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The Time Series Model For Non – Performing Loans

The Case Of Albania

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***Abstract*—The high level of troubled loans is one of the main problems of the banking sector in Albania. To cover potential losses by Non – performing loans banks must calculate and own a certain level of regulatory capital.**

Credit risk is the biggest risk to which the banking system is exposed, because credit takes the main weight in the active banking system. The assessment and management of the Non – performing loans plays an important role in the economic and financial stability of the country, the region and wider. This analysis focuses on troubled loans and analyzes their performance in years. This work sharply shapes troubled credits for the case of Albania for 2002-2020.

Keywords—NPL, ARIMA, forecast.

INTRODUCTION

Troubled loans are among the basic terms used in analysing banks' operations and bank risks. These are loans, for which, essentially, payment on the part of customers is of certain time delay. Usually, the regulator determines exactly the time of delay through which a loan is included in the troubled credit group. More often than not, it's a delay of 90 days or more.

In accordance with the regulator's rules and requirements, each bank must single out provisions for these troubled loans, or simply reserves to cover losses from the possible credit payment. Usually, as the delay increases, the required provisions increase. These provisions are a cost to the bank and affect its profit, and ultimately also on its capital, or the estimated need for additional capital.

In Albania, there are currently 12 second-level banks, licensed by the Bank of Albania and operating throughout Albania. By the end of 1995, six second-rate banks had been licensed from the central bank, two of which had entirely state capital.

The banking system has then grown rapidly, bringing the number of banks in 2008 to 16, where only 3 of them were entirely with local capital. Already in Albania, 12 banks, 10 foreign-capital banks and 2 locals operate. The Bank of Albania is the only authority for licensing banks to exercise banking activities in Albania.

LITERATURE REVIEW

In their work, (Celiku. E & Luci. E, 2003) they have tried to analyze the link that exists between the macroeconomic situation and several other factors and troubled loans in transition countries and in the case of Albania. From this analysis it turns out that the effect of the macroeconomic situation plays an important role in Albania for the level of troubled loans. While the experience of transition countries suggests that improving the law is another important factor in reducing problem loans.

A study with the aim of assessing macroeconomic factors on the probability of not paying a loan to Albania was done by (|Shijaku and Ceca 2010). Using the Wilson framework (1997), they find that the troubled loan rate, approaching the possibility of default, is determined by the real growth rate, the foreign currency interest rate and the exchange rate against the euro.

The reason the troubled loan rate is influenced by "foreign currency" variables lies in the heavy weight that occupies troubled foreign currency loans in the Albanian banking system. They expand the model built (2010) to analyze various factors that may affect different foreign currency loan portfolios. The adoption of the new credit risk management regulation by the Bank of Albania increases the opportune cost for a bank which invests in foreign currency loans, so a gradual shift towards the loan portfolio is expected. In terms of transmission channels, this can reinforce the central bank's policy shocks and, on the other hand, affect credit quality significantly.

For 2003-2013, however, it shows that problems caused by the economic crisis, lower income coming from immigrants and the fact that banks were not careful in providing loans in the early years of the transition have caused a steady increase in troubled loans. In this situation, micro and macroeconomic analysis is carried out the environmental factors where banks operate. The analysis concludes that by Johansen co-integration results, troubled loans and five other variables: real GDP, unemployment,

inflation, credit interest rate, remittances are integrated with each other, but in the long term this co-integration is weak.

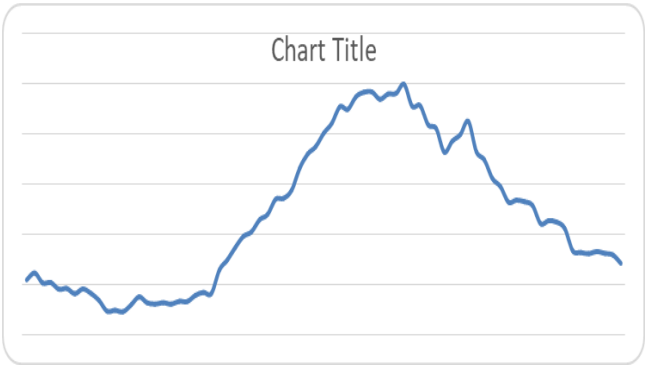
In their study they analyzed the annual NPL for 2003-2016. They say that after 2008, as a result of the global financial crisis, the Albanian banking system experienced an increase in high levels of problem loans, reaching the highest level in 2013 by 23.5%. Compared to other candidate countries and potential EU candidates, during the period 2013-2015 Albania had the highest level of NPLs. Meanwhile, together with Kosovo, both are rated at the lowest level of financial mediation in this group.

