SHORT TERM ALBANIAN GDP FORECAST: "ONE QUARTER TO ONE YEAR AHEAD"

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Abstract

In forecasting, macroeconomic variables such as GDP play an important role for policy makers and for the assessment of the future state of the economy. In this paper, different models to forecast quarterly GDP growth in Albania will be presented. The first group of models bases on ARIMA structures. These models are applied directly once on GDP series and then to the main economic activities which are been used to derive GDP. The second group of models for forecast uses VAR model, and the last group are refereed on by the bridge models. In cases were bridge models are used, variables with different frequencies are forecasted for the missing period. After that, all the series are aggregated at quarterly frequencies and are used for GDP forecast. Hence, the bulk of the material is to give comparisons of those models to forecast Albanian quarterly economic growth from one quarter up to four quarters ahead in a pseudo-real time setup.

Keywords: Forecasting, quarterly GDP, ARIMA models, VAR models

Introduction

Macroeconomic policy decisions in real time, in many cases are based on incomplete data. This problem is more acute in developing economies, where economic data become available in a later time. Building economic indicators in short-term period helps in a more accurate prediction of the current and next period. These are crucial steps for decision makers, which rely on these projections for analyzing and planning the economy in the long term. The increase of the number of high-frequency data has spurred interest in forecasting methods that rely on a large number of variables. Therefore, macroeconomic indicators are often published with a lag in time, so quarterly, GDP is released three months after the quarter has finished in the case of Albania.

Because of this delay, short-term forecasting of quarterly GDP using monthly and quarterly indicators, which are available earlier in time, is well motivated. However, weeks before the publication of the latest GDP figure, several monthly and quarterly indicators has gradually become available for the full quarter. These indicators are usually closely related to real economic activity in the broad sense and they include foreign trade statistics, retail trade, industrial production, or other alternative monthly indicators that provide timely information, such as price statistics, financial variables and survey data. Thus, the availability of quick information offers potential opportunities for improving the accuracy of GDP forecasts.

The aim of this paper is to address some of the models used to forecast current and several subsequent periods. Also, some of the models used to forecast real GDP growth, which is probably the most important macroeconomic indicator is summarized in this paper. These models can be grouped into two parts, namely: the models using seasonal adjustment methods, regression and ARIMA models and models that are particularly suitable for dealing with large real-time data sets.

GDP forecast has evolved with the growing use of linear autoregressive models. Therefore, Sims in 1980, forecasts American GDP using a linear VAR model; later, Litterman, in 1986, extends this work using the Bayesian VAR models. Engle and Granger in 1987 pointed out possible co-integration between GDP and monetary aggregate M2 using Vector Error Correction Modeling. They worked with these models on US data and later on Gupta was used for the same approach in 2006 to forecast South African GDP. Apart from linear modeling for forecasting GDP, many other authors have worked and developed non-linear methods; like Markov Switching models, Hamilton (1989) models, Clements and Krolzig (1998).

Another approach that is more adequate is the Bridge Equations method, which combines linearity and aggregation. Some authors who have also worked on these models are Baffigi, Golinelli and Parigi (2004), and Diron (2008). These models focuses on some of the indicators correlated more with estimated variable; alternatively, factor models are based on a great numbers of indicators. Stock and Watson (2002) have proposed these models with an extension development by Bernanke and Boivin (2003), Forni et al. (2005), and Kapetanios and Marcellino (2006).

However, a number of studies have concluded that these models are useful for improving the assessment of the current and short-term economic outlook. Barhourni et al. (2008) found out that in the Euro area countries, models that exploit timely monthly releases perform better than quarterly models. Among the set of models they considered, factors models, which exploit a large number of releases, do generally better than other models based on small information sets. Similarly, Giannone et al. (2008) and

Matheson (2010) found out that the dynamic factor model provides better out-of-sample forecasts relative to several benchmarks for the U.S. and New Zealand.

Beginning from this great variety of models developed on time, the focus of this paper is on three of them which are an autoregressive model, bridge equations and vector autoregressive models to forecast Albanian GDP growth. The models will forecast in a pseudo-real time setup in the way to allow the comparisons of the results.

