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USING AN ALTERNATIVE APPROACH TO BUILD AN EMPIRICAL MODEL TO FORECAST LIQUIDITY NEEDS OF THE ALBANIAN BANKING SECTOR

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Disclaim: The views expressed in this paper are those of the author only and do not reflect that of the Bank of Albania. The author is grateful to Mr. Alajdin Orizaj for his valuable comments and suggestions.

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ABSTRACT

This paper provides a simple new empirical alternative approach, which is based on daily data for the period 2008-2020 and various binary indicators, and it builds a set of econometric models that can be easily used to predict short-term and medium-term liquidity needs in the banking system over a chosen time horizon. The analysis of the forecast accuracy for each of them relies on the results of simple statistical tests. These tests are related to the Root Mean Squared Error and the Absolute Mean Error and the 'Theil U' coefficient test, as well as the statistical test results of the correlation between their predicted and actual values for each of the indicators. This assessment includes also analysis performed in relation to an alternative approach that aggregates all forecasts into a single composite indicator, expressed as an average indicator, which is assumed to reflect more clearly the expected final position of the interbank market in relation to its liquidity needs, which can serve to understand better the reasons for deviating from these expectations.

Key words: Daily forecast, liquidity management, TGARCH and OLS, dummy variables, seasonality and forecast evaluation errors.

JEC: C22, C51, C53, C59.

1. INTRODUCTION

The central Bank of Albania, is responsible for designing and implementing the monetary policy in Albania, through which it aims to achieve and maintain price stability, as well as support and guarantee the stability of the financial sector. For this reason, in addition to setting up the key policy rate, it achieves this responsibility by also actively carrying out operations in the open market, by injecting and withdrawing liquidity in the interbank market, the foreign exchange market and the government securities market. On the one hand, the bank aims to achieve its main objective over a chosen time horizon. On the other hand, by injecting and withdrawing liquidity through operations in the open market, it also aims to reflect its monetary policy stance. Besides, the central bank[1] conducts operations in order to maintain the lack of liquidity within a certain band. This is the case if the one-day trading rate in the interbank market does not fluctuate around the base rate. In this way, it aims to orient the short-term interest rates in the interbank market near this norm and reduce any deviation from this norm, which may obstruct the achievement of its main objectives. In this case, the underlying premise is that shortages of liquidity means the inability of banks to acquire cash or means of payment at low cost, which could lead to unpreventable failures of institutions. If this is the case, it could result into some sort of spill-over and contagion effects, which may ultimately engulf the financial system more broadly with significant implications on the real economy. In this regard, when central banks enter into transactions to implement their monetary policy, they necessarily make use of their own balance sheets.

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[1] *As the issuer of the national currency, among other principal objectives, Bank of Albania aims to promote a smooth operation of payments systems to ensure a safe and fast circulation of the currency in the economy at minimum costs, prevent systemic risk, and safeguard the stability of financial institutions and markets. This includes also its objective to promote financial system stability by regularly identifying and analysing risks and threats to financial stability and fulfilling the needs of the economy for cash, fit for circulation. See also Bank of Albania (2021) "The medium-term development strategy of the Bank of Albania 2022-2024", approved by the Supervisory Council of the Bank of Albania, Decision No.55, dated 24.11.2021.*

Whether central banks[2] are undertaking open market operations (OMO) to inject or drain funds from the banking system, or allowing the banks to use standing facilities to borrow or deposit funds, the central bank's balance sheet will be impacted, while the funds in question are commercial bank balances held at the central bank. Ideally, operations undertaken to implement policy should have a predictable impact on the economy, via the banking system. This means that the central bank needs to know the context in which it is operating: what is the current availability of commercial-bank balances compared with the level of demand, and how is this expected to change in the near term, requiring an accurate current picture and good forecast of the central bank's likely future balance sheet[3].

This means that liquidity management by central banks refers typically to the framework, set of instruments, and the rules that a central bank as a lender of last resort follows in managing the needs of systemic liquidity, consistent with the ultimate goals to prevent possible systemic crisis. This means that, as Cecchetti and Disyatat (2010) put forward, central banks modulate liquidity conditions by changing both the level of short-term interest rates and influencing the supply of bank reserves in the interbank market. While the central bank liquidity management is assumed to have short-term effects in financial markets, its long-term implications on asset price and securities as well as on the real sector and lending conditions are more profound. It is from this standpoint that a central bank decides to adjust its market operations over a chosen time horizon in order to reflect its policy stance. For these reasons, central banks tend to forecast banks' free reserves and estimate excess reserves, because they believe that a disequilibrium, whether too much or too little liquidity, tends to promote a typical passive behaviour by banks, which is undesirable by the central bank. Similarly, central banks may need to react also in order to continue implementing an appropriate monetary policy stance. If there is a shortage of

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[2] *Cabrero, et al., (2002) state that a central bank has at its disposal three different types of instruments which determine the market liquidity for banks reserves: minimum reserves, standing facilities and open market operations. A detailed account of the Bank of Albania's monetary policy instruments and procedures can be found at the Bank of Albania (2020).*

[3] *See among other Ruffer and Stracca (2006); and Gray (2008).*

liquidity, then the central bank will (almost) always supply the need. There have been a few occasions where a central bank has not been able to supply sufficient cash to meet the economy's needs, notably when there is hyperinflation or civil unrest (or in one Latin American country, when the central bank printers went on strike) and people may then resort to barter or increased dollarization. But this is very unusual. As regards shortages of commercial bank reserves held at the central bank, the risk is that a shortage would mean that payments could not be cleared at the end of the day. In order to avoid this risk, central banks have in place credit standing facilities (CSFs). This policy instrument normally aims to supply liquidity via open market operations (OMO). This is assumed would help them to avoid spikes in market overnight interest rate that would place such rate at the worst scenario outside the upper bounds of the interest rate corridor. On the other hand, commercial banks might have sufficient balances for payment purposes, but be short of reserve balances in terms of meeting reserve requirements (RRs) or liquid asset ratios (LARs). Since the interest rate penalty of a shortfall is typically the same as for accessing the credit standing facilities or higher, the impact on banks' behaviour will be similar, so that central banks will supply the necessary liquidity via open market operations. In any case, liquidity will nearly always be supplied, albeit possibly at a high price, so that ex-post liquidity shortages are unusual. A bank may of course end a period with reserves lower than its target, but this is not a 'free' option as there will be an interest rate penalty and central banks will normally work on the assumption that each bank aims, at least, to meet its reserves target and manage liquidity accordingly.

It is from this perspective and in the implementation of its monetary policy that the central bank is encouraged to analyse and forecast the short-term and medium-term liquidity needs in the banking system. First, this comes as a result of changes in autonomous and non-autonomous liquidity factors over the forecasting horizon. For most central banks, including the Bank of Albania, among the main indicators that relates to autonomous factors are those associated with information on net government balances and transfers, cash circulation, and net government securities that are issued and maturated in the form of T-Bills and bonds, in both foreign and domestic currency. Similarly, there are also other components that refer to non-autonomous factors that affect the level of liquidity needs. These factors are those related with credit and deposit standing facilities, repo, degree of participation on government borrowing, banks' reserve holdings with central bank and central bank intervention in the market through demand of foreign reserve. Second, it comes also because of its duty as a central bank to supply and withdraw from the market that amount of liquidity consistent with a desired and efficient level to achieve its primary objectives. In this sense accurate forecasting of liquidity needs in the banking system, by the central bank, is essential, as they affect the expectations of counterparties of being short or long of liquidity at the end of the required reserve maintenance period, and consequently at all times. This normally plays an important role in the implementation of monetary policy, since it is the main aspect that forms the basis of maturity in the yield curve. On the other hand, the central bank attempts to provide liquidity through its open market operations in a way that, after taking into account its forecast effects of autonomous liquidity factors, counterparties can fulfil their reserve requirements on average over the reserve maintenance period, without systematic resource to the standing facilities. If the central bank provides more (less) liquidity than this benchmark, counterparties will have to use at the end of the reserve maintenance period the standing facilities, which will push the overnight rate towards the relevant standing facility rate as soon as this liquidity imbalance becomes obvious. More precisely, in an efficient market, the overnight rate will correspond to the weighted rates of the standing facilities provided by the central bank, whereby the weights correspond to the respective probabilities that the market assigns to being short or long of liquidity, at the end of the reserve maintenance period.

This implies that the liquidity need of the banking system reflects the extent to which a market within a given country, allows assets to be bought and sold at stable and transparent prices. However, this refers to the efficiency or easiness of converting an asset or value into cash without affecting its price in the market, which may consequently have implications for monetary and financial stability [Gray (2008)]. From this point of view, accurate forecasts on future short-term and long-term liquidity needs of the financial (banking) sector, are crucial for three reasons. First, as Bindseil (2001) suggests, this set of information affects expectations of central bank, as well as those of the counterparties being short or long of liquidity at the end of the maintenance period, and consequently the overnight rate, which normally plays an important role in the implementation of monetary policy with respect to the fact that it constitutes the basis maturity in the yield curve. Second, as BIS (2012) advocates, the management process of the intraday or intra-period liquidity needs and risks, constitutes the key element of the central bank's overall risk-management liquidity framework and the crucial challenge to meet payment and settlement obligations on a timely basis, both normally and under unstressed conditions, contributing, thus, to the smooth functioning of this system without provoking spikes in market interest rates. Therefore, in the context of empirical analysis, the main advantage of forecasting future liquidity needs, including the concrete identification of these needs through each of the autonomous and non-autonomous factors, is related to the possibility of creating a transparent balance of behaviour between the central bank and the main actors in the interbank money market. In this sense, the problem that wrong signals outside the central bank's objectives can be transmitted to the market in this way, is insignificant. In this equilibrium, it allows the central bank to manage perfectly overnight interest rates within the accepted corridor, at least on the day of the open market operation, enabling the least possible fluctuations of liquidity imbalances at the end of the maintenance period, and understanding exactly which of the components drives market liquidity needs.

Against this backdrop, the paper develops a set of simple empirical models that would be easily used to anticipate the future needs of market liquidity, using a framework of partitioning liquidity into autonomous and non-autonomous factors. For this reason, this paper follows a three step approach. First, we collect a set of daily data providing information for both autonomous and non-autonomous factors over the period 2008 – 2020. This dataset is adjusted then accordingly to a 7-day week approach. Second, we build a series of empirical models that would be easily used to predict the need for and supply of short-term and long-term liquidity in the interbank market according to each component of autonomous and non-autonomous factors. In each of this models, upon the suggestions of Gray (2008) and Katsalirou (2019), the dependent variable is expressed as a function of a set of dummy variables. These variables are assumed to reflect better all components effecting liquidity needs associated with seasonality, trends or special days or weeks, etc. The specified models are estimated, then, using a Target Generalized Autoregressive Conditionally Heteroscedastic (TGARCH) model approach. The set of estimated coefficients and models are used, then, to forecast each of the components. The accuracy of this forecast data are analysed using a within-sample approach up to a 9-week period ahead horizon. Finally, the forecast error accuracy is analysed, then, by making use of two alternative different approaches. The first approach analyses the size of the error term by focusing mainly on the deviation of actual levels of liquidity needs from anticipate ratio. This includes the use of a set of simple statistical tests, among which are the Root Mean Squared Error (RMSE) test, the Mean Absolute Error (MAE) and the Theil Inequality Coefficient test, applied on error terms retrieved from all the models over the whole forecasting sample as suggested by existing literature[4]. This indicator shows the deviation of the actual liquidity values from the forecasted levels, which in this case includes a comparison between our in-sample forecast data with actual data according to different modelling and estimation specification technique. Through this analysis, we come to understand if the central bank could use this approach to predict and thus better manage the various liquidity needs of the banking system in the future. This means that if the central bank can obtain a previous forecast ratio with the lowest value of the estimated error, then it can factorize this advantage into the future and make the corresponding adjustments in its plan to meet the needs for liquidity of the banking system in accordance with its strategy for the implementation of monetary policy. The second approach gauges upon the results of a simple correlation test between the actual and predicted values. This approach helps us identify the strength ability of our proposed binary approach to capture and to forecast events from current data and knowledge that there are episodes affected by either seasonal and/or non-seasonal driving factors, which are non-easily anticipated by other approaches.

[4] *See among other Bliemel (1973); Granger and Newbold (1973); and Ahlburg (1984).*

The value added of this paper is two-fold. First, for liquidity management purposes, this paper serves the objective of the central bank by providing forecasts related to both short-term and long-term needs. This is supposed to help the central bank to understand better the dynamic of liquidity needs and to keep them close to a level deemed to be appropriate and efficient, and to help portfolio managers to devise less costly trading strategies for such needs, undoubtedly, at least until the end of two mandatory reserve-re requirement maintenance periods. Second, this paper provides a clear attempt to better understand the amount of excess and/or lack of liquidity in the interbank market. This information can help the central bank achieve the main objective of monetary policy in order to maintain the overnight rate close to its policy rate and to keep the shortage within a certain band, where it has been observed that the overnight rate in the interbank market fluctuates around the base rate. This is also expected to reduce volatility and uncertainty, thereby reducing the costs of managing the liquidity need. Anticipating this need can be used in this way to predict with their help, the course of the overnight rate, and to make sure that this rate fluctuates around the base rate. Finally, this material further supports the process of developing the analytical and forecasting capacities in the central bank, which aims to further improve the quality of the formulation and implementation of the monetary policy, and thus maintaining and developing the framework of instruments related to this policy as well as aiming to increase its effectiveness and flexibility. This is also the medium-term development strategy of the Bank of Albania for the coming years.

The results of this paper present a series of important findings, which strongly support the effectiveness of using the empirical approach with daily data and binary indicators to forecast liquidity needs of the Albanian banking system, as a complementary alternative for the implementation of monetary policy according to its medium- and long-term strategy. In this manner, results show that the Bank of Albania can rely on this predictive alternative to better manage the need for liquidity through open market operations, by injecting or withdrawing liquidity from it, as in cases where it aims to maintain a shortage within a set band, as well as in those in which the goal is to keep the one-day trading rate in the interbank market around its base rate. First, it was observed that the application of this method captures quite well the needs for liquidity characterized by the trend, seasonal and non-seasonal factors, as well as those related to special and unpredictable days. This is also due to the fact that the error rate associated with each of the prediction models that were built to capture these characteristics, is relatively low. Even the results of a simple correlation test between the actual and predicted levels are relatively high in each case, which is another qualitative indicator that further supports the proposed approach. Second, it was realized that the effectiveness of these results is improved even more if we move from the prediction of daily needs to the aggregation of these needs at weekly and/or monthly levels. In any case, however, the results remain relatively better for indicators related to autonomous factors. This includes forecasting indicators related to government revenues and transfers to other institutions and, to a greater extent, cash in circulation. On the other hand, for the non-autonomous factors, the proposed approach provided results that constituted satisfactory information on the forecast levels for the indicators related to the deposit and credit situation, reserve requirements and, to some extent, those related to the net value of the participation of the central bank, namely the Bank of Albania, in the auctions of government securities. The analysis of other results based on an alternative approach that aggregates all the forecasts made into a single indicator expressed as an average indicator, which is assumed to reflect more clearly the expected final position of the interbank market in relation to its needs for liquidity and the reasons for the deviation from these expectations, suggests that a combination of all these forecasts provides a relatively better orientation overview of the position of market needs and a more coherent aspiration for achieving the objectives of the Bank of Albania regarding the monetary policy implementation.

The rest of the paper is structured as follows. Section 2 provides the literature review. Section 3 explains the methodological approach and the data. Section 4 analyses the empirical results. Final remarks and any policy implications are provided in the last section.

2. THE METHODOLOGY AND THE DATA

2.1.An alternative approach of specifYing A forecasting model for liquidity needs of the banking system

The Bank of Albania analyses and forecasts regularly the banking system's liquidity needs over different time horizons. The liquidity needs of the banking system result from the minimum reserve requirements imposed on credit institutions. It is also a function of changes related to autonomous factors, which are normally beyond the direct control of the Bank of Albania. Such factors can be banknotes in circulation, government deposits with the Bank of Albania, as well as foreign reserve assets and domestic financial assets. Furthermore, since not all the banking system's liquidity in excess of minimum reserve holdings is available for trading, due to binding credit and counterparty limits (ceilings or floors) that banks have with each-other based on their perceptions of risk, not all excess liquidity can be traded. From this point of view, not all the liquidity of the banking system is available for trading. Thus, together with the level of autonomous factors, the Bank of Albania needs to analyse the need for liquidity, the corresponding amount of which will be a function of adaptation according to banks in need. It must adequately value excess liquidity that is no longer available for trading. It must adequately value, also, excess liquidity that is no longer available for trading. In other words, the Bank of Albania should anticipate and estimate the excess liquidity considered to be not available for trading. Thus, based on the analysis of the liquidity situation and the forecast of autonomous factors, the Bank of Albania calculates the size of open market operations. These factors enable banks to meet their reserve requirement obligations over a certain period without having to use standing facilities to borrow or deposit funds, such as overnight loans or deposits. In the event that the size of the operations is not correct and the obtained difference is not corrected within the specified period, the banks are forced to use the permanent facilities. Thus, in the case of a low injection, the short-term rates in the interbank market will go towards the loan rate, or towards the deposit rate, in case we are dealing with a higher injection.

However, unlike interest rates in capital markets that are more difficult to predict, liquidity needs of the banking system are found to be more stable and persistence in time, which allows central banks to forecast more accurately [Cao, et al., (2013)]. This process is largely related to the process of anticipating the liquidity needs to obtain a reliable target of banks' idle reserves, thereby ensuring an efficient management of bank resources through the weekly conduct of Open Market Operations (OMO), by injecting or withdrawing liquidity from it. On the one hand, this is related to the obligation that banks have to maintain an account with the central bank. At the same time, banks must maintain the required minimum level of mandatory reserve, as well as the corresponding changes of autonomous factors for the corresponding period [Katsalirou (2019)]. On the other hand, in the case of Albania, the central bank performs the relevant operations in order to maintain the shortage within a certain band, in cases where it is observed that the one-day trading rate in the interbank market fluctuates around the base rate. This norm is approved by the Supervisory Council of the central bank. This serves also as the minimum rate for requests in liquidity injection auctions. At the same time, it is used to convey to economic actors the stance of the Bank of Albania's monetary policy, as well as to implement the relevant policy for guiding short-term trading rates in the interbank market close to the base rate and to reduce its deviation from this rate. From this point of view, the two main components related to the prediction of the need for liquidity of the banking system, through the OMO forecast that come to fore are: the optimal level of demand for total bank reserves (ODR) and the estimated level of supply of total bank reserves on the day of OMO (OSR), expressed as follows:

$$FOMO_t = BLS_{t-1} + ODR_t - OSR_t \tag{1}$$

Where, BLS_{t-1} is the state of market liquidity situation at lag 1 (t-1); $FOMO_t$ is equal to the OMO forecast for the day of trading.

To forecast monetary aggregates, ODR_t and OSR_t, in an effort to derive the OMO forecast, the authorities face a number of problems, among which is determining the sum of liquidity coming from autonomous factors and the capacity to make use of econometric forecasting approach for such purposes. The former is related to the fact that the primary target for OMO is to determine the difference the difference between the estimated supply and demand for liquidity money under an equilibrium condition. In case if the size of the operations is not adequate and this difference is not corrected by the end of the period, then the banks are forced to use permanent facilities. This action would result in short-term interbank market rates moving towards the loan rate in the case of a lower injection, or towards the deposit rate in the case of a higher injection. However, in arriving at the ultimate target for OMO, the excess supply should be adjusted in order to accommodate a set of factorised components in a given period. These factors, as Gray (2008) states, may happen that are not directly influenced by the decision-making process of the central bank.