Using bank loan data for the period 2008-2014 we find evidence that the loan given to the private sector has not responded proportionally to the specific performance changes of economic sectors, as well as the risk of sector credit. In some cases, assessments are even in contrast to the theoretical expectations and rational behavior of banks. They find evidence that banks have continued to finance economic sectors with poor macroeconomic performance and high credit risk, as well as failing to support positive and efficient contribution sectors. The results also show that banks' capital level plays an important role in credit distribution for some sectors. It is generally noted that banks' behaviour is not uniform to sectors of the economy and depends on the bank's characteristics and model.

TROUBLED CREDIT TREND IN ALBANIA

Albania recorded the highest level of troubled loans in its banking sector from 17 countries in Central, Eastern and Southeast Europe during the 12 months to September 2018, according to a report made public by the European Bank's Coordination Initiative in Vienna. Only two countries are above the 10% threshold in CESEE (Albania at 12.9% and Croatia with 10.2%). Serbia recorded the biggest improvement in the NPL report at the CESEE. The level of NPLs in Serbia decreased by 5.8 percentage points year-on-year. The figures show a steady downward trend in NPL reports in Albania every month after March 2014, a trend that appears in the following graph

Fig 1. Monthly Trend of Troubled Loans



Source: Bank of Albania (2021) Author calculation

The situation regarding troubled loans has continued to improve even in the CESEE since the last report, with NPL volumes reaching the lowest level in eight years (37.9 billion euros on September 30, 2018 for the region), and the NPL report reached 4.4%. Further sales of NPLs by banking investors have affected the decline in the volume of NPLs, while this activity reached 3.1 billion euros in 2018. Since the launch of the NPL Initiative in 2014, significant oversight arrangements and tax reforms have been implemented to address NPLs.

Creating the conditions for a healthy NPL market (although not yet perfect) contributed to the ability of banks to devalue a large portion of stocks. However, there is still a lot of work. Progress has been made in recent years to reduce the level of NPLs, but more needs to be done to mitigate changes within the banks themselves to prevent and sustainably manage NPLs in the long run. The level of non-performing loans at the end of December reached 8.11%, marking a slight decrease of 0.09 percentage points compared to the end of 2019. This is the lowest level in 12 years, since 2008, according to statistics published by the Bank of Albania.

Although 2020 was difficult for the banking system, as a result of the pandemic, this is not reflected in the indicator of non-performing loans, due to the measures of the Bank of Albania, which enabled the postponement of loan installments by almost six months (March-August), while space was created for banks to restructure loans without penalties and without deteriorating the status of borrowers by the end of 2020. Such a framework has favored the stability of the non-performing loan ratio and a recovery of fast lending activity. Throughout 2020, the level of non-performing loans was at stable levels, at around 8.2%.

December was the first month that banks would begin restructuring deferred loans during the pandemic period (the deferral deadline was August, but banks start classifying non-performing loans after three months, ie after November), but a regulation of the Bank of Albania in mid-January this year, decided to postpone until March 31 the temporary measures that allow banks not to reclassify restructured loans as bad. The decision of the Bank of Albania allows the banks to continue the restructuring without classifying these liabilities as bad loans. A similar action to that of the Bank of Albania has been taken by the counterpart authorities of other European countries.

While the growth of non-performing loans was slowed down in 2020, the consequences of the pandemic are expected to be reflected throughout this year.

The decline in GDP and the rise in unemployment during 2020 certainly create real and objective difficulties in the performance of businesses and in the employment of individuals. These difficulties translate financially into insolvency. So not all loans will be repaid on a regular basis. Despite the positive effects

of the moratorium, cases of closure (bankruptcy) and inability to find a new job are not excluded. This means that bad loans in 2021 will have other behaviors.

Banks have started to take precautions, increasing provisions in general, so as not to be found unprepared by any possible scenario

The pandemic has brought about a slight increase in the non-performing loan ratio for individuals. Data from the Bank of Albania show that at the end of April, the ratio was 5.47%, while in March last year, at the time of the pandemic, it was 5.21%.

The indicator marked the most significant increase in September and October last year, a period that coincides with the end of the almost six-month moratorium on installment payments imposed by the Bank of Albania, with the cooperation of commercial banks. In October, the non-performing loan ratio reached 5.8%, a level that so far can be considered as the peak of the crisis effect on the quality of the loan portfolio for households.

MEASURES TAKEN TO MANAGE BAD LOANS AS A RESULT OF THE COVID-19 PANDEMIC.

As a result of the Covid-19 pandemic, the level of non-performing loans is expected to increase.

The Bank of Albania is studying new measures to respond to a possible increase in the non-performing loan ratio during 2021.

Two possible measures could be to shorten the repayment period of bad loans, as well as to extend the term of the out-of-court restructuring regulation of bad loans in more than one bank.

