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C O N T E N T

SEASONAL ADJUSTMENT OF TIME SERIES OF MONTHLY CONFIDENCE SURVEYS, MAY 2019

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ABSTRACT

In April 2019, confidence surveys monthly data covered a three-year time horizon[1], a minimum time span that is necessary to control for the presence of seasonality in the series. The purpose of this material is to determine whether the monthly series show patterns of seasonality, explaining the steps of the seasonal adjustment procedure that are followed in case the seasonal component is present. The procedure of removing the seasonal component helps the analysis of the series and allows the comparison of the results from one month to the other. Seasonal adjustment is the first step in the statistical processing of the balance series at a monthly frequency, which will be followed up in the future with the aggregation process at sector and economy level.

INTRODUCTION

Time series may exhibit seasonal patterns, which are defined as fluctuations that are repeated in the same period of the year, in the same direction and size.[2] Seasonal adjustment is the process during which the seasonal effects are removed from a time series, with the main purpose of facilitating the analysis of long-term trends and short-term fluctuations. Whereas, seasonal adjustment methods are techniques that decompose time series into its components, unobserved, with different dynamic features. However, seasonal adjustment should not be considered as a process that is automatically performed. Each time series is analysed for features in their pattern in order to determine (1) whether the series exhibits seasonal behaviour, (2) whether the seasonal behaviour is independent of the series level, (3) whether the seasonal adjustment will be performed at an aggregated or disaggregated level and (4) the method for seasonal adjustment.

[1] *Confidence surveys started to be conducted under the European Commission's harmonization program in May 2016. One of the changes that accompanied this shift was the increase in their frequency from quarterly to a monthly basis.*

[2] *The size is the same in the model known as the additive model. If the size of seasonality is not the same, but depends on the level of the series, then we have to deal with a seasonal multiplicative model.*

Despite the need to address the above mentioned issues related to the seasonal adjustment of time series, we point out some commonly agreed conclusions that the available literature in this area offers[3]:

a. Seasonal adjustment helps in the identification of important characteristics of a time series such as direction, turning points and consistency with other economic indicators.
b. The seasonally adjusted series should never replace the original series because: during seasonal adjustment, some of the information is lost; increased uncertainty because there is no single choice of the proper method of seasonal adjustment; the seasonally adjusted series undergoes revisions whenever new observations are added.
c. The seasonal adjustment does not intend to smooth a series and the irregular component is part of the seasonally adjusted series.
d. Regarding the choice between the direct and indirect method of seasonal adjustment[4], the indirect method is the most effective when the subcomponents do not have similar characteristics to each other.
e. In the case of short time series, less than 5 years of monthly data, it is difficult to identify a stable seasonal structure and grows the risk of major revisions of the seasonally adjusted series when new observations are added.[5]

In the case of the results obtained from our monthly frequency confidence surveys (CS), seasonal adjustment allows to compare month-to-month results and helps in the identification of the moving direction and turning points. In the questionnaires used in the confidence surveys, businesses are asked to give their opinion excluding seasonal fluctuations when making quarterly comparisons. Meanwhile, consumers are asked to make a comparison with the previous 12 months, eliminating theoretically the seasonal changes. However, the experience with quarterly surveys and the tests that will be discussed below regarding the monthly frequency series indicate the presence of the seasonal component. We point out that in the case of CS time series with monthly frequency, the decision-making on the above mentioned issues is also hampered, because their length is at the minimum allowed to adjust for seasonality, three years with monthly frequency.[6]

The second part explains in more details the process of identifying the monthly CS time series that show a seasonal pattern. The monthly balances of the CS that are selected to be seasonally adjusted are shown in the third part, to close out with some conclusions and recommendations for future work.

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3 *ECB (2003): "Seasonal Adjustment", November 2003 and IMF (2014): "Update of Quaterly National Account Manual: Concepts, Data sources and Compilation", Chapter 7, Seasonal Adjustment.*

4 *In the direct method, are seasonally adjusted the aggregated series of higher levels as for example confidence indicators at a sectorial level. In the indirect method are seasonally adjusted the constituent balances, which are then aggregated at higher levels.*

5 *This risk is greater if seasonal adjustment techniques are selected based on models, such as SEATS than in the case when methods based on moving averages, such as X12, are used.*

6 *McDonald-Johnson, K. et al. (2010): "Seasonal Adjustment Diagnostics Checklists", Census Bureau Guideline.*

2. THE IDENTIFICATION OF THE SEASONAL COMPONENT

Seasonal adjustment methods decompose the original series (X_t) into 4 components: the trend-cycle component (T_t), the seasonal component (S_t), the calendar component (C_t), and the irregular component (I_t). These are unobserved components and should be evaluated by considering the observed time series (original series). There are two main combinations of how these components are linked to each other: the additive combination and the multiplicative combination.

In the additive model, the original series is the sum of the components: $Xt = Tt + St + Ct + It$. The additive model assumes that the unobserved components are independent of each other. The seasonally adjusted series is obtained by subtracting the seasonal and calendar components from the original series: $X_t^a = Xt – (St + Ct) = Tt + It$. In the multiplicative model, the original series Xt is expressed as the production of unobserved components: $Xt = Tt * St * Ct * It$. In this model it is assumed that the size of the unobservable component is proportional to the series level, the seasonality increases with the increase of the series level: $X_t^a = Xt / (St * Ct) = Tt * It$.

For the implementation of seasonal adjustment in practice, among the most popular methods are *Census X12* and *X13* developed by the United States of America, as well as *TRAMO/SEATS* developed by the Bank of Spain. They not only allow the choice between several alternatives, but at the same time include tests that control for the presence of seasonality in a time series.[7] Among the features that characterize the X12 method is the fact that it contains a modelling component, which serves to identify extreme values, level shifts for a series, and whether calendar effects are applicable. The X12 also offers a wide range of statistical diagnostics that allow the monitoring of the seasonal component stability.[8]

The set of the X12 program statistics for assessing the quality of seasonal adjustment is explained in this material according to Velzen et al. (2011) and IMF (2014).9 The indicators referred to as M1 to M11 describe how successful was the seasonal decomposition. They get values from 0 to 3, where a value between 0 and 1 is considered an acceptable value. The lower the value of the indicator, the better evaluated is the aspect addressed by the indicators, while when their value is greater than 1, the indicator signals potential problems related to the tested seasonal adjustment process.

[7] *We emphasize once again that seasonal adjustment should not be applied over a series that does not show seasonal movements or show seasonal movements that are not easily identifiable (IMF (2014)). As Mazzi and Savio (2005) point out, in the absence of a theoretical consensus, there is a set of criteria proposed in the literature to assess the quality of seasonal adjustment. The authors argue that there are some aspects of seasonal adjustment that can be evaluated and each of them has different criteria that can be used as a reference.*

[8] *European Commission (2006). European Economy. Special Report No.5. The Joint Harmonised EU Programme of Business and Consumer Surveys. Directorate-General for Economic and Financial Affairs.*

[9] *This set of statistics is defined and interpreted in detail by Dominique Ladiray and Benoit Quenneville (2001). Seasonal Adjustment with the X-11 Method, Lecture Notes in Statistics, Springer-Verlag, New York. Marcel van Velzen, Roberto Wekker and Pim Ouwehand. (2011). Method series. Seasonal adjustment, Method series (2011). Statistics Netherlands.*

These statistics are then synthesized in another indicator referred to as the Q indicator, which is a weighted average of 11 quality indicators, which also moves at an interval of 0 to 3. As argued in IMF (2014), the aggregate indicator from M statistics provides a general estimate of all the diagnostics performed on the quality of the seasonal adjustment process. This is because each M indicator evaluates different aspects of the seasonal adjustment process, making it impossible to use each of them as a single indicator in the overall assessment of the quality of seasonal adjustment. In principle, seasonal adjustment should not be performed if all these statistics receive unacceptable values, while this process can be executed even if some of the M indicators have values greater than 1. Below are briefly described the quality indicators, in terms of the aspect which they estimate in the seasonal adjustment process:

» **M1 indicator – the contribution of the irregular component to the series fluctuations**. The M1 indicator measures the relative contribution of the irregular component to the series changes. If the contribution is high, this means that the irregular component causes more fluctuations than the seasonal component in the series. Consequently, it is difficult to distinguish the seasonal component from the irregular one.
» **M2 indicator – the contribution of the irregular component to the stationary series**. Like the aforementioned indicator, the M2 indicator also estimates the contribution of the irregular component to the series variance or the stationary series. A high value of M2 indicates that even the irregular component is relatively high.
» **M3 indicator – the ratio of the irregular component to the trend**. In order for the seasonal pattern to be correctly identified, it is important that the fluctuations in the irregular component are not very large compared to the fluctuations in the trend. By definition, the M3 indicator measures the ratio between fluctuations in these two components and is of high value in the case of a flat trend.
» **M4 indicator – the degree of connection in the irregular component.** One of the most important assumptions about the irregular component is the lack of connection between two consecutive data points in the time series. In the contrary, if there is a strong connection between them, the irregular component may not have this nature, and to examine this feature we refer to indicator M4.
» **M5 indicator – the number of months for which the cyclic component dominates in average terms the irregular component of a series.** It is an indicator that, like M3, examines the changes in the irregular component to changes in the trend - cycle component. Even this indicator gets high values in the presence of a flat trend in the series.
» **M6 indicator – the ratio of the irregular component to the seasonal component.** This indicator controls whether the standard 3x5 filter is suitable for the tested series. A high value of M6 may suggest that the ratio of the irregular component to the seasonal component or is too small or too large for the applied filter. IMF (2014) argues that M6 indicator compares the stability of seasonality in annual terms with the changes in the irregular component and may suggest the use of filters with different

lengths to differentiate the performance of the seasonal behaviour from movements in the irregular component.

» M7 indicator – the seasonal pattern identifier. *M7* estimates the relationship between the moving and stable seasonality. Among the quality indicators, it is also known as the most important indicator for the seasonal adjustment process. If *M7* is higher than 1, the series may not be adjusted for seasonality. Basically, the indicator serves to determine the degree of seasonal effect identification in a series. If the seasonal pattern is identified with difficulty, the error in absolute terms in the seasonal component is large. The high values of the *M7* may indicate a prevalence of the moving seasonal pattern compared to the stable one. As suggested in IMF material, this indicator can also be used as a test for the presence of seasonality in the original series.
» M8 – M11 indicators – changes in seasonal behaviour over the years. These indicators evaluate the extent to which the seasonal behaviour is subject to change in a series. If there are strong changes in this pattern, the seasonal filters of program X12 cannot accurately identify the seasonal behaviour, causing the error to be high. In particular, if the seasonal pattern, in recent years, changes significantly, the problem may be greater, as the error in the estimates, especially for the most current period, may be higher. Changes in the seasonal behaviour can occur in two ways. Firstly, the seasonal behaviour can be affected by arbitrary fluctuations and, secondly, it may be characterized by systematic increases or decreases. M8 and M10 indicators evaluate arbitrary fluctuations in the seasonal behaviour, while M9 and M11 estimate the rise or decline of the seasonal pattern systematically.

The method that we follow to examine the seasonality of the monthly survey series of confidence surveys is Census X12, in the Eviews program, using the additive model. We have only considered the additive model because: (i) the seasonal fluctuation magnitude does not depend on the series level and (ii) the time series obtained from the surveys contain negative values. Also, the calendar component is considered zero since the data received from CS are of a qualitative nature, and the opinion expressed from businesses and consumers in general is not affected by the working days of a particular month. In addition, this is also the approach followed by us in treating the seasonality of the quarterly series of confidence surveys.

Regarding the selection between aggregate or disaggregated seasonal adjustment, the latter is chosen. The main reason for this choice is that the monthly balances series we have got from the monthly CS seem to exhibit an uneven seasonal behaviour. In this case the literature suggests a seasonal adjustment at the disaggregated level, and then aggregating the adjusted series into higher level indicators (sector or economy). Also, the length of the series, which is still short, would increase the uncertainty over the decision whether the constituent components of monthly balances have similar characteristics.

The decision whether the original series received from the monthly survey will be adjusted for seasonality or not is based on two statistical diagnostics that control for the presence of seasonality[10]:

(i) The first group includes the quality statistics described above, focusing on M7 and Q (columns "b" and "c" in Table 1). The smaller the value of these indicators, the higher the certainty for the presence of seasonality in the given series. In general, the accepted limit value is 1.

(ii) It is also taken into consideration, the result of a second statistical diagnostics computed by the X-12 program, known as a combined test (column "d" of the table). This test controls for the presence of seasonality, and if it is present, it is further tested if the seasonal factors are stable enough over the years. The results of this combined test are summarized in the assertions:

1. *Identifiable seasonality is present;*
2. *Identifiable seasonality is probably not present;*
3. *Identifiable seasonality is not present.*

As it is pointed out in the IMF material (2014), if the program shows the result "Identifiable seasonality is not present", the series should not be subject to seasonal adjustment. So, if the combined test verifies assertion (1) or (2), the series is considered to have a seasonal component, and as such to be adjusted.

RESULTS

The following table summarizes the results of these tests. The seasonally adjusted series are those for which the value of M7 is less than 1 and in the combined test show the assertions (1) or (2). [11] There are cases that although M7 is slightly lower than 1, because the combined test verifies assertion (3) "Identifiable seasonality is not present", the series is considered without seasonal component and as such is not adjusted for seasonality. As a reflection of the above judgments, column "e" represents the final assessment whether the series should be adjusted for seasonality or not.