First, the exogenous factors are commonly known or often referred as 'autonomous factors'. These factors are those items in the central bank balance sheet that are neither related to monetary policy operations, nor linked to current account holdings of credit institutions [Gonzalez-Paramo (2007)]. These factors are related, hence, to central bank activities or services, but neither are determined by the central bank's liquidity management nor by counterparties [Cabrero, et al. (2002)]. However, they represent the sum of primary liquidity available to banks stemming from a regular adjustment process related to the central bank's exclusive right to issue national banknotes and coins with legal tender and to supply the economy with currency within a given period of time[5]. In the perspective, a central bank, in order to determine the ultimate target for OMO, needs to forecast exactly those exogenous factors that are problematic, or outside of its influence, which in this case are those that are not under its direct control. This factors may turn out to be decisive in the correct determination of the liquidity needs of the banking system. For most central banks, including the Bank of Albania, the main items are those that are closely related with net government balances, cash circulation, and net government borrowing, which are expressed mathematically, as follows:

[5] *See among other Bhattacharyya and Sahoo (2011). This volume is not related, however, to flows as a result of the regular supply of the economy with currency carried out by the central bank to achieve monetary policy objectives upon which it uses the appropriate monetary instruments.*

$$AF_t = \left[GOV_{exp_t} - GOV_{rev_t} + GOV_{trans_t^{from}} - GOV_{trans_t^{to}}\right] + GOV_{TB_t^{mat}} - GOV_{TB_t^{issue}} + CC_{rev_t} - CC_{pay_t} \quad (2)$$

Where, AF_t present the total level of liquidity components that are linked to autonomous factor at time t. This set of components are assumed to be exogenous to the decision-making of the central bank. It includes, as presented in equation (2), a set of four different indicators. The first group includes financial flows related to government operational activity as referred to government expenditure (GOV_{exp_t}) and revenues (GOV_{rev_t}). The second group consists of liquidity flows related to the total level of money transferred by the government in the form of capital support, either current or capital transfers, to other public budgetary institutions $(GOV_{trans_t^{TO}})$. This group includes also the total level of money transferred by other public budgetary institutions that have to transfer a proportion of their revenues to the central government $(GOV_{trans_t^{FROM}})$. The third group represents liquidity flows referring to $GOV_{TB_t^{issue}}$ and $GOV_{TB_t^{mat}}$ that consist of the total level of government borrowing issued a time t through T-Bills and the total level being maturated at that given time t. The last group, includes liquidity flows are related to the two components of cash in circulation, which represent cash going in and out of the banking system, namely to CC_{rev_t} and CC_{pay_t}. By taking to account that each set of these variables represent, in other words, their net values, then, by construction, equation (2) can be also transformed into a simpler equation, expressed mathematically, as follows:

$$AF_t = \left[\Delta GOV_t + \Delta GOV_{trans_t}\right] + \Delta GOV_{TB_t} + \Delta CC_t \quad (3)$$

Where, ΔGOV_t represents the net difference between government expenditure and revenue; ΔGOV_{trans_t} represents the net difference between government transfers to and from other public budgetary institutions; ΔGOV_{TB_t} represents the net difference between government T-Bills being issued and maturated; and ΔCC_t represents the net difference of money circulation.

Second, the internal (endogenous) factors related to market liquidity patterns are commonly known or often referred as 'non-autonomous factors (NAF). These factors, including open market operations, are controlled by the central bank. In this sense, their flows are entirely determined by her decision-making [Gray (2008)]. In this context, the central bank needs to forecast also those endogenous factors that might be problematic when determining the ultimate target for OMO. However, in this case, these are the factors on which central banks have some sort of information already and are, consequently, assumed to be somewhat under the control of central banks. For most central banks, including the Bank of Albania, the main items under this category are related to those market liquidity components that are determined by the set of instruments that are related to credit and deposit standing facilities, repo, degree of participation on government borrowing, banks' reserve holdings with central bank and central bank intervention in the market through demand of foreign reserve, which are expressed mathematically, as follows:

$$\begin{aligned} NAF_t = {} & BoA_{repo_t}^{issue^{total}} - BoA_{repo_t}^{mat^{total}} + BoA_{loan_t^{issue}} - BoA_{loan_t^{mat}} \\ & - BoA_{deposit_t^{issue}} + BoA_{deposit_t^{mat}} + BoA_{IR_t^{buy}} - BoA_{IR_t^{sell}} \\ & + BoA_{RR_t^-} - BoA_{RR_t^+} + BoA_{TB_t^{issue}} - BoA_{TB_t^{mat}} \end{aligned} \qquad (4)$$

Where, $BoA_{repo_t}^{issue^{total}}$ and $BoA_{repo_t}^{mat^{total}}$ represent the total level of regular liquidity injection and withdrawal operations in the banking system through One Week Repurchase Agreement (REPO) standing facility time t; $BoA_{loan_t^{issue}}$ and $BoA_{loan_t^{mat}}$ represent the total level of liquidity provided to the market by "overnight" lending standing facility and that are maturated at time t; $BoA_{deposit_t^{issue}}$ and $BoA_{deposit_t^{mat}}$ represent the total level of liquidity related to "overnight" deposit standing facility; $BoA_{RR_t^+}$ and $BoA_{RR_t^-}$ represent the total level of liquidity that has been added up or lowered down at time t by banks due to the required reserve remuneration rate set by the central bank, which all banks operating within a country have to respect; $BoA_{TB_t^{issue}}$ and $BoA_{TB_t^{mat}}$ represent that part of the components related directly with market liquidity, which come in and out of the market due to the involvement of the central bank in the government security auctions and that are related to the level being issued and/or maturated at time t[6]; $BoA_{IR_t^{buy}}$ and $BoA_{IR_t^{sell}}$ represent that component of market liquidity that is determined by

[6] *It is assumed that this market liquidity indicators can determine also the decision of the central bank to buy or sell these securities in the secondary market with the aim of managing liquidity needs in the banking system.*

the degree of central banks strategic decision making in managing foreign reserve holdings, which carries out operations in the foreign exchange market without prejudice to the exchange rate regime; and Δ represents the net difference of each component belonging to NAF. Or, as previously, equation (4) can be re-written, expressed mathematically, as follows:

$$NAF_t = \Delta BoA_{repo_t} + \Delta BoA_{loan_t} - \Delta BoA_{deposit_t} + \Delta BoA_{RR_t} + \Delta BoA_{TB_t} + \Delta BoA_{IR_t} \quad (5)$$

In addition, given that both AF_t and NAF_t represent net differences, then market liquidity situation at time t is a function of actual level of bank liquidity position at the previous time, $t\text{-}1$, plus the ratio liquidity ratio determined by AF_t and NAF_t at time t, which is expressed mathematically as follows:

$$MLS_t = BLS_{t-1} + AF_t + NAF_t \quad (6)$$

Where, BLS_t refers to bank liquidity surplus. In other words it refers to an important indicator of liquidity conditions for a given day measures, excess or deficient reserve position, which can be calculated as the difference between compliance on a given day and the reserve requirement, expressed mathematically as follows:

$$BLS_t = \overline{RR}_t + ER_t \quad (7)$$

Where, $\overline{RR}_t$ is the average monthly required reserve remuneration rate; ER_t the total level of excess reserve or the daily compliance, which might be positive or negative; is the number of days passed in the maintenance period. By integrating equation (1), then equation (7) is transformed, expressed mathematically as follows:

$$BLS_t = \overline{RR}_t + ODR_t - OSR_t \quad (8)$$

Or, simply as:

$$BLS_t = \overline{RR}_t + FOMO_t \quad (9)$$

This means that in order to meet its monetary policy objectives, the central bank, depending on the liquidity forecasts, determines if there is a liquidity shortage in which case its policy would be expansionary, and vice-versa, contractionary if there is excess liquidity. In this context, decisions on sound liquidity management are based on liquidity forecasts. This helps the central bank to keep liquidity at a level consistent with the acceptable rate of short-term interest rate. This instrumental rate is assessed in this study by the overnight rate and the extent to which the rate falls within the bound level, as presented in Figure 1 in the Appendix. In this case, the literature[7] suggests that the main instrument to be forecasted should refer to autonomous factors, namely cash in circulation, net government balances and foreign exchange transactions, which can be impacted also by seasonality and trend effects. However, based on what Gonzales-Paramo (2007) argues, other instruments need to be anticipated as well, because since their maturity lies from one week to a couple of weeks, it is not enough to know them ex-post at longer term periods. Further, all the set of patterns related to these indicators are not directly or at least visibly experiencing non-seasonal patterns, but as Cabrero, et al. (2002) suggest, might display momentary patterns that might be related to either a special day or week development, and so on with month, quarter, etc., or to other episodes, e.g. bank holidays, Christmas, etc., all of which require a different strategical approach to identify the exact deterministic components that would allow us to anticipate liquidity needs with the slightest errors.

In this sense, developments related to these indicators are not directly influenced by non-seasonal factors. However, as Gray (2008) suggests, they may exhibit a behaviour related to momentary factors, which in turn may be influenced by the developments of a particular day or week, or of the corresponding month and quarter. These elements require following a different approach to precisely identify each of these defining components. Only in this way can we be sure that the forecast of the need for liquidity will be carried out with the smallest errors. As stated by Gray (2008), multiple seasonality can be presented as an essential issue in forecasting a daily level. According to this model, each of the constituent components can be decisive for determining the market's needs for liquidity. According to the suggestions of Cabrero, et al. (2002),

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[7] *See among other Gray (2008); Molnár (2010); and Katsalirou (2019).*

this constitutes one of the main challenges for identifying relevant needs. Regarding this challenge, Figure (2) to (12) show graphically that such issues are proven to exist more or less with respect to all the deterministic components of market liquidity needs. It is, therefore, upon such patterns presented through this set of Figures that a set of dummy (binary) variables are constructed to account for these momentary patterns, which are represented as follows:

$$AF_t \int D_{Time}\,; D_{Trend}; D_{Special} \tag{10}$$

And,

$$NAF_t \int D_{Time}\,; D_{Trend}; D_{Special} \tag{11}$$

Where, D_{Time} is a vector of factors that are assumed to be associated with special issues that might be related either to day-to-day activities or weekly patterns, and more broadly to monthly, quarterly and yearly phenomena, which are assumed to also capture all the patterns that contribute to or are linked with seasonality that might be either weekly, monthly, quarterly and so on; D_{Trend} is a vector of dummy variables that represents any possible trend movements in the patterns of the data that are either weekly or monthly, and quarterly and/or annually; $D_{Special}$ is a vector of dummy variables that captures all information related to special moments that might be related either to particular days or weeks, and so on months, quarters and years. These indicators are used them in the empirical specifications approach on the assumption that they can better capture the performance of the liquidity flows associated with these episodes for each period of time. For this reason, their inclusion is assumed to allow us to minimize the size of the forecast error terms in order to predict the banking system's liquidity needs more accurately. This means that, given the characteristics of each of the liquidity components as presented in Figure (2) to (12), then the level of volume of each of the individual liquidity components, related either to AF_t or NAF_t, are forecasted using a simple empirical autoregressive model according to which our liquidity component is a function of seasonal or non-seasonal patterns.

For this reason, each of the model approach includes only binary (dummy) variables, and no macroeconomic or financial variables. The decision not to include this sort of variables is simple. The idea is that since both AF_t and NAF_t consist of daily information including a set of X_t variables, representing either macroeconomic or market-based, financial variables and so on, is expected to have no value added information from the content of using either monthly or quarterly information from such data[8]. For example, Figure (2) shows that on average or in most cases, government expenditure (GOV_{exp_t}) and revenues (GOV_{rev_t}) are characterised by patterns that are specifically related to special days. For example, Figure (2) shows that on average or in most cases, government expenditure $(GOV_{expenditure_t})$ and revenues $(GOV_{revenue_t})$ are characterised by patterns that are specifically related to special days. In the case of $GOV_{revenue_t}$ these special days are related to the periods upon which most of the firms and self-employed individuals pay their tax duties related to social and health contribution tax. In the case of $GOV_{expenditure_t}$ these daily patterns are related to the first days of the months during which higher levels of government expenditures are mainly due to salaries being paid by the government to public servants employees. Similarly, such visual analysis suggests that these liquidity components are also affected in the same way by patterns related to weekly, month and quarterly issues, and most importantly by those patterns which, on an annual basis, show that there exists an upward trend in both cases. For this reasons, and based on such observable patterns, government expenditure is forecasted using an empirical regression that is expressed as a set of different equations that capture different patterns, as highlighted in Figure (2), which are as follows:

[8] *One solution might be interpolating data to a higher frequency, but this might expose them to errors coming from this data generating process.*

$$GOV_t^{exp} = \alpha_{gov_{exp}} + \beta_{1_{exp}} D_{dom_1} + \ldots + \beta_{i_{exp}} D_{dom_i} + \delta_{1_{exp}} D_{dow_1} + \ldots + \delta_{i_{exp}} D_{dow_i} + \theta_{i_{exp}} D_{week_i} + \ldots + \theta_{i+n_{exp}} D_{week_{i+n}} + \rho_{i_{exp}} D_{M_i} + \ldots + \rho_{i+n_{exp}} D_{M_{i+n}} + \pi_{i_{exp}} D_{Q_i} + \ldots + \pi_{i+n_{exp}} D_{Q_{i+n}} \quad (12)$$

$$GOV_t^{exp} = \alpha_{gov_{exp}} + \beta_{1_{exp}} D_{dom_1} + \ldots + \beta_{i_{exp}} D_{dom_i} + \delta_{1_{exp}} D_{dow_1} + \ldots + \delta_{i_{exp}} D_{dow_i} + \theta_{i_{exp}} D_{week_i} + \ldots + \theta_{i+n_{exp}} D_{week_{i+n}} + \rho_{i_{exp}} D_{M_i} + \ldots + \rho_{i+n_{exp}} D_{M_{i+n}} + \pi_{i_{exp}} D_{Q_i} + \ldots + \pi_{i+n_{exp}} D_{Q_{i+n}} + \varphi_{1_{exp}} D_{trend^-_{week}} + \varphi_{2_{exp}} D_{trend^+_{year}} \quad (13)$$

$$GOV_t^{exp} = \alpha_{gov_{exp}} + \beta_{1_{exp}} D_{dom_1} + \ldots + \beta_{i_{exp}} D_{dom_i} \quad (14)$$

$$+ \delta_{1_{exp}} D_{dow_1} + \ldots + \delta_{i_{exp}} D_{dow_i} + \theta_{i_{exp}} D_{week_i} + \ldots + \theta_{i+n_{exp}} D_{week_{i+n}} + \rho_{i_{exp}} D_{M_i} + \ldots + \rho_{i+n_{exp}} D_{M_{i+n}} + \pi_{i_{exp}} D_{Q_i} + \ldots + \pi_{i+n_{exp}} D_{Q_{i+n}} + \varphi_{1_{exp}} D_{trend^-_{week}} + \varphi_{2_{exp}} D_{trend^+_{year}} + \omega_{1_{exp}} D_{sd_1}$$

$$GOV_t^{exp} = \alpha_{gov_{exp}} + \beta_{1_{exp}} D_{dom_1} + \ldots + \beta_{i_{exp}} D_{dom_i} + \delta_{1_{exp}} D_{dow_1} + \ldots + \delta_{i_{exp}} D_{dow_i} + \theta_{i_{exp}} D_{week_i} + \ldots + \theta_{i+n_{exp}} D_{week_{i+n}} + \rho_{i_{exp}} D_{M_i} + \ldots + \rho_{i+n_{exp}} D_{M_{i+n}} + \pi_{i_{exp}} D_{Q_i} + \ldots + \pi_{i+n_{exp}} D_{Q_{i+n}} + \varphi_{1_{exp}} D_{trend^-_{week}} + \varphi_{2_{exp}} D_{trend^+_{year}} + \omega_{1_{exp}} D_{sdm_1} + AR_1 + \cdots + AR_n + MA_1 + \cdots + MA_n \quad (15)$$

$$GOV_t^{exp} = \alpha_{gov_{exp}} + \beta_{1_{exp}} D_{dom_1} D_{wd} + \ldots + \beta_{i_{exp}} D_{dom_i} D_{wd} + \delta_{1_{exp}} D_{dow_1} D_{wd} + \ldots + \delta_{i_{exp}} D_{dow_i} D_{wd} + \theta_{i_{exp}} D_{week_i} D_{wd} + \ldots + \theta_{i+n_{exp}} D_{week_{i+n}} D_{wd} + \rho_{i_{exp}} D_{M_i} D_{wd} + \ldots + \rho_{i+n_{exp}} D_{M_{i+n}} D_{wd} + \pi_{i_{exp}} D_{Q_i} D_{wd} + \ldots + \pi_{i+n_{exp}} D_{Q_{i+n}} D_{wd} + \varphi_{1_{exp}} D_{trend^+_{week}} D_{wd} + \varphi_{2_{exp}} D_{trend^+_{year}} D_{wd} + \omega_{1_{exp}} D_{sdm_{exp_i}} D_{wd} + AR_1 + \cdots + AR_i + MA_1 + \cdots + MA_i \quad (16)$$

Where, D_{dom_1} represents a dummy variable capturing patterns occurring the first day of each month and so on up to D_{dom_i}, which represents a dummy variable capturing patterns occurring the last day of each month[9]; D_{dow_i} symbolizes a dummy variable that captures respectively all patterns occurring within each day of the week; D_{week_i} is related to a dummy variable that accounts for all developments happening respectively in each week of the year; D_{M_i} is related to a dummy variable that accounts for all developments happening, respectively, in each month of the year; D_{Q_i} is related to a dummy variable that accounts for all developments happening, respectively, in each quarter of the year; $D_{trend^-_{week}}$ represents a dummy variable accounting for a possible trend occurring as a common pattern each week of the year, where the positive (+) sign signifies that the variable exhibits a positive upward trend, and vice versa the negative (-) sign suggests a negative downward trend; $D_{trend^+_{year}}$ represents a dummy variable which suggests that our variable of interest in this case is effected by a positive (upward) trend occurring on average regularly in yearly basis. Those dummy variables capturing trends patterns either related to monthly or quarterly basis are recognized by $D_{trend^+_{month}}$ or $D_{trend^-_{month}}$ and $D_{trend^+_{quarter}}$ or $D_{trend^-_{quarter}}$; $D_{sdm_{exp_i}}$ represent a dummy variable capturing all elements related to special days of the months, where in this case analysis shows that the first days within each months are those which account for the highest level of government expenditures mainly due to salaries being paid by the government to public servants employees. For this reason, $D_{sdm_{exp_i}}$ takes the value of 1 during the 2nd day of the month up to the 6th day of the month, and 0 otherwise; D_{wd} represents a dummy variables accounting for all working days and non-working days including also bank holidays, taking a value of 0, if it is a day belonging to either Saturday or Sunday, and 1 otherwise. Finally, $AR_1 + \cdots + AR_i + MA_1 + \cdots + MA_i$ components of the forecast model approach represent a set of autoregressive terms (AR_i) and moving average (MA_i) errors indicators. This means that the evolving variable of interest is regressed on its own lagged (i.e., prior) values. In this case, this is represented by a set of autoregressive terms (AR_i), and another set of moving average (MA_i) errors, which suggests that the actual regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past.