The write-off of bad loans has been the measure with the main impact on reducing the non-performing loan ratio over the last five years. In 2015, the Bank of Albania adopted a regulation obliging banks to offset classified loans lost for more than five years. In total, since the beginning of the write-off process, in January 2015, 65 billion ALL or about 525 million euros of lost loans have been written off. The value of written-off loans is about 130% of the present value of non-performing loans and gives a clear idea of the great impact that write-offs have had on the clearing of the banking sector portfolios.

In an effort to encourage further cleaning of portfolios, the Bank of Albania decided from the beginning of 2020 to shorten the deadline for off-balance sheet loans from three years to two years. This may have given a new impetus to the write-offs, especially in December, which is the period when banks usually take over most of them. This year, the Bank of Albania may consider a further shortening of this deadline, in order to further clear the bad loans from the banks' portfolio (Bank of Albania, n.d.).

EMPIRICAL ANALYSIS

Models ARIMA

The autoregressive integrated moving average model (ARIMA) has been proved to be an efficient and reliable method for dealing with the univariable time series. The emphasized advantage is that the ARIMA model does not need any additional variables just based on the values of its historic observations. And the required conditions previous to conduct the ARIMA model process should be satisfied with two conditions; one is that it should be a stationary time series, and the other is the recommended minimum amount of the sample data is at least 50(G. E. Box and G. C. Tiao,, 1975).

Autoregressive (AR) models were first introduced by (Yule, 1926). Furthermore, they were supplemented by (Slutsky, 1937) who introduced the Moving Average (MA) models. It was (Wold, 1938) who combined both the AR and MA models and showed that ARMA processes could be used to model all stationary time series as long as the proper order of AR is p, and q, the number of terms MA to be appropriately specified. So a time series X_t can be modeled as a combination of past values x_t and / or past error e_t. The approach proposed by (Box, G.E.P., and Jenkins, G., 1970) became known as the Box-Jenkins methodology for ARIMA models, where the letter "I", between AR and MA, stood for the word "integrated". ARIMA models and the Box-Jenkins methodology became very popular in the 1970s among academics, especially when shown through empirical studies (Cooper, 1972; Nelson, 1972; Elliot, 1973; Narasimham et al., 1974; McWhorter, 1975; Armstrong, 1978) that they can surpass classical econometrics with large models and complex models, known at the time, in a variety of situations.

Autoregressive (AR) model

An autoregressive model of order p, AR (p), can be expressed as:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t$$

where ε_t is the error term in the equation; where ε_t a white noise process, a sequence of independently and identically distributed (i.i.d) random variables with $E(\varepsilon_t)$ = 0 and $var(\varepsilon_t) = \sigma^2$; i.e. $\varepsilon_t \sim iidN(0, \sigma^2)$. In this model, all previous values can have additive effects on this level Y_t and so on; so it's a long-term memory model.

Moving-average (MA) model A time series $\{Y_\square\}$ is said to be a moving-average process of order q, MA (q),if:

$$Y_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \quad \varepsilon_{t-q} + \varepsilon_t$$

This model is expressed in terms of past errors as explanatory variables. Therefore only q errors will effect on $Y_\square$, however higher order errors don't effect on Y_t; this means that it's a short memory model.

Autoregressive moving-average (ARMA) model A time series {Y_t} is said to follow an autoregressive moving-average processof order p and q, ARMA (p, q), process if:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

ARIMA Models The ARMA models can further be extended to non-stationary series byallowing the differencing of the data series resulting to ARIMA models. The general non-seasonal model is known as ARIMA (p, d, q): where with three parameters; p is the order of autoregressive, d is the degree of differencing, and q is the order of moving-average.

The general form of the ARIMA model (p, d, q) is:

$$\Delta^d Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-}$$

where $\Delta Y_t = Y_t - Y_{t-1}$

If the data have seasonal influences the models will be in a wider form and are called SARIMA (p, d, q) (P, D, Q)4 models where P, D and Q are the respective orders of AR, I and MA but for sezonality where k is the frequency of the series (which for us will be quarterly for GDP)

Model estimation: using computation algorithms to arrive at coefficients that best fit the selected ARIMA model. The most common methods use Maximum Likelihood Estimation (MLE) estimation.