[10] *For longer time series, these tests also identify whether seasonality is stable in time or not.*
[11] *These series (monthly balances, not and seasonally adjusted where seasonality is present) are graphically presented in the annex of this material.*

Table 1. The results of the tests for the presence of seasonality

Questions	M7	Q	Combined test	Should the series be seasonally adjusted?
(a)	(b)	(c)	(d)	(e)
INDUSTRY				
Production trend observed over the past 3 months	0.888	0.69	Identifiable seasonality probably not present	Yes
Assessment of order – book levels	0.939	0.82	Identifiable seasonality is not present	No
Assessment of export order – book levels	1.821	1.34	Identifiable seasonality is not present	No
Assessment of stocks of finished products	1.076	0.83	Identifiable seasonality is not present	No
Production expectations over the next 3 months	0.797	0.88	Identifiable seasonality is not present	Yes
Employment expectations over the next 3 months	0.571	0.73	Identifiable seasonality probably not present	Yes
CONSTRUCTION				
Building activity development over the past 3 months	0.641	0.62	Identifiable seasonality probably not present	Yes
Main factors currently limiting your building activity: none	1.887	1.67	Identifiable seasonality is not present	No
Main factors currently limiting your building activity: insufficient demand	2.127	2.28	Identifiable seasonality is not present	No
Main factors currently limiting your building activity: weather conditions	0.682	1.04	Identifiable seasonality probably not present	Yes
Main factors currently limiting your building activity: shortage of labour force	0.853	1.13	Identifiable seasonality probably not present	Yes
Main factors currently limiting your building activity: shortage of material and/or equipment	2.491	2.45	Identifiable seasonality is not present	No
Main factors currently limiting your building activity: financial constraints	1.476	1.94	Identifiable seasonality is not present	No
Main factors currently limiting your building activity: other factors	3.000	2.76	Identifiable seasonality is not present	No
Evolution of your current overall order books	1.245	0.96	Identifiable seasonality is not present	No
Employment expectations over the next 3 months	0.660	0.78	Identifiable seasonality probably not present	Yes
SERVICES				
Business situation development over the past 3 months	0.550	0.61	Identifiable seasonality probably not present	Yes
Evolution of the demand over the past 3 months	0.917	0.86	Identifiable seasonality probably not present	Yes
Demand expectations over the next 3 months	0.831	1.07	Identifiable seasonality probably not present	Yes
Evolution of employment over the past 3 months	1.765	1.65	Identifiable seasonality is not present	No
Evolution of employment over the next 3 months	1.136	1.58	Identifiable seasonality is not present	No
TRADE				
Business activity (sales) development over the past 3 months	0.440	0.36	Identifiable seasonality is present	Yes
Volume of stock currently hold	1.441	1.89	Identifiable seasonality is not present	No
Orders expectations over the next 3 months	0.569	0.53	Identifiable seasonality probably not present	Yes
Business activity expectations over the next 3 months	0.628	0.65	Identifiable seasonality probably not present	Yes
Employment expectations over the next 3 months	1.690	1.95	Identifiable seasonality is not present	No
CONSUMERS				
Financial situation over the last 12 months	1.150	0.55	Identifiable seasonality is not present	No
Financial situation over the next 12 months	1.425	1.00	Identifiable seasonality is not present	No
General economic situation over the last 12 months	1.227	1.05	Identifiable seasonality is not present	No
General economic situation over the next 12 months	1.627	1.18	Identifiable seasonality is not present	No
Unemployment expectations over the next 12 months	0.830	0.84	Identifiable seasonality probably not present	Yes
Major purchases	0.735	0.42	Identifiable seasonality probably not present	Yes
Major purchases expectations	1.473	0.93	Identifiable seasonality is not present	No
Savings at present	1.510	1.05	Identifiable seasonality is not present	No
Savings over the next 12 months	2.099	1.21	Identifiable seasonality is not present	No
Statement on the financial situation of the household	1.774	1.48	Identifiable seasonality is not present	No

CONCLUSIONS

The material presents the procedure followed at the Bank of Albania regarding the seasonal adjustment of the monthly balances of business and consumer confidence surveys, publishing for the first time the original and the seasonally-adjusted monthly series. Despite the guidance provided to businesses and consumers that are part of confidence surveys, to take into account the seasonal fluctuations while providing answers to the questionnaires, the presence of seasonal factors is still present. This is also confirmed by our experience with the quarterly balances of confidence surveys, as well as the international practice that deals with monthly balances. The presence of seasonality in business and consumer monthly estimates and expectations has been tested through the Census X12 method. In this method, the seasonal adjustment model chosen to control for the presence of the seasonal component of the monthly confidence survey series is additive.

Regarding the selection of the monthly balances of confidence surveys that should be subject to the seasonal adjustment process, we have prioritised on meeting the condition that the seasonal adjustment results should be of an acceptable quality. Based on the quality tests, as well as the combined test, 15 series from 42 monthly confidence surveys balances have been seasonally adjusted. With the addition of new data, the monthly series will be periodically analysed for the presence of seasonality, the same procedure followed for the quarterly series of confidence surveys. This analysis is planned to be conducted once a year for all observation balances. We emphasize that the seasonal treatment requires special care, especially in the case of short-time series, to guarantee the quality of seasonal adjustment. The enrichment with data of the monthly series will consolidate the technical estimate of the seasonal component, enabling also the publication of aggregated confidence indicators and the economic sentiment indicator at monthly frequency in the future.

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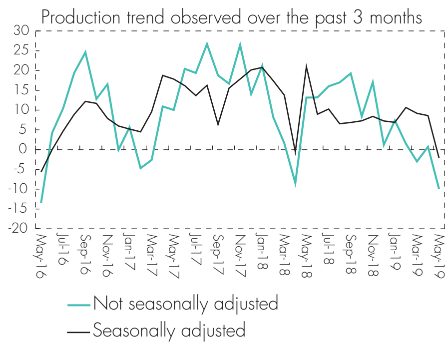
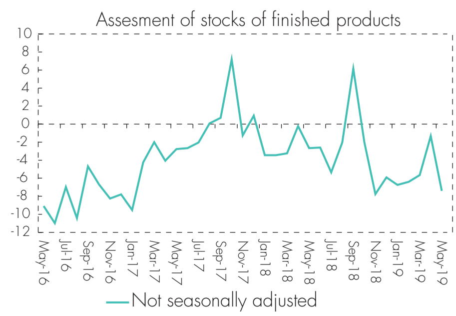
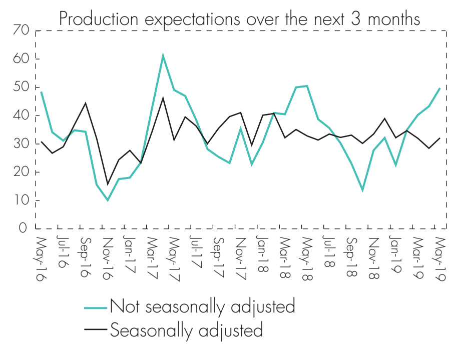
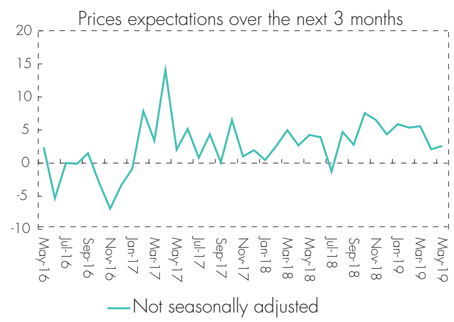
ANNEX

Chart 1. Industry monthly balances



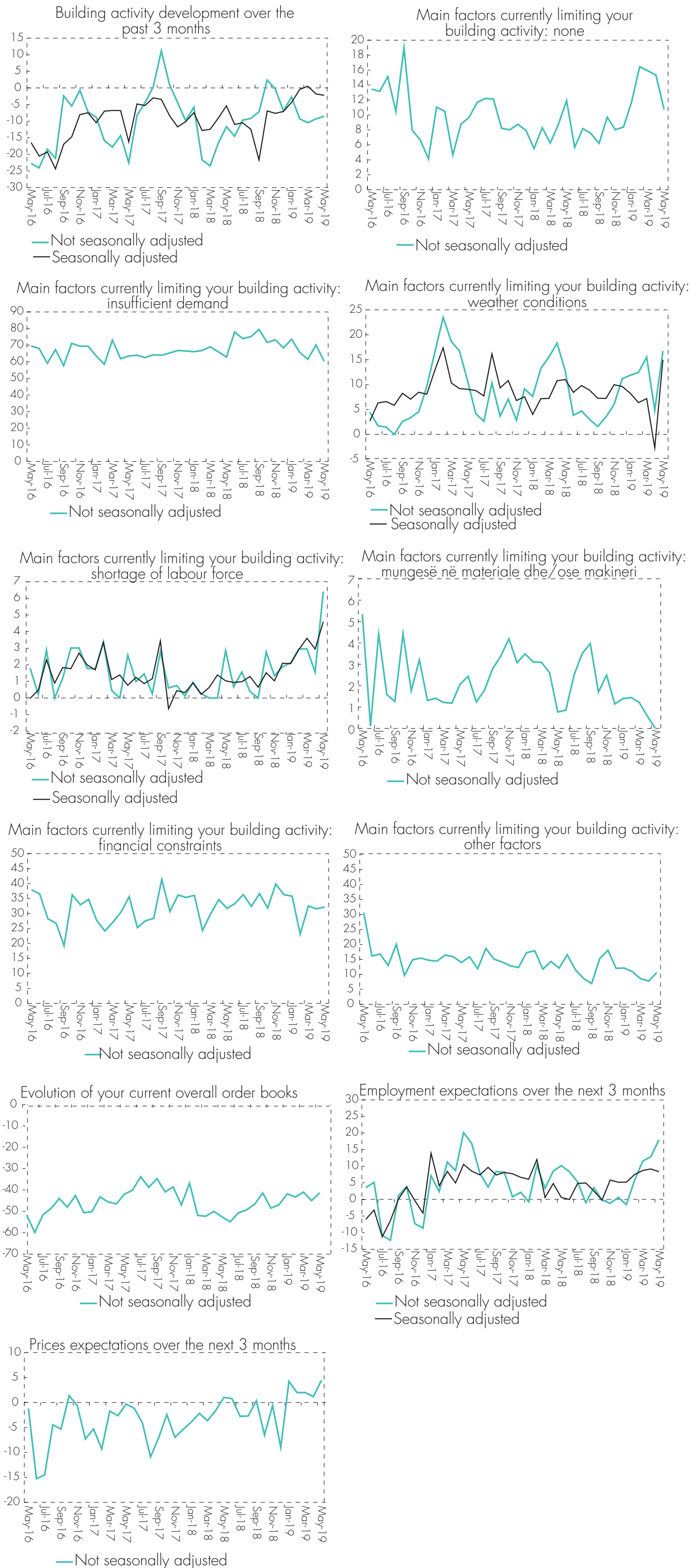






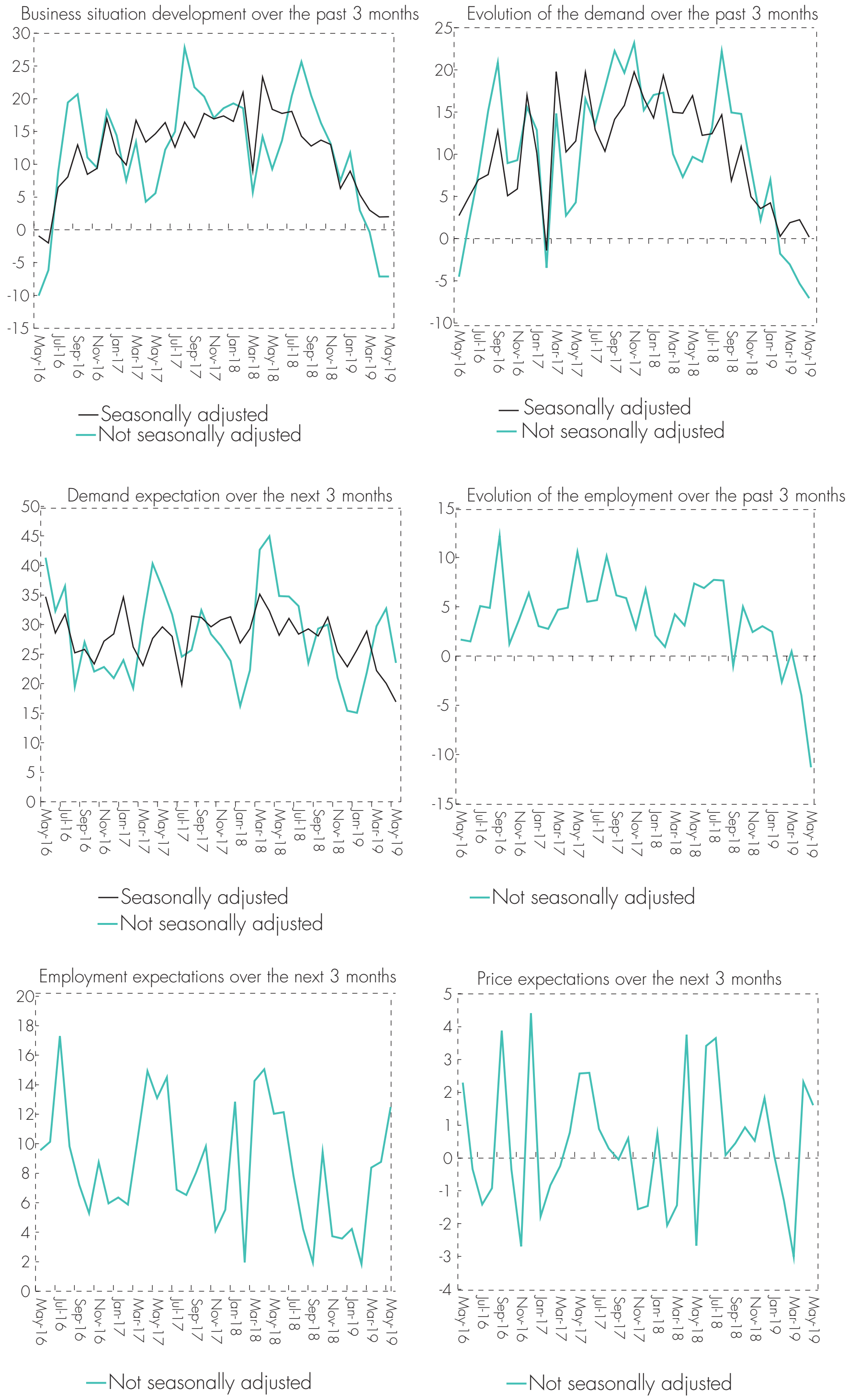
Source: Business Confidence Survey, Bank of Albania.

Chart 2 Construction monthly balances



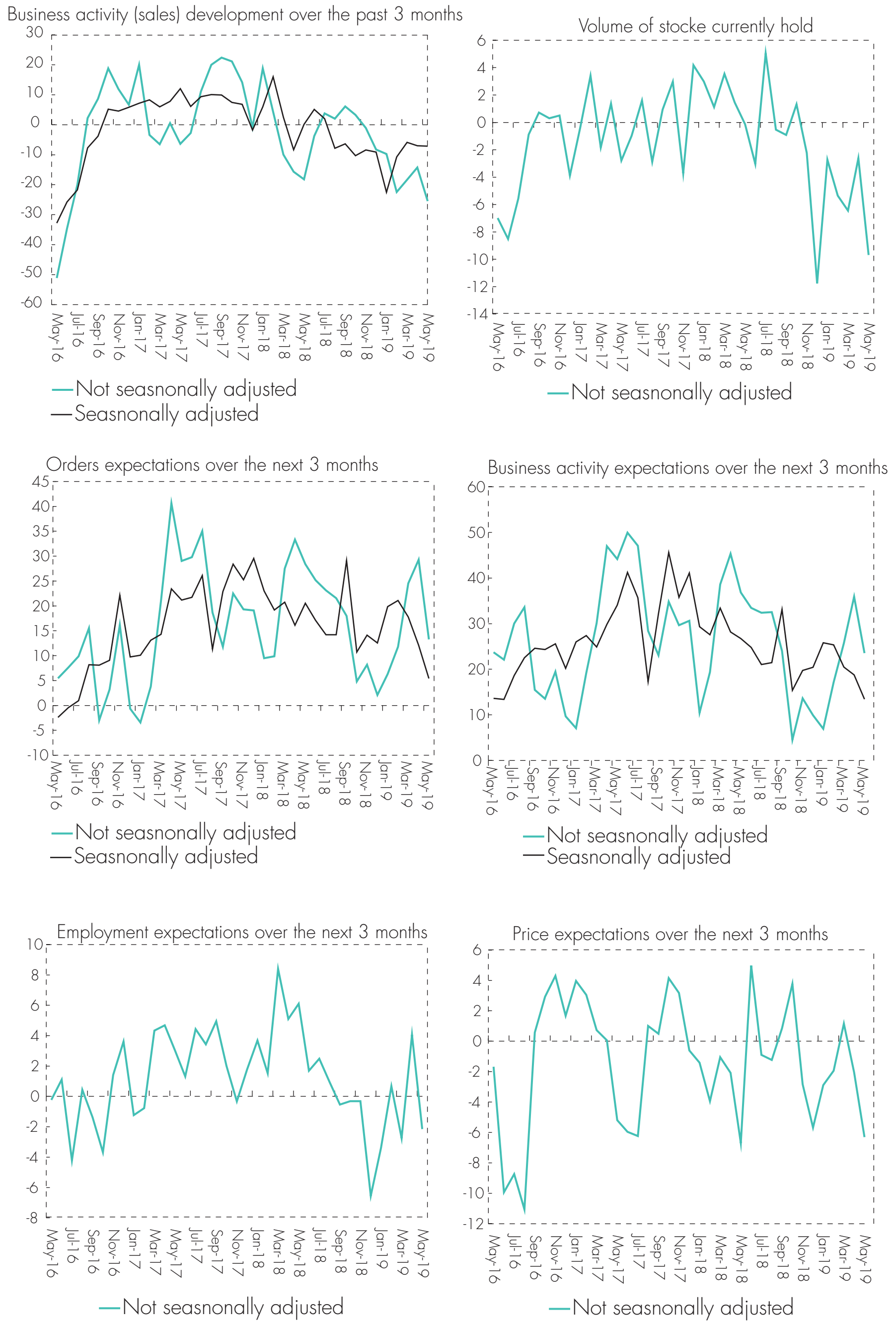
Source: Business Confidence Survey, Bank of Albania.

