SHORT-TERM FORECAST OF PRIVATE CONSUMPTION AND INVESTMENTS IN ALBANIA

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ABSTRACT

Private consumption is the most important component of aggregate demand, while private investment is the most dynamic component of it. Short-term forecast of consumption and investment make an important contribution to the decision-making process of central banks. In this material three types of models are developed and tested for consumption and investments, using monthly and quarterly data. The models constructed for each component are: (i) Bridge Models, (ii) Indicator Models, and (iii) Factor Models. The estimation period is from the first quarter of 2005 to the first quarter of 2016. The forecasting accuracy of these models is carried out through a pseudo ex-post forecast exercise. To be able to carry out the exercise, the estimation period is shortened until the first quarter of 2014 and the remaining period is forecasted ex-post.

"All models are wrong, but some are useful"
George Box, 1979

1. INTRODUCTION

This material presents different models that can be used for short-term forecasting of consumption and private investments in Albania. These are the two most important components of aggregate demand. Private consumption is the component with the largest share in aggregate demand; its weight is about 80%. Total investments have a smaller share, about 28%, but have much more volatility, determining thus the dynamics of aggregate demand. The private component of investments is estimated to have a share of about 77% of total investment in the economy.

INSTAT published quarterly data for economic growth by expenditure approach for the first time in July 2015. The time series start from 2008, in nominal terms, and from 2009 in real terms. Preliminary data are published 15 weeks after the end of the reference quarter. Forecasting models, meanwhile, aim to fill in with data the quarters for which national accounts have not yet been published (one to two quarters, depending on the forecasting time). Also, the forecasting models aim to filter all information from the available short-term indicators and project the path of consumption and investments over

the next two quarters. Specifically, during a typical forecasting round, all the information from quantitative and qualitative indicators is employed, available very quick in time, or that have leading properties, to provide an estimation for one quarter before (backcast), the current quarter (nowcast) and two coming quarters (nearcast).

Several methods of short-term forecasting economic time series are developed in the literature and the practice of central banks. Their goal is the same: to link high frequency indicators or more rapidly available in time indicators, with national account indicators. The two most commonly used methods are bridge models and factor models. Angelini et al. (2008) estimates models using monthly indicators to forecast euro area GDP for the current quarter (nowcast). The authors conclude that factor-based bridge models produce more accurate estimates than traditional bridge equations. One of the conclusions of this paper is that survey indicators are valuable for short-term forecasts.

Runstler and Sedillot (2003) study the predictive capability of bridge models, where monthly indicators are available only partially in a quarter. For this, they combine univariate bridge equations to predict GDP growth, with monthly time series models to predict observations for missing monthly indicators. They show that, when monthly indicators are to be forecasted, the GDP forecast results do not only depend on the bridge models but also on the time series models that are used to forecast monthly indicators. Arnostova K. et al. (2009) estimate the predictive performance of 6 short-term forecast models for the Czech Republic: VAR models with two variables, bridge models, principal component with monthly frequency, principal component with quarterly frequency, and a Dynamic Forecast model using the Kalman filter technique. According to Gerdrup and Nicolaisen (2011), the set of models used in the Norwegian Bank includes VAR models, bridge-modelling models, factor (monthly and quarterly) and DSGE models. Feldkircher et al. (2015) use four variants of bridge models and a dynamic factor model for the short-term GDP forecast of seven Central, Eastern and Southern European countries. They use signals from all possible short-term indicators, utilizing the possible leading properties of the variables with monthly or quarterly frequency, or those variables which are available sooner. Esteves and Rua (2012) share the experience of the Bank of Portugal with short-term forecasting and the methodology used to obtain projections in the case of the Portuguese economy. The most commonly used methods are bridge and factor models.

In the first material regarding the prediction of consumption and private investments in Albania, Vika and Abazaj (2013) aim to assess the performance of private consumption and investments in Albania, and identify the most important indirect indicators for their forecast.