[9] *This is suitable way to approach properly those months with 30 days or less than that, as it is February.*

This means that this set of indicators are fitted to time series data either to better understand the data or to predict better future points in the series (forecasting) on the assumption that future levels are also a function of passed values (behaviour). At the same time, this set of indicators are also useful to account for any deterministic component that drives liquidity needs that is non-seasonal by type, or discretion, and as such is either captured by (AR_i), or by (MA_i) terms. The reduced form of equation (16) and equation (17) with regards to GOV_t^{exp}, is expressed mathematically as follows:

$$gov_t^{exp} = A_{gov_{t-1}^{exp}} + \varphi_{gov_1^{exp}} D_{trend_{year}^{+}} + \varphi_{gov_2^{exp}} D_{trend_{week}^{-}} + \omega_{gov_1^{exp}} D_{sdm_{exp_1}} + AR_i + MA_i \tag{17}$$

$$gov_t^{exp} = A_{gov_t^{exp}} D_{wd} + \varphi_{gov_1^{exp}} D_{trend_{year}^{+}} D_{wd} + \varphi_{gov_2^{exp}} D_{trend_{week}^{-}} D_{wd} + \omega_{gov_1^{exp}} D_{sdm_{exp_1}} D_{wd} + AR_i + MA_i \tag{18}$$

Where, $A_{gov_t^{exp}}$ represents all the components that determine GOV_t^{exp}, including the constant term, and are related to special elements associated with time and seasonality; and all other coefficients $[\varphi_{gov_1^{exp}}; \varphi_{gov_2^{exp}}; \omega_{gov_1^{exp}}]$ will be estimated from the model specification. Others are as previously described. One thing that is noticed in equation (17) and (18) is the fact that $D_{trend_{year}^{+}}$ and $D_{trend_{week}^{-}}$ exhibit opposite sign. This means that these liquidity components share the same upward trend during the year, and the same downward trend during the week. This means that these components are mostly effected by patterns occurring mostly at the beginning of the week and fewer in the following days. However, on annual basis, it suggests that patterns (volumes) are lower at the begging of the year and increase towards the end of the year. These patterns are also found to be the case with other components, which are explained as follows.

Similar, government revenues (GOV_{rev_t}) are predicted using the same approach as previously, and thus, its level is predicted using an empirical model that accounts for such seasonal patterns by expressing it through a set of equations, which are built also upon the linear function as in the case of equation (12) to (18), but with some differences, expressed mathematically as follows:

$$GOV_t^{rev} = A_{gov_t^{rev}} + \varphi_{gov_1^{rev}} D_{trend_{year}^{+}} + \varphi_{gov_2^{rev}} D_{trend_{week}^{-}} + \omega_{gov_1^{rev}} D_{sdm_{rev_1}} + \omega_{gov_2^{rev}} D_{sdm_{rev_2}} + AR_i + MA_i \quad (19)$$

$$GOV_t^{rev} = A_{gov_t^{rev}} D_{wd} + \varphi_{gov_1^{rev}} D_{trend_{year}^{+}} D_{wd} + \varphi_{gov_2^{rev}} D_{trend_{week}^{-}} D_{wd} + \omega_{gov_1^{rev}} D_{sdm_{rev_1}} D_{wd} + \omega_{gov_2^{rev}} D_{sdm_{rev_2}} D_{wd} + AR_i + MA_i \quad (20)$$

Where, $D_{sd_{rev_1}}$ is a dummy variable accounting for the period during which firms and self-employed individuals pay their income tax, therefore taking a value of 1 during day 14th up to day 16th of the months, and 0 otherwise; $D_{sd_{rev_2}}$ is a dummy variable accounting for the period during which firms and self-employed individuals pay their tax duties related to social and health contribution tax, and therefore takes a value of 1 during day 19th up to day 21st of each month, and 0 otherwise. Others are as previously described, but with the difference that coefficients, to be estimated, account for the effects related to GOV_{rev_t}.

In addition, as with regards to other liquidity indicators, Figure (3) shows that component of cash circulation, as represented by both payments (CC_{pay_t}) and revenues (CC_{rev_t}), are also characterised by seasonal and non-seasonal patterns. These patterns, in this case, refer respectively to special days during the week or month. There are also patterns that are related to monthly and quarterly patterns such as upward trends in their volumes. For these reasons, their model specification is based similarly on the previous approach, and in each case their equation is expressed through the set of equations, as follows:

$$CC_t^{pay} = A_{CC_t^{pay}} + \varphi_{CC_1^{pay}} D_{trend_{dom}^{-}} + \varphi_{CC_2^{pay}} D_{trend_{moy}^{+}} + \varphi_{CC_3^{pay}} D_{trend_{qoy}^{+}} + \varphi_{CC_1^{pay}} D_{trend_{yearly}^{-}} + \left[\omega_{CC}^{pay} D_{sdm_{CC_t}^{pay}}\right] + AR_i + MA_i \quad (21)$$

$$CC_t^{pay} = A_{CC_t^{pay}} D_{wd} + \varphi_{CC_1^{pay}} D_{trend_{dom}^{-}} D_{wd} + \varphi_{CC_2^{pay}} D_{trend_{moy}^{+}} D_{wd} + \varphi_{CC_3^{pay}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{CC_1^{pay}} D_{trend_{yearly}^{-}} D_{wd} + \left[\omega_{CC}^{pay} D_{sdm_{CC_t}^{pay}} D_{wd}\right] + AR_i + MA_i \quad (22)$$

$$CC_t^{rev} = A_{CC_t^{rev}} + \varphi_{CC_1^{rev}} D_{trend_{dom}^{-}} + \varphi_{CC_2^{rev}} D_{trend_{moy}^{+}} + \varphi_{CC_3^{rev}} D_{trend_{qoy}^{+}} + \varphi_{CC_1^{rev}} D_{trend_{yearly}^{-}} + \left[\omega_{CC}^{rev} D_{sdm_{CC_t}^{rev}}\right] + AR_i + MA_i \quad (23)$$

$$CC_t^{rev} = A_{CC_t^{rev}} D_{wd} + \varphi_{CC_1^{rev}} D_{trend_{dom}^{-}} D_{wd} + \varphi_{CC_2^{rev}} D_{trend_{moy}^{+}} D_{wd} + \varphi_{CC_3^{rev}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{CC_1^{rev}} D_{trend_{yearly}^{-}} D_{wd} + \left[\omega_{CC}^{rev} D_{sdm_{CC_t}^{rev}}\right] D_{wd} + AR_i + MA_i \quad (24)$$

Where, $D_{sdm^{pay}_{cc_t}}$ represents the patterns happing particularly on a regular basis during a set of days, called as special days of the months, that consist from the 2nd day to the 6th day of the month, for which this dummy variable takes a value of 1, and 0 otherwise; $D_{sdm^{rev}_{cc_t}}$ represents the patterns happing particularly on a regular basis during a set of days, called as special days of the months, that consist from the 19th day to the 21st day of the month, for which this dummy variable takes a value of 1, and 0 otherwise. Others are as previously described.

The next indicator to be a determining factor of AF_t is related to government transfers (GOV_{trans_t}), which is divided between government transfers from $(GOV^{from}_{trans_t})$ and to $(GOV^{to}_{trans_t})$ other public institutions. These elements, as proved by graphical analysis on Figure (4), are also effected by seasonal and non-seasonal patterns which are related to annual trends, special days of the week and month, as well as with monthly and quarterly issues. For these reasons, the set of equations as related to these indicators is expressed as follows:

$$\begin{aligned} GOV^{from}_{trans_t} = {} & A_{gov^{from}_{trans_t}} + \varphi_{gov^{from}_{trans_1}} D_{trend^{+}_{weekly}} + \varphi_{gov^{from}_{trans_2}} D_{trend^{+}_{dom}} + \varphi_{gov^{from}_{trans_3}} D_{trend^{+}_{moy}} \\ & + \varphi_{gov^{from}_{trans_4}} D_{trend^{+}_{qoy}} + \varphi_{gov^{from}_{trans_5}} D_{trend^{+}_{yearly}} + \omega_{gov^{from}_{trans_1}} D_{sdm_{gov^{from}_{trans_1}}} \\ & + \omega_{gov^{from}_{trans_2}} D_{sdm_{gov^{from}_{trans_2}}} + AR_i + MA_i \end{aligned} \tag{25}$$

$$\begin{aligned} GOV^{from}_{trans_t} = {} & A_{gov^{from}_{trans_t}} D_{wd} + \varphi_{gov^{from}_{trans_1}} D_{trend^{+}_{weekly}} D_{wd} + \varphi_{gov^{from}_{trans_2}} D_{trend^{+}_{dom}} D_{wd} \\ & + \varphi_{gov^{from}_{trans_3}} D_{trend^{+}_{moy}} D_{wd} + \varphi_{gov^{from}_{trans_4}} D_{trend^{+}_{qoy}} D_{wd} \\ & + \varphi_{gov^{from}_{trans_5}} D_{trend^{+}_{yearly}} D_{wd} + \omega_{gov^{from}_{trans_1}} D_{sdm_{gov^{from}_{trans_1}}} D_{wd} \\ & + \omega_{gov^{from}_{trans_2}} D_{sdm_{gov^{from}_{trans_2}}} D_{wd} + AR_i + MA_i \end{aligned} \tag{26}$$

$$\begin{aligned} GOV^{to}_{trans_t} = {} & A_{gov^{tom}_{trans_t}} + \varphi_{gov^{to}_{trans_1}} D_{trend^{-}_{weekly}} + \varphi_{gov^{to}_{trans_2}} D_{trend^{+}_{moy}} + \varphi_{gov^{to}_{trans_3}} D_{trend^{+}_{qoy}} \\ & + \varphi_{gov^{to}_{trans_4}} D_{trend^{-}_{yearly}} + \left[\omega_{gov^{to}_{trans}} D_{sdm_{gov^{to}_{trans}}} \right] + AR_i + MA_i \end{aligned} \tag{27}$$

$$\begin{aligned} GOV^{to}_{trans_t} = {} & A_{gov^{tom}_{trans_t}} D_{wd} + \varphi_{gov^{to}_{trans_1}} D_{trend^{-}_{weekly}} D_{wd} + \varphi_{gov^{to}_{trans_2}} D_{trend^{+}_{moy}} D_{wd} \\ & + \varphi_{gov^{to}_{trans_3}} D_{trend^{+}_{qoy}} D_{wd} + \varphi_{gov^{to}_{trans_4}} D_{trend^{-}_{yearly}} D_{wd} \\ & + \left[\omega_{gov^{to}_{trans}} D_{sdm_{gov^{to}_{trans_t}}} D_{wd} \right] + AR_i + MA_i \end{aligned} \tag{28}$$

Where, $D_{sd_{gov^{from}_{trans_1}}}$ and $D_{sd_{gov^{from}_{trans_2}}}$ represent to dummy variables reflecting the tendency of $GOV_{trans^{FROM}_t}$ with regards to special patterns that happen to occur, on a continuous basis, almost exactly on the same period of each month. These patterns occur during the period from 2nd to the 6th day of each month as it is assumed to be captured by $D_{sd}{}_{gov^{from}_{trans_1}}$ and from the 18th to the 23rd day of each month as it is assumed to be captured by $D_{sd}{}_{gov^{from}_{trans_2}}$. For this reason, these dummies take a value of 1 during these days, and 0 otherwise. $D_{sdm}{}_{gov^{to}_{trans_t}}$ represent dummy variables reflecting the tendency of $GOV_{trans^{to}_t}$ with regards to special patterns that happen to occur on a continuous basis almost exactly on the same period of each month, which occur to be day 7th to day 16th of the months, and for this reason it takes a value of 1 during these days, 0 otherwise.

The next indicator (GOV_{TB_t}) is an autonomous factor-related component that refer to the total level of government securities that are issued $(GOV^{issue}_{TB_t})$ in the form of treasury bills and bonds, in both foreign and domestic currency each week on a regular basis, as well as the level being maturated $(GOV^{mat}_{TB_t})$ each week, on a regular basis. These indicators, as presented graphically on Figure 5, share nearly the same patterns as government revenues and expenditure, with the difference that both of them exhibit also some patterns that as related especially to the fourth day of the week. For these reasons, both of them are expressed as follows:

$$GOV^{issue}_{TB_t} = A_{gov^{issue}_{TB_t}} + \varphi_{gov^{issue}_{TB_1}} D_{trend_{\bar{m}oy}} + \varphi_{gov^{issue}_{TB_2}} D_{trend_{\bar{q}oy}} + \omega_{gov^{issue}_{TB}} D_{sdm}{}_{gov^{issue}_{TB}} + \tau_{gov^{issue}_{TB}} D_{sdw}{}_{gov^{issue}_{TB}} + AR_i + MA_i \tag{29}$$

$$GOV^{issue}_{TB_t} = A_{gov^{issue}_{TB_t}} D_{wd} + \varphi_{gov^{issue}_{TB_1}} D_{trend_{\bar{m}oy}} D_{wd} + \varphi_{gov^{issue}_{TB_2}} D_{trend_{\bar{q}oy}} D_{wd} + \omega_{gov^{issue}_{TB}} D_{sdm}{}_{gov^{issue}_{TB}} D_{wd} + \tau_{gov^{issue}_{TB}} D_{sdw}{}_{gov^{issue}_{TB}} D_{wd} + AR_i + MA_i \tag{30}$$

$$GOV^{mat}_{TB_t} = A_{gov^{mat}_{TB_t}} + \varphi_{gov^{mat}_{TB_1}} D_{trend_{\bar{m}oy}} + \varphi_{gov^{mat}_{TB_2}} D_{trend_{\bar{q}oy}} + \omega_{gov^{mat}_{TB}} D_{sdm}{}_{gov^{mat}_{TB}} + \tau_{gov^{mat}_{TB}} D_{sdw}{}_{gov^{mat}_{TB}} + AR_i + MA_i \tag{31}$$

$$GOV^{mat}_{TB_t} = A_{gov^{mat}_{TB_t}} D_{wd} + \varphi_{gov^{mat}_{TB_1}} D_{trend_{\bar{m}oy}} D_{wd} + \varphi_{gov^{mat}_{TB_2}} D_{trend_{\bar{q}oy}} D_{wd} + \omega_{gov^{mat}_{TB}} D_{sdm}{}_{gov^{mat}_{TB}} D_{wd} + \tau_{gov^{mat}_{TB}} D_{sdw}{}_{gov^{mat}_{TB}} D_{wd} + AR_i + MA_i \tag{32}$$

Where, $\omega_{gov^{mat}_{TB}}$ is a vector of coefficients $[\omega_{gov^{mat}_{TB_1}}; \omega_{gov^{mat}_{TB_2}}; \omega_{gov^{mat}_{TB_3}}; \omega_{gov^{mat}_{TB_4}}]$ to be estimated that captures the effect of $D_{sdm}{}_{gov^{mat}_{TB}}$, which is a vector of special days of the months that share the same patterns occurring on a regular basis each month, on the same days. $D_{sdm_{gov_{TB}^{mat}}}$ takes a value of 1 during day 7th up to day 10th and from day 19 up to day 22 of the months, and 0 otherwise. $\tau_{gov_{TB}^{issue}}$ is a coefficient to be estimated that captures the effect of those patterns occurring on the same day of the week, which in this case is the fourth day of the week (Thursday). For this reason $D_{sdw_{gov_{TB}^{issue}}}$ takes a value of 1, if it is the fourth day of the week, and 0 otherwise. These element hold the same characteristics also in the case of $GOV_{TB_t}^{mat}$, but with the difference of entering the model with a lag effect.

Following this, the central bank also offers standing facilities for overnight deposits and loans, which, apart from fulfilling the reserve requirement, are instruments available to second-tier banks without any quantitative restrictions and which serve to invest excess liquidity or borrow liquidity with a one-day term. As suggested by Molnar (2010), they are mainly recognized as stable tools that support the daily liquidity management of credit institutions. In this context, Figure (6) in the appendix shows the performance of liquidity flows related to the instrument of permanent facilities such as overnight credit. This indicator is provided by the Bank of Albania and constitutes a short-term debt instrument that is made available to second-tier banks and is dictated by an autoregressive behaviour. This characteristic feature is also accompanied by other developments, the performance of which shows an upward trend with a seasonal character, but also by episodes which are estimated to be related to specific days in which the banks at the end of the actions result in a lack liquidity. Under these conditions, they make a request for overnight loans in order to meet the necessary level of reserve requirements. This includes the required reserve level that each of the banks must maintain during the relevant period and is calculated by applying the required reserve rate for each category of liabilities included in the reserve base. For this reason, in the case of the one-day deposit issued $(BoA_{dep_t}^{issue})$ and matured $(BoA_{dep_t}^{MAT})$, their behavior or expectations are assumed to be a function according to an empirical approach expressed as a model specified as follows:

$$BoA_{dep_t}^{issue} = A_{BoA_{dep_t}^{issue}} + \varphi_{BoA_{dep_1}^{issue}} D_{trend_{moy}^{+}} + \varphi_{BoA_{dep_2}^{issue}} D_{trend_{qoy}^{+}} + \varphi_{BoA_{dep_3}^{issue}} D_{trend_{year}^{+}} + \omega_{BoA_{dep_i}^{issue}} \left[B_{BoA_{dep_i}^{issue}} \right] + AR_i + MA_i \tag{33}$$

$$BoA_{dep_t}^{issue} = A_{BoA_{dep_t}^{issue}} D_{wd} + \varphi_{BoA_{dep_1}^{issue}} D_{trend_{moy}^{+}} D_{wd} + \varphi_{BoA_{dep_2}^{issue}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{BoA_{dep_3}^{issue}} D_{trend_{year}^{+}} D_{wd} + \omega_{BoA_{dep_i}^{issue}} \left[B_{BoA_{dep_i}^{issue}} D_{wd} \right] + AR_i + MA_i \tag{34}$$

$$BoA_{dep_t}^{MAT} = A_{BoA_{dep_t}^{MAT}} + \varphi_{BoA_{dep_1}^{MAT}} D_{trend_{moy}^{+}} + \varphi_{BoA_{dep_2}^{MAT}} D_{trend_{qoy}^{+}} + \varphi_{BoA_{dep_3}^{MAT}} D_{trend_{year}^{+}} + \omega_{BoA_{dep_i}^{MAT}} \left[B_{BoA_{dep_i}^{MAT}} \right] + AR_i + MA_i \tag{35}$$

$$BoA_{dep_t}^{MAT} = A_{BoA_{dep_t}^{MAT}} D_{wd} + \varphi_{BoA_{dep_1}^{MAT}} D_{trend_{moy}^{+}} D_{wd} + \varphi_{BoA_{dep_2}^{MAT}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{BoA_{dep_3}^{MAT}} D_{trend_{year}^{+}} D_{wd} + \omega_{BoA_{dep_i}^{MAT}} \left[B_{BoA_{dep_i}^{MAT}} D_{wd} \right] + AR_i + MA_i \tag{36}$$

Where, $\omega_{BoA_{DEP_i}^{MAT}}$ is a vector of coefficients $[\omega_{BoA_{DEP_1}^{mat}}; \omega_{BoA_{DEP_2}^{mat}}; \omega_{BoA_{DEP_3}^{mat}}]$ that captures the effect of $B_{BoA_{DEP_i}^{MAT}}$, representing a vector $[BoA_{DEP_{t-n}}^{MAT} * D_{sdm_{BoA_{DEP_t}^{MAT}}}]$ multiply by D_{wd}, where $D_{sdm_{BoA_{DEP_t}^{MAT}}}$ represent the set of patterns occurring on regular basis between day 23rd to day 25th of each month. This means that the model includes three explanatory variables where each of them accounts individually for developments according on a regular basis in each of the days linked to the 23rd up to day 25th of each month. For this reason, $D_{sdm_{BoA_{DEP_t}^{MAT}}}$ takes a value of 1 during day 23rd up to day 25th of each months, and 0 otherwise. This is approach is followed also on similar basis with regards to $BoA_{DEP_t}^{issue}$. Others are as previously described.