Chart 3 Services monthly balances



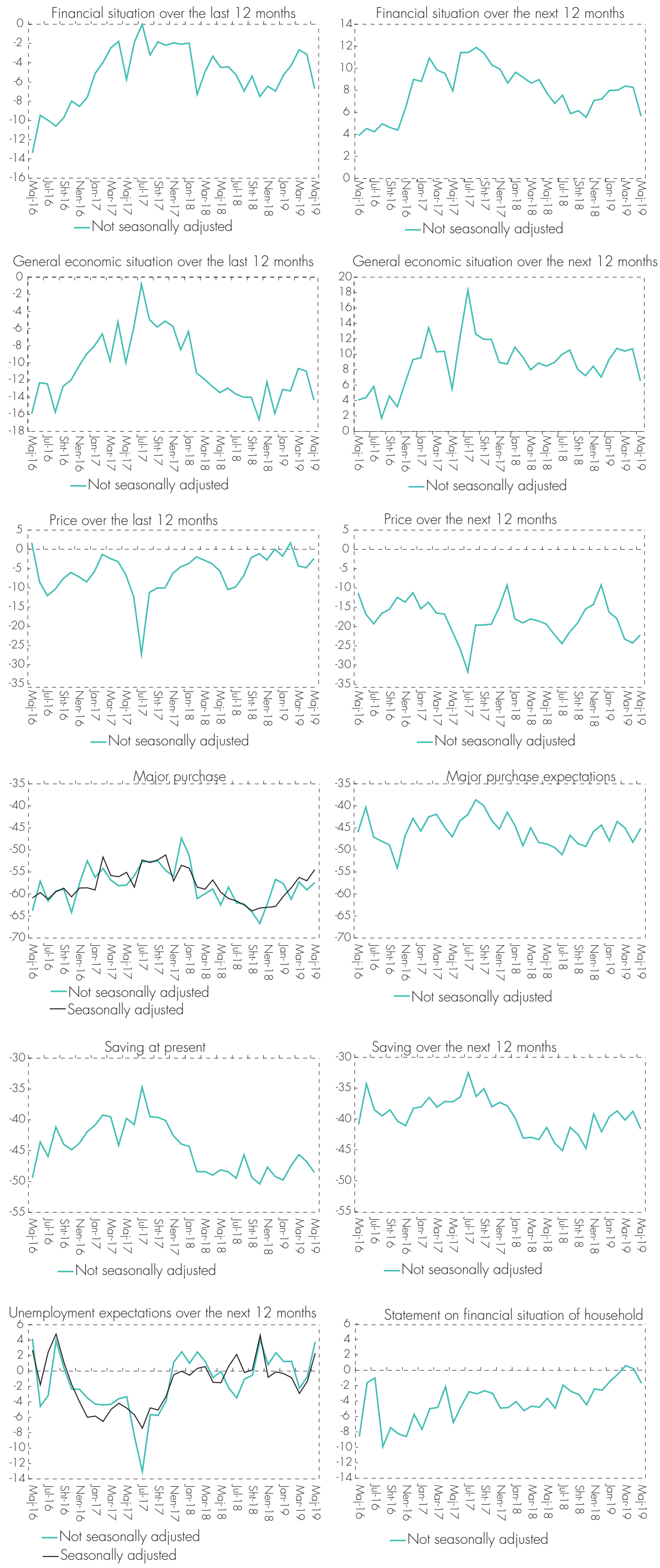
Source: Business Confidence Survey, Bank of Albania.

Chart 4 Trade monthly balances



Source: Business Confidence Survey, Bank of Albania.

Chart 5 Consumer monthly balances



Source: Consumer Confidence Survey, Bank of Albania.

SHORT-TERM FORECAST OF INFLATION A DISAGGREGATED APPROACH

Ermelinda Kristo, Gent Hashorva, Monetary Policy Department, Bank of Albania

ABSTRACT

Monitoring inflation and forecasting its developments in the short-term helps the decision-making process of monetary policy. The purpose of this material is to review one of the old models used to forecast inflation using the disaggregating approach. This model has performed poorly in the recent years, with the division into categories and their explanatory variables needing revisions. This material proposes a more adequate regrouping of total inflation and new models to forecast each component. According to the new method, the forecasted inflation is the aggregated product of the forecasted components, using the respective weights in the CPI basket. The criteria used to choose the best forecasting model for each component is the minimization of the forecast error in an out-of-sample forecasting exercise.

INTRODUCTION

Inflation is an important indicator of the economic performance of the country. As in many other countries, the main objective of monetary policy in Albania is price stability. Monitoring and forecasting the performance of prices in Albania helps assess the current and expected situation and the decision-making of the monetary policy. The forecasting performance of the portfolio of short-term forecast models is assessed every year. The purpose of this study is to review one of the short-term models for forecasting inflation, the method that starts from individual forecasts of its components (bottom up approach). The study addresses the following main issues: number of composing groups of headline inflation; best forecasting method for each group; and, set of explanatory variables for each group.

The new forecasting model of headline inflation presented in this study is based on the disaggregation of the total CPI index in 5 composing groups and the forecast for each component (Part 2.1). Forecasted headline inflation is the combination of the forecasted components aggregated using the respective weights in the total index. The tested methods for forecasting the inflation of each component were: simple univariate equation, multivariate equations which use several explanatory variables, standard VAR and Bayesian VAR (Part 2.2). The criteria for choosing the best model for each component were their forecast accuracy. Forecasting accuracy was measured by minimizing the forecasting error in an out-of-sample forecast exercise (Part 3).

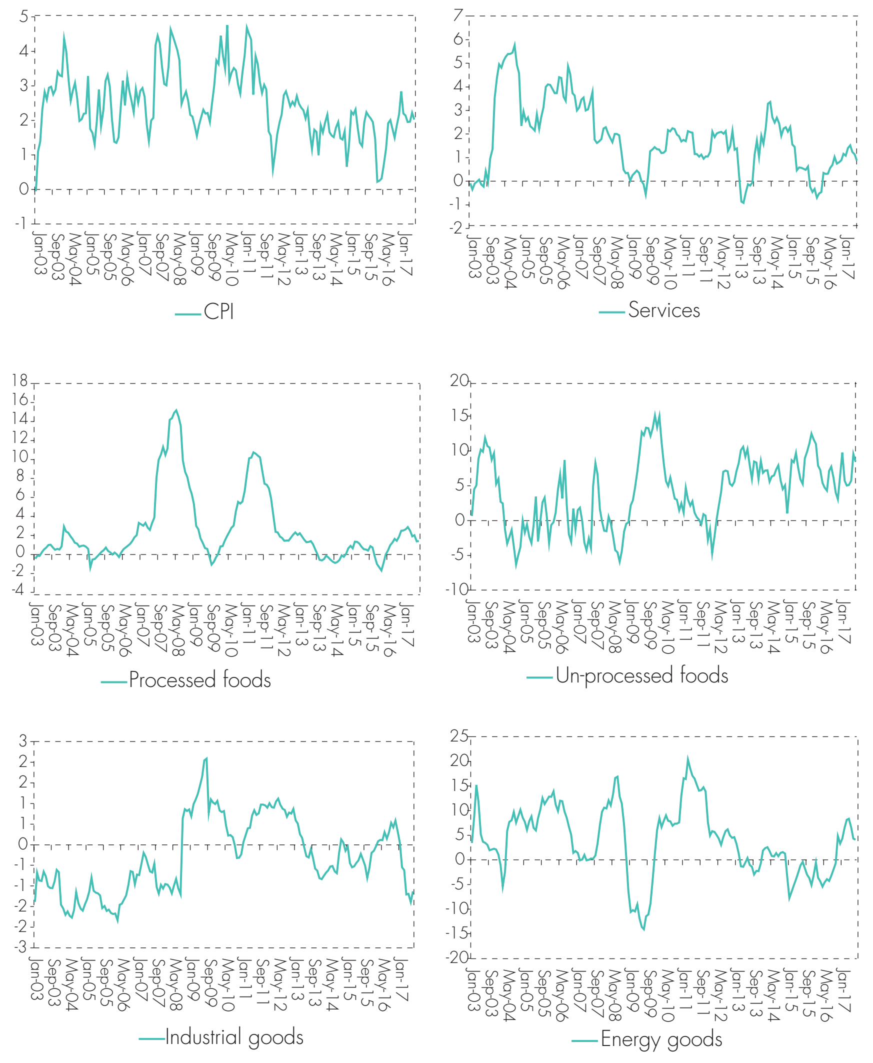
2. DATA AND MODELS

2.1 DATA

The database consists of: (i) the dependent indicators, the sub-groups of the total index of consumer prices; and, (ii) a number of indicators, potential explanatory variables of inflation, from the external economic environment, real domestic economy, monetary sector and indicators from surveys.

The disaggregation of the total CPI index in 5 sub-groups[1] (unprocessed food, processed food, industrial goods, energy goods[2] and services) aims mainly at

Chart 1 Headline inflation and its components, annual changes in %



Source: INSTAT and authors' calculations.

[1] *Actually the separation of total index consists in 6 components, since we have also separated the index of commodities with administered prices including "Payment for drinking water", "Payment for electricity" and "Pharmaceutical products", and has a 7% share of the CPI basket. The inflation of this group will be projected in the future based only on judgement, to be later aggregated with the inflation of the other groups forecasted by the models.*

[2] *In the category "Energy goods" are included* ***oil***, ***fuel*** *and* ***fire wood****.*

modelling the different components, with typical behaviour, affected by different factors. The disaggregation into these components is done in accordance with the methodology of ECB (European Central Bank) on inflation disaggregation, used in its periodic analyses and the forecast process. The behaviour of prices of each component is presented in Chart 1 below.

The selection of potential explanatory variables was led by the economic theory, the current experience in forecasting inflation, as well as the experience of other central banks in the short-term forecast inflation process. In the end, following the approach from general to specific, in the models, we kept only the variables that resulted statistically significant for all periods estimated. The explanatory variables that resulted significant in the best specifications of the models are listed in the following Table.

Table 1 Explanatory indicators used for forecasting inflation by components

Explanatory indicators	Frequency	Source
Food and beverage price index WB (IUshqim)	Quarterly	World Bank
Salary in the processing industry sector (Pagaind)	Quarterly	Short-term statistics, INSTAT
Salary in services sector* (Pagasherb)	Quarterly	Short-term statistics, INSTAT
Salary in the non-food processing industry sector (Pagaindp)	Quarterly	Short-term statistics, INSTAT
Value added in the agriculture sector (vshb)	Quarterly	National accounts, INSTAT
ALL/EUR exchange rate (Kurs_E)	Monthly	Bank of Albania
Oil price abroad (Oil)	Quarterly	World Bank
Excise rate on fuels (Akc)	-	Official Journal, QBZ
Consumer credit (kredkons)	Monthly	Bank of Albania
Domestic output prices in the processing industry (PPI)	Quarterly	Short-term statistics, INSTAT
NEER	Monthly	Bank of Albania

** Measured from the nominal average salary only for services covered by short-term statistics.*

2.2 FORECAST MODELS

We have considered forecast models that are regularly used by other central banks for the short-term forecast of inflation. They are simple linear models (equation with one variable), multivariate linear models (equation with several explanatory variables), standard VAR models and Bayesian VAR models (BVAR). All models are estimated by using the annual changes of the variables.

- The estimated simple linear model is an auto-regressive model AR(1). It is used as a benchmark model to compare the forecasting performance of other models.
- *Linear multivariate* equations explain the annual changes in prices of each component, using different explanatory variables. These models have the advantage that allow for more flexibility in the choice of time lags of explanatory variables. As usual in short-term forecast practice, all equations include the first lag of the depending variable as an explanatory variable.
- *VAR models* explain the behaviour of a set of endogenous indicators, in function of their past values. They are extensively used in the process of forecasting macroeconomic indicators due to their simplicity, flexibility and ability to adapt better to the data. We have assessed VAR models by

choosing the lag length of 4 quarters[3]. As a first step, VAR models were estimated with a high number of variables, but the lowest forecast error was reached by specifications with a more limited number of explanatory indicators (at the end were used only the indicators included in the simple equations).

- *BVAR models*, proposed initially by Litterman (1980) as an alternative to standard VAR models, resolve the issues of the assessment of many parameters. BVAR is used with success to forecast inflation in many other central banks[4]. BVAR combines prior knowledge on VAR's parameters with information from explanatory indicators, thus minimizing significantly the parameters that are not statistically relevant. The priors chosen for the BVAR as well as more detailed information on the choice of the best specification of BVAR models are provided in Annex 1.

2.3 CHOOSING THE BEST MODEL

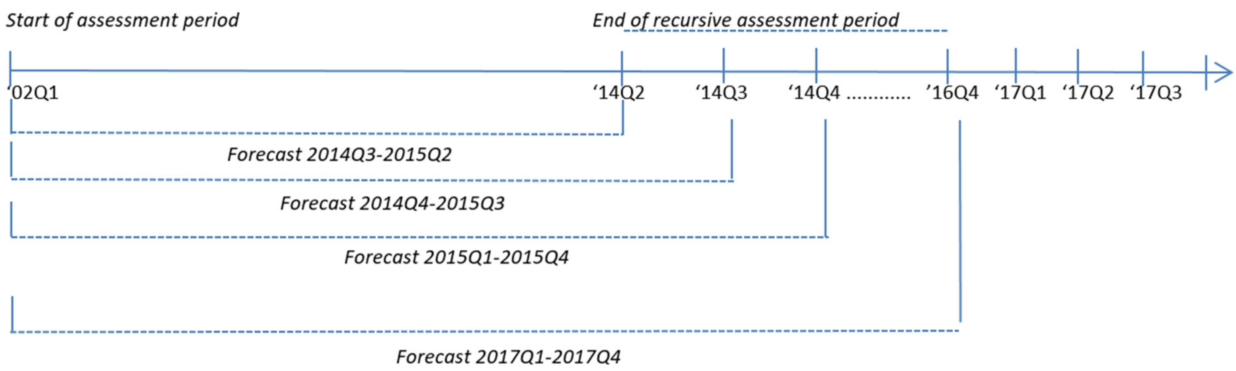
In order to judge the forecasting ability of the models, we conducted a pseudo out-of-sample exercise. For this purpose, we divided the time period 2002Q1 - 2017Q4 in two sub-periods. Initially, the models are estimated for the period 2002Q1 - 2014Q2 and the forecast for 4 quarters ahead is obtained (in fact, we obtained forecasts for the past values of 2014Q3 till 2015Q2). Then the estimating period increases with one observation and the model is re-estimated and 4 other forecasts for the period ahead are taken. This procedure is repeated recursively 11 times, until the entire length of the time series is used. This way, the last assessment period is up to 2016 4, and the short-term forecasts are obtained for the period 2017Q1 - 2017Q4. The projected values for each forecast round for the period after one, two, three and four quarters, are compared with the actual values of the inflation of each period. The accuracy of the forecast for each horizon is quantified through the RMSE indicator, which is calculated for one to four quarters forecasting horizons, according to the formula:

$$\text{RMSE}_h = \sqrt{\frac{\sum_{2014T3+h}^{2016T3+h}(forecast - actual\,inflation)2}{T}}\text{, where h=1, ..., 4 quarters.}$$

This method applied on each model for each component is described schematically in the following figure.