Based on the experience of other central banks and the availability of data in Albania, this material presents three types of forecast models for each component of the aggregate demand, consumption and private investment: bridge models, indicator models and factor models. The forecasting quality of the models is estimated by imitating out of sample forecasting testing. This

means that a part of the time horizon for which we have data will be omitted from the estimation period and a forecast for that period will be produced. This procedure will be performed in a recursive manner, by estimating the models after adding each additional quarter (recursive pseudo out of sample forecasting). As a final step, the forecasts provided in this manner are compared with the actual data we have for consumption and investments. Forecast errors are calculated for four forecast horizons.

The material is organized as follows: the second part explains the models used; the third part explains the indicators that are used; in the fourth part are presented the results of the forecasting ability of the three models, comparing them with the results of a simple autoregressive model.

2. THE MODELS

We can classify short-term forecasts in two large groups. The first group aggregates the quantitative forecasts of many models. These include bridge models and indicator models. In the second group the opposite happens. First, information is aggregated from all short-term indicators and then direct forecasts for consumption and investments are taken. This group includes the factor models.

1- Bridge models. These models are based on simple regression which bridge low frequency dependent variable (GDP, consumption, investments, etc.) and high frequency explanatory variables (short-term indicators). In our case, monthly indicators are used to predict consumption and investments with quarterly frequency.

In practice, this procedure goes through several steps. First, the candidate monthly series with forecasting properties for consumption and investments are selected based on judgment, the economic link and their availability. Subsequently, the monthly series considered are transformed into quarterly by averaging, summing or taking the value of the last month of the quarter, depending on the nature of the series. In the third step, the series are tested in statistical terms. For this, the results of the correlation analysis are used. Once this selection process passes, a bridge between the short-term indicators and the indicator to be explained (consumption or investment) is estimated:

$$y_t = \alpha + \sum_{j=1}^{4} \alpha_j y_{t-j} + \sum_{m=1}^{M} \sum_{k=0}^{4} \alpha_{m,k} x_{m,t-k} + \varepsilon_t \qquad (1)$$

Where y is the annual change in consumption or private investment, x are M quarterly aggregated monthly short-term indicators. As is common in the literature, all specification of bridge-type models also include autoregressive terms.

In order to make possible the forecast of consumption and investments in real time, it is necessary to predict the developments of monthly indicators. For this,

ARIMA models are used to extend the monthly series. In some cases, these projections are corrected based on the expert judgment, for example in the case of consumer credit, investment credit or VAT revenue. This correction may be based on past mistakes or on additional information on the expected performance of the explained variables.

Bridge models have the advantage of using simple estimation techniques, but the success of their use depends on the right choice of monthly frequency indicators. Forecasting performance from bridge models can be improved if there are used a number of them, because, depending on the month when the forecasting is done, different indicators have different predictive power.

2- Indicator models. In addition to the monthly frequency indicators, some indicators with quarterly frequency have leading properties or are available earlier than national accounts. These indicators are employed in a simple equation models to explain private consumption and investments. All the equations are estimated by the Autoregressive Distributed Lag (ARDL) method, where the maximum allowed lag time is set to 4 quarters:

$$y_t = \alpha + \sum_{j=1}^{4} \alpha_j y_{t-j} + \sum_{i=1}^{I} \sum_{k=0}^{4} \alpha_{i,k} X_{i,t-k} + \varepsilon_t \qquad (2)$$

Where *y* is the annual change in consumption or private investment, and *X* are short-term indicators with quarterly frequency. Initially, general models are automatically estimated, based on the ARDL method. Then more specific form of the models is obtained by excluding those time lags that are not statistically important or do not have the expected sign (general to specific approach). After each exclusion, the validity of the reduced model is checked again[1].

3- Factor models. One of the forecasting models that have become very popular in the literature in the recent years is the factor model. Its main assumption is that movements between macroeconomic indicators have a common element, which can be filtered and used for forecasting. This model assumes that the behaviour of each variable can be disaggregated into two components: the common component and an individual component, specific to each series. The main advantage of this method is that the common component of a large number of indicators can be represented by a limited number of common factors. Thus, through this method are created artificial series (factors), which aggregate the developments of a broad database. The method of static component components was used to identify common factors.