On the other hand, in the case of liquidity component related to overnight credit facility issued by the central bank $(BoA_{LOAN_t}^{issue})$ and maturated $(BoA_{LOAN_t}^{MAT})$ at a later period of time, in the analysis as presented graphically in Figure (7), we identified elements that these indicators experience some monthly patterns that are common during some specific days close to the new deadline of the reserve requirement set up. In this case, however, we do not see any other patterns that might be related with seasonal or trend effects. That is why, in this case, both these indicators are forecasted using the same approach upon which their behaviour is a function of a set of indicators expressed as follows:

$$BoA_{loan_t}^{issue} = A_{BoA_{loan_t}^{issue}} + \omega_{BoA_{loan_i}^{issue}} \left[B_{BoA_{loan_i}^{issue}}\right] + AR_i + MA_i \tag{37}$$

$$BoA_{loan_t}^{issue} = A_{BoA_{loan_t}^{issue}} + \omega_{BoA_{loan_i}^{issue}} \left[B_{BoA_{loan_i}^{issue}} D_{wd}\right] + AR_i + MA_i \tag{38}$$

$$BoA_{loan_t}^{mat} = A_{BoA_{loan_t}^{mat}} + \omega_{BoA_{loan_i}^{mat}} \left[B_{BoA_{loan_i}^{mat}}\right] + AR_i + MA_i \tag{39}$$

$$BoA_{loan_t}^{mat} = A_{BoA_{loan_t}^{mat}} + \omega_{BoA_{loan_i}^{mat}} \left[B_{BoA_{loan_i}^{mat}} D_{wd}\right] + AR_i + MA_i \tag{40}$$

Where, as it is the case explained previously, $\omega_{BoA_{loan_i}^{issue}}$ is a vector of coefficients $[\omega_{BoA_{LOAN_1}^{issue}}; \omega_{BoA_{LOAN_2}^{issue}}; \omega_{BoA_{LOAN_3}^{issue}}; \omega_{BoA_{LOAN_4}^{issue}}]$ that captures the effect of $B_{BoA_{loan_i}^{issue}}$, representing a vector of $[BoA_{loan_{t-n}}^{issue} * D_{sdm_{BoA_{loan_t}^{issue}}}]$, where $D_{sdm_{BoA_{loan_t}^{issue}}}$ represent the set of patterns occurring on a regular basis between day 21st to day 24th of each month. This means that the model includes four explanatory variables. Each of them accounts individually for developments occurring on regular basis in each of the days linked to the 21st up to day 24th of each month. For this reason, $D_{sdm_{BoA_{loan_t}^{mat}}}$ takes a value of 1 during these days, and 0 otherwise. In the case of $\omega_{BoA_{loan_i}^{mat}}$, these set of coefficients captures the effect of developments associated with maturity of loan following the next days. For this reason $D_{sdm_{BoA_{loan_t}^{mat}}}$ takes value of 1 for the days between 22nd and 25th of each months, and 0 otherwise. In the case of $BoA_{loan_t}^{issue}$ and $BoA_{loan_t}^{mat}$ we found no evidence of trend episodes occurring with the indicators. For this reason we did not include any dummy variables that captures such effects. Others have been previously explained already.

The next indicator serving as a model, is the level of repo provided on each regular week by the Bank of Albania $(BoA_{repo_t}^{issue})$ and maturated on the given date $(BoA_{repo_t}^{mat})$. These indicators, presented as patterns in Figure 8, are also affected by some monthly patterns that are common during some specific days close to the new deadline of the reserve requirement set up, but we do not see any other patterns that might be related with seasonal or trend effects. These events coincide close to the new deadline for (maintaining) the establishment of the new required mandatory reserve holdings, beyond which no other factors are observed that may be related to seasonal effects or the downward or upward trend as explained above. For these reasons, as with $BoA_{LOAN_t}^{issue}$ and $BoA_{LOAN_t}^{MAT}$, they are forecasted during an empirical model that is expressed as follows:

$$BoA_{repo_t}^{issue} = A_{BoA_{repo_t}^{issue}} + \varphi_{BoA_{repo_1}^{issue}} D_{trend_{qoy}^{+}} + \varphi_{BoA_{repo_2}^{issue}} D_{trend_{yearly}^{+}} + \omega_{BoA_{repo}^{issue}} D_{sdm_{BoA_{repo_t}^{issue}}} + AR_i + MA_i \tag{41}$$

$$BoA_{repo_t}^{issue} = A_{BoA_{repo_t}^{issue}} D_{wd} + \varphi_{BoA_{repo_1}^{issue}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{BoA_{repo_2}^{issue}} D_{trend_{yearly}^{+}} D_{wd} + \omega_{BoA_{repo_i}^{issue}} \left[B_{BoA_{repo_i}^{issue}} D_{wd}\right] + AR_i + MA_i \tag{42}$$

$$BoA_{repo_t}^{mat} = A_{BoA_{repo_t}^{mat}} + \varphi_{BoA_{repo_1}^{mat}} D_{trend_{qoy}^{+}} + \varphi_{BoA_{repo_2}^{mat}} D_{trend_{yearly}^{+}} + \omega_{BoA_{repo_i}^{mat}} \left[B_{BoA_{repo_i}^{mat}}\right] + AR_i + MA_i \tag{43}$$

$$BoA_{repo_t}^{mat} = A_{BoA_{repo_t}^{mat}} D_{wd} + \varphi_{BoA_{repo_1}^{mat}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{BoA_{repo_2}^{mat}} D_{trend_{yearly}^{+}} D_{wd} + \omega_{BoA_{repo_i}^{mat}} \left[B_{BoA_{repo_i}^{mat}} D_{wd}\right] + AR_i + MA_i \tag{44}$$

Where, akin to the previously explained case, $\omega_{BoA_{repo_i}^{issue}}$ is a vector of coefficients $[\omega_{BoA_{repo_1}^{issue}}; \omega_{BoA_{repo_2}^{issue}}; \omega_{BoA_{repo_3}^{issue}}; \omega_{BoA_{repo_4}^{issue}}]$ that captures the effect of $B_{BoA_{repo_i}^{issue}}$, representing a vector of $[BoA_{repo_{t-n}}^{issue} * D_{sdm_{BoA_{repo_t}^{issue}}}]$, where $D_{sdm_{BoA_{repo_t}^{issue}}}$ represents the set of patterns occurring on a regular basis between day 21st to day 24th of each month. This means that the model includes four explanatory variables. Each of them accounts individually for developments occurring on a regular basis in each of the days linked to the 21st up to day 24th of each month. For this reason, $D_{sdm_{BoA_{REPO_t}^{issue}}}$ takes a value of 1 during these days, and 0 otherwise. In the case of $\omega_{BoA_{repo_i}^{mat}}$, these set of coefficients capture the effect of developments associated with maturity of loan following the next week.

On the other hand, liquidity flows are determined by the execution of open market regulatory operations, such as liquidity flows related to (reverse) repurchase agreements with maturities of one day, one month and three months. The purpose of their use is to adjust the unexpected fluctuations in the market. This liquidity instrument is provided upon request by banks operating in Albanian financial market that need an additional capital, which is outside the regular level provided each week by the Bank of Albania. This set of REPO can be at longer maturity that can last up to three months, represented by $BoA_{repo_t}^{issue^*}$ and $BoA_{repo_t}^{mat^*}$. In this case, Figure

9, shows that developments are common with respect to annual upward/downward trends and some non-seasonal patterns that refer to a sort of autoregressive behaviour related to monthly and quarterly specific issues, and for these reasons, they are expressed mathematically as follows:

$$BoA^{issue^*}_{repo_t} = A_{BoA^{issue^*}_{repo_t}} + \varphi_{BoA^{issue^*}_{repo}} D_{trend^+_{yearly}} + \omega_{BoA^{issue^*}_{repo_i}} \left[B_{BoA^{issue^*}_{repo_i}}\right] + AR_i + MA_i \tag{45}$$

$$BoA^{issue^*}_{repo_t} = A_{BoA^{issue^*}_{repo_t}} D_{wd} + \varphi_{BoA^{issue^*}_{repo}} ?_{trend^+_{yearly}} D_{wd} + \omega_{BoA^{issue^*}_{repo_i}} \left[B_{BoA^{issue^*}_{repo_i}} D_{wd}\right] + AR_i + MA_i \tag{46}$$

$$BoA^{mat^*}_{repo_t} = A_{BoA^{mat^*}_{repo_t}} + \varphi_{BoA^{mat^*}_{repo}} D_{trend^+_{yearly}} + \omega_{BoA^{mat^*}_{repo_i}} \left[B_{BoA^{mat^*}_{repo_i}}\right] + AR_i + MA_i \tag{47}$$

$$BoA^{mat^*}_{repo_t} = A_{BoA^{mat^*}_{repo_t}} D_{wd} + \varphi_{BoA^{mat^*}_{repo}} D_{trend^+_{yearly}} D_{wd} + \omega_{BoA^{mat^*}_{repo_i}} \left[B_{BoA^{mat^*}_{repo_i}} D_{wd}\right] + AR_i + MA_i \tag{48}$$

Where, as it is the case explained previously, $\omega_{BoA^{issue^*}_{repo_i}}$ and $\omega_{BoA^{mat^*}_{repo_i}}$ are vectors of coefficients $[\ \omega_{BoA^{issue^*}_{REPO_1}}; \omega_{BoA^{issue^*}_{repo_1}}; \omega_{BoA^{issue^*}_{repo_3}}; \omega_{BoA^{issue^*}_{repo_4}}\ ]$ and $[\ \omega_{BoA^{mat^*}_{repo_1}}; \omega_{BoA^{mat^*}_{repo_2}}; \omega_{BoA^{mat^*}_{repo_3}}; \omega_{BoA^{mat^*}_{repo_4}}\ ]$ that capture the effect of $BoA^{issue^*}_{repo_t}$ and $BoA^{mat^*}_{repo_t}$, representing a vector of $[BoA^{issue^*}_{repo_{t-n}} * D_{sdm_{BoA^{issue^*}_{repo_t}}}]$ and $[BoA^{mat^*}_{repo_{t-n}} * D_{sdm_{BoA^{mat^*}_{repo_t}}}]$ where $D_{sdm_{BoA^{issue^*}_{repo_t}}}$ represents the set of patterns occurring on a regular basis between day 21st to day 24th of each month and $D_{sdm_{BoA^{mat^*}_{repo_t}}}$ represents the set of patterns occurring on a regular basis between day 20 to day 23 of each month. This means that each model includes four explanatory variables. Each of these variables accounts individually for developments according on a regular basis in each of the days linked to those days of the month. For this reason, $D_{sdm_{BoA^{issue^*}_{repo_t}}}$ and $D_{sdm_{BoA^{mat^*}_{repo_t}}}$ takes a value of 1 during these days, and 0 otherwise. This is the reason anticipate their liquidity flows is based upon a linear empirical function, expressed as follows:

$$BoA^{issue^{total}}_{repo_t} = BoA^{issue}_{repo_t} + BoA^{issue^*}_{repo_t} \tag{49}$$

And,

$$BoA^{mat^{total}}_{repo_t} = BoA^{mat}_{repo_t} + BoA^{mat^*}_{repo_t} \tag{50}$$

Then,

$$\Delta BoA_{repo_t} = BoA^{issue^{total}}_{repo_t} - BoA^{mat^{total}}_{?epo_t} \tag{51}$$

Another important indicator is related to the liquidity flows as a result of required level of reserve subject to which are banks and branches of foreign banks licensed by the Bank of Albania. The reserve base includes liabilities resulting from the acceptance of funds from banks, reflected in their accounting balance, in ALL and in foreign currency. The basis of the foreign currency reserve consists of liabilities in dollars and liabilities in euros, where liabilities in euros, in addition to liabilities in the common currency, include all liabilities in other currencies, except for the dollar converted at the fixed rate of the Bank of Albania on the last day of base period[10]. Therefore, as represented by BoA_{RR}^{+} and BoA_{RR}^{-}, their flows[11] level during the maintenance period are forecasted based on the analysis of their graphical performance, as represented in Figure (10). The former represents any level of holdings being added up. The latter represents any level of holdings being lowered down. Figure 10 shows also that these indicators exhibit moment patterns related commonly with day 23 to day 25 of the months, and other than that, patterns have an autoregressive behaviour that are not seasonal apart for showing some relationship with trend effect over time. As in earlier case, the forecasting approach for these indicators is also done by building an empirical model that in each case is expressed also following the same approach, with some different personalized elements, which are shown as follows:

$$BoA_{RR_t}^{+} = A_{BoA_{RR_t}^{+}} + \varphi_{BoA_1^{+}} D_{trend_{qoy}^{+}} + \varphi_{BoA_2^{+}} D_{trend_{yearly}^{+}} + \omega_{BoA_{RR_i}^{+}} \left[B_{BoA_{RR_i}^{+}} \right] + AR_i + MA_i \quad (52)$$

$$\begin{aligned} BoA_{RR_t}^{+} = {} & A_{BoA_{RR_t}^{+}} D_{wd} + \varphi_{BoA_1^{+}} D_{trend_{qoy}^{+}} D_{wd} + \varphi_{BoA_2^{+}} D_{trend_{yearly}^{+}} D_{wd} \\ & + \omega_{BoA_{RR_i}^{+}} \left[B_{BoA_{RR_i}^{+}} D_{wd} \right] + AR_i + MA_i \end{aligned} \quad (53)$$

$$BoA_{RR_t}^{-} = A_{\square oA_{RR_t}^{-}} + \varphi_{BoA_1^{-}} D_{trend_{qoy}^{-}} + \varphi_{BoA_2^{-}} D_{trend_{yearly}^{+}} + \omega_{BoA_{RR_i}^{-}} \left[B_{BoA_{RR_i}^{-}} \right] + AR_i + MA_i \quad (54)$$

$$\begin{aligned} BoA_{RR_t}^{-} = {} & A_{BoA_{RR_t}^{-}} D_{wd} + \square_{BoA_1^{-}} D_{trend_{qoy}^{-}} D_{wd} + \varphi_{BoA_2^{-}} D_{trend_{yearly}^{+}} D_{wd} \\ & + \omega_{BoA_{RR_i}^{-}} \left[B_{BoA_{RR_i}^{-}} D_{wd} \right] + AR_i + MA_i \end{aligned} \quad (55)$$

[10] *For banks subject to minimum reserve requirements, the balance sheet data at the end of the month are used to determine the reserve base for the maintenance period starting in the next calendar month.*

[11] *The reserve ratio is the percentage of the required reserve base held at the Bank of Albania. The Bank of Albania may change the reserve ratio at any time with a decision of its Supervisory Council. The Bank of Albania requires all banks and branches of the foreign banks licensed by Bank of Albania, operating within the territory of the Republic of Albania and having accounts on the payment system of the Bank of Albania, to hold minimum reserves.*

Where, as it is the case explained previously, $\omega_{BoA^{+}_{RR_i}}$ and $\omega_{BoA^{-}_{RR_i}}$ are vectors of coefficients $[\omega_{BoA^{+}_{RR_1}}; \omega_{BoA^{+}_{RR_2}}; \omega_{BoA^{+}_{RR_3}}]$ and $[\omega_{BoA^{-}_{RR_1}}; \omega_{BoA^{-}_{RR_2}}; \omega_{BoA^{-}_{RR_3}}]$ that capture the effect of $BoA^{+}_{RR_t}$ and $BoA^{-}_{RR_t}$ representing a vector of $[BoA^{+}_{RR_{t-n}} * D_{sdm_{BoA^{+}_{RR_t}}}]$ and $[BoA^{-}_{RR_{t-n}} * D_{sdm_{BoA^{-}_{RR_t}}}]$ while $D_{sdm_{BoA^{-}_{RR_t}}}$ represents the set of patterns occurring on a regular basis between day 23 to day 25 of each month, and represents the set of patterns occurring on a regular basis between day 24 to day 26 of each month. This means that each model includes also three explanatory variables. Each of these variables accounts individually for developments according on a regular basis in each of the days linked to those days of the month. For this reason, as in the previous cases, $D_{sdm_{BoA^{+}_{RR_t}}}$ and are two dummy variables that each of them takes a value of 1 during these days, and 0 otherwise.

Furthermore, among other crucial element being modelled in this analysis is the component related to the involvement of the Bank of Albania in buying (issuing) government T-Bills and their maturation according to their duration. The indicator, in each case as Figure 11 demonstrates, is affected by autoregressive behaviour and trend patterns that are either monthly related or quarterly. For these reasons, both of them are forecasted using an empirical model expressed as follows:

$$BoA_{TB_t^{issue}} = A_{BoA_{TB_t}^{issue}} + [\varphi_{BoA_{TB_i}^{issue}} D_{trend_i^{issue}}] + AR_i + MA_i \tag{56}$$

$$BoA_{TB_t^{issue}} = A_{BoA_{TB_t}^{issue}} D^{*}_{dow} + [\varphi_{BoA_{TB_i}^{issue}} D_{trend_i^{issue}} D^{*}_{dow}] + AR_i + MA_i \tag{57}$$

$$BoA_{TB_t^{mat}} = A_{BoA_{TB_t}^{mat}} + [\varphi_{BoA_{TB_i}^{mat}} D_{trend_i^{mat}}] + AR_i + MA_i \tag{58}$$

$$BoA_{TB_t^{mat}} = A_{BoA_{TB_t}^{mat}} D^{*}_{dow} + [\varphi_{BoA_{TB_i}^{mat}} D_{trend_i^{mat}} D^{*}_{dow}] + AR_i + MA_i \tag{59}$$

Where, $\varphi_{BoA_{TB_i}^{issue}}$ and $\varphi_{BoA_{TB_i}^{mat}}$ are vectors of coefficients $[\varphi_{BoA_{TB_1}^{issue}}; \varphi_{BoA_{TB_2}^{issue}}; \varphi_{BoA_{TB_3}^{issue}};]$ and $[\varphi_{BoA_{TB_1}^{mat}}; \varphi_{BoA_{TB_2}^{mat}}; \varphi_{BoA_{TB_2}^{mat}}]$ that captures the trend effects as represented by $D_{trend_i^{issue}}$ and $D_{trend_i^{mat}}$ that are vectors of seasonal trends being represented by $[D_{trend^{+}_{moy}}; D_{trend^{+}_{qoy}}; D_{trend^{+}_{yearly}}]$; D^{*}_{dow} is a dummy variables. It captures the special day in which auctions related to government securities are organized by the Bank of Albania. Analysis suggests that this episodes occur on a special same day once in two weeks. This special day corresponds to be the fourth day of the week (Thursday). This means that in two weeks there is only one episode happening. This episode takes place the next two weeks on the same day as before. For this reason, D^{*}_{dow} takes a value of 1 if it is the fourth day of the week corresponding to the auction week, and 0 otherwise.