[3] The selection of the time lag in VAR has a dilemma: the higher the time lag chosen, the less precise will be the coefficients due to the reduction of the degrees of freedom. On the other hand, the lower the time lag, the higher is the risk of excluding time dynamics between variables and the presence of auto-correction. We have chosen for all models a 4 quarter time lag, which it is often suggested by the various statistical criteria used to choose the appropriate time length.

[4] See e.g.: Benalal, N., (2004) on forecasting inflation in the euro area; Kapetianios, G et al. (2007) forecasting inflation and GDP at the Bank of England; Andersson and Lof (2007) for the Bank of Sweden; Carrera c. and Ledesma A. (2014 in forecasting inflation at the Bank of Peru; Bjornland, H. et al. (2008) on forecasting at the Bank of Norway; Akdogan, K. (2012) in forecasting inflation at the Bank of Turkey.



3. RESULTS FROM COMPARING FORECASTING PERFORMANCES

In this part we present the forecasting results of the five inflation components and compare the forecasting performance of the different models for each component. Results will be provided only for the models with the final explanatory variables selected:

- *Processed foods*. The selected explanatory variables to explain the inflation of this group are: global food and beverage price index, salary in the processing industry sector and the ALL/EUR exchange rate;
- *Unprocessed foods*. The selected explanatory variables are the ALL/EUR exchange rate and the value added of the agriculture sector;
- *Energy goods*. The selected explanatory variables are the oil price abroad and a dummy variable to capture the impact of the change in the fuel import excise rate. This indicator takes the value 1 for the entire period after 2010 Q3, when the excise of 37 lek per litre of imported oil was established.
- *Services*. The selected explanatory variables to explain the inflation of services are the salary in this sector, non-processed food prices (which are raw material in the sub-category restaurants) and consumer credit.
- *Industrial goods*. Inflation is explained by the salary in the processing industry sector (without the food industry), the output price index in this industry, as well as the performance of the NEER indicator.

The results of the pseudo out-of-sample forecast exercise for the five components of inflation are summarised in Table 2. The RMSE of each model is compared with the RMSE of the reference model. Relative RMSE =$RMSE_{model}/RMSE_{model\_AR}$. From the formula, a relative RMSE lower than 1 indicates that the model forecasts better than the reference model.

For the category of processed foods the BVAR model has a lower RMSE than the reference model for a time horizon up to three quarters. The VAR model and the multivariate equation performed poorly compared with the simple model AR(1). This result is the same for all three models for the 4 quarters ahead forecast. In conclusion, the model selected to forecast the inflation of processed foods is the BVAR model. For the category non-processed foods, the model of the multivariate equation had a better forecasting performance. This model forecasted better than the simple model AR(1) up to four quarters (for the one quarter forecasting horizon this models in fact had a similar RMSE with that of the reference model). The multivariate equation had the best relative performance for the inflation of the category energy goods as well. For the inflation of the group of services, the BVAR model and the multivariate equation had the best relative performance. The VAR model manages to explain better only the inflation of services over the one quarter time horizon. The BVAR model had the absolute lower RMSE, and was selected to explain the inflation of this group. For the category of industrial goods all three models performed relatively better than a simple AR model. In absolute terms, the model BVAR has the lowest RMSE.

Table 2 Relative RMSE of forecasting models

Processed food			
Forecasting horizon	VAR	BVAR	Equation
h=1	1.11	0.75	1.17
h=2	1.43	0.78	1.23
h=3	1.76	0.87	1.26
h=4	2.07	1.03	1.26
Unprocessed foods			
Forecasting horizon	VAR	BVAR	Equation
h=1	1.19	1.08	1.01
h=2	1.51	1.20	0.97
h=3	1.77	1.36	0.95
h=4	1.76	1.39	0.97
Energy goods			
Forecasting horizon	VAR	BVAR	Equation
h=1	0.94	0.85	0.97
h=2	1.07	1.01	0.93
h=3	1.20	1.17	0.95
h=4	1.37	1.37	1.10
Services			
Forecasting horizon	VAR	BVAR	Equation
h=1	0.91	0.83	1.09
h=2	1.15	0.91	0.94
h=3	1.07	0.88	0.90
h=4	1.20	0.92	0.84
Industrial goods			
Forecasting horizon	VAR	BVAR	Equation
h=1	0.75	0.83	0.95
h=2	0.83	0.83	0.85
h=3	0.92	0.84	0.83
h=4	1.18	0.98	1.02

In conclusion, based on the forecasted results for each component, the total prices index, CPI, is aggregated and the forecast error is calculated for all four forecasting horizons. In order to aggregate total inflation we used the group weights according to the relevant period. For example, to aggregate the total index of 2017 are used the respective weights: 27.5% processed goods, 16.9% non-processed goods, 15.5% industrial goods, 5.3% energy goods, 27.4% services and 7.4% goods with administered prices[5]. A simple autoregressive AR(1) model was chosen as the benchmark model for the total

[5] *For the purpose of this exercise, in order to calculate total CPI, the actual historical data of the index of administrated prices products were used.*

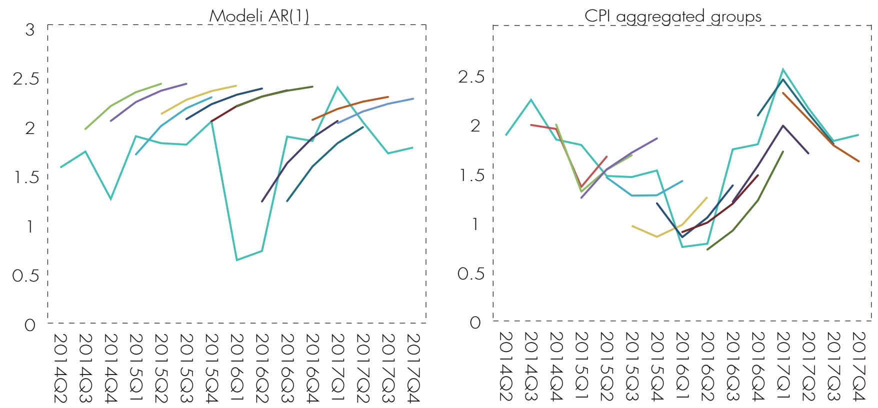
index as well. The forecast error of headline inflation is lower that the forecast error of individual groups. Table 3 shows the absolute RMSE indicator (column two) and the relative RMSE (column three). For all four forecasting horizons, the relative RMSE registered values lower than 1.

Table 3 Absolute and relative forecasting performance

Forecasting horizon	Absolute RMSE	Relative RMSE ($RMSE_{CPIaggregated}/RMSE_{model\_AR}$)
h=1	0.33	0.53
h=2	0.37	0.49
h=3	0.36	0.45
h=4	0.43	0.51

Final results of headline inflation forecast by groups, after the selection of the best models for each component, are reflected in the following figure. The 11 round of forecast shown in the Chart in the right are close to the actual inflation dynamic, compared with the forecasts of the reference model (Chart in the left).

Chart 2 Results of pseudo out-of-sample forecast (total CPI, annual change, in %)



Source: ?.

4. CONCLUSIONS

In this material we presented a new model of inflation forecast based on the disaggregation approach by groups. Based on the results of the out-of-sample forecasting exercises, the model which will be used to forecast inflation of each component will be: Bayesian VAR for the category of processed foods, industrial goods and services; multivariate simple equation for non-processed foods and energy goods. The following drawbacks should be kept in mind when reading these results: (i) the short period of performing the out-of-sample forecast exercise, only 11 quarters; and (ii) the recent years have been characterized by sudden movements in headline inflation and inflation by category, and their forecast has been more difficult. Repeating the same exercise in another time period may give different results.

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ANNEX 1 CHARACTERISTICS AND THE SELECTION OF BVAR MODELS

The use of bayesian methods in the assessment of VAR requires the use of prior knowledge of its parameters. Instead of eliminating the time lags of the variables in a classic VAR model (when they are not statistically significant), BVAR minimizes their parameters. During the use of BVAR models for forecasting, two are the main issues that must be addressed: (i) first is deciding the prior for inflation; and (ii) second, deciding the weight that we will give this prior. To be successful, applied prior density must impose a certain structure on VAR, which will reflect the nature of data. Following the methodology of Litterman and based on the practice that has shown that the macroeconomic time series, in general, are very persistent, the prior selected for inflation is the random walk behaviour. Thus, all the VAR equations have a behaviour similar with that of random walk: $y_t=a_0+y_{t-1}+e_t$.. The bayesian technique is used to update the prior with the information contained in the set of variables[6]. In this model, the parameters assessed may be seen as a weighted average of the parameters of prior distribution with the parameter suggested by the set of variables (the likelihood function). These weights are very much affected by our belief on the prior distribution. If we have strong belief in the prior, i.e. inflation behaves as random walk, we apply a very small variance of prior distribution parameters (tight prior) and give more weight to the model of random walk. If we want to give a smaller weight to the initial assumption, we give a very small weight to the prior and apply a higher variance (loose prior) to its parameters. The determination of this parameter, i.e. the weight that we will give to the prior, will be guided by the forecasting performance. In this way we select that variance/parameter, that minimizes the forecast error[7]. Thus, the selection criterion will be the forecast accuracy, measured by the minimization of the RMSE indicator. RMSE is calculated for the forecasting horizons 1 to 4 quarters. For each BVAR on each inflation category we have selected the weighting parameter (λ) that gives the lowest RMSE. The values of RMSE for each weighting parameter selected for each model are shown in the following tables.

[6] *The Bayesian theorem combines data from prior density with the likelihood function (evidenced from the data) to determine posterior density. We may define the weight we will give to the prior data, compared with the evidence gathered during the assessment of VAR data, by modifying the parameters of Bayesian VAR (hyper-parameters).*

[7] *In Eviews, who has included the prior Minnesota distribution proposed by Litterman, the λ parameter, which defines how much confidence we have in the prior distribution, initially it is given the lowest value of 0.01. This is a value that expresses the highest confidence in prior distribution and models inflation as a simple autoregressive process. Then we increase the parameter λ from 0.1 to its highest value of 0.99. The highest value of λ represents a very small confidence in prior distribution and gives more weight to data gathered by explanatory indicators. By applying this value of the parameter, inflation is basically modelled only by information gathered from the other data.*

Table 1 RMSE of the Bayesian VAR model for different λ coefficients

1. Processed food				
	Forecasting horizon			
Λ lambda	h1	h2	h3	h4
0.0	0.0092	0.0151	0.0189	0.0207
0.1	0.0076	0.0121	0.0152	0.0178
0.2	0.0074	0.0120	0.0159	0.0199
0.3	0.0075	0.0125	0.0171	0.0218
0.4	0.0076	0.0130	0.0181	0.0231
0.5	0.0077	0.0134	0.0189	0.0241
0.6	0.0078	0.0139	0.0197	0.0251
0.7	0.0079	0.0143	0.0205	0.0261
0.8	0.0080	0.0147	0.0212	0.0270
0.9	0.0082	0.0151	0.0219	0.0278

2.Energy goods				
	Forecasting horizon			
Λ lambda	h1	h2	h3	h4
0.0	0.0348	0.0508	0.0589	0.0624
0.1	0.0326	0.0478	0.0556	0.0543
0.2	0.0313	0.0489	0.0606	0.0628
0.3	0.0306	0.0492	0.0625	0.0667
0.4	0.0302	0.0493	0.0632	0.0684
0.5	0.0300	0.0494	0.0636	0.0693
0.6	0.0299	0.0496	0.0639	0.0699
0.7	0.0299	0.0498	0.0641	0.0703
0.8	0.0299	0.0500	0.0643	0.0706
0.9	0.0300	0.0502	0.0645	0.0707

3.Services				
	Forecasting horizon			
Λ lambda	h1	h2	h3	h4
0.0	0.0062	0.0099	0.0131	0.0163
0.1	0.0058	0.0088	0.0112	0.0135
0.2	0.0054	0.0082	0.0102	0.0122
0.3	0.0052	0.0080	0.0100	0.0120
0.4	0.0051	0.0080	0.0100	0.0122
0.5	0.0050	0.0081	0.0102	0.0125
0.6	0.0050	0.0083	0.0103	0.0128
0.7	0.00504	0.0085	0.0105	0.0132
0.8	0.0051	0.0087	0.0107	0.0135
0.9	0.0051	0.0088	0.0108	0.0137

4.Goods				
	Forecasting horizon			
Λ lambda	h1	h2	h3	h4
0.0	0.0030	0.00391	0.00480	0.00764
0.1	0.0029	0.00362	0.00477	0.00763
0.2	0.0029	0.00374	0.00487	0.00733
0.3	0.0028	0.00371	0.00492	0.00726
0.4	0.0027	0.00365	0.00499	0.00732
0.5	0.0027	0.00360	0.00507	0.00743
0.6	0.0026	0.00359	0.00517	0.00755
0.7	0.0026	0.00359	0.00527	0.00767
0.8	0.0025	0.00361	0.00536	0.00779
0.9	0.0025	0.00363	0.00544	0.00789

5.Non-processed foods				
	Forecasting horizon			
Λ lambda	h1	h2	h3	h4
0.0	0.0267	0.0293	0.0308	0.0385
0.1	0.0262	0.0288	0.0329	0.0399
0.2	0.0272	0.0331	0.0416	0.0500
0.3	0.0280	0.0362	0.0469	0.0560
0.4	0.0285	0.0382	0.0500	0.0594
0.5	0.0289	0.0395	0.0518	0.0615
0.6	0.0291	0.0403	0.0530	0.0628
0.7	0.0293	0.0409	0.0538	0.0636
0.8	0.0294	0.0413	0.0543	0.0641
0.9	0.0295	0.0416	0.0547	0.0645

ANNEX 2 REPRESENTATION OF MULTIVARIATE EQUATIONS

Table 2 Estimation results of individual equation models

Category	Processed food (UP)		Unprocessed food (UPP)		Energy (E)		Services (Sh)		Industrial goods (M)	
Explanatory indicators and respective parameters	UP (-1) ***	0.69	UPP*** (-1)	0.65	E (-1)***	0.48	Sh (-1)***	0.72	M (-1)***	0.72
	Iushq***	0.07	Kursi_E***	0.33	Oil***	0.15	Pagash(-3)***	0.02	PPI(-4)***	0.04
	Pagaind**	0.06	Vsh_B**	-0.30	Excise**	0.01	UPP(-2)***	0.04	Pagaindp(-4)***	0,016
	Kursi_E(-4)***	0.10					Kredkons**	0.01	NEER (-5)***	0.04
R2		0.92		0.69		0.89		0.79		0.85

****) the coefficient is statistically significant for the 99% level and **) the coefficient is statistically significant for the 95% level.*

SHORT-TERM FORECAST OF PRIVATE CONSUMPTION AND INVESTMENTS IN ALBANIA

JULY 2016

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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.