1. Models specification for GDP forecasting

This section describes some of the main models that can be used to forecast quarterly GDP. Selection of the model treated in this paper is based especially on the suitability for predicting GDP. In theory, there is a huge range of available methods, but attention is being paid to filter out those that are applied in many countries and those that have shown good results. Parallel to the theoretical progress in the treatment of time series, is the increase in the amount of economic data available. The increase of new indicators or the higher their frequencies, instead of making predictions easier, have placed researcher in a very difficult situation if they have to implement all the indicators available or to stay only on those that have a direct impact on the indicator estimated.

The objective of the material is to present models that can be applied only from historical information of the series to complex models, which are based on many time series. The models considered here are only a small subset of the range of methods available, but these represent the standard set of tools used in many policy-making institutions.

2.1 Bridge Models

The bridge equation is perhaps the most widely used method for forecasting quarterly GDP using monthly indicators. Bridge models use timely indicator to generate a certain variable of interest for which the information is still unavailable. This approach comprises of using a large set of monthly indicators, most of which are available with very short delay, and quarterly series, which comes mostly from GDP components. In general, the monthly series does not cover the entire quarter but provides a basis for extrapolation.

As mentioned by Klein and Park (1993) concerning the U.S. case, "most economic variables can be projected from fitted AR1MA equations". Based on ARIMA, we can forecast for missing months or even for quarters ahead. Once the values are obtained, it is possible to construct a variable with a quarterly frequency, for instance by taking three-months quarterly averages. For instance, if we are in the month of January and we want to forecast the first quarter, we forecast the independent indicators up to the month of March.

Then the 'filled' period of the higher- frequency variable can be temporally aggregated to the lower frequency. These values are then plugged into the lower-frequency bridge equation time series model. Therefore, the indicators can be forecasted with any preferred model like AR, ARIMA, VAR or Bayesian vector autoregressive model (BVAR). In contrast, to use a specific forecast model, one can also encounter a no-change forecast, where the latest available information is used to represent the information content of the current period.

In general, in Bridge Models, suitable short-term indicators (Klein and Sojo 1989) explain the aggregate GDP or GDP components. In fact, Bridge Models can be specified either as different equations for the main GDP components or as a single equation for the aggregate GDP. In the first case, the model is labeled 'demand-side'; in the second case, it is labeled 'supply-side'. The choice of the Bridge Models explanatory variables is based on the researchers' experience and several statistical testing procedures, rather than on causal relationships. Bridge equations are more useful for now casting and short-term forecasting. Forecasting the indicators over a longer time would transmit larger forecasting errors into the primary forecasting model due to iterative forecasting uncertainty of the higher-frequency variable.

2.2 ARIMA models

Autoregressive-integrated-moving-average (ARIMA) models are mathematical models of the autocorrelation in a time series, which can be used to produce forecasts and backcasts. They have three parts; autoregression part (AR), the integration parts (I) and the moving average part (MA). ARIMA models are widely used in many fields and in many cases, they are known as the ‘Box-Jenkins’ approach following the work done by Box and Jenkins (Box G. and Jenkins G. 1970). They can contribute in understanding physical systems by revealing something about the physical process that builds persistence into the series.

ARIMA models can also be used to predict behavior of a time series from past values alone. Such a prediction can be used as a baseline to evaluate possible importance of other variables to the system. Before using ARIMA models, we have to be sure that we have a stochastic series in the way that our forecast is accurate as possible. Once a model describes the sample behavior of the data in a satisfactory way, it can be used as a basis for forecasting.

In this part, a forecasting procedure for a stochastic linear model is presented. This means that if GDP will be forecasted directly using ARIMA models, it is important to make it firstly stochastic; otherwise it is important to make each of them a stochastic series if ARIMA models will be used to forecast the component of GDP and later to predict GDP as sum of the components.