Finally, Figure 12 shows patterns for another component that determines the level of liquidity in the market, which is related to the level of foreign reserve (BoA_{IR_t}) that a central bank, in this case the Bank of Albania, buys $(BoA_{IR_t^{buy}})$ and sells $(BoA_{IR_t^{sell}})$ according to their strategic management of reserve holdings. However, analysis suggests that Bank of Albania through our sample time has used this instrument by only buying reserve ad not selling it. Therefore, we have only modelled $BoA_{IR_t^{buy}}$, which is expressed as follows:

$$BoA_{IR_t^{buy}} = A_{BoA_{IR_t^{buy}}} + [\varphi_{BoA_{IR}^{buy}} D_{trend^{+}_{qoy}}] + AR_i + MA_i \tag{60}$$

$$BoA_{IR_t^{buy}} = A_{BoA_{IR_t^{buy}}} D_{wd} + [\varphi_{BoA_{IR}^{buy}} D_{trend^{+}_{qoy}} D_{wd}] + AR_i + MA_i \tag{61}$$

Where, $\varphi_{BoA_{IR}^{buy}}$ captures the trend effects as represented by $D_{trend^{+}_{qoy}}$ that is a dummy variable reflecting the quarterly trend of $BoA_{IR_t^{buy}}$. Others are as previously explained.

2.2.the Estimation approach of the forecasting model

One crucial element that is worth to consider, referring to the focus of this paper, is the fact that most of financial time series data with high frequency, as it is in this study[12], have shown that their conditional distribution exhibit several stylized features such as excess kurtosis, negative skewness, outliers and leverage effects,

[12] *In this case, data analysis as represented in Figure 1, with regards to overnight rate volatility, and in Figure 2 to 13, referring to patterns of both autonomous and non-autonomous factors, suggest that these data display a great extent of market seasonality, comprising weekly, monthly and annual patterns plus some calendar effects, and also some degree of volatility, which can be defined as a measure of the dispersion in a probability density.*

time-varying volatility, and volatility clustering. These stylized facts are important enough to demonstrate the need to find and adapt a perfect strategy for identifying each of the components and/or defining features that explains the modelling of volatile behaviours. On the other hand, these elements carry and imply other important limitations for modelling and assessing accurately the volatility of the behaviour of financial indicators. This is a difficult obstacle for predicting future (expected) needs for liquidity, for which market players and investors in the financial sector are fully interested. This means that estimating the volatility in this case is very crucial, since it is among the main components that determine the ability to anticipate correctly expected liquidity needs of the banking system. It is notable, however, that model specification is important for at least three reasons. First, anticipating future liquidity needs typically incorporates properties related to forecast volatility. Second, volatility in the financial market for liquidity needs is not directly observable and as a result there is increasing need for an efficient modelling approach that can capture such volatility patterns. Similarly, identifying each of the deterministic components of liquidity needs, makes the modelling of each indicator not simple, and requires a special identification strategy of such components given that we are dealing with daily data.

For these reasons, to capture these stylised facts in our dataset and to solve these issues, all models that take a specification approach as expressed in equation (12) to (16), are estimated using a threshold Generalized Autoregressive Conditionally Heteroscedastic (TGARCH) model of stochastic volatility approach, proposed by Zakoian (1994). This is an alternative approach, among the variety of forms, known as GARCH(p, q) models, which is popular for measuring and forecasting volatility by financial practitioners [Goldman and Shen (2018)]. It allows to model volatility dynamics as a threshold model to accommodate the regime switching in volatility, while volatility follows a GARCH process within each regime[13], where p and q are positive integers that define the resulting GARCH model and its forecasts. In most of these cases a TGARCH(1, 1) is sufficient and is most generally used

[13] *These volatilities are used to value the options as usual, but the amount of historical data necessary for a good volatility estimate remains significant. Usually, several dozen, and even up to hundreds, of data points are required to obtain good GARCH estimates.*

mainly in analysing and forecasting financial time-series data to handle leverage effects and to ascertain their conditional variances and volatilities, and assumes that the conditional variance is defined as a linear function of lagged conditional variances and squared past developments, which takes the form of:

$$Y_t = X_t\gamma + \varepsilon_t \tag{62}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta D\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{63}$$

$$D_{t-1} = \begin{cases} 1 \ \varepsilon_{t-1} < 0 \\ 0 \ \varepsilon_{t-1} \geq 0 \end{cases} \tag{64}$$

Where, the first equation's dependent variable (Y_t) is a function of exogenous variables (X_t) with a Gaussian (or other distribution) error term (ε_t), considered to be a series of innovations that are usually assumed to be independent identically distributed (i.i.d.) with a zero-mean random variable; and γ is an asymmetric term capturing risk aversion. The second equation estimates the variance (squared volatility σ_t^2) given information at time t, of the GARCH(p, q) model for the time series, which depends on a historical mean (ω), news about volatility from the previous period, measured as a lag of the squared residual from the mean equation (ε_{t-1}^2), and volatility from the previous period (σ_{t-1}^2), and coefficients, α and β are GARCH parameters[14]; added term δ reflects a degree of asymmetric response in the GARCH term[15].

This means that TGARCH approach, as suggested by different authors[16], is another volatility model approach that can be viewed as a special case of the random coefficient GARCH model, and its advantage over other methods is that it is built to address irregular pattern of variation of an error term, or variable, in a statistical model. The TGARCH models also relax the linear restriction on the conditional variance dynamics. Essentially, where there is heteroscedasticity, observations do not conform to a linear pattern.

[14] *As Goldman (2017) suggests, in a TGARCH model both coefficients, and , in the GARCH model are allowed to change to reflect the asymmetry of volatility due to negative shocks.*

[15] *Goldman and Shen (2018) suggest that by allowing both ARCH and GARCH parameters to change with negative news results in better statistical fit and smaller information criteria.*

[16] *See among others Engle (1982); Glosten, et al. (1993); and Zakoian (1994).*

Instead, they tend to cluster. Though GARCH approach has been proved to be relatively adequate for explaining the dependence structure in conditional variances, the literature suggests that this approach contains some important limitations, one of which is that they may fail to capture the stylised fact that the conditional variance tends to be different at different time horizon. That is why in our analysis, however, specification as addressed in equation (15) and (16), whose reduced form are expressed through equation (17) and (18), are re-estimated using also a simple Ordinary Least Squares (OLS) as a robustness check analysis[17]. The OLS, as a proper optimal in the class of linear unbiased estimators, however, requires that regression errors are normal and identically and independently distributed. The latter implies that the explanatory variables are exogenous, where errors are serially uncorrelated and homoscedastic and there is no perfect multicollinearity. The decision to the OLS estimator is also related to the fact that the stylized facts, however, show that drivers of liquidity patterns can also be described by an autoregressive behaviour that may be potentially captured by including some AR and MA terms in the model specification, and according to the assumptions stated above, their inclusion makes errors serially uncorrelated and normally distributed. This implies that the OLS estimation approach is the maximum likelihood estimator that is strongly believed to provide also minimum-variance mean-unbiased estimation, at least when the errors have finite variances.

2.3.some other data issues

The sample consists of daily data for the period January 1, 2008 up to Mars 03, 2020. The dataset consists of a total number of 4749 observation. Data on deposit standing facility represent stock value. The rest of the data represent flow values. All indicators represent end period values. Their values are based on daily data according to a week with 7-day approach. The information related to this dataset is taken from the Bank of Albania. Given the assumptions that ε_t is i.i.d. distributed variable with D(0,1) and

[17] *A similar identification and forecasting strategy follows also in the spirit of that proposed by Box and Tiao (1975) and Bell and Hillmer (1983), and is used by Cabrero, et al. (2002) for such forecasting purposes.*

independent of σ_t, we examine the conditions for the existence of stationary properties as well as the mean in the TGARCH model. That is why all data have been analysed for such properties using the Augmented Dickey Fuller and Phillip Perrot Unit Root Test analysis[18], upon which all the data enter the model specification as explained above in level based on the results of unit root approach. This means that all data, besides binary variables (dummy), have been analysed for their stationarity properties. All indicators enter the model in their nominal values.

[18] *Results can be provided upon request.*

3. ANALYSIS OF THE EMPIRICAL RESULTS

In this section, we explore the extent to which our proposed empirical approach has the ability to accurately forecast liquidity needs of the banking system in the case of Albania, with respect to an aggregated level and to each of the individual deterministic component belonging either to autonomous or non-autonomous factors. The idea is to check whether the proposed approach is capable to anticipate with the smallest error term each of the deterministic component of market liquidity needs and whether a combination of this set of the individual forecasts, could provide an alternative approach with a smaller error term. The standard time series literature, however, assumes that there is a true model for a given time series and that this model is known before it is fitted to the data. After the 'true' model is fitted to the data, the same model is, then, used for forecasting their behaviour in the future. Regarding econometric models, the model may be incorrectly specified apriority or the estimated parameters may be mistakenly assumed to be fixed, at a time when their size is changing over time. In addition, the typical uncertainty problem associated with forecasting specific times series, as it is the case, arises because the used model is defined, fitted and tested using the same set of data, which comes as the expected future values are assumed to be mostly a function of an autoregressive behaviour. One model that seems to fit the underlying data best, may be selected as a 'winner', despite that the other models seem to be a very close fit to the one selected, and hence an aggregation approach might be an alternative possibility. This means that the properties of an estimator may depend not only on the selected model, but also on the selection process.

For this reason, two elements are worth considering when checking the quality of forecast accuracy. One of these elements is related to the need to choose the right forecast time horizon, which in our case is selected upon the suggestions of Gray (2008). This author reveals that, for the purpose of liquidity management, the central bank ideally needs to undertake a daily forecast for the coming weeks, in particular, at least until the end of the current reserve maintenance period[19]. However, as this author suggests, if the set of monetary policy instruments of the central bank includes longer term operations, then, there is a good case for producing a rough forecast of the central bank balance sheet for the next few coming months, which should serve as an alternative approach to provide a coverage upon expectations according to such maturities. As argued by him, there might be also some interaction between the length of the maintenance period, and the central bank's ability to produce an accurate forecast. For these reasons, anticipating future liquidity needs is exercised by forecasting daily levels of such needs up to 9 weeks ahead. This time horizon covers at least two months of current reserve maintenance periods. This is assumed to be appropriate for our analysis, which, as suggested, should serve to anticipate the expectation on market liquidity situation from the short term to the medium and long term. A 5-week period forecast horizon is also exercised, and results from both approaches are compared with each other for analysis purposes. This analysis is expected to also provide us with a better understanding on the ability to forecast liquidity needs in the short term over the medium to long term.

The other element is to choose a suitable approach to evaluate ex post forecast accuracy by gauging the quality of the predicted values that each of the forecasting models produce. This approach is conducted for all the specified models as expressed in equation (12) to (16) and estimated by TGARCH and OLS approach as explained previously. In this case, the existing literature recommends among two alternative approaches to evaluate forecast accuracy. One way is to use an error metric approach. This metric approach calculates the forecast accuracy, also called forecast error. This indicator shows the deviation of the actual liquidity values from the forecasted levels, which in this case includes a comparison between our actual data and the in-sample forecast data according to each model and estimation specification technique. This means that if the central bank can calculate the smallest-level of error in the previous forecast it can than factor this into future ones and make the relevant adjustments to its plan on liquidity needs adjustment approach. This

[19] *The author suggests that in case daily data are not available, as it might be the case with some of the components, then a weekly forecast might be needed to be used instead, until data availability can be improved.*

means that we compare forecasted data with actual data and at the same time, we compare also the performance of such forecasts among different estimation techniques. Such comparison approach is arranged by analysing daily data. This includes also analysis of the error term performance based on weekly approximation. This approximation embraces both a 5- and a 9-week-period horizon, and includes analysis for all individual model specification. This would serve to have an understanding over the short-term as well as medium- to longer-term expectation on market liquidity situation. This choice is taken, upon the suggestions by Gray (2008), who believes that one longer than 5 weeks would be very unusual, and might give the market, or banks, too much freedom upon their behaviour to fulfil supervisory binding rules. However, according to this author, if by extend the analysis period from a one or two weeks to four-five weeks would allow for a significant improvement in liquidity management, then this set up should be considered, which is what has been done in this study approach. This approach[20] is a suitable way to quantify the performance of a model and quantitatively compare among the different models. This gives us a way to gauge objectively how well the model executes its tasks. A common intuition process of scrutiny to this set of analysis, as in the case of Cabrero, et al., (2002), is to work out the forecast error metric, based on a set of simple statistical accuracy-evaluation tests, according which the given indicator is forecasted. This rigorous approach includes analysing of the error term accuracy through a set of statistical value related to Root Mean Squared Error (RMSE) test and the Mean Absolute Error (MAE) test applied on error terms retrieved from all the models over the whole forecasting sample as suggested by existing literature[21]. All these statistic tests provide a measure of understanding the distance of the true values from the forecasted values. They are particularly useful for comparing the fitness of different regression models. Since they are negatively-oriented scores, then, the lower their values the better the quality of a certain given model, which in other words is understood as its ability to best "fit" a set of data with actual reality. The results on RMSE and MAE are presented in Figure (13) and (14). Those

[20] *One has to bear in mind that even though there are multiple metrics, each one provides specific information that may or may not be suitable for our analysis given the data involved in making the predictions.*

[21] *See among other Bliemel (1973); Granger and Newbold (1973); and Ahlburg (1984).*

related to Theil Inequality are presented in Figure (15). These results represent the performance of all models over the whole forecasting period (9 weeks)[22] as performed by the TGARCH and the OLS approach.

Starting with the a set of sensitive analysis, results of this paper present a series of important findings, which strongly support the effectiveness of using the empirical approach with daily data and binary indicators for forecasting the liquidity needs of the Albanian banking system, as a complementary alternative for the implementation of monetary policy according to its medium- and long-term strategy. This means that the Bank of Albania can rely on this predictive alternative to better manage the need for liquidity through open market operations, injecting or withdrawing liquidity from it, as in cases where it aims to maintain a shortage within a set band, as well as in those in which the goal is to keep the one-day trading rate in the interbank market around its base rate. First, based on a number of different analyses, it was observed that the results are relatively stable despite the specifications of the models and different evaluative and predictive approaches. Also, the effectiveness of each of the models seems to be reliable, because each of them has performed well enough to predict relatively accurately each of the liquidity components close to their real value. This is confirmed by the results of the RMSE and MAE tests, as presented in Figure (13) and (14). This set of results shows that the statistical value of each of them is relatively low. This is due to the fact that the average difference between the predicted values in each case and the actual values in the data set, which is assumed to be what happened in reality, is relatively small. This difference falls within 1 percent of the true data. On the one hand, this implies that all models have performed almost well enough to provide errors that are relatively close to zero. On the other hand, it also implies that almost all the estimated coefficients and fits, in each of the specified alternative models, give optimistic results in that the performance of the forecast error term provided, according to the in-sample forecasting approach, considered as a new data set, is on average close to the original data. So this confirms once again

[22] *Analysis on a 5-week approach has also been conducted, and results can be provided upon request.*

that all models have a good fit. This makes those models and the evaluation approach followed in each case an important instrument in order to predict, in time and with relatively high accuracy, the future expectations of the banking system's liquidity needs. This is also the main evaluation criterion of a certain metric if its main goal is to predict an indicator with relatively high accuracy. This means that more than one of them can be used to anticipate liquidity needs.

Second, mixing results from different approach or constructing a composite forecast by averaging their forecasts values, however, would be more appropriate. On the one side, it is well known that different models capture different patterns of the data. On the other side, liquidity needs may change through time, e.g. changing seasonality or structural breaks, which are harmonised using different models. This means that this approach can allow us to use them for different parts of the data and averaging their outcomes might be a relatively reasonable approach to have better forecast error. However, since forecast error is also an essential criterion in shortlisting the best performing model among different forecasting models, results on RMSE and MAE scores across all models, suggest that fully specified models as expressed in equation (15) and (16), have almost the lowest scores. This characteristic is evident in almost all cases. Similarly, models estimated through TGARCH approach provide better lower scores than those estimated through OLS techniques. This means that both these elements are essential to produce the lowest error in predicting values for the target variable, which in this case is related to liquidity needs. These findings, including those on daily data, are confirmed also by the results of RMSE and MAE. The results of these tests, which are complementary to correlation test, are found to be relatively lower for those that show a higher degree of parallel matching among daily and weekly patterns of real data with those produced through the set of forecast process.

The best measure of model fit, however, among a different set of statistics tests available for forecast evaluation, is the Theil's Inequality Coefficient test. This test provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values and is also useful for comparing different forecast methods[23]. Results of this test are reported in Figure (15) in theAppendix. Its statistical value is relatively different for each of the forecasted liquidity indicators, but in most cases it is less than 1. Their robustness check is reflected by relatively similar results in all empirical models evaluated, and includes those models evaluated through the TGARCH and OLS approach. This means that in these cases each of the in-sample forecasts complies relatively well with the actual values of the given sample. This means that the models specified according to the approach proposed in this paper have managed to capture relatively well the actual values, in return causing the error values to be relatively small. On the one hand, this means that binary indicators are qualitatively usable to accurately predict each of the liquidity indicators and thus better understand the liquidity needs of the banking system. For this reason, the approach implemented in each case can be used quite well for the prediction of each of the liquidity indicators, including an out-of-sample approach. On the other hand, this is a relatively strong evidence since it proposes that the empirical approach is actually a better way to predict liquidity flows than using those associated with a naive assumption (random walk). This conclusion is valid at least for those liquidity indicators in the case of which the statistical value of the "Theil U" coefficient is lower than 1. However, results imply that this sort of conclusion holds better in two cases. One of the cases is related to models that include a relatively larger number of explanatory indicators. The other case is related to the models evaluated according to the TGARCH approach, although for some indicators the forecast remains qualitatively valid even in the case when the OLS approach is used instead. This stands almost clearly for indicators related to autonomous factors. This is confirmed in the case of all the approaches evaluated empirically. This means that an empirical approach remains qualitatively better at predicting autonomous factors than what can be provided by an alternative approach associated with naive assumptions. This means that empirical approach can be a good and qualitatively alternative approach to anticipate the short-term and long-term expectation over market liquidity situation and its needs with regards to autonomous factors.

[23] *Theil's U statistic is a relative accuracy measure that compares the forecasted results with the results of forecasting with minimal historical data. It also squares the deviations to give more weight to large errors and to exaggerate errors, which can help eliminate methods with large errors.*

However, regardless of the results of this test, the empirical method can also be qualitatively useful for predicting non-autonomous liquidity indicators, because its value closer or even higher than 1 in some cases related to such indicators, can actually be related with random factors that the autoregressive approach fails to capture. This conclusion can be supported, furthermore, by calling in results of another alternative approach. This method measures the accuracy of the error according to the results that gauge the dynamics followed by the actual values of each indicator compared to those forecasted empirically through the in-sample approach, which are then analysed as presented graphically. Results in this case are presented graphically through Figure (16) to (19) for each of the components belonging to the group of autonomous factors. Each of those related to the group of non-autonomous factors are shown in Figure (20) to (25). Figures (26) and (27) represent the results of such analysis for both autonomous and non-autonomous factors aggregated as a single composite indicator. Analysis related to these results includes daily and weekly flows. At the same time, the results related to the progress of the weekly differences that emerge from the differences of actual and forecasted ratio for each of the evaluation approaches, are also reported, as well as a summary progress according to the 9-week and 5-week time horizon, obtained respectively through each of the estimation technique, namely the TGARCH and the OLS approach. This set of figures (graphs), as explained above, includes also a mean forecasting rate. This rate is related to the mean value of all the different forecasting rate through the different specification and estimation techniques.

This set of figures (graphs), as explained above, include also a mean forecasting rate. This rate is related to the mean value of all the different forecasting rate through the TGARCH and OLS technique. As it is commonly known in statistics, an important property of the mean value of a given indicator is that it includes every value in the dataset as part of the calculation. It is also the only measure of central tendency where the sum of the deviations of each value from the mean is always zero. In this case, the mean approach is assumed to account upon a general behaviour, hence, eliminating in this way any occasional deviations due to momentary episodes.