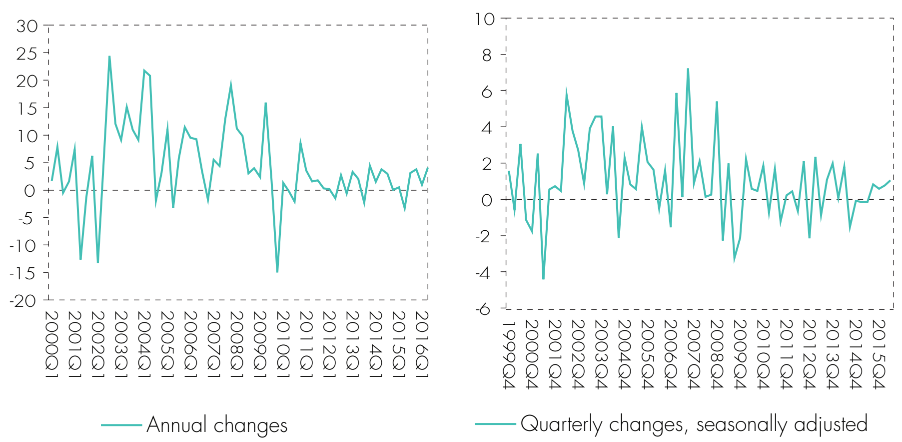
[2] *nterest rates were also tested transformed in annual changes in percentage points.*

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.

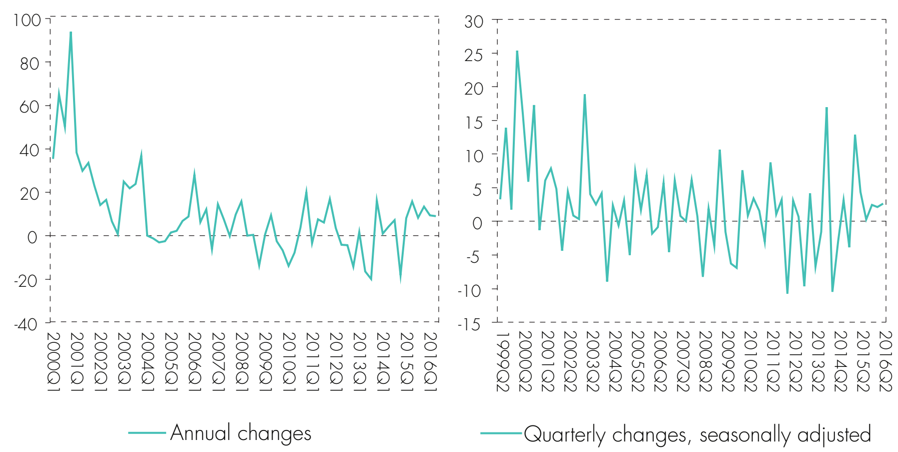
Some of the short-term indicators that were left out of the models and can be considered later to enter the group of explanatory variables are: incomes from remittances, interest rates on credit, exchange rate, inflation rate, import data of passenger cars and credit standards for individuals.

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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INFLATION EXPECTATIONS VERSUS UNCERTAINTIES AND TIME HORIZONS: THE CASE OF ALBANIA

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ABSTRACT

Inflation expectations represent one of the monetary policy transmission mechanism channels to be continuously explored, especially in the Inflation Targeting regime. This article tries to re-evaluate the accuracy and the features of quantitative inflation expectations in Albania, until the end of 2018. The study concludes that the accuracy of inflation expectations have been improved over time. The rationality tests, in general, re-confirm the presence of a weak rational component in inflation expectations. Also, as long as medium-term inflation expectations are higher than short-term ones, they might be considered more in line with the Bank of Albania (BoA) medium-term inflation target, suggesting a satisfactory degree of public confidence in the monetary policy decision-making.

Keywords: Inflation expectations, Accuracy, Rationality.

JEL-Classification: E52, E31, C83, C52.

1. INTRODUCTION

Central banks, especially those under Inflation Targeting (IT) monetary policy regimes, emphasize the importance of inflation expectations, in order to maintain price stability and 'well-anchored' inflation rates to the medium-term objective. Understanding the evolution of inflation expectations is a key issue of the implementation and success of an IT regime, already adopted by many emerging economies during the 2000s.

Because of the forward-looking feature of the monetary policy decision-making process in general, and particularly in the case of the IT, inflation expectations represent a very important tool in this framework. If this channel works well, the monetary policy becomes more rational. Under an IT regime, inflation expectations signal more or less the degree of confidence in the central bank and the credibility of the public in the inflation target [1]. If expectations result close to the target over the medium term, they indicate that the public strongly

[1] *The views in this article are those of the author and do not necessarily reflect those of the Bank of Albania. I would like to thank the Department of Statistics and Applied Informatics at the Faculty of Economy of the University of Tirana, inviting me in the 8th International Conference "Information Systems and Technology Innovations - Fostering the As-A-Service Economy" and the participants in the 6th Session "Big Data", where I presented the main results till 2017:Q1 (Tirana, June 2017). This article represents new results generated from an updated database (until the end of 2018).*

believes that the central bank will do the best to steer inflation to the target, despite short-term deviations. Under these circumstances, the rate of changes in prices and wages would tend to be in line with the inflation target by resulting more immune to temporary inflation fluctuations. This allows central banks to largely ignore short-term price fluctuations and adopt a medium to long-term approach, in order to maintain price stability. Otherwise, if inflation expectations were not consistent with the inflation target, maintaining price stability would be a difficult task. In this case, expectations for a higher inflation rate would likely be reflected in higher wages and prices, affecting consumption and domestic demand, and increasing inflationary pressures. Exploring the evolution of inflation expectations is also an important information for modelling and forecasting purposes.

This article will focus exclusively on the quantitative approaches of inflation expectations, measured through the direct method according different agents and time horizons in the case of Albania[2]. The second section briefly summarizes the main concerns in assessing inflation expectations giving examples from different countries under an IT regime. A short explanation of the database is presented in the third section. In the fourth one, the results of accuracy indicators and rationality tests are summarised and analysed. The last section presents the main conclusions of the re-evaluations.

2. ASSESSING INFLATION EXPECTATIONS – A CHALLENGING TASK

In the IT framework, besides other channels of the monetary policy transmission mechanism, expectations remain a challenging one for two important reasons: *firstly*, because inflation expectations cannot be measured directly; *secondly*, testing the feature of inflation expectation - if they represent a rational, adaptive, or mixed behaviour - is really crucial for the monetary policy in an IT regime.

The reason for raising the first concern is because inflation expectations are an unobservable variable. As a consequence, alternative methods - direct and indirect ones - are usually implemented for their assessment. Central banks use mostly the survey-based method. Different economic agents are interviewed periodically, regarding future inflation over short, medium and long-term horizons. The questions are formulated for getting qualitative or quantitative answers.

A range of indirect methods, mostly probabilistic approaches, based on normal and uniform distributions, are implemented to quantify ***the answers from the qualitative questions*** [2]. In addition, the balanced-based method is used, as a possible alternative for assessing inflation expectations [2]. The qualitative questions regarding expected inflation are usually found in business and consumer confidence surveys. We get the percentages of answers according to each option (three or five options). Applying a set of statistical formulas and

[2] *For more details on the approaches and measurement methods applied in BoA, see [2].*

transformations suggested from different distributions on these percentages, combining them with past/current published inflation rate, we achieve the assessments for expected inflation rates.

Assessing the inflation expectations on ***survey-based quantitative answers, relates to the direct method***, because the users get the expected inflation rates for different agents and time horizons. This quantitative and direct information might be collected from both confidence surveys and professional and financial agents' surveys.

By addressing the second concern - two main components come into the formation of inflation expectation: the adaptive; and the rational one. It is very important to emphasize that inflation expectations obtained through surveys may reflect various situations. The surveys method allows us to obtain information about agents' expectations on inflation, but it does not necessarily mean that the formation of their expectations is economically correct [3]. According to Basdevant (2003) [4], it might happen that inflation expectations reflect current and recent past inflation situation. Thus, they are mostly affected by inflation rates at the moment the survey is carried out. The latter suggests that in the formation of inflation expectations, the component which adapts the expected values in view of the current and recent past ones is playing the most important role. In this case, literature defines inflation expectations as "adaptive". Empirical studies have shown that the data obtained from surveys may reflect much more current and past values of inflation rather than predict future inflation rates [5], [1], [2]. However, even when obtained inflation expectations are strongly correlated to its current and past values, this does not exclude the possibility that they might have a forward-looking component to some extent, which is widely known as the "rational" part of the inflation expectations. In the case of New Zealand, one of the pioneers of the IT regime, the findings of Basdevant (2003) [4] highlight that inflation expectations are the result of the combination between forward-looking behaviour and past developments of inflation. In addition, he concludes that the way economic agents form their inflation expectations might change over time. Is this the case of Albania? Have the agents used all the available information at the moment they formed their expectations including information related to current and future decisions of monetary policy?

Three main benefits, all interrelated, are associated with an IT regime. *First*, inflation targeting successfully lowers inflation and makes it less volatile [6]. *Second*, it reduces the real costs of disinflation [7]. *Third*, it anchors long-term inflation expectations at, or very close to, the inflation target [8]. Empirical literature has found stronger evidence of such benefits for emerging economies than for advanced economies. Focusing on the third benefit, the evidence from different central banks emphasizes that the medium and long-term expectations may remain well-anchored, even if inflationary pressures signal higher inflation for the future periods, such as in 2008 periods of higher inflationary pressures from commodity prices. Another case, the opposite one, consists of the lower inflationary pressures during and after 2012 to nowadays. The slowdown trend of global demand during and after the crises affected the commodity and oil prices in international markets, leading inflation and inflation expectations to minimum rates.

Based on the consensus forecast results for various countries, Martínez (2008) [9] concludes: "…it became clear that there is no guarantee that expectations will remain anchored even under an inflation - targeting regime". The majority of cases (the darker cells in the last column, Table 1) demonstrate that inflation expectations for 2009 measured in October 2008, remained significantly above the target, due to inflation increases from commodity prices' shocks. A large number of emerging economies faced this situation.

Table 1. Inflation target and inflations expectations

Countries	Inflation target (%)	Inflation expectations (%) for 2009 (survey Oct. 2008)
Advances Economies		
Australia	2-3	3.2
Canada	2	2.1
New Zealand	1-3	3.3
Norway	2.5	2.8
Sweden	2(+/-1)	2.5
Switzerland	<2	1.4
UK	2	2.9
Emerging Economies		
Brazil	4.5(+/-2)	4.7
Chile	3(+/-1)	4.5
Colombia	3.5-4.5	4.9
Czech Rep.	3(+/-1)	3.1
Hungary	3(+/-1)	3.9
Korea	2.5-3.5	3.6
Peru	2(+/-1)	4.1
Philippines	5-6	7.1
Poland	2.5(+/-1)	3.5
South Africa	3-6	7.1
Turkey	4	8.5
	Inflation target (%)	Inflation expectations for 2009 & 2010* (surveys conducted over 2008 & 2009, respectively)
Albania*	3% (+/-1) or 2-4%	2.43% (financial agents) – for 2009
Albania*	3% (+/-1) or 2-4%	2.73% (financial agents) – for 2010

Source: Martínez (2008)– data from Consensus Forecast (Oct' 2008). Additional information by the author

*Note: *) Author's calculations derived from Financial Agents Survey of BoA - a professional survey, as well as based on [9].*

In the Albanian case (last 2 rows, Table 1), financial agents' inflation expectations formed during the period 2008-2009 for inflation rates over next 4 quarters of 2009 and 2010 experienced an upward trend, also. The latter has reflected the higher inflationary pressures mainly due to imported inflation at the moment of collecting assessments from financial agents. Even so, inflation expectations remained significantly lower than the target for 2009, but approaching BoA's target in 2010.

3. SURVEYS AND INFLATION EXPECTATIONS DATABASE

This study will analyse quantitative approaches only regarding accuracy and rationality features in the case of Albania, for perceived inflation, 1 year and 2 years ahead horizon. The quantitative data are obtained from questions in: a) business confidences surveys; b) consumer confidences surveys; - both carried out quarterly - c) financial agents' (FA) survey "Survey of Professional Forecasters", carried out monthly. The above-mention surveys are organised and published by the BoA[3].

The confidence surveys are conducted in collaboration with INSTAT (since May 2016, at monthly frequency based on the Project for Harmonisation of Confidence Surveys, supported by the European Commission). Quantitative questions on inflation expectations appear at monthly and quarterly questionnaires. In this study, the quarterly ones are considered only, because they are formulated at the same way for consumers and businesses of all sectors participating in the survey (industry, construction, services, and trade). This question at quarterly questionnaires for both groups, regarding annual inflation expectations is as follows [10]:

How do you think will the inflation change after a year? It will...
1. Increase 0-2%
2. Increase 2-4%
3. Increase above 4%
4. Decrease

After eliminating the outliers, the formulas of weighted/simple mean have been applied in order to calculate the expected inflation rates, according businesses and consumers. The inflation expectations series are updated till 2018:Q4, but starting at different moments of time: for businesses in 2009:Q1 and for consumers in 2005:Q1.

Besides the confidence surveys, BoA collects inflation expectations from FA, monthly. Then monthly data are transformed into quarterly ones applying a simple mean. In this survey, there are questions about annual inflation expectations at different time horizons and based on two different formulations of questions as following [10]:

1st: Based on your opinion how much do you expect to be:
1. Annual inflation rate currently (perception for the current month) ____% (perception)
2. Annual inflation rate 1 year after ____% (at a short term horizon)
3. Annual inflation rate 2 years after ____% (at a medium term horizon)
4. Annual inflation rate 3 years after[4] ____% (at a medium to long term horizon)

[3] Detailed information at the link: https://www.bankofalbania.org/Monetary_Policy/Surveys_11282/Inflation_expectations/
[4] 3-years horizon will not be discussed in this article because of too few observations.

2nd: How do you assess the probability for annual inflation rates?

Annual Inflation	After 1 year	After 2 years	After 3 years
< 0 % (-1 - 0%)			
0 – 1%			
1 – 2%			
2 – 3%			
3 – 4%			
> 4% (4 - 5%)			
Total (%)	100	100	100

Note: The total according columns must be 100%.

Both questions intend to calculate the expected inflation rates. In addition, the second one signals the probability distribution of inflation intervals, indicating if there is significant shift over or below the target value (3%)[5]. The time series data for FA's survey start in 2007:Q4 for perceived and 1 year ahead inflation expectations, and in 2010:Q1 for a 2 years horizon. Data for FAs are also updated till 2018:Q4.

In principle, the actual annual inflation rates at quarterly bases are compared to the time series generated from surveys. The difference between actual inflation (A_t) and expected inflation (EXPt-4/t-8) obtained from surveys at t-4/t-8 quarters before, is called forecast error (FE)[6].

4. ACCURACY AND RATIONALITY OF DIRECT INFLATION EXPECTATIONS: RESULTS AND ANALYSES

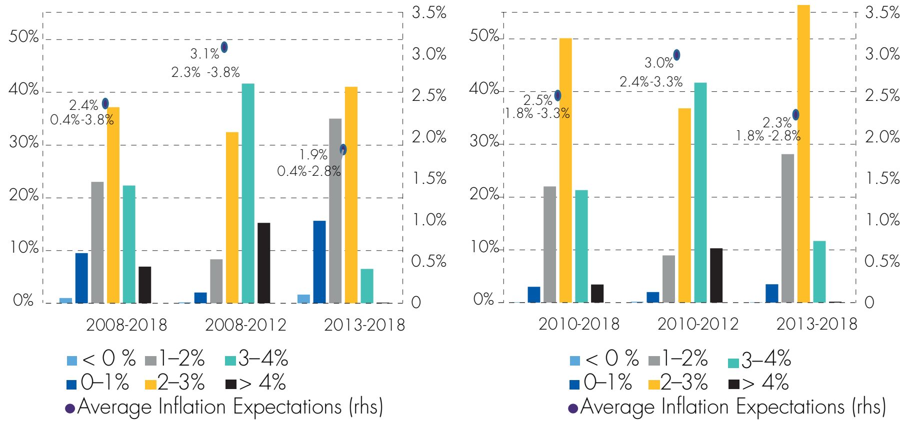
Numerous analyses can be carried out through surveys data. Figure 1presents the probability distribution according to inflation intervals in the 2nd alternative of the question for FAs over 1 year and 2 years horizons, respectively. We can conclude that the expectations for a 2 years horizon are better-anchored versus the target (3%) than those of one year horizon, over the whole sample and 2 sub-periods. But, we cannot conclude on: (i) which are the most accurate ones with respect to the actual inflation rates? ; (ii) are 2 years horizon expectations more rational than short-term ones? ; (iii) is there any substantial difference between the previous results on accuracy indicators and rationality tests and those that take into account even the additional information from the last three years (2015:Q2 – 2018:Q4)?