The factor model can be estimated separately, both for monthly frequency data as well as quarterly frequency data. After testing both ways, it was chosen to go through a factor model, which summarized information from both monthly (aggregated into quarterly frequency) and quarterly frequency data, because the number of explanatory variables is relatively small. Time series that lead the consumption or investment series are shifted back in time, according to the number of the leading quarters. In order to have series with

[1] *Campos, J et al (2005).*

the same time length, some of the time series are forecasted with the ARIMA models. In this way, all the information from the database is summarized from the first 2 principal components in the case of private consumption and one principal component in the case of private investment. In the case of private consumption, the two main components explain 63% of the variance of the entire explanatory variables database. In the case of private investment, the first selected component explains 57% of the variance of all the private investor explanatory variables.

Once the principal components are filtered, they are treated as observed indicators and are employed in an OLS equation to explain the consumption and investment dynamics. Autoregressive terms are also included, the same as in the case of bridge and indicator models:

$$y_t = \alpha + \sum_{j=1}^{4} \alpha_j y_{t-j} + \sum_{m=1}^{2} \alpha_m F_m + \varepsilon_t \qquad (3)$$

Factor models have the advantage of aggregating information form a large number of indicators. But, unlike other models, the use of common factors makes it harder to judge how the short-term indicators have impacted the final forecast.

3. DATA

The database of possible indicators with forecasting properties was created by considering data from the fiscal sector, the financial sector, the foreign trade and qualitative data from confidence surveys and bank lending surveys. Their choice was guided by the economic rationale, the way that national account are calculated and their relationship with the dependent variable measured based on the cross correlation analysis. Quantitative indicators were transformed in annual changes, with the exception of interest rates, which was kept in level[2]. The indicators from surveys and the uncertainty indicator were kept at level because previous studies at the Bank of Albania have found that their level is related to the annual economic growth changes. All series with a small coefficient of correlation with the annual changes of private consumption and private investments were removed. Then, after testing the linear correlation and their explanatory power after the models were run, a good part of the series was also removed by keeping in the end only those series that had the closest connection. Table 1 and 2 summarize the main features of the selected series.

[2] *nterest rates were also tested transformed in annual changes in percentage points.*

Table 1. The list of short-term indicators for forecasting private consumption.

Indicator	Source	Period availability	Publication time lag	Transformation
Monthly frequency indicator				
1.Imports of food	INSTAT	2005 Q1	1 month	The sum of the 3 months of the quarter, Annual changes
2.Revenues from VAT	Ministry of Finance	1999 Q1	3 weeks	The value of the last month of the quarter, Annual changes
3.Credit to individuals	Bank of Albania	2001 Q1	1 month	The value of the last month of the quarter, Annual changes
4.Trade confidence indicator	Bank of Albania	2002 Q4	3 weeks	The value of the last month available, Level
5. Services confidence indicator	Bank of Albania	2002 Q4	3 weeks	The value of the last month available, Level
6. Consumer confidence indicator	Bank of Albania	2003 Q2	3 weeks	The value of the last month available, Level
7.Uncertainty indicator	Bank of Albania	2003 Q2	3 weeks	The value of the last month available, Level
Quarterly frequency indicator				
1.Individuals demand for credit	Bank of Albania	2006 Q4	3 weeks	Level
2.Wages and salaries index	INSTAT	2003 Q1	3 months	Annual changes

Private consumption series is available with quarterly frequency, starting from 2009. The private real consumption series for the period 2009-2016 is published from INSTAT. For the period 1999-2008, private consumption with yearly frequency was disaggregated in quarterly series, using the dynamics of the retail trade index[3].

Chart 1 Private consumption growth.

Source: INSTAT and own calculations.

Quantitative data with monthly frequency are: imports of food from foreign trade data, revenues from value added tax (VAT), bank credit to individuals. Once transformed depending on their nature, they are used in the first group of models, bridge models.

Quantitative data with quarterly frequency is only the wage and salaries index. It is based on the publication of INSTAT on "Structural Business Statistics".

Survey data are: confidence indicator in trade, services and consumers, also the uncertainty indicator. Beggining from 2016, confidence indicators are available with monthly frequency. Based on bank lending survey results, the

[3] *Pro-rata Danton temporal disaggregation method.*

balance on credit demand from individuals is taken, as estimated from the bank experts. It has quarterly frequency. The uncertainty indicator is constructed based on disaggregated consumer confidence survey data.