Supposing a specific series gives $\{y_1, y_2, ..., y_t\}$, the interest is in a forecast of y_{t+k}. Thus, it will be preferable that this value $\hat{y}_{t+k}$ should be as accurate as possible. This is usually measured with Mean Squared Errors criterion (MSE) which is defined as:

$$MSE = E\left[\left(y_{t+k} - \hat{y}_{t+k}\right)^2\right]$$

The minimum of MSE for y_{t+k} is given by the information $\{y_1, y_2, ..., y_t\}$ available at time t: $\hat{y}_{t+k} = E\left(y_{t+1} \middle| y_1, ..., y_t\right)$

Also, it has to be specified under normal hypotheses that the solution will be a linear combination of the observed values $\{y_1, y_2, ..., y_t\}$. This linear combination can be easily derived from ARIMA (p, q) process at time t +k.

$$y_{t+k} = \beta_1 y_{t+k-1} + ... + \beta_p y_{t+k-p} + \lambda_1 a_{t+k-1} + ... + \lambda_q a_{t+k-q}$$

The expectation of $\hat{y}_{t+k}$ based on the information that exist until time "t" is given by:

$$\hat{y}_{t+k} = E\left(\beta_1 y_{t+k-1} + ... + \beta_p y_{t+k-p}\right) + E(\lambda_1 a_{t+k-1} + ... + \lambda_q a_{t+k-q}\Big)$$

This expectation is given under the assumption that a_t are independent over time (white nice).

2.3 VAR models

When there is an uncertainty that a variable is exogenous, then a natural extension of transfer function analysis is to treat each variable symmetrically. If it will be taken into consideration of a case with two variables and let the time path of y_t be effected by the current and past realizations of x_t, and vice versa for x_t, thus, the system will result to two equations:

$$y_t = b_{10} - b_{12} x_t + \gamma_{11} y_{t-1} + \gamma_{12} x_{t-1} + \varepsilon_{yt}$$

$$x_t = b_{20} - b_{21} y_t + \gamma_{21} y_{t-1} + \gamma_{22} x_{t-1} + \varepsilon_{zt}$$

These two equations constitute a first order vector autoregression (VAR). The same logic is even for higher order VAR models. VAR allows studying of the dynamic relationships between different variables including (possibly) contemporaneous interrelations. As other models, those can be used for forecasting. The lag length pi can be determined using the SIC method. Based on much empirical evidence, it has been concluded that VAR models produce forecasts, which set a high standard of comparison for most alternative methods such as univariate time series models or large-scale macro-models. This is majorly true for long series and in the case of real macroeconomic variables such as GDP. Nevertheless, in a higher order model, there can be a large number of coefficients estimates. Since unrestricted VARs are over parameterized, forecast may be unreliable.

2.4 Results

The results of this material contain four different methods for forecasting quarterly GDP growth. Firstly, it is necessary to mention that in Albania, Quarterly GDP published seasonally is not seasonally adjusted. From three approaches, GDP is estimated only by production approach allocated in seven big sectors of the economy. Therefore, this model uses seasonal adjusted series, which allows the comparisons of economic growth with the previous quarter. The series were taken from the first quarter of 2003 until the second quarter of 2013. Analysis was done for sample 2003Q1 to 2012Q2. Thus, the period from 2013Q3 to 2013Q2 is left for forecast comparisons.

The first model is based on ARIMA models on GDP series. In this case, it uses only GDP series and applies an autoregressive of random 1 (ar(1)) and a moving average of random 1 (ma(1)) model.

$$\log GDP = c + AR(1) + MA(1)$$

The second model is based on ARIMA models on economic activities. For each of the seven economy was found an acceptable ARIMA model which is been used to forecast each of them for the period 2012Q3 – 2013Q2. After that GDP is derived as some of the sectors, this method can be considered an indirect one as models are applied on the component of the aggregated series.

The third model is a bridge model. The variables that are found to be significant are available earlier in time of GDP publication; so, they are forecasted for missing periods with different ARIMA. The variables are with monthly frequencies and are forecasted for missing period. The quarterly series are produced as an average of respective monthly data.

$$\log\mathrm{GDP} = \beta_0 + \beta_1 \log TVSH + \beta_2 \log CPI$$

Where:

TVSH – income from value added taxes

CPI – Consumer Price Index

The chosen variables are also seasonally adjusted as they even have very significant seasonal effects like quarterly GDP. The method of seasonal adjustments is the same as the one used to adjust quarterly GDP series and has been applied on the series with lower frequencies.