We use three evaluation criteria to assess the performance of the model(Wayne A. Woodward, Henry L. Gray, Alan C. Elliott, 2017), respectively, are the mean squared error (MSE), the root mean square error (RMSE), MAE the mean absolute error and the mean absolute percentage error (MAPE); the formulations are detailed as follows:

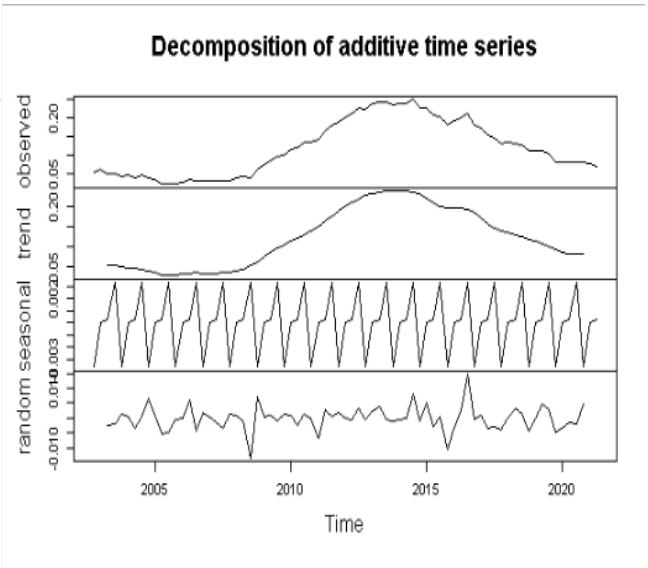
$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right|, \quad MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_t - F_t|,$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_t - F_t)^2, \quad RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_t - F_t)^2}$$

Where Y_t are the current values of the series and F_t are the predicted values of the series.

The NPL series is decomposed into trend components and cyclic components.

Fig. 2. *Decomposition of the NPL series*



Source: Authors calculation

The estimated model for NPL with quarterly data for the period quarter 2002 to quarter 2 of 2021. is the SARIMA model. The evaluated model is given in the table below

TABLE 1 The estimate model for NPL

Series: NPLT
ARIMA(1,2,3)(2,0,0)[4]

Coefficients:

	ar1	ma1	ma2	ma3	sar1	sar2
	-0.4700	-0.1948	-0.2806	-0.3585	0.1901	0.3998
s.e.	0.3299	0.3275	0.2035	0.1541	0.1562	0.1096

sigma^2 estimated as 6.553e-05: log likelihood=249.85
AIC=-485.7 AICc=-483.98 BIC=-469.67

Training set error measures:

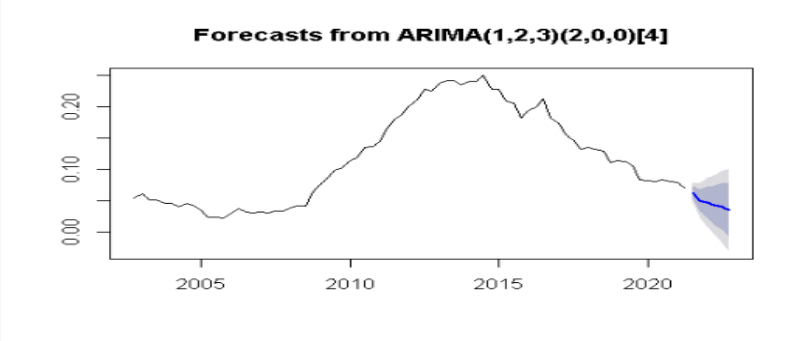
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-0.00031	0.00765	0.00571	0.5420517	6.85188	0.24324	-0.00850

Source: Author calculation

We use the selected model for the forecast for 6 consecutive periods and we have the

forecast presented in the figure and the values in the table.

Fig. 1 *The forecast for NPL with ARIMA model*



Source: Authors calculation

TABLE 2 The value forecast for NPL

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021 Q3	0.06304324	0.052669069	0.07341742	0.047177314	0.07890917
2021 Q4	0.05078231	0.033476517	0.06808810	0.024315385	0.07724923
2022 Q1	0.04802925	0.023303939	0.07275457	0.010215147	0.08584336
2022 Q2	0.04360030	0.013254869	0.07394572	-0.002809029	0.09000962
2022 Q3	0.04078338	0.003697890	0.07786886	-0.015933981	0.09750074
2022 Q4	0.03547130	-0.008103291	0.07904589	-0.031170286	0.10211289

Source: Authors calculation

Based on the evaluated ARIMA model, it can be seen that the NPL trend will be declining during the following year. This is a good sign for the economy in general and for the

banking sector in particular.

CONCLUSIONS

NPL assessment and management plays an important role in the economic and financial stability of a country. Creating the conditions for a healthy NPL market contributes to the ability of banks to devalue a large part of stocks.

Although 2020 was difficult for the banking system, as a result of the pandemic, this is not reflected in the indicator of non-performing loans, due to the measures of the Bank of Albania, which enabled the postponement of loan installments by almost six months (March-August), while space was created for banks to restructure loans without penalties and without deteriorating the status of borrowers by the end of 2020. Such a framework has favored the stability of the non-performing loan ratio and a recovery of rapid lending activity

From the analysis made using the evaluated SARIMA model and the selected model we use for forecasting and based on the evaluated ARIMA model it is seen that the NPL trend will be declining throughout the year.

This is a good sign for the economy in general and for the banking sector in particular.

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