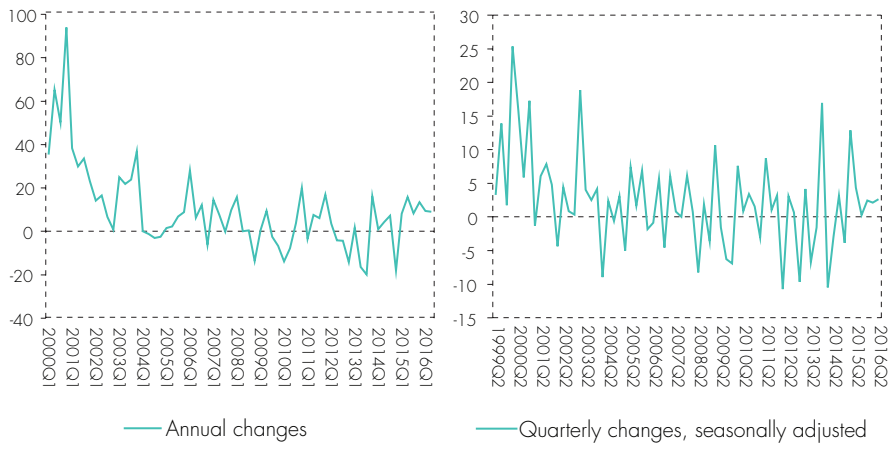
Some of the short-term indicators that were left out of the models and can be considered later to enter the group of explanatory variables are: incomes from remittances, interest rates on credit, exchange rate, inflation rate, import data of passenger cars and credit standards for individuals.

Table 2. The list of short-term indicators for forecasting private investments.

Indicator	Source	Period availability	Publication time lag	Transformation
Monthly frequency indicator				
1. Imports of machinery and equipment	INSTAT	2002 Q1	3 weeks	Sum of three months of the quarter, Annual changes
2. Industry confidence indicator	BCS, Bank of Albania	2002 Q2	3 weeks	The value of the last month available, Level
3. Construction confidence indicator	BCS, Bank of Albania	2002 Q2	3 weeks	The value of the last month available, Level
4. Demand in economy, average of balances	BCS, Bank of Albania	2002 Q2	3 weeks	The value of the last month available, Level
5. Orders from exports	BCS, Bank of Albania	2002 Q2	3 weeks	The value of the last month available, Level
Quarterly frequency indicator				
1. Remittances	Bank of Albania	2004 Q1		Sum of three months, annual change
2. Businesses financial situation	BCS, Bank of Albania	2002 Q2	3 weeks	The value of the last month available, Level

According to national accounts data, gross fixed capital formation, also known as total investments, is reported as an aggregate (doesn't separate public from private investments). To separate the series from one another and to estimate only the series of private investments, from the total of investments in nominal terms are subtracted the public investments (central and local government together). In order to obtain real values, the overall deflator of investments is assumed as common for both types.

Chart 2 Private investments growth.



Source: INSTAT and own calculations.

Quantitative data that are used for the short-term forecast of private investments are: imports of machinery and equipment, with monthly frequency, and remittances with quarterly frequency.

Qualitative data with monthly frequency are: confidence indicators in industry, in construction, the balance of demand in the economy and exports orders in the industry sector. Also the series of businesses financial situation is taken from the quarterly frequency confidence surveys.

Some of the indicators that did not resulted significant and need to be considered at a later time, after the lengthen of time series, are: foreign direct investment inflows, capacity utilization rate, credit for investments, exchange rate, construction permits, interest rates.

4. FORECASTING QUALITY

Unlike medium-term forecasting, where theoretical consistency is important for a model, in short-term forecasting the empirical relation of data with forecasting performance is more relevant. Following, the forecasting performance of the models is tested by evaluating several steps.

