quarter, whereas in the second all data are assumed available for the current quarter (SC2). The first scenario is meant to account for the fact that this series is available earlier than the rest of the data. The European Automobile Manufacturers Association publishes vehicle registration data with a delay of about two weeks from the end of the respective month, whereas the Romanian National Institute of Statistics publishes the industrial production index and other macroeconomic series with a delay of around six weeks.

The two scenarios are benchmarked against a simple AR(1) model of GDP growth (Equation 3). Where GDP_t^Q is the quarterly GDP growth rate at time *t*. α, β, and ε_t are the constant, parameter the lagged value of the GDP growth rate, and error term, respectively.

$$GDP_t^Q = \alpha + \beta GDP_{t-1}^Q + \varepsilon_t \qquad (3)$$

The AR(1) model uses only the previous quarter GDP growth rate as the independent variable. Therefore we would like to determine the benefit of using monthly indicators instead of past GDP data. The forecasts and actual values are presented in Fig. 2. The root-mean-square error (RMSE) and mean absolute error (MAE) are reported in Tab. 1. The performance of our model is superior to the AR(1) projection with lower errors, and as expected this improves under the second scenario. Nevertheless this performance is not consistent across all four forecasts. This is likely due to the limited number of variables used.

Fig. 2: GDP growth - actual and forecast (%)



Source: Authors' calculations, GDP Actual from European Central Bank

Tab. 1: Forecast errors

	GDP AR (1)	GDP SC1	GDP SC2
RMSE	0.83	0.70	0.66
MAE	0.70	0.64	0.62

Source: Authors' calculations

The Romanian economic environment is highly volatile compared to that of Western countries. Apart from external shocks, it is also vulnerable to an unstable political landscape. Decisions which can significantly affect the economy are made by government decree without public consultation and seemingly without any input from economists or policy experts. The performance of our forecasts may be considered low, but in this context we believe that results are encouraging. This is reinforced by the fact that we use only four explanatory variables which do not account for the development of the financial sector or the expectations of consumers and managers.

The bridge equation methodology used in this paper has proved to be a valid approach, paving the way for the development of more comprehensive models. Variables which we believe may add to the accuracy of the projections are: business and consumer confidence survey data, consumer credit volumes, industrial production in Germany and Italy (Romania's main trading partners), and real interest rates. Capital market data such as the main stock exchange index is unlikely to be particularly useful as its importance to the Romanian economy is low. In 2018 the total market capitalization of the Bucharest Stock Exchange stood at around 31 bn. EUR, according to the institution's website[1]. This represented approximately 15% of GDP. However this assertion should also be tested. A larger number of indicators could be exploited through a factor model, but this may be hard to interpret and implement in practice.

Conclusion

We constructed a bridge equation model for forecasting Romanian GDP growth in the current quarter and the next by means of monthly indicators (new passenger car registrations, unemployment, and industrial production and retail trade indices). These are chosen due to their high correlation with the GDP.

The model was tested under two scenarios. In the first only car registration data was assumed to be available for the first month of the current quarter, while in the second all monthly indicators are assumed to be available for the current quarter. We found that the model performs better on average compared to an AR(1) forecast, and that the accuracy improves under the second scenario as more data is used. However the performance is not consistent. This is likely due the limited number of variables used leading to specification errors, as well as the volatile nature of the Romanian political and economic landscape.

The aim of this study was not to develop a working model which could accurately project short-term GDP growth. Instead, our goal was to see if the use of monthly data can be a viable option in this regard. Despite its shortcomings, the small model used proves that the bridge equation methodology may be successfully applied to Romania and potentially to other East European countries. Reaching a performance level similar to that of models implemented for developed countries would be difficult due to the lower stability of Eastern European economies which could imply the existence of nonlinear relationships that cannot be captured by linear models such as OLS. Data availability and quality issues represent a further obstacle. This is not restricted to the length of the series, as some highly relevant indicators used for developed countries may not exist. For example, the OECD composite leading indicator which is designed to signal turning points in the business cycle is not computed for Romania.

Limitations notwithstanding, the bridge equation approach represents a potentially fruitful area for future research. As noted in the previous section, this should involve the use of more variables and exploiting the timeliness of survey and financial data. A reasonably accurate

[1] https://www.bvb.ro/TradingAndStatistics/Statistics/GeneralStatistics ; accessed April 03, 2019

model may prove a practical tool in the short-term business planning process. It could also benefit policymakers by allowing for the early identification of potential near-term imbalances in the economy.

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