Similarly, this set of analysis is also reported through Figure (28) to (31). The idea is to see whether individual forecast and aggregated forecast data can help the Bank of Albania anticipate liquidity needs with the smallest error, so that it can maintain the monetary policy rate within its primary objectives. An additional similar set of analysis is also conducted upon the comparison between the aggregated actual versus the estimated liquidity market position. This comparative analysis is based also on the in-sample forecast approach. These results are shown graphically through Figure (32) and (33). They also include the scenario with (including) and without (excluding) the net indicator of the Bank of Albania's REPO component, expressed as the difference between issued and maturated REPOs. This is accomplished also with a complementary analysis. It assesses the degree upon which our empirical approach overestimates or underestimates actual data over a 9-week period and according to each estimation approach explained previously. These results are reported in Figure (34). Results in Figure (35) report the same data analysis approach, but in this case they are organised according to autonomous and non-autonomous factors, as well as a mean ratio of all the forecasted indicators. The combination of all this set of approaches is expected to mitigate any potential pitfall confusion concerning our analysis.

Graphical analysis, using daily data and the in-sample approach, shows that almost all dummy specified models have managed to capture the dynamics of the actual behaviour of each of the indicators relatively well. On the one hand, these results are relatively better and more homogeneous in the case of indicators related to autonomous factors. On the other hand, even in the case of other indicators, the forecasting performance remains equally good to the point that their daily flows at the given time are not characterized by a momentary condition, which constitutes an exceptional case (outlier). This means that the approach with binary (dummy) indicators proposed in this paper manages to capture the autoregressive developments quite well. This conclusion is qualitatively evident in the case of forecasting the flow level related to the government's net balance and net money in circulation, and to some extent it is also related to the net performance of government securities. For specific indicators, this relates to government revenues and government transfers from other public institutions compared to those of their counterparts, namely government expenditures and government transfers to other institutions. These are expected results since the analysis, based on other results[24], suggests that government spending and government transfers to other institutions exhibit a relatively more volatile behaviour given also their higher standard deviation rate. This means that these indicators are less stable compared to other indicators and as a result their prediction becomes a little more difficult, although the accuracy of their prediction is better according to the quality of the prediction through the TGARCH approach. This is confirmed both in the case of analysis with daily data and in the case of aggregation with weekly frequency. Similarly, weekly aggregation of the differences between the actual and predicted values, as well as those for longer-time horizons, which are related to the aggregated performance according to the 5-week and 9-week period, confirm that the progress of the forecast remains relatively quite good. However, findings through the last approach show that the results are relatively mixed. In some cases, the magnitude of the error is found to be smaller, such as in the case of forecasts through the TGARCH approach.

In other cases, it turns out that the OLS approach has performed better, making this characteristic a momentary condition rather than a limitation related to the way a model is specified. For example, in the case of government revenues and transfers to other institutions, and at a higher extend with regards to cash in circulation, all specified models have generally managed to anticipate relatively well all patterns through the 9-week-period analysis framework. This is confirmed also by the high rate of correlation, as shown by the results of a simple correlation test released between actual and anticipate values. For some of the indicators belonging to autonomous factors, the rate of correlation is almost close to 100 percentage. These results look relatively better in a 5-week framework. On the other hand, for some of them, results show that the differences between each specified model and their sample mean value, are relatively small in their case. This means that for some of them, all specified models have performed relatively

[24] *These results are based on a simple statistical test as it is the standard deviation and can be provided upon request.*

similar, despite their differences in the methodological aspects. This is why for some of them and almost in all cases, the specified models have produced a results in which the difference between the actual and forecasted value are close to zero. This means that for these indicators, all specified models have managed to anticipate relatively well any extend of patterns related to market seasonality and calendar effects, as well as special moments of time, which are all components that make the modelling and the anticipation of each indicator not simple. This is, however, not the case of the results with regards to net government securities, in which, although all models have managed to relatively capture the big picture, they all failed to recognise the specific elements that might be also related to outliers. This is the case with daily patterns referring to net government securities. However, when discussing about the weekly performance, results show a better portrayal.

In addition, analysis on the each of the non-autonomous factors show that almost all the dummy specified models have managed to also capture, almost relatively well, the dynamics of the actual behavior of each of these indicators. In this case, simple graphical visual orientation based on daily data show that almost all specified model have performed relatively well in terms of anticipating the level of net deposit and lending standing facility. This is also true for indicators related to REPO, reserve requirements and to some degree with the net value of indicator related to participation of the central bank, namely the Bank of Albania, into auction on government securities. These results are expected given that this set of indicators are characterised by low volatility, which is also proven by the results of a simple standard deviation test[25]. This means that all these indicators exhibit a more consistent behaviour, which make them more reliable and easy to forecast, with a greater proportion of predictive accuracy. A comparative analysis, among the main non-autonomous factors driving liquidity flows as expressed by equation (4), shows relatively the same picture and properties, but with some differences from case to case. For example, with regard to deposit standing facility, findings using daily estimation show that all models have managed to capture patterns related to working day or non-working days, but the anticipated level for both

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[25] *These results can be provided upon request.*

issued and maturated ratio, is visibly below the actual level. On the other hand, in the case of credit standing facility, results show that all empirical approaches have managed to capture outlier patterns, but with a time inconsistency lag. This is also reflected at their ratio aggregated on weekly basis. However, in both cases, results show that their net daily and weekly differences are relatively close to the actual value through a 9-week period analysis framework. This is why their mean value is almost close to zero. This is due also to the fact that the difference in these ratio is related to the fact that some models have provided us with overestimated results and some by contrast, have underestimated it. This means that our range of specified models have managed to provide information that is relatively close to the actual ratio, despite the time inconsistency or underestimated value of reported liquidity flow levels. On the other hand, results based on the statistical value of the RMSE approach show that the error term is lower for maturated levels of deposit standing facility. This is confirmed also through the results of MAE. This is also the case with lending standing facility. However, results based on the correlation test as reported in Appendix show a high degree of co-movements for deposit standing facility, which goes at almost relatively close to 100 percentage. This is a property for both issued and maturated deposits. On the other hand, such relatively high ratio are also the property of lending standing facility, but only at the first two weeks. This means that for some of them, all specified models have performed relatively similar despite their differences in the methodological aspects.

Furthermore, results on anticipated level of REPO standing facility provide some supportive evidence on the performance of empirical results related to error accuracy. These results show that all specified models have managed to capture relatively well the flows of regular weekly REPO issued by the Bank of Albania. This is also the case with the other counterparts related with the level maturated on a weekly basis. However, all approaches referring to these two indicators have overestimated the actual level. This is evidently seen more clearly also as data are aggregated on a weekly basis and explicitly better visualised in the comparison between actual and anticipate level. This situation is also found to be the main reason explaining the overestimation that was found on the aggregated level of non-autonomous factors, and despite this lack of accuracy, all models have managed to cope with the changing flows accordingly to each pattern occurring on each specific week. This is the reason that explains also the fact that the daily and the weekly net differences are relatively close to zero. Some models, as seen in Figure (26) in the Appendix, have even managed to provide overall forecasts, which are relatively very close to the actual level. Empirical approach has also managed to fit well with the episodes in which extra REPO have been provided to banks in order to support them upon their demand for liquidity. This result is evident on both daily and weekly patterns, as the value anticipated on non-auction days is relatively close to zero as the actual value shows, which than jumps only on two special days. Looking at REPO patterns from the diagnostic point of view of statistical tests, however, results from RMSE and MAE are mixed. Some models have performed better for REPO issued and some others, for those maturated. Nonetheless, results from correlation test show a high degree of co-movement between actual and anticipated levels, which in some case goes as high as 85 percentage.

Furthermore, among the other remaining components, results of graphical analysis of Figure (22) and (24) suggest that empirical models have performed relatively well in the case of anticipating the flow of reserve holding and the Bank of Albania's participation in the auction of government securities. In both cases, results show that all models have performed relatively well in spotting between those days in which these instruments are actively used and those days for which there is zero "buying" or "selling". This means that in each case, our model specification approach shows a relatively good understanding of the patterns belonging to flows related to both type of factors contributing to increasing and decreasing liquidity in the market. This is the main contributor that explains the reason that the differences, either on a daily or weekly basis, between the actual and forecasted value are relatively small and close to zero. Statistical results of the diagnostic tests confirm also these patterns. For both these indicators, results of correlation test suggested a relatively high degree of co-movement between actual and forecasted values. In the case of reserve requirements, this ratios goes as far as nearly 90 percent. On the other hand, results on

RMSE and MAE, show that each specified models have performed much better to provide a forecast accuracy with a smaller error term, particularly in the case when forecasting the liquidity flows related to T-Bills issued by the central bank. This is also the case with the forecasting of liquidity flows related to banks' demand to reduce their reserve holding at the central bank.

Finally, results demonstrate that all specified models have managed to anticipate relatively well the state of bank liquidity position. Graphical analysis of Figure (29) and (31) show that the anticipated level, which is the sum of autonomous and non-autonomous factors, as estimated individually, is relatively close to the actual level. This ratio is almost the same for all specified models, as the difference between them and the mean value is relative small, given that in all cases the difference between them falls below 1 percent of error term. This means that the aggregation of levels forecasted from autonomous and no-autonomous factors, show a relatively adequate approach used to anticipate daily liquidity needs related to bank liquidity position. This is also visible in the case of weekly aggregation. In this case, results provide a clear picture suggesting that the forecasting ratio follows relatively well the upwards and downwards trends of bank liquidity needs. This is also confirmed by the net value of weekly differences, as analysis of these results show that the differences between actual and anticipated level during some of the weeks, are relatively close. Some of the models have anticipated flows that are clearly close to the actual level. This means that all specified models have generally managed to anticipate relatively well all patterns through the 9-week-period analysis framework. However, in some moments, such as in week 3 and 4, these differences get relatively bigger. This is also the case when we analyse results reported in Figure (30). In both cases, it corresponds with the extra repo flows provided by the Bank of Albania. Despite this pitfall, in case when we compared actual with anticipated flows, results as reported in Figure (32) in the Appendix, suggested a relatively sound fit between them. Some models overestimated actual values and others have underestimated them. This means that the anticipated level for each of the liquidity component individually, provides us with results that include also the error terms, which in some cases is positive and in other cases is negative, and this is due to the fact that some models overestimate and other ones underestimate the anticipated ratio. However, a solution to this might be to get the mean value of all models, an approach which in our case proves a relatively high fitness ratio. This mean ratio approach shows that the anticipated level reaches almost 97 percent of the actual values, if we include repo component. This ratio is higher if we exclude this component.

4. CONCLUSIONS

The Bank of Albania is responsible for designing, approving and implementing the monetary policy in the case of Albania. In so doing, its primary aim is to achieve and maintain price stability, as well as to support and guarantee the stability of the financial sector. For this reason, it sets up the key policy rate, which is the main policy instrument. On the other hand, following this responsibility, it also carries out active operations in the interbank market, the foreign exchange market and the government securities market. This includes the use of indirect market instruments, which are related to the typical short-term market interest rate and to the adjustment of the appropriate level of supply of bank liquidity in the interbank market, over a chosen time horizon. The former approach indicates that the Bank of Albania uses its benchmark policy rate that is the interest rate of the repurchase (reverse) agreements with one week maturity. The latter policy approach means that the Bank of Albania regulates the need for liquidity in the financial sector by injecting and withdrawing liquidity in the open market. These transactions are conducted through regular weekly auctions. This means that Bank of Albania aims to achieve its main objective by regulating the need for liquidity in the interbank market in a chosen time horizon, through which it can satisfy the operational target of monetary policy and the set of monetary instruments used to finalize the monetary policy goals. On the other hand, by injecting and withdrawing liquidity in the open market, it aims to reflect its monetary policy stance, which serves also to guide short-term trading interest rates in the interbank market close to the monetary policy rate and to reduce any deviation from this rate that may prevent it from achieving its main objective in the future. This means that apart from the conduct of monetary policy, a vital responsibility of the central bank, in this case, is to perform better the role of lender-of-last-resort, and to prevent, or at least, to mitigate financial and market instability by actively managing liquidity consistent with the ultimate goals: to reflect its policy stance and gain the benefits of achieving market stability. Similarly, it means that the central bank adjusts its market operations by determining the conditions that equilibrate supply and demand in the market for liquidity over a chosen time horizon. If the market holds either too much or too little liquidity, it is then expected to respond in a way which may be detrimental to the central bank's goal. It is from this standpoint, therefore, that the central bank analyses and forecasts the need for short-term and long-term liquidity in the market, which fluctuates as a result of changes related to autonomous and non-autonomous factors.

Against this background, this paper addresses these issues, and, in doing so, it provides a view of the central bank liquidity forecast operation process that is tied more closely to their underlying purpose from the lender-of-last-resort perspective, by connecting this case to a small open economy, namely Albania. The aim of this paper, therefore, is twofold. The first aim is to explore the possibility of forecasting the liquidity needs by using an empirical approach that is not based on macroeconomic and financial variables. Rather, it uses an alternative approach that forecasts liquidity needs by using binary indicators with daily data. There exists two advantages of using this approach. One of them is that binary variables are easily estimated and constructed. The other one is that it can solve for any time concerned, inconsistency problems related to the existing actual macroeconomic and financial series indicators that consist of low frequency data. The idea is that although there may be some certainty on an average amount of liquidity that may be demanded by the market, still uncertainty to optimise such needs remains high due to drivers that are not macroeconomic and financial in nature. This is because liquidity needs can be impacted by factors related to seasonal volatility as well as other factors related to certain individual days or periods when more liquidity is demanded. This includes, for instance, those cases if there are large tax payments due, or a large transaction (a securitisation, or a bond launch), or around the end of certain months when banks want to be able to present larger liquid balances on their balance sheets or simply a large volume of payments, e.g. around Christmas, when payments and income flows uncertainty is higher for individual banks. For these reasons, it is only by using this binary approach that will allow us to construct indicators that account for this set of seasonal and non-seasonal patterns. The second aim is to understand which of the liquidity drivers, either related to autonomous or/and non-autonomous factors, affects mostly such needs. There is also another aim that is related to the need to understand how to structure liquidity operations, combining the OMO, SFC and reserve requirements periods, such that errors in the liquidity forecast have less impact and there are higher benefits of market stability on such issue.

In this sense, this paper pertains more to the monetary policy strategy of managing the banking system's liquidity needs, rather than the monetary policy stance to such issues, which aims, nonetheless, to treat it in the long-term perspective. On the other hand, this paper could not have come at a more auspicious time than now, when many countries, among them Albania, are operating through means of indirect monetary policy instruments and for that purpose, among other things, intend to derive the quantity of liquidity that should be withdrawn or injected into the economy through open market operations. It is reasonable that the objective has been to keep inflation at a low and stable level, but with the new strategy of the Bank of Albania, the second objective is also to achieve it by making sure that the intermarket interest rate remains within the framework of interest corridors, as the main instrument to achieve stability in the financial (banking) sector as well. In recognition of those objectives, this paper augurs well in filling the capacity gap in liquidity forecasting as an essential input in the design of sound monetary policy managements in a small open economy, namely Albania. This means maintaining day-to-day liquidity to steer interest rates within the interest rate channel that is the range between policy and deposit facility rate in the open market operations.

The value added of this paper is twofold. First, for the purpose of liquidity management, this paper serves the objective of the central bank by providing both short-term and long-term forecasts. This is assumed to help the central bank to better understand the dynamic of liquidity needs, and to help conceptualize a short-term aspiration that would be less costly on such needs, certainly until at least the end of the current two coming reserve maintenance period. Second, this paper is a clear attempt to understand better and clearer the amount of missing or excess liquidity in the money market, and how it can make use of this information to influence the short-term interest rate and thereby helping the central bank to achieve the primary objective of monetary policy. This is expected also to reduce the volatility and uncertainty, thereby plummeting liquidity management costs. Forecasting of liquidity can be used thereby to forecast the overnight interest rate. Finally, this material supports the developing process of the analysis and forecasting framework, aimed at further improving the quality of the monetary policy formulation and implementation, thereby maintaining and developing the framework of monetary policy instruments, in order to increase its effectiveness and flexibility. This is also the medium-term development strategy of the Bank of Albania for 2019-2021.

The results of this paper present a series of important findings, which strongly support the effectiveness of using the empirical approach with daily data and binary indicators to forecast liquidity needs of the Albanian banking system, as a complementary alternative for the implementation of monetary policy according to the strategy in the medium and long term. This means that the Bank of Albania can rely on this predictive alternative to better manage the need for liquidity through open market operations, injecting or withdrawing liquidity from it, as in cases where it aims to maintain a shortage within a set band, as well as in those in which the goal is to keep the one-day trading rate in the interbank market around its base rate. First, it was observed that the application of this method captures quite well the needs for liquidity characterized by the trend, seasonal and non-seasonal factors, as well as those related to special and unpredictable days. This is also due to the fact that the error rate associated with each of the prediction models that were built to capture these characteristics is relatively low. Even the results of a simple correlation test between the actual and predicted levels are relatively high in each case, which is another qualitative indicator that further supports the proposed approach. Second, it was realized that the effectiveness of these results is improved even more if we move from the prediction of daily needs to the aggregation of these needs at weekly and/or monthly levels. In any case, however, the results remain relatively better for indicators related to autonomous factors. This includes forecasting indicators related to government revenues and transfers to other institutions, and to a greater extent to cash in circulation. On the other hand, for the non-autonomous factors, the proposed approach provides results that are satisfactory regarding the forecast levels for the indicators related to the deposit and credit situation, reserve requirements, and to some extent those related to the net value of the participation of the central bank, namely the Bank of Albania, in the auctions of government securities. The analysis of other results based on an alternative approach that aggregates all the forecasts made into a single indicator expressed as an average indicator, which is assumed to reflect more clearly the expected final position of the interbank market in relation to its needs for liquidity and the reasons for the deviation from these expectations, suggests that a combination of all these forecasts provides a relatively better orientation overview of the position of market needs and a more coherent aspiration for achieving the objectives of the Bank of Albania for the implementation of its monetary policy.

However, the analysis in this paper is not a fully completed comprehensive piece of work. Future research and further analysis is needed. First, as it is the case with forecast analysis, it is important to evaluate forecast accuracy using genuine forecasts. Consequently, the size of the residuals or the error accuracy is a crucial method to gauge how well the model executes its tasks, but this approach is not a reliable indication of how large true forecast errors are likely to be. The accuracy of forecasts can only be determined by considering how well a model performs on new data that were not used when fitting the model. Second, the forecast evaluation test statistics applied in this paper, are affected by outliers more than other things. When taking the value 0, the percentage error becomes infinite or it is not defined, and the degree distribution is highly skewed, which is a major disadvantage upon the evaluation of such forecast accuracy metric. Similarly, since errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable. Similarly MAE is commonly used to measure forecasting errors, but it can be deceiving when dataset contains numbers close to zero, or in intermittent numbers. Similarly MAE is commonly used to measure forecasting errors, but it can be deceiving when dataset contains numbers close to zero, or in intermittent numbers. The Weighted Average Percentage Error is an alternative approach, in what it is seen particularly useful when dealing with low volume data, as it weights the error over the total true values. However, all these metrics are symmetric, which means that they don't take into account whether the forecast is over-predicted or under-predicted. This can be relevant for some problems (it is not the same to have too much stock than not enough) that should be taken into account. The third concern upon the proposed strategy of forecasting liquidity needs is related to the relatively high number of dummies used, some of which may cover the same variables (days, months, quarters), leading potentially to multicollinearity. Although, such concerns did not result in our current analysis, it still remains a matter that should be considered in future analysis, and an alternative approach to solve it might be either to linearly combine the independent variables, such as adding them together, or perform an alternative analysis designed for highly correlated variables, such as principal components analysis or partial least squares regression. Furthermore, the monetary instruments used by Bank of Albania includes longer-term operations, with maturity of several months going from 3 months up to 1 year. Perhaps this is a good reason that future work should at least produce rough forecasts of the bank's balance sheet for the next few months, in order to provide a context for those longer-term operations. Managing and knowing the amount of liquidity missing in the money market is expected to have a crucial effect on the overnight rate. Therefore, future research should also address at least the extent to which liquidity components effect this rate. The main idea is to see how and to what extend market liquidity situation can steer overnight rate closer to the policy rate. Finally, as it known, every Tuesday, the Bank of Albania publish its expectation over the mean level of autonomous factor, of the non-tradable liquidity and the mean value of liquidity that central bank is ready to offer on the weekly regular auction. A great interest would be to analyse how this forecast level improves the ratio offered by the Bank of Albania, which is another element for future work.