The last model that was applied is a vector autoregressive models VAR. Even in VAR models and bridge models, some variables are earlier in time, so the series of variables are available at the latest quarter.

$$\log GDP = \beta_1 \log PPI + \beta_2 \log TVSH + \beta_3 \log PUN + \beta_3 \log M2$$

$$Where:$$

$$PPI - producer\ price\ index$$

$$TVSH - incimes\ on\ value\ added\ taxes$$

$$PUN - Number\ of\ employees\ at\ industry\ sector$$

$$M2 - Agregated\ monetary\ M2$$

The table below shows the results of all methods. At the same time, there were even two published series.

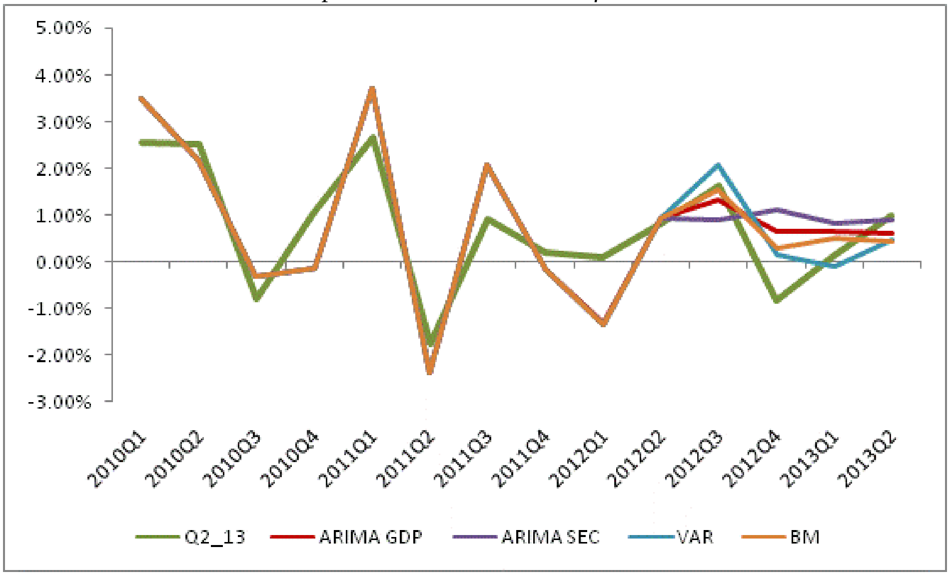
Table 1: Results of different models to forecast GDP growth

Quarters	Published data		Forecasted data			
	Q2_12	**Q2_13**	**ARIMA GDP**	**ARIMA SEC**	**BM**	**VAR**
2010Q1	3.50%	2.56%	3.50%	3.50%	3.50%	3.50%
2010Q2	2.17%	2.55%	2.17%	2.17%	2.17%	2.17%
2010Q3	-0.30%	-0.78%	-0.30%	-0.30%	-0.30%	-0.30%
2010Q4	-0.12%	1.08%	-0.12%	-0.12%	-0.12%	-0.12%
2011Q1	3.71%	2.68%	3.71%	3.71%	3.71%	3.71%
2011Q2	-2.38%	-1.75%	-2.38%	-2.38%	-2.38%	-2.38%
2011Q3	2.06%	0.93%	2.06%	2.06%	2.06%	2.06%
2011Q4	-0.19%	0.22%	-0.19%	-0.19%	-0.19%	-0.19%
2012Q1	-1.33%	0.09%	-1.33%	-1.33%	-1.33%	-1.33%
2012Q2	0.93%	0.82%	0.93%	0.93%	0.93%	0.93%
2012Q3		1.63%	1.32%	0.90%	1.53%	2.07%
2012Q4		-0.83%	0.65%	1.11%	0.30%	0.16%
2013Q1		0.14%	0.64%	0.81%	0.49%	-0.10%
2013Q2		1.01%	0.62%	0.90%	0.44%	0.46%