First, all models are assessed for the same period of time, 2005 Q1 - 2014 Q4 (except the model that has as explanatory variable the households' demand for lands by VAK, which have a shorter period). Then, the forecast for four quarters is obtained, 2015 Q1 to 2015 Q4, the forecasting error is calculated, comparing it with the actual values of private consumption and investments. The next step is to extend the assessment period by on quarter, up to 2016 Q1 and again forecast four quarters in the future. This procedure is repeated by adding each time a quarter. The test does not take into account the actual set of data available for the quarters for which the forecasting quality is tested, so the impact that results of the data test of previous periods is taken into account.

In addition to measuring the forecasting error in absolute terms, a simple autoregressive model has been build, for both consumption and private investments. Based on this model forecasting errors within the choice were also generated. These have served as a benchmark to assess the relative short-term forecasting error.

Forecasting errors are calculated for all time horizons from 1 up to 4 quarters. They are compared in absolute and relative terms. Tables 3 and 4 compare the results of RMSE for private consumption and tables 5 and 6 for private investments. For private consumption, in absolute terms, the bridge models have a lower average RMSE, compared with the second and the third model. In relative terms, in Table 4 is presented the forecasting error for each model on each forecasting horizon as a ratio of the models' RSME against the RMSE of a simple AR model of consumption. A ratio higher than 1 indicates that the models' forecasting error is higher than the forecasting error of the simple autoregressive model. As we can see, in average, the three models perform better than the auto regressive models and the ratio is lower than 1. Again, the first model has the lowest ratio. The factor model has the lowest performance.

Table 3 Forecasting quality assessment, absolute, private consumption

RMSE	+1Q	+2Q	+3Q	+4Q	Average
M1.	1.9	2.1	1.7	2.2	2.0
M2.	3.4	3.7	3.5	3.6	3.6
PC	2.8	3.1	3.2	3.5	3.2
Average	2.4	2.8	2.8	3.2	2.8
AR1.	2.8	3.7	3.9	3.9	3.6

Table 4 Forecasting quality assessment, relative, private consumption

RMSE	+1Q	+2Q	+3Q	+4Q	Average
M1.	0.87	0.89	0.96	1.10	0.96
M2.	0.89	0.91	1.00	1.11	0.98
PC	0.95	0.98	1.08	1.35	1.09
Average	0.90	0.92	1.01	1.19	1.01
AR1.	1.00	1.00	1.00	1.00	1.00

The following tables present the results of forecasting within the choice of private investments. In this case, the forecasting quality from bridge models is similar to the quality of indicator models. In relative terms, the first model forecasts better than the autoregressive model up to three quarter in the future. The second model's forecast is worse than the AR model after the 3 quarter. The third model had a better performance, in relative terms up to the second quarter. In average, for all three models, forecasting is more precise compared with the simple AR model only for the first two quarters.

Table 5 Forecasting quality assessment, absolute, private investment

RMSE	+1Q	+2Q	+3Q	+4Q	Average
M1.	10.6	11.3	11.8	9.3	10.8
M2.	10.8	11.6	12.3	9.4	11.0
PC	11.6	12.5	13.3	11.4	12.2
Average	10.9	11.8	12.4	10.0	11.3
AR1.	12.2	12.8	12.3	8.4	11.4

Table 6 Forecasting quality assessment, relative, private investment

RMSE	+1Q	+2Q	+3Q	+4Q	Average
M1.	0.87	0.89	0.96	1.10	0.96
M2.	0.89	0.91	1.00	1.11	0.98
PC	0.95	0.98	1.08	1.35	1.09
Average	0.90	0.92	1.01	1.19	1.01
AR1.	1.00	1.00	1.00	1.00	1.00

Comparing the models of the two indicators, consumption and investments, the former models have a higher forecasting quality than the latter ones. However, the result of this test must be interpreted cautiously, since the short history of national accounts publication, the short period of assessment, has affected the period on which the test was held as well.

5. CONCLUSIONS

In this study, were presented three models for short-term forecasting of consumption and private investments. Short-term forecast models of private consumption, in average terms, have better at forecasting models than a autoregressive model. Short-term forecast models for private investments, in average terms, have better forecasting than an autoregressive models only for the first two quarters. Overall, the bridge models have a better forecasting performance. Currently, at the Bank of Albania, in the process of short-term forecasting of consumption and private investments, are use only the first and the second models. It would be interesting to compare with conclusions with the enrichment and lengthening of the time series.

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