LITERATURE

Ahlburg, D (1984) "Forecast evaluation and improvement using Theil's decomposition." Journal of Forecasting, Vol. 3, 345-351.

Bank of Albania (2020) "The medium - term development strategy of the Bank of Albania 2020-2022." Not Periodic Publications / Special Publication.

Bell, Wlliam, and Steven Hillmer (1983) "Modelling time series with calendar variation." Journal of the American Statistical Association, Vol. 78, 526-534.

Bhattacharyya, Indranil, and Satyananda Sahoo (2011) "Comparative statics of Central Bank Liquidity Management: Some Insights." Economics Research International, Vol. 2011, Article ID 930672.

Bindseil, Ulrich (2001) "Central bank forecasts of liquidity factors: quality, publication and the control of the overnight rate." European Central Bank Working Paper Series No. 70, July (2001).

BIS (2012) "Monitoring indicators for intraday liquidity management." Basel Committee on Banking Supervision, July (2012).

Bliemel, F (1973) "Theil's forecasting accuracy coefficient: A clarification." Journal of Marketing Research, Vol. 10, 444-446.

Box, George, and George Tiao (1975) "Intervention analysis with application to economic and environmental problems." Journal of the American Statistical Association, Vol. 70, 70-79.

Cabrero, Alberto, Gonzalo Camba-Mendez, Astrid Hirsch, and Fernando Nieto (2002) "Modelling the daily banknotes in circulation in the context of the liquidity management of the European Central Bank." Bank of Spain, No 0211, May (2002).

Cao, Charles, Timothy Simin, and Ying Wang (2013) "Do mutual fund managers time market liquidity?" Journal of Financial Market, Vol. 16(2), 279-307.

Cecchetti, Stephen, and Piti Disyatat (2010) "Central Bank Tools and

Liquidity Shortages." FRBNY Economic Policy Review, August 2010.

Ganley, Joe. (2004) "Surplus Liquidity: Implications for Central Banks." In Lectures from Centre for Central Banking Studies, Bank of England.

Glosten,Lawrence, Ravi Jagannathan, and David Runkle (1993) "On the relation between the expected value and the volatility of the nominal excess return on stocks." The Journal of Finance, Vol. 48(5), December (1993), 1779-1801.

Goldman, Elena, and Xiangjin Shen (2018) "Analysis of asymmetric GARCH volatility models with applications to margin measurement." Bank of Canada Staff Working Paper, No. 2018-21, Bank of Canada, Ottawa.

Gonzales-Paramo, M. Jose (2007) "The challenges to liquidity management in the Euro Area: The perspective of the ECB." a speech at the Annual European Treasury Symposium, Berlin January 25 (2007).

Granger, C. and P Newbold (1973) "Some comments on the evaluation of economic forecasts." Applied Economics, Vol. 5, 35-47.

Grant, Kathryn, Gertjan Vlighe, and Andrew Brigden (2004). "Assessing the stability of narrow money demand in the United Kingdom." Bank of England Quarterly Bulletin, Summer (2004).

Barabás, Judit, and Major Tamás (2010) "Liquidity management operations at the National Bank of Hungary." National Bank of Hungary Occasional Papers.

Gray, Simon (2008) "Liquidity forecasting." Centre for Central Banking Studies Handbook, June (2008), No. 27.

Katsalirou, Irene (2018) "Forecasting liquidity and conducting credit operations." ECB Central Banking Seminar Frankfurt am Main, 12 July 2018.

Katsalirou, Irene (2019) "Forecasting liquidity and conducting credit operations." ECB Central Banking Seminar Frankfurt am Main, 4 July 2019.

Molnár, Zoltán. (2010) "About the interbank HUF liquidity – what does *the MNB's new liquidity forecast show?" MNB Bulletin, December (2010).*

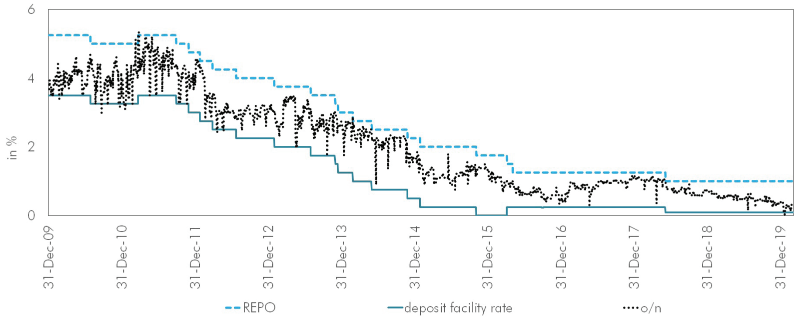
Norat, Mohamed (2008) "Forecasting banknotes." Centre for Central Banking Studies Bank of England Handbook, December (2008), No 28.

Ruffer, Rüffer and Livio Stracca (2006) "What is global excess liquidity, and does it matter?" ECB Working Paper no. 696.

Zakoian, Jean-Michel (1994) "Threshold heteroskedastic models." Journal of Economic Dynamics and Control, Vol. 18 (5), 931-955.

APPENDIX

Figure 1. Interest Rate Corridor Pass-through: 2009 – 2019.

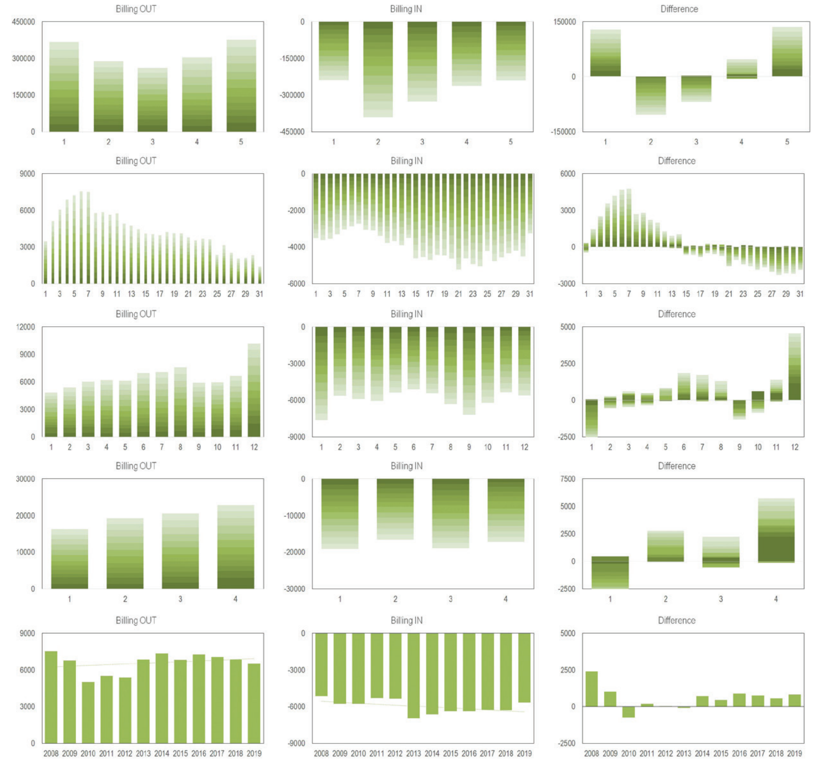


Source: Bank of Albania, Author's Calculations

Figure 2. Government Revenue and Expenditure Patterns [in ALL].

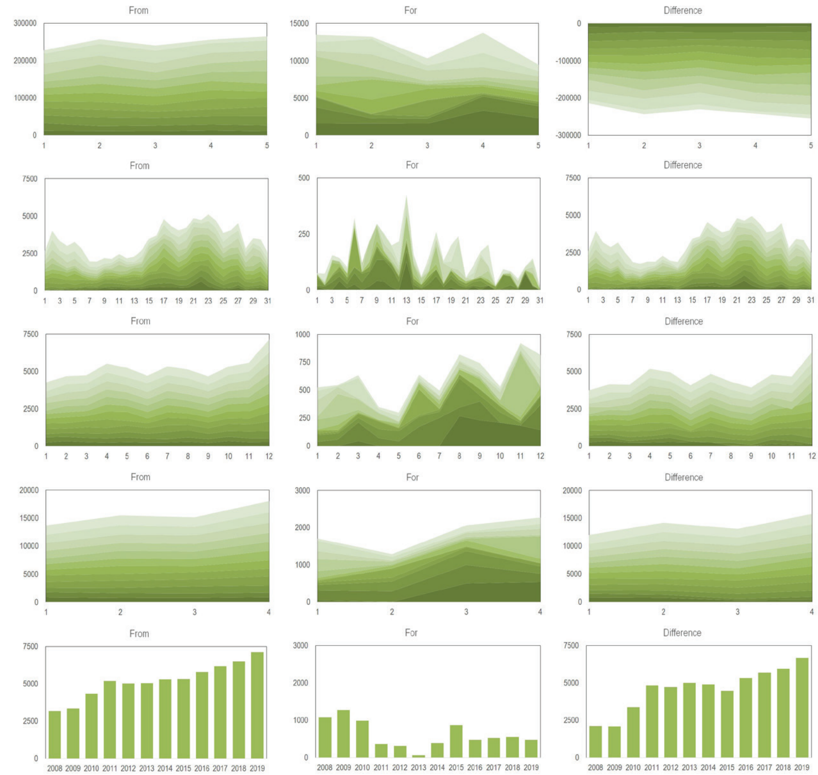
Source: Bank of Albania, Author's Calculations

Figure 3. Treasury Billing In (Revenue) and Billing Out (Payment) Patterns [in ALL].



Source: Bank of Albania, Author's Calculations

Figure 4. Government Transfers To and From Other Public Budgetary Institutions Patterns [in ALL].



Source: Bank of Albania, Author's Calculations

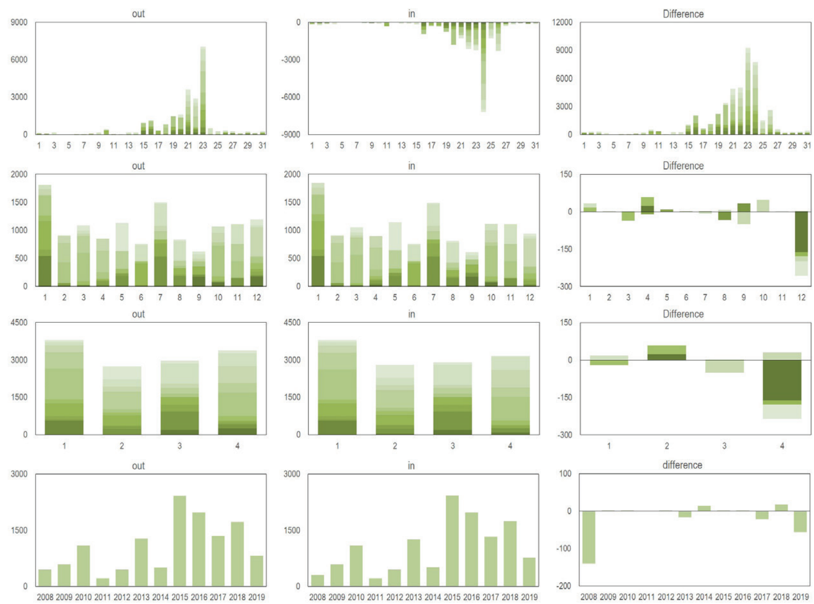
Figure 5. Government T-Bills Patterns [in ALL].

Source: Bank of Albania, Author's Calculations

Figure 6. Banks' Total Deposits: Matured Vs Issued [in ALL].

Source: Bank of Albania, Author's Calculations

Figure 7. Lending Facility: Issued Vs Matured [in ALL].

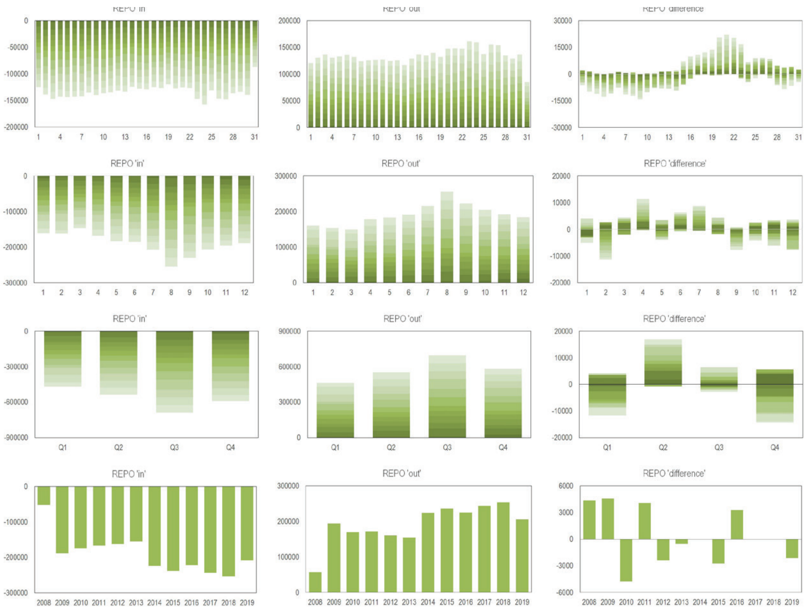


Source: Bank of Albania, Author's Calculations

Figure 8. Additional REPO Support: Issued vs Matured [in ALL].

Source: Bank of Albania, Author's Calculations

Figure 9. Regular REPO Support: Issued vs Matured [in ALL].



Source: Bank of Albania, Author's Calculations

Figure 10. Bank's Reserve Holding Patterns [in ALL].

Source: Bank of Albania, Author's Calculations

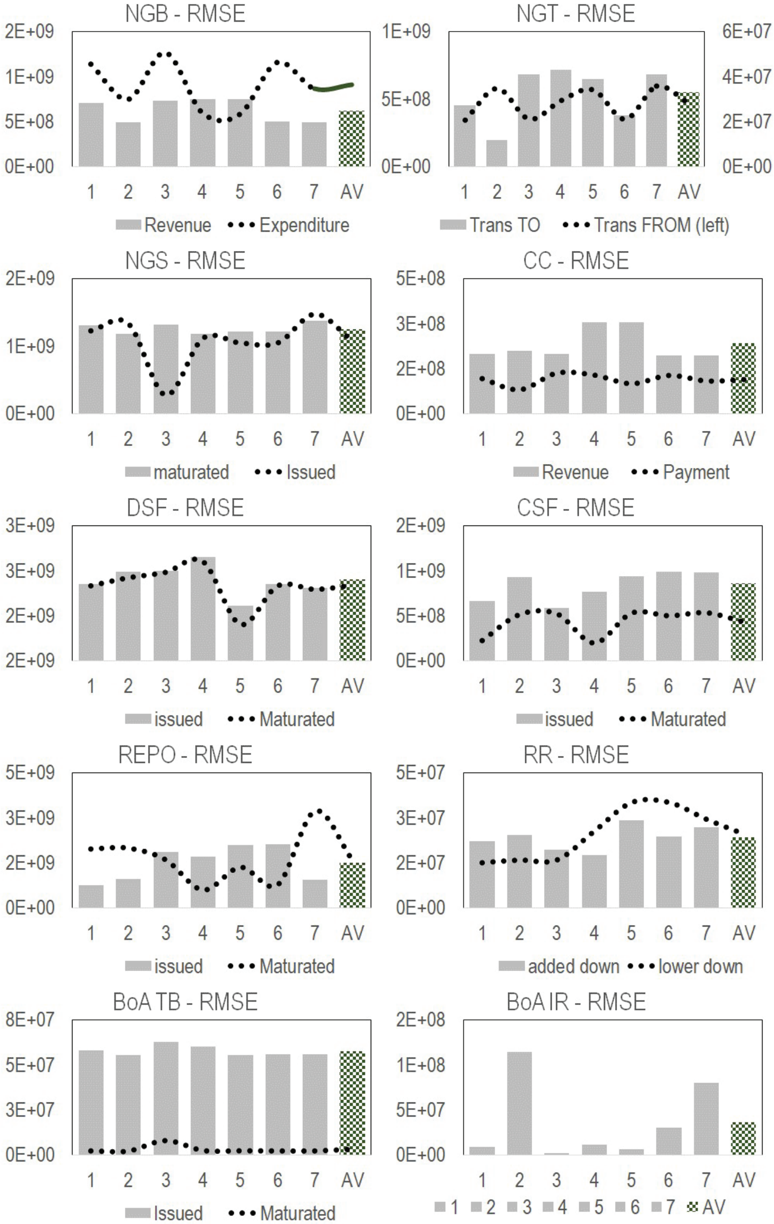
Figure 11. Bank of Albania T-Bills Intervention Patterns [in ALL].

Source: Bank of Albania, Author's Calculations

Figure 12. Bank of Albania Foreign Exchange Reserve Patterns [in ALL].