In order to answer to the above questions, the results of accuracy statistics and rationality tests are provided and compared.

[5] *Before January 2015, the target was defined as 3% with a tolerance band of +/-1 pp, or 3% (+/-1pp) = 2%-4%.*

[6] *Example: the published annual inflation rate of 2010:Q1 must be differenced with annual expected inflation collected in 2009:Q1, in the case of the one year (4 quarters) horizon (FE_4); in the case of the 2 years (8 quarters) horizon, the published annual inflation rate of 2011:Q1 must serves as a reference for (FE_8).*

Figure 1 Probability distribution of inflation expectation for 1 year horizon (lh) & 2 years horizon (rh); Average inflation expectations according different periods of time



Source: BoA, and author's calculations.

4.1 ACCURACY INDICATORS: MAIN RESULTS

The results regarding the accuracy indicators for the annual inflation expectations obtained from the quantitative approaches only, according Businesses, Consumers and FA, are presented in Table 2. Before discussing the main results, it is important to highlight that a larger sample size theoretically would influence them.

Table 2. Results of Accuracy Indicators for quantitative inflation expectations*

	Up to 2015:Q1 Previous study's period [2]			Up to 2018:Q4 New results		
Agents	ME	RMSE	TIC	ME	RMSE	TIC
1. Businesses - 4 quarters/1 Year	0.22	0.91	0.76	0.23	0.83	0.73
2. Consumers - 4 quarters/1Year	0.51	1.25	0.63	0.39	0.99	0.87
3. Financial Agents (FA)						
- 4 quarters/ 1 Year	-0.54	1.16	0.87	-0.51	1.02	0.85
- 8 quarters/ 2 Years	-1.26	1.37	0.96	-1.06	1.18	1.02

Source: Author's calculations.

*Note: * Mean Error (ME); Root Mean Square Error (RMSE); Theil Inequality Coefficient (TIC)[7].*

Businesses and consumers tend to underestimate the annual inflation rates for four quarters ahead. The last results show that the size of underestimation is decreasing for consumers, but remains almost the same for businesses. FAs have expected higher inflation rates after 4 and 8 quarters compared to the published inflation. The negative values of ME indicate that inflation has been over-estimated by FAs, in average terms. RMSE for all agents has decreased over time, signalling higher accuracy of inflation expectations for short and medium-term horizons. Businesses remain the most accurate forecasters over the short-term horizon.

Inflation expectations of consumers have improved till 2018:Q4, in terms of ME and RMSE.

[7] *Formulas and explanations in [2], pages 23-24.*

Inflation expectations of FAs demonstrate improvements in terms of ME, RMSE and TIC over the short-term horizon.

Over the medium term, the ME and RMSE indicators have been reduced, meanwhile the TIC is slightly deteriorated. The TCI results indicate that monitoring inflation expectation through the surveys approach is helpful as long as they continue to generate better results than a naïve one. However, the result should be taken with caution because of the small size effect generated by limited number of observations for medium-term inflation expectations series.

4.2. RATIONALITY TESTS: MAIN RESULTS

The accuracy analysis sheds light and helps to accomplish the rationality tests already addressed for the Albanian case in a previous paper [2]. As it is already mentioned, the tests' procedures will focus on the quantitative expectations only, according to various agents and time horizons. We would be able to identify possible changes in the behaviours of their rational and adaptive components over time. The empirical work on rationality tests is based on a rich literature [11] previously used for Albania up to 2015:Q1 [2].

Test results for the updated quantitative approach of inflation expectations up to 2018:Q4, are presented in the Table 3.

*Table 3. Rationality tests**

	RATIONALITY TESTS INTERPRETATIONS**		
Rationality Tests	Test 1	Test 2	Test 3
Explanations of tests	$\pi_t - \pi^e_{t-k} = \alpha + \varepsilon_t$ It must that H0: $\alpha = 0$ (t); p-value (*** high significance). *Insignificant = rationality accepted*	$\pi_t = \alpha + \beta\pi^e_{t-k} + \varepsilon_t$ It must that H0: $\alpha = 0$, $\beta = 1$ Wald-Test; for small p-values, rationality is not accepted, i.e. when high significance is reported (***) the rationality will be highly rejected. *For p-values greater than 10% the rationality will be accepted.*	$\pi_t - \pi^e_{t-k} = \alpha + \beta(\pi_{t-1} - \pi^e_{(t-k)-1}) + \varepsilon_t$ It must that H0: $\beta = 0$; if otherwise (i.e. significant), rationality will be rejected (t); p-values (high significance, when ***) *Insignificant = rationality is accepted*
Quantitative Inflation Expectations according: Agents and Horizons			
Businesses 4 quarters/1 Year Nr. Obs. = 37	(1.40); 0.17 (insignificant) Rationality – accepted	(p=0.38; 0.36) Rationality – accepted	Highly rejected (4.0); 0.00 (***)
Consumers 4 quarters/1Year Nr. Obs. = 52	Highly rejected (2.5); 0.005 (***)	Highly rejected (p=0.01; 0.007)	Highly rejected (5.4); 0.00 (***)
Financial Agents			
Perception Nr. Obs. = 44	(-1.12); 0.2 (insignificant) Rationality – accepted	(p=0.24; 0.2) Rationality – accepted	(1.31); 0.16 (insignificant) Rationality – accepted
4 quarters/1 Year Nr. Obs. = 34	Highly rejected (-3.3); 0.012 (***)	Highly rejected (p=0.004; 0.000)	Highly rejected (3.55); 0.00 (***)
8 quarters/2 Years Nr. Obs. = 21	Highly rejected (-5.2); 0.00 (***)	Highly rejected (p=0.000; 0.000)	Rationality no-rejected (1.8); 0.065 (*)

Source: Author's estimates;
Note :) The blue coloured areas show presence of rational component.*
*** Explanations on the rationality tests in [2], pages 30-33.*

Test results evidence no significant changes compared to those from the beginning of 2015. In general, they confirm the weak presence of the rational component. The tests reject the rationality hypothesis for inflation expectations over a one-year horizon in the case of FAs. The inflation expectations of FAs are rational for a very short-term horizon, when they assess the perceived inflation (3/3 tests confirm the rationality hypothesis). Businesses are more rational than other agents when they form their inflation expectations four quarters ahead: 2/3 tests significantly accept the presence of the rational component. For longer-time horizons (8 quarters), inflation expectations of FAs are more in line with the inflation target (3%). However, the rationality feature remains suspicious: one test only, does not fully reject the rationality hypothesis.

The results should be considered with caution, for three main reasons: *firstly*, the limitations generated from small samples in the testing process; *secondly*, economic and financial literacy remain at a low level for assessing the inflation and economic outlook, despite intensified efforts for enhancing the financial education for general public during recent years; *thirdly*, the time this data belongs to. Focussing on the third reason, it is important to emphasise that a lower degree or lack of rationality in inflation expectations of agents in emerging countries is not a surprise. In addition, the rationality declines in times of crisis and high uncertainties, because it is more difficult for market agents to include and select the appropriate information when they form their expectations. Studies and empirical evidence show that even in advanced economies, inflation expectations, particularly those for short-time horizons, have resulted non-rational (Sweden, Germany, Norway, England, etc.). Meanwhile, the medium-term ones remain more in line with the target due to the high confidence of the public in the central banks and the monetary policy implementation. A similar behaviour is identified in the case of inflation expectations in Albania.

5. CONCLUSIONS

Inflation expectations represent an important factor, especially for economies that have adopted the IT regime. Furthermore, inflation expectations are assessed as a good indicator for the credibility of the central bank, reliability of inflation target and as an appropriate tool for maintaining prices stability. Inflation expectations represent also an essential ingredient in modelling and medium-term forecasting inflation. Given the above-mentioned reasons, inflation expectations represent a monetary policy transmission mechanism channel, to be continuously monitored and improved, even in the Albanian case.

As an unobservable variable, inflation expectations' data have been obtained using indirect methods. The most widely used is the survey one. This method has been applied by BoA since 2003, and firstly was focused on qualitative assessments of inflation expectations. Since 2006, BoA has gradually developed the quantitative direct measurements of inflation expectations, according different agents and horizons. This article tries to shed light on the accuracy and the nature of quantitative inflation expectations in Albania until the end of 2018.

Different accuracy indicators have been calculated and various rationality tests have been run, covering a longer period of time than in the previous studies. The results suggest that the accuracy of inflation expectations has increased over time. The accuracy results support the information obtained through inflation expectations for the future short to medium-term inflationary pressures.

Tests' results on the rationality did not signal significant changes compared to the previous estimates, which covered data until the beginning of 2015. In general, they confirm the weak presence of the rational component and the dominance of the adaptive one when the different agents form their expectations. The presence of rationality is suspicious for the medium-term inflation expectations. But, at the same time the inflation expectation rates are higher than the short-term ones. The medium-term inflation expectations are more in line with the BoA's inflation target indicating a higher confidence in the monetary policy decision making.

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THE IMPACT OF EXTERNAL MACRO FACTORS ON NPL OF THE BANKING SYSTEM

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1. INTRODUCTION

In economies with bank-dominated financial systems, periods of economic distress are associated with deterioration of borrowers' balance sheet and increase in non-performing loan ratio. The recent global financial crisis only reinforced such premise. Non-performing loan (NPL) ratio has increased across bank-based financial systems like EU member countries and peripheral economies.

The ratio of non-performing loans to outstanding loans is a common indicator of ex-post credit risk. Given that markets build on credit risk measures to form expectations, a credit risk indicator plays significant impact in the economy. An upward trend of the NPL ratio has at least two direct implications for the capacity of the banking system to finance the economy and for the macroeconomic equilibrium. On one side, higher NPL ratio bites on the capital adequacy ratio of lending banks leading to a diminished capacity to lend. On the other, the increasing NPL ratio can be an indicator of already highly indebted borrowers keeping the lenders at bay. The expectations of continuing weak aggregate demand and already highly indebted pool of borrowers may deteriorate the expected ability to pay of the average borrower. Therefore, even banks with sufficient capacity to lend may still refrain from lending.

A final point is that a bank not affected by capital adequacy ratio, may still limit the supply of loans due to the fear of buying existing loans of other banks that may become non-performing in the near future. When an obligation is not paid within a time frame of 90 days, that financial obligation is classified as non-performing[2]. Within this time frame a borrower already unable to pay is still a good borrower. The time lag provides an opportunity for the borrowing firm with sufficient collateral to engage in borrowing contracts in order to pay an existing loan or attempt a riskier strategy to save defaulting on the existing loan. Undoubtedly, it can easily be the case that both, low lender capital adequacy ratio and risk-shifting behaviour of over-indebted borrowers that stand behind low bank financing in an economy.

High NPL ratios are closely related to costly financial crises and are a critical indicator monitored by investors, supervising authorities and markets. The high

[1] *Many thanks go to Mr. Altin Tanku, Head of Research Department, for his feedback and suggestions and to Ms. Diana Shtylla and Ms. Adela Bode from the Financial Stability Department for their helpful cooperation in obtaining the write-offs to construct the NPL ratios. The errors and views expressed are those of the author and do not necessarily reflect those of the Bank of Albania.*

[2] *The criteria may change in different economies.*

costs are related to the inter-linkages between the deterioration of the asset quality of financial intermediaries and the business cycle in the economy. The links allow for the propagation of small financial or macroeconomic shocks to exacerbate the boom-bust cycles of the economy (Bernanke, Gertler, & Gilchrist, 1999). While in a market-based economy, like US, bank loans are not the dominant form of firm financing, the feedback mechanism between firm's ability to pay its debts and the economy is similar. In both environments, bank-based or market-based economies, financial crises have high economic costs (Haugh, Ollivaud, & Turner, 2009).

The depth of the recent crisis raised the interest in the modelling of macroeconomic factors that matter for the dynamic behaviour of the non-performing loans. The literature on the approaches used to capture the dynamics of credit risk is rich, both at aggregate and individual bank level. Chan-Lau (2006) make a very useful review of the broader specter of approaches used to analyze the probability of default. He lists examples of models used by central banks or private financial institutions using various approaches. I focus here only on macroeconomic models which shed light on the interrelationship between credit risk and macroeconomic factors.

To a large extent the literature on the macroeconomy-based models that investigate determinants of NPL ratio has expanded in two directions. Early research promoted studies that evaluate the impact of the aggregate macroeconomic indicators in determining the NPL ratio at aggregate level. These studies attempt to capture the elasticity and response of NPL ratio subject to macroeconomic shocks.

Typical macroeconomic indicators like GDP, unemployment, interest rates, exchange rates, inflation and alternative types of asset prices are common factors in explaining NPLs. I refer to Rinaldi & Sanchis-Arellano (2006) and Makri et al. (2014) relevant to Euro area, to Nkusu (2011) for a study with 26 advanced economies from 1998 to 2009 and Castro (2013) for the impact of macroeconomic factors on NPL ratio in southern Euro area economies. Recent studies on emerging economies are Radivojevic & Jovovic (2017) for the period 2000-2011, or De Bock & Demyanets (2012) for a sample of data in 25 emerging countries, 1996-2010. With a more regional focus are studies investigating dynamics of NPL in the Eastern European economies. A World Bank (2008) report at the peak of the crisis suggests strong adverse effects from the global financial crisis in terms of the bank asset quality in these economies (for a non-exhaustive list see Jakubík & Reininger (2014), Klein (2013), Beckmann et al. (2012)). Jakubík & Reininger (2014) investigate macro determinants of economy-wide NPLs in a group of CESEE economies and find that GDP growth is the main driver of NPLs in those economies. Klein (2013) evaluates the determinants of non-performing loans in CESEE during 1998–2011.

Due to the vast literature and the variety of approaches employed, similar to Jakubík & Reininger (2014), this study relies on a macro-approach that uses macro variables as determinants of aggregate NPL ratio in the banking system. A more in-depth review of literature employing these latter approaches to explain other indicators of bank asset quality (LLPs) or bank-specific and sector-specific asset quality indicators is provided by Foglia (2009) or Čihák (2007) and more recently by Dent et al. (2016). Bank-specific factors that capture bad management, cost efficiency, poor loan underwriting, screening and monitoring are critical for the NPL ratio of individual banks[3]. A combination of macro and bank-specific factors is a common practice aiming at better forecasting models at bank level following the work of Berger & DeYoung (1997).

There are few earlier studies of Bank of Albania that have analyzed the dynamics of NPL in Albania. Shijaku & Ceca (2009) take a macro perspective to examine the elasticity of the aggregate (transformed) NPL ratio to key macro variables like GDP, inflation rate, domestic interest rates, exchange rate and foreign interest rate in a stationary VAR with quarterly data for a relatively short period of time, 2001-2007. In Shijaku & Ceca (2011) the authors take a mixed micro-macro perspective to analyse individual banks' NPLs using macro indicators. They examine NPLs of a panel of banks for the period 2005-2009 at quarterly frequency. In addition, there are several other studies at the Bank of Albania that evaluate the impact of macroeconomic factors on the quality of bank assets in a broader framework (see Dushku and Kota (2013), Kalluci and Kodra (2010), Dushku and Vika (2011)). Unlike the earlier studies, the focus here is on external macroeconomic factors, particularly on foreign (international) business cycles. In the next section I describe the data used to this end.