Source: INSTAT and author work

The first series in the table (Q2_12) is the series where we are based on for our models. The second one (Q3_12) is the last publication that is available in Albania for quarterly GDP estimations. From the published data, even the revision of series which has great impact on estimation can be seen. In addition, four other columns contain the results achieved based on different methods used. In the graph below, all the methods and the published series are shown. Therefore, in the period before the second quarter of 2012, the difference between the two series is only due to the revised policy.

Graph 1: Forecasted series of GDP.



Source: INSTAT and author work

For all the models, tests are done on residuals for normality, serial correlation and stationary. Each of the models passed all the tests and after that, they were used for forecasting.

Since forecast is an unknown phenomena, hence, much interest is to know which of them performs better. For this purpose, different forecasted models should be compared with each other. Therefore, the basis for this comparison is related to the idea to have the lowest error and variance of the forecasted series. These objectives were tested to determine exactly which one performs better. Some of these are:

Bias: $BIAS = \frac{1}{k}\sum_{t=T}^{T-1+k} e_{t+h}, \quad e_{t+h} = y_{t+h} - \hat{y}_{t+h}$

Standard Error: $SE = \sigma_e, \quad \sigma_e^2 = \frac{1}{k}\sum_{t=T}^{T-1+k}(e_{t+h} - BIAS)^2$

Mean Squared Forecast Error: $MSFE = \frac{1}{k}\sum_{t=T}^{T-1+k} e_{t+h}^2$

Root of Mean Squared Forecast Error: $RMSFE = [\frac{1}{k}\sum_{t=T}^{T-1+k} e_{t+h}^2]^{\frac{1}{2}}$

Mean Absolute Percentage Error: $MAPE = \frac{100}{k}\sum_{t=T}^{T-1+k}\left|\frac{e_{t+h}}{y_{t+h}}\right|$

Except direct estimation, can be used and another method known as Theil's U Statistic can also be used:

$$U = \sqrt{\frac{\sum_{t=1}^{k} (FPE_{t+h} - APE_{t+h})^2 / k}{\sum_{t=1}^{k} APE_{t+h}^2 / k}}$$

Where:

FPE – percentage change of forecast

APE – actual change

$$FPE_{t+h} = (\frac{\hat{y}_{t+h} - y_t}{y_t}) \text{ and } APE_{t+h} = (\frac{y_{t+h} - y_t}{y_t})$$

The Theil U-statistic is also a measure to compare model forecasts $E\{y_{t+h}\} = \hat{y}_{t+h}$ with naive forecasts $E\{y_{t+h}\} = y_t$ model. If U<1, this means that our model is better than naive models, otherwise there are no reason to use this model. The results of the tests for all the models are shown in the table below.

Table 2: Comparisons of results

Methods	ARIMA GDP	ARIMA SEC	BM	VAR
BIAS	129	316	-304	24
SE	1,786	2,498	1,361	953
MSFE	3,200,224	6,292,809	1,779,018	902,978
RMSFE	1,789	2,509	1,334	950
MAPE	0.65	0.94	0.42	0.38
U	0.54	0.75	0.40	0.29

Source: Author work

From the results of the tests, we can see that VAR model has a better performance and it has the lowest values compared to all tests.

Conclusion

In this paper, we compared four different models to forecast quarterly GDP growth in Albania. Based on the models that were used, it can be said that VAR model outperforms other models because for the entire test, it has the lowest values. For VAR models, founding four variables that have correlation with each other can be used to forecasting GDP.

ARIMA models have a worst forecast performance compared with other models; but again, they perform better than naïve models because Theil's U Statistic is lower than 1.

For bridge models, to explain quarterly GDP, more significant variables are incomes from value added taxes and consumer price index. This relates more with the fact that most of the quarterly economic activities have estimation based on the indicator of turnover. In addition, as the series are at constant prices, one of the deflator used in quarterly series is CPI.

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