2. DATA AND THE VAR METHODOLOGY

I define the NPL ratio for each subgroup of non-performing loan (NPL) according to (i) the currency in which the loan is denominated and (ii) the type of borrower. On this basis, the NPL ratio in a subcategory 'j' is the ratio of non-performing loans to the stock of loans within that particular subcategory 'j'.

$$nplR_t^j = \frac{npl_t^j}{Outstanding\_loans_t^j} \qquad \forall j = indLek,\ coLek,\ indFx,\ coFx,\ total \qquad (1)$$

Since the NPL ratio takes values between 0 and 1 it is a common practice to perform logit transformation of such that:

$$LnplR_t^j = \ln\left({}^{1}\!/_{nplR_t^j} - 1\right) \qquad (2)$$

For the sake of later reference, note that $\{LnplR_t^j\}$ is inversely related to $\{nplR_t^j\}$, such that an increase in the latter shows up as a decline in the former. The 'j' superscript is defined by (i) *the currency of denomination, domestic or foreign, and (ii) the type of borrower*, individual household or (non)corporate sector. Based on these two criteria there are four NPL ratios, which following the logit transformation are defined as[4]:

[3] See Williams (2004) EU banks data 1990-1998, Podpiera & Weill (2008) with Czech banks NPLs, Jiménez & Saurina (2006), Louzis et al. (2010) with Greek banks data, Dash & Gaurav (2010), Beckmann et al. (2012).

[4] This format of NPL ratio takes into account the write-offs that have taken place since 2015 as reported in the periodic Financial Stability Reports of Bank of Albania. I include the write-offs as they are not a reduction of NPL due to macroeconomic factors, but rather an ad-hoc procedure.

(1) $LnplR_t^{indLek}$ NPL ratio of individual households in domestic currency,

(2) $LnplR_t^{coLek}$ NPL ratio of corporate and non-corporate firms in domestic currency,

(3) $LnplR_t^{indFx}$ NPL ratio of individual households in foreign currency,

(4) $LnplR_t^{coFx}$ NPL ratio of corporate and non-corporate firms in foreign currency,

Having defined the NPL indicator, the vector of variables is now:

$$Y_t^j = \{y_t^*, R_t, E_t, LnplR_t^j\} \qquad \forall j = indLek, coLek, indFx, coFx \qquad (3)$$

where y_t stands for a measure of international business cycle, R_t stands for a measure of opportunity cost of monetary funds, E_t is nominal exchange rate and $LnplR_t^j$ is the logit transformed NPL ratio in category 'j' as defined in equation (2).

From a review of literature, different measures can be obtained for each of the three macroeconomic variables $\{y_t^*, R_t, E_t\}$. While the arguments for the choice of variables can take quite some space, for practical reasons I have chosen the macroeconomic variables as shown in Chart 1.

Chart 1. Definition of macroeconomic variabiles in the VAR equations.

	Description
y_t^*	Log of the industrial production of Euro area (monthly change).
R_t	The interest rate of Lek deposits, as a proxy of the opportunity cost of funds, in cases when ratios of NPL to credit stock in domestic currency, $\{LnplR_t^{indLek}\}$ and $\{LnplR_t^{coLek}\}$, are specified in the vector Y_t^J (monthly change).
R_t^*	The spread between 12-month Euribor rate and interest rate of Lek deposits, a proxy of the opportunity cost of funds, when ratios of NPL to credit stock in foreign currency, $\{LnplR_t^{indFx}\}$ and $\{LnplR_t^{coFx}\}$ are specified in the vector Y_t^J (monthly change).
E_t	Log of nominal effective exchange rate (monthly change).

I have chosen the industrial production of Euro area as an alternative indicator of foreign business cycles. Based on a study at the Bank of Albania, the synchronization of business cycles in Albania and Euro area is weak (Yzeiraj, 2012). It lends support to the view that Euro area output does not overlap with business cycles that arise due to domestic factors. In particular, the series used - euro area industrial production - captures the turning points of the recent global financial crisis and is available on monthly basis. I employ Vector Autoregressive (VAR) Models to analyze the response of NPL ratio following macroeconomic shocks. In a compact form the VAR equation is:

$$Y_t = X_t B + u_t \qquad (4)$$

where $X_t = \{Y_{t-1}, \dots Y_{t-p}\}$ is a $T(x)p$ matrix of independent variables and deterministic terms, B is a $n(x)p$ matrix of coefficients and $u_t \sim N(0, \Sigma)$. The moving average representation of the VAR allows to identify the impulse response functions (IRF) of each variables subject to exogenous shocks.

$$Y_t = \sum_{i=0}^{\infty} \Theta_i \, u_{t-i} = \sum_{i=0}^{\infty} \Xi_i \varepsilon_{t-i} \qquad \Xi_i = \Theta_i A_0^{-1} \qquad (5)$$

The *(j,k)* element of Ξ_i in (5) is the impact of the k^{th} structural shock on j^{th} variable at horizon i.

2.1 MODEL SPECIFICATION

I set up VAR equations for each subgroup of non-performing loan (NPL) ratio for each subcategory 'j'. The vector of variables Y_t^j shown in equation (3) can now be written as[5]:

$$Y_t^{indFx} = \{y_t^*, R_t^*, E_t, LnplR_t^{indFx}\} \qquad (3.1)$$

$$Y_t^{coFx} = \{y_t^*, R_t^*, E_t, LnplR_t^{coFx}\} \qquad (3.2)$$

$$Y_t^{indLek} = \{y_t^*, R_t, E_t, LnplR_t^{indLek}\} \qquad (3.3)$$

$$Y_t^{coLek} = \{y_t^*, R_t, E_t, LnplR_t^{coLek}\} \qquad (3.4)$$

The expected impulse response functions (IRFs), from a theoretical perspective and consistent with earlier studies in the introduction, are shown in Chart 2. Expected IRFs should show that, an increase in E_t (depreciation) and in R_t^* (higher cost of funds) should lower the $LnplR_t^{Fx}$ for both types of borrowers (that is raise the NPL ratio of the loan portfolio in foreign currency). Similarly a positive shock on the cost of funds in domestic currency (increase in R_t) should lower $LnplR_t^{Lek}$ for both borrowers (raise the NPL ratio of the loan portfolio in domestic currency). Finally, an upturn in international business cycles should lead to higher $LnplR_t^j$ variable (lower the NPL ratio) of any borrower in both currencies.

Chart 2. Expected signs of based on VAR impulse responses upon a shock in $\{y_t^*, R_t, E_t\}$.

(+) shock in	IR of $\{LnplR_t^{Lek}\}$	IR of $\{LnplR_t^{Fx}\}$	NPL ratio
(+) y_t^*	(+)	(+)	lower
(+) R_t	(-)	...	higher
(+) R_t^*	...	(-)	higher
(+) E_t	(-)	(-)	higher

(*) Note: From equation (2), the inverse relationship between the "$nplR_t^j$" and the logit transformed variable "$LnplR_t^j$" assumes that an increase in the latter, "$LnplR_t^j$", is a decline in the NPL ratio, or an improvement of asset quality of banks.

[5] *Alternative measures of the opportunity cost of monetary funds yield similar results, though not as good diagnostics. For NPL in domestic currency the variable R_t is replaced by the spread between 12 month TB yield and the deposit rates in Lek, as a proxy. The results for those alternative measures are not included in this article. For NPL in foreign currency the variable R_t^* is replaced by the spread between 12 month Euribor and one-month Euribor rate, as a proxy of the opportunity cost of funds. The results, not reported in this article, are very similar to the ones reported here.*

3. RESULTS

In appendix I show the impulse responses from the different VARs with the set of variables as defined in equations (3.1) to (3.4).

- NPL ratios of loan portfolios in foreign currency.

Impulse responses in Figure 1 and Figure 2 based on VAR estimations with the vectors Y_t^{indFx} and Y_t^{coFx}, from equations (3.1) and (3.2), indicate that

$LnplR_t^{infFx}$ and $LnplR_t^{coFx}$ ratios <u>decline</u> (<u>higher</u> NPL ratio) following a positive shock in nominal effective exchange rate (depreciation) for both type of borrowers in foreign currency, individual households and firms (the graphs in the bottom row of each figure),
$LnplR_t^{infFx}$ and $LnplR_t^{coFx}$ ratios show weak or no significant response to positive shocks in opportunity cost of funds (higher R_t^*), and
$LnplR_t^{infFx}$ and $LnplR_t^{coFx}$ ratios go up – indicating a decline of NPL - following a positive aggregate demand shock (y_t^*), or an upturn in foreign economic activity.

<< Figure 1 here >>

<< Figure 2 here >>

These IR functions are consistent with expected sign reactions of (transformed) NPL ratios in Chart 2. Note that the IR functions in the first row of each figure indicate a zero response of (y_t^*) following shocks in any of the variables, except own shocks. This results is due to the restrictions I have set in the VAR to impose exogeneity of aggregate demand variable (y_t^*) in the short and the long run. This restriction is motivated by the fact that Euro are industrial production is an exogenous source of business cycles in the domestic economy. It is therefore not affected by other domestic variables contemporaneously or at any lag[6].

Forecast error variance decompositions indicate that exchange rate explains around 9-10 % of NPL fluctuations over the 12-month horizon for both, the individual and the corporate loan portfolio, in foreign currency (Chart 3 and Chart 4). Foreign business cycle fluctuations explain a much smaller, or insignificant, fraction of NPL fluctuations in foreign currency. Around 80-90% of these fluctuations is explained by own exogenous shocks in NPL.

- NPL ratios of loan portfolios in domestic currency.

Impulse response for VARs with NPL ratios $LnplR_t^{indLek}$ and $LnplR_t^{coLek}$ in Figure 3 and Figure 4 of appendix indicate little response of NPL ratio to either macroeconomic variables. The low response of NPL ratios in domestic currency to macroeconomic variables is well captured by the low percentage of NPL ratio fluctuations explained by macro shocks. More than 90% of these

[6] *Getting rid of the restrictions does not change the conclusions drawn from IRFs and variance decompositions.*

fluctuations are explained by exogenous shocks in NPL ratios (Chart 5 and Chart 6 in appendix). Neither exchange rate nor opportunity cost explain a significant share of these fluctuations, while foreign business cycles capture up to 6 % of the total fluctuations observed in NPL ratio in domestic currency.

<< Figure 3 here >>

<< Figure 4 here >>

The results obtained from these basic tests are similar to those found on earlier works on credit risk like Shijaku & Ceca (2009), (2011). In Shijaku & Ceca (2009) the authors report that exchange rate and foreign interest rate have significant effect on credit risk measured by NPL ratio, while GDP growth shocks has a negligible effect. In Shijaku & Ceca (2011) and Dushku and Vika (2011), the authors confirm earlier results regarding the impact of exchange rate and interest rate. The possibility to investigate NPLs in domestic and foreign currency is explored in In Shijaku & Ceca (2011), but do not report evidence of a satisfactory economic and statistical model for the portfolio in foreign currency separately. In Kalluci and Kodra (2010) the authors find that nominal exchange rate, real effective *exchange rate* REER, 12 month yield and 3 month yield are all significant in explaining NPL. GDP is significant only in explaining the NPL of corporate firms[7]. Similarly Dushku and Kota (2013) find exchange rate and interest rate significant in explaining total NPL in single equation models. The high explanatory power of exchange rate is common among most studies mentioned.

4. CONCLUSIONS

The results from the econometric experiment are consistent with the theoretical predictions and with the findings from earlier studies in Albania. Yet the results are not very encouraging as a large share of NPL fluctuations is explained by exogenous own shocks.

The low power of macroeconomic factors to explain the NPL fluctuations could be due to different causes. I am listing the most relevant few arguments why impact of macro factors on NPL ratios turns low in the current framework.

- A key reason could be of a statistical nature. The NPL ratios are non-stationary variables. When using the monthly changes of the series we lose quite some information. A possible solution is the use vector error correction models.
- Absence of a reliable monthly series of business cycles or aggregate demand for the domestic economy may be one reason for the low

[7] *In Kalluci and Kodra (2010) the authors include a variety of indicators to explain the NPL of individual and corporate firm loans portfolios, like rental prices, export prices, M3, house prices and real effective exchange rate (REER) in addition to standard indicators GDP, opportunity cost and exchange rate. They find that exchange rate, REER, 12 month yield, 3 month yield are all significant in explaining NPL. GDP is significant only in explaining the NPL of corporate firms.*

response of NPL ratios to aggregate demand. Using the quarterly GDP series interpolated into a monthly series did not serve the purpose in this set up.

- The impact of bank-specific factors may be critical in driving the aggregate NPL ratio for the whole banking sector. The stock of private sector loans was very low at the beginning of the sample period and the market for loans has been dominated by a few banks initially. In the second half of the sample considered here a different set of banks are the dominant ones leading the lending market. The use of panel data may capture these bank-specific factors.

There could be many other factors which weigh at different degrees in different period of time. A more elaborate investigation of NPL ratios would require taking into account the above three factors.

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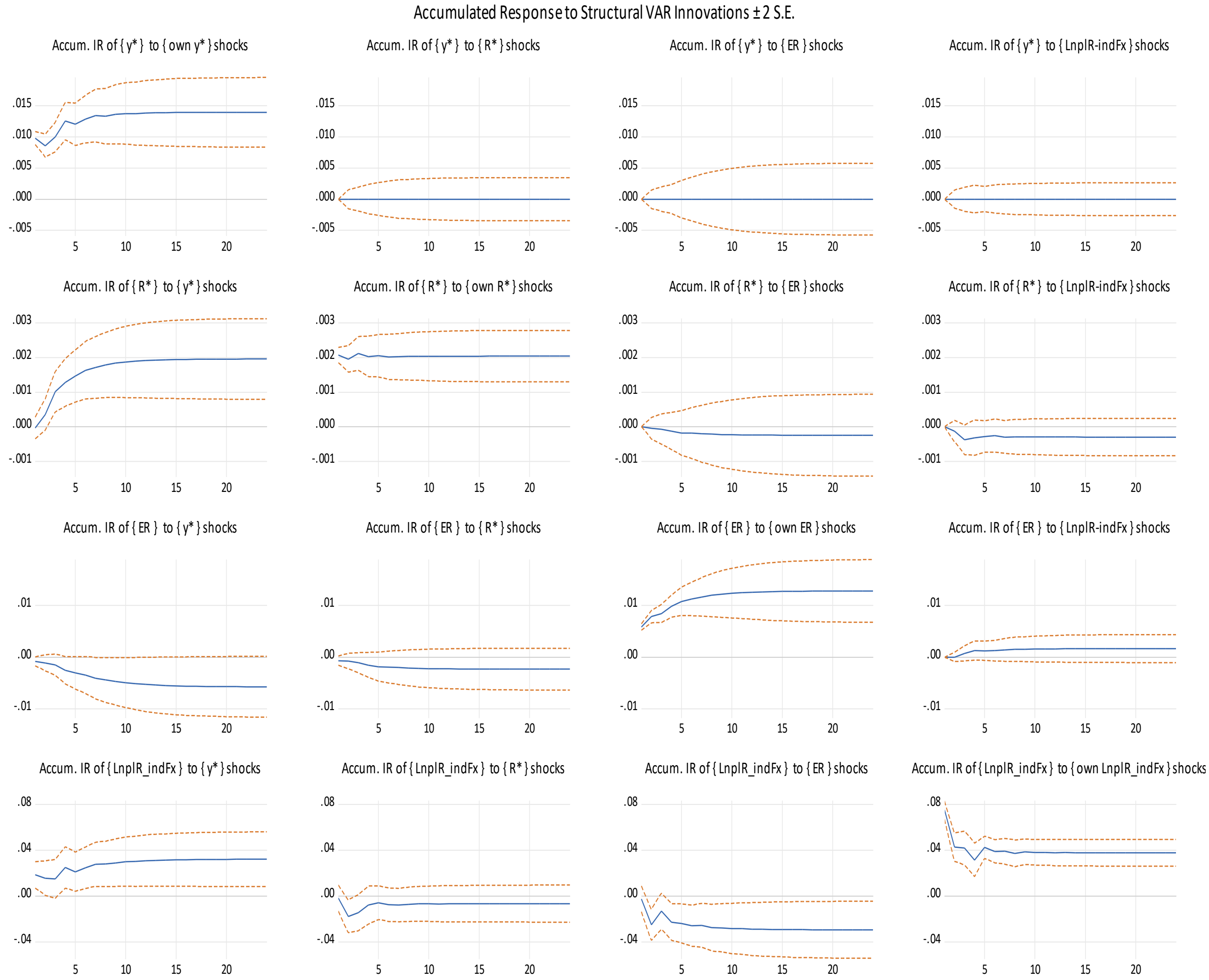
APPENDIX

Figure 1. IRFs from VAR in equation (3.1) with the vector of variables Y_t^{indFx}.

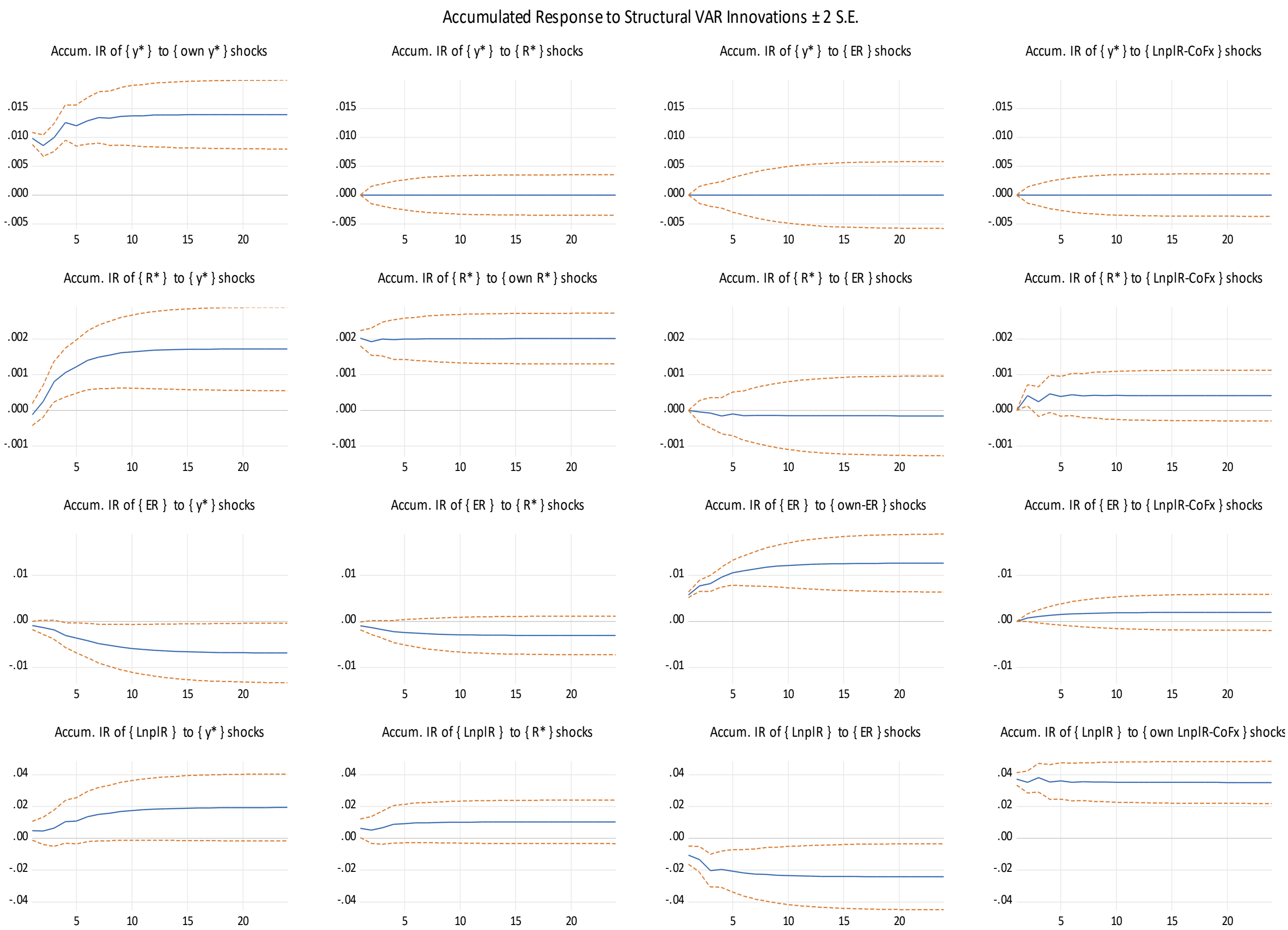


(*) Note: From equation (2), the inverse relationship between the "$nplR_t^j$" and the logit transformed variable "$LnplR_t^j$" assumes that an increase in the latter, "$LnplR_t^j$", is a decline in the former variable, NPL ratio, or an improvement of asset quality of banking system.

Chart 3. Forecast Error Variance Decomposition of $\{LnplR_t^{indFx}\}$

Period	S.E.	y^* shock	R^* shock	ER shock	$LnplR^{indFx}$ (own) shock
1	0.07764	6	0	0.1	94
4	0.09135	5	4	8.9	82
8	0.09238	6	4	8.8	82
12	0.09241	6	4	8.8	82

Figure 2. IRFs from VAR in equation (3.2) with the vector of variables Y_t^{coFx}.

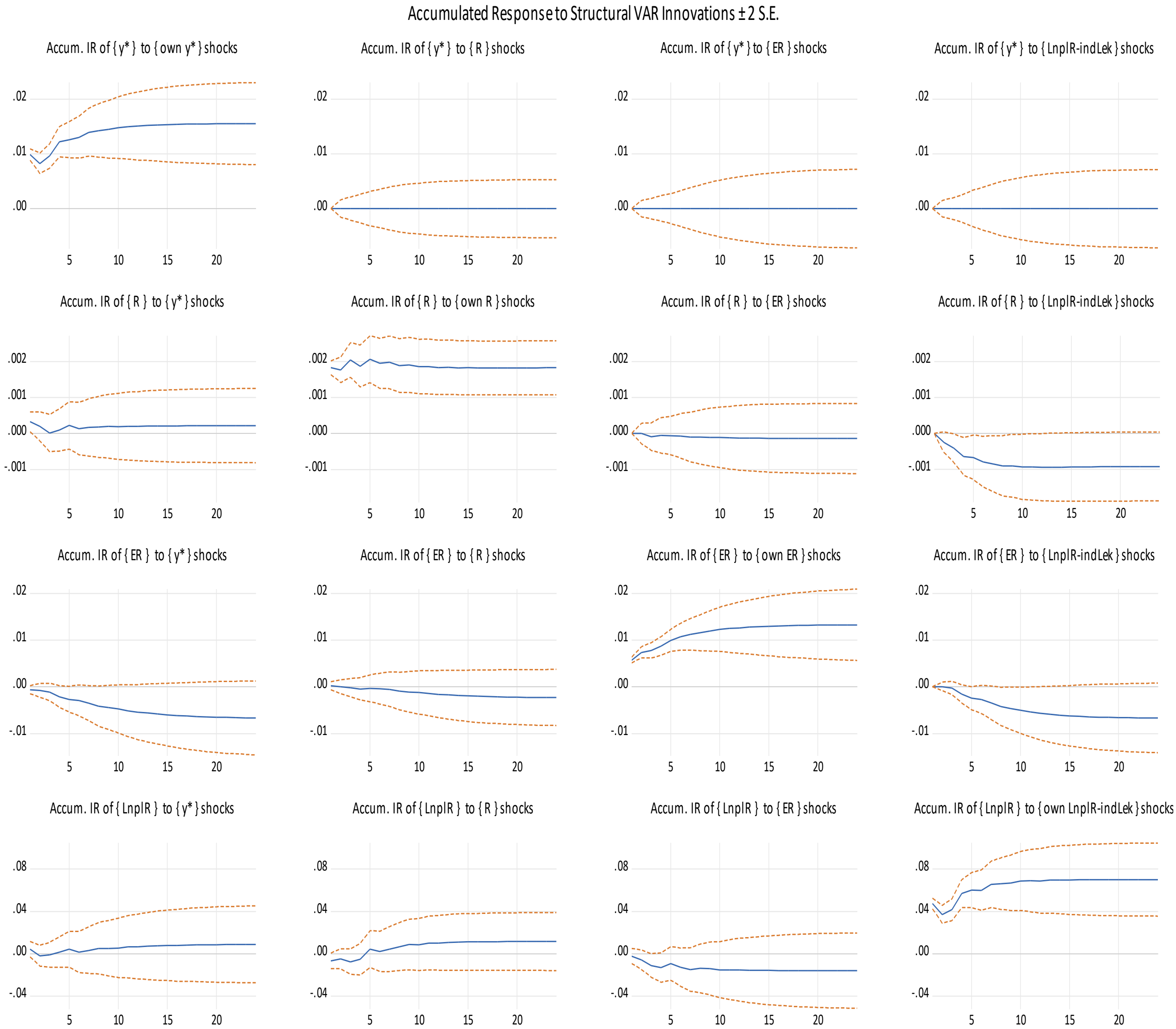


(*) Note: From equation (2), the inverse relationship between the "$nplR_t^j$" and the logit transformed variable "$LnplR_t^j$" assumes that an increase in the latter, "$LnplR_t^j$", is a decline in the former variable, NPL ratio, or an improvement of asset quality of banking system.

Chart 4. Forecast Error Variance Decomposition of $\{LnplR_t^{coFx}\}$.

Period	S.E.	y^* shock	R^* shock	ER shock	$LnplR^{CoFx}$ (own) shock
1	0.03958	1	3	7.1	89
4	0.04086	3	3	10.1	85
8	0.04105	3	3	10.2	84
12	0.04108	3	3	10.2	84

Figure 3. IRFs from VAR in equation (3.1) with the vector of variables Y_t^{indLek}.

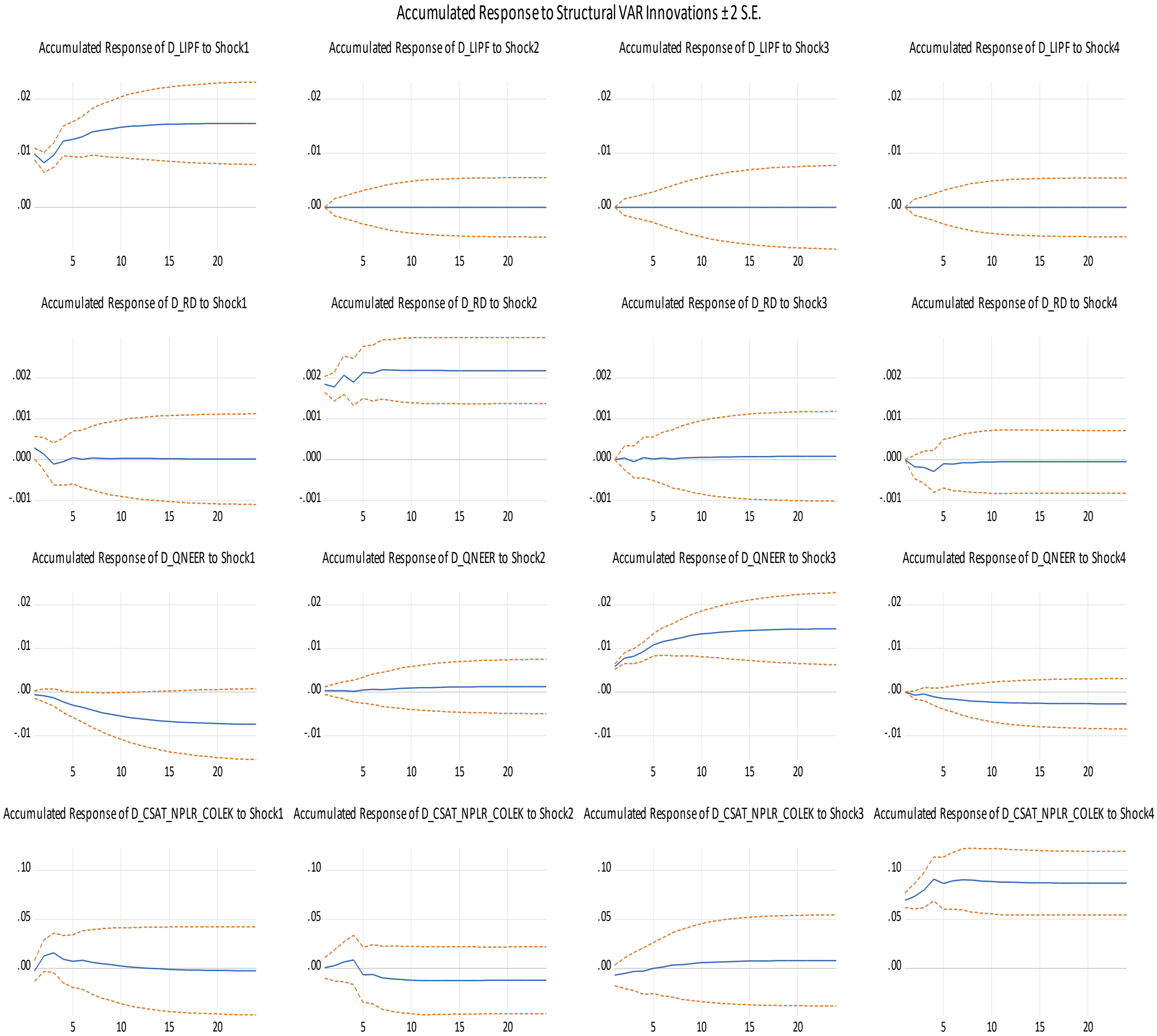


(*) Note: From equation (2), the inverse relationship between the "$nplR_t^j$" and the logit transformed variable "$LnplR_t^j$" assumes that an increase in the latter, "$LnplR_t^j$", is a decline in the former variable, NPL ratio, or an improvement of asset quality of banking system.

Chart 5. Forecast Error Variance Decomposition of $\{LnplR_t^{indLek}\}$

Period	S.E.	y^* shock	R^* shock	ER shock	$LnplR^{indLek}$ (own) shock
1	0.04814	1	2	0	97
4	0.05272	2	2	2	94
8	0.05463	3	6	3	89
12	0.05474	3	6	3	88

Figure 4. IRFs from VAR in equation (3.2) with the vector of variables Y_t^{coLek}.



(*) Note: From equation (2), the inverse relationship between the "$nplR_t^j$" and the logit transformed variable "$LnplR_t^j$" assumes that an increase in the latter, "$LnplR_t^j$", is a decline in the former variable, NPL ratio, or an improvement of asset quality of banking system.

Chart 6. Forecast Error Variance Decomposition of $\{LnplR_t^{coLek}\}$

Period	S.E.	y^* shock	R^* shock	ER shock	$LnplR^{CoLek}$ (own) shock
1	0.06984	0	0	1	99
4	0.07337	6	0	1	93
8	0.07533	5	5	1	89
12	0.07539	6	5	1	89