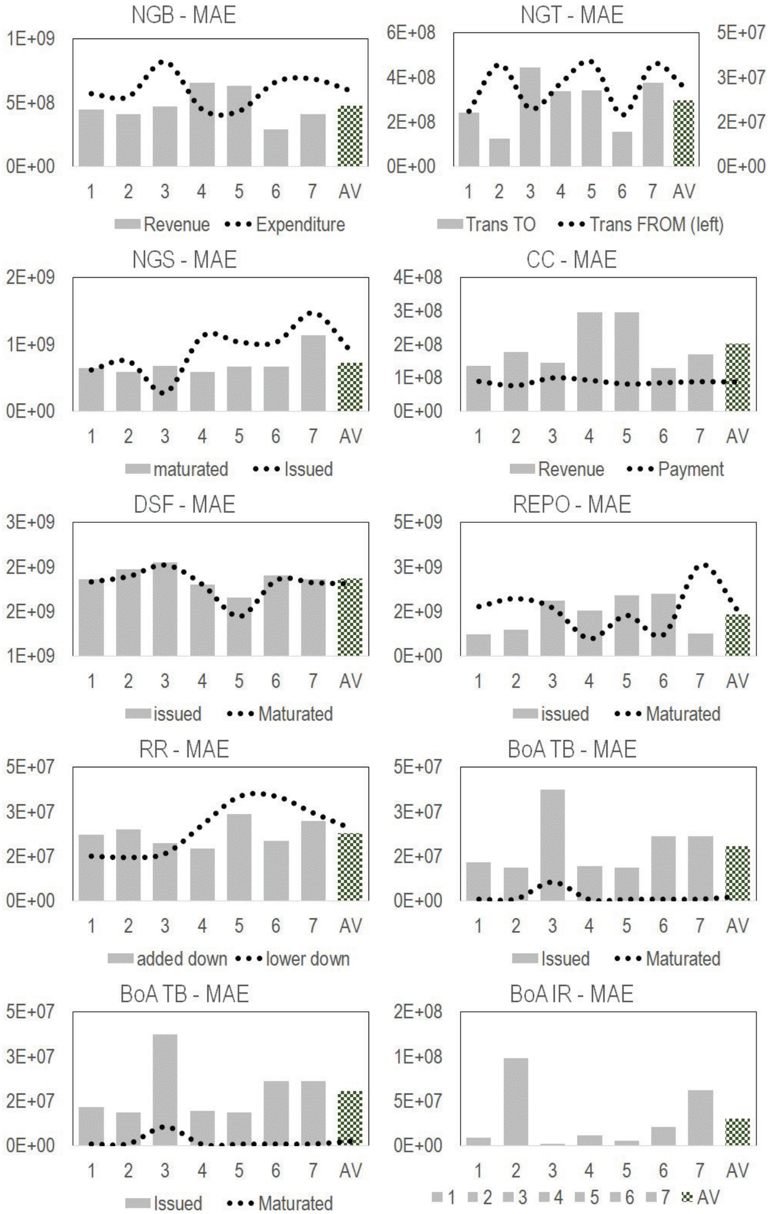
Source: Bank of Albania, Author's Calculations

Figure 13. Results of the results of Root Mean Square Error (RMSE).



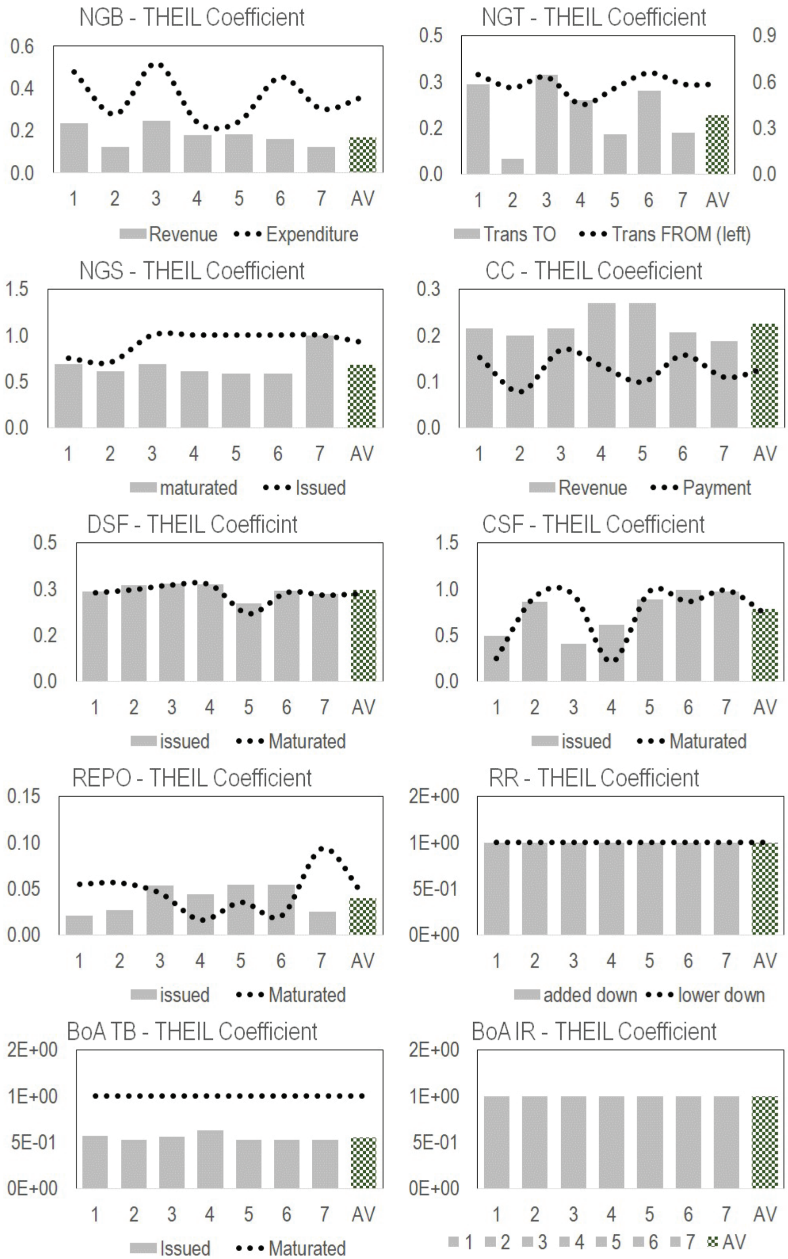
Source: Bank of Albania, Author's Calculations

Figure 14. Results of the Mean Absolute Error (MAE).



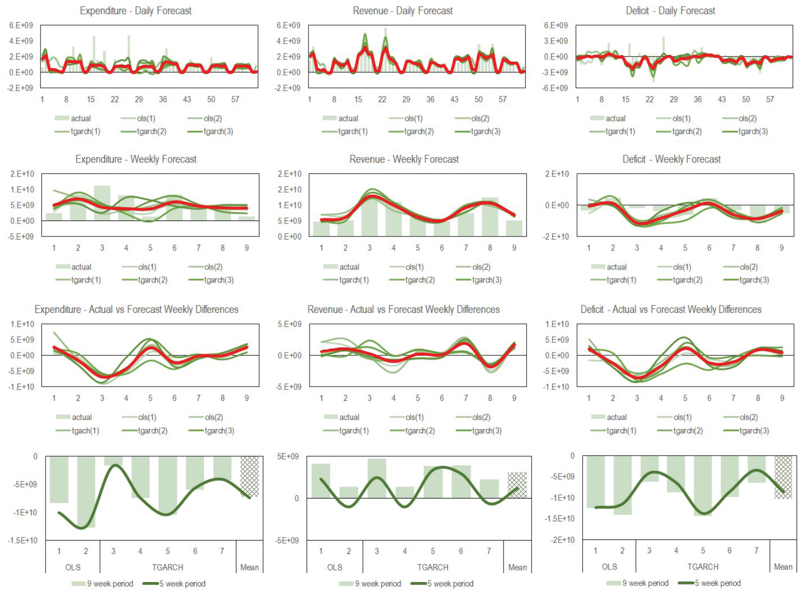
Source: Bank of Albania, Author's Calculations

Figure 15. Results of the Theil Coefficient.



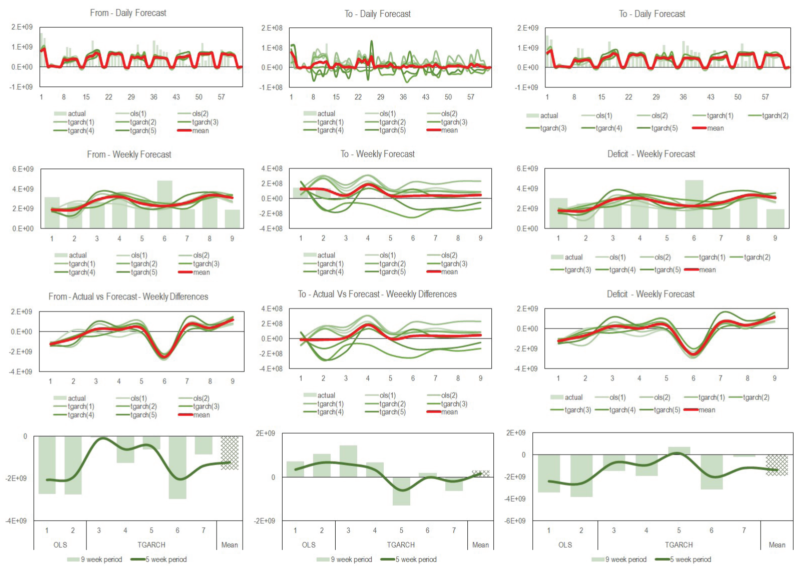
Source: Bank of Albania, Author's Calculations

Figure 16. The Level of Government Total Expenditure and Revenue [in ALL].



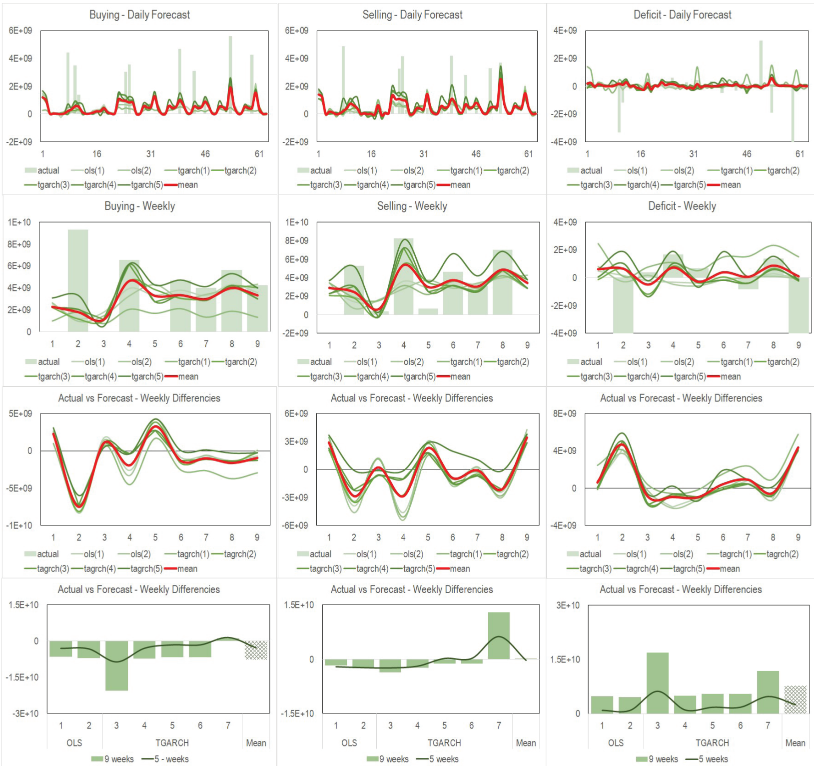
Source: Bank of Albania, Author's Calculations

Figure 17. The level of Government Transfers From and To other Budgetary Public Institutions [in ALL].



Source: Bank of Albania, Author's Calculations

Figure 18. The level of Government T-Bills Issued and Maturated [in ALL].



Source: Bank of Albania, Author's Calculations

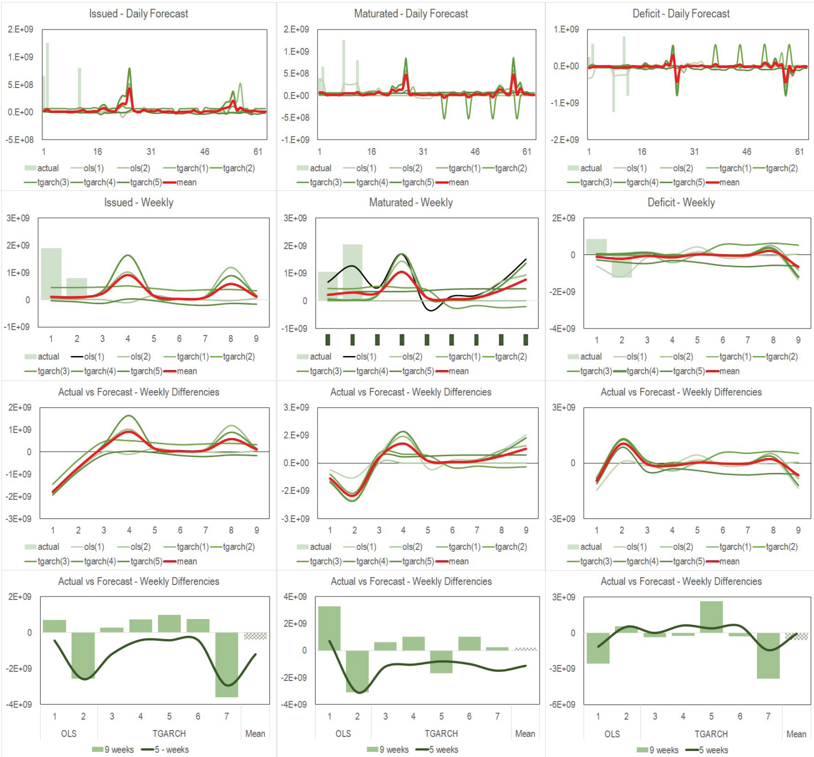
Figure 19. The Level of Cash in Circulation [in ALL].

Source: Bank of Albania, Author's Calculations

Figure 20. The Total Level of Bank Deposits: Maturated Vs Issued [in ALL].

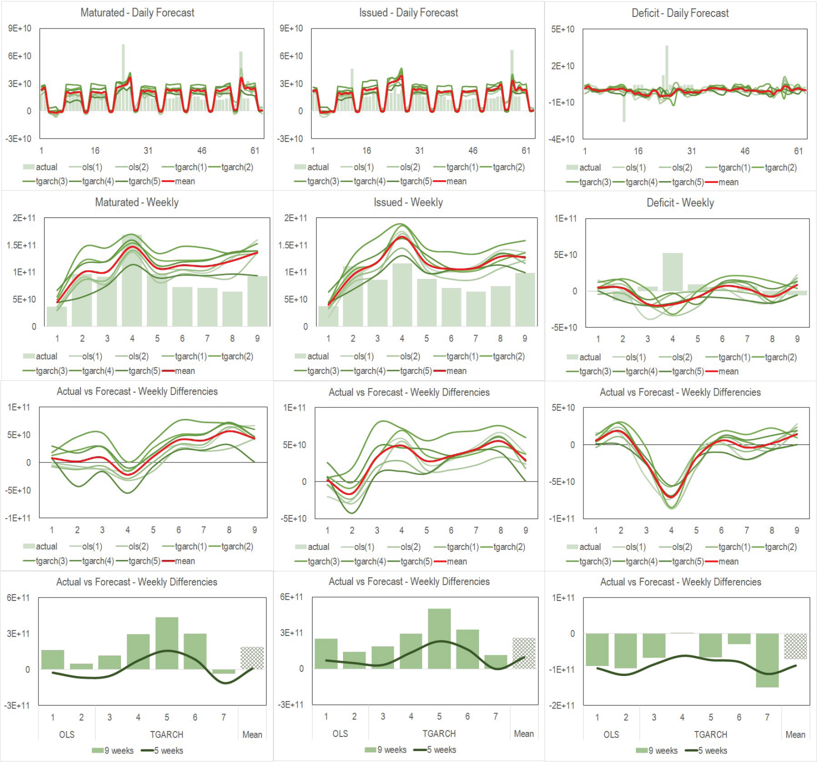
Source: Bank of Albania, Author's Calculations

Figure 21. The Total Level of Bank Loan Facility: Maturated Vs Issued [in ALL].



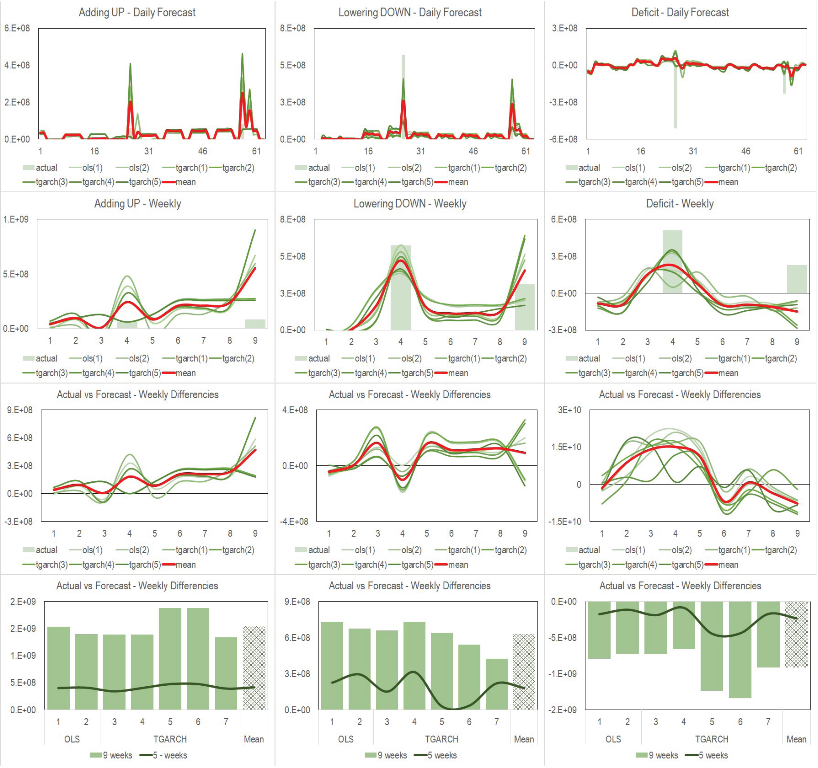
Source: Bank of Albania, Author's Calculations

Figure 22. The volume of Bank of Albania's REPO Issued and Maturated [in ALL].



Source: Bank of Albania, Author's Calculations

Figure 23. The Volume of Bank Reserve Holdings: Adding UP Vs Lowering Down [in ALL].

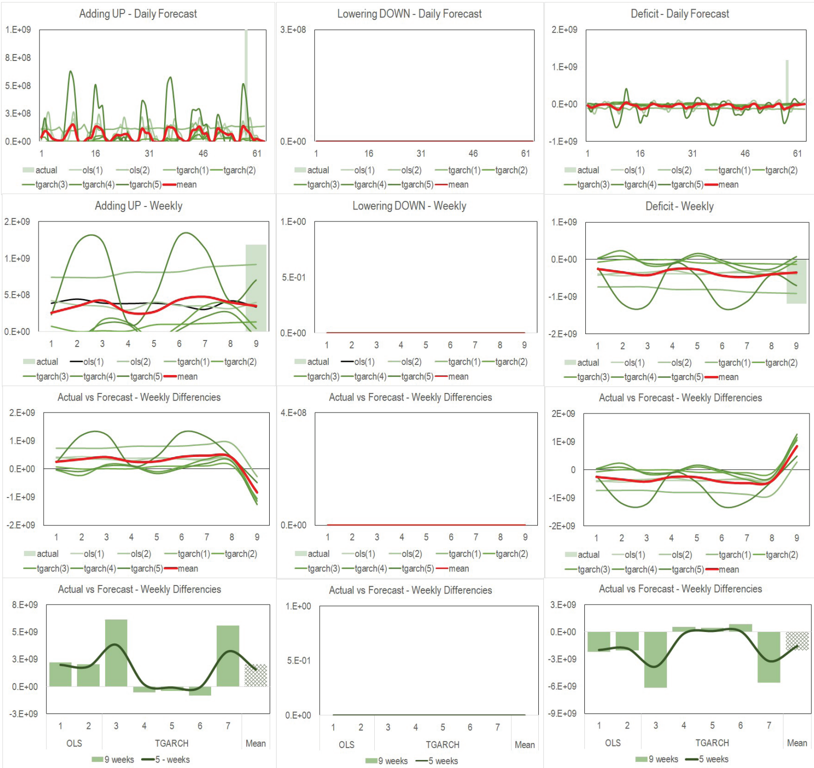


Source: Bank of Albania, Author's Calculations

Figure 24. The Volume of Bank of Albania T-Bills: Buying Vs Selling [in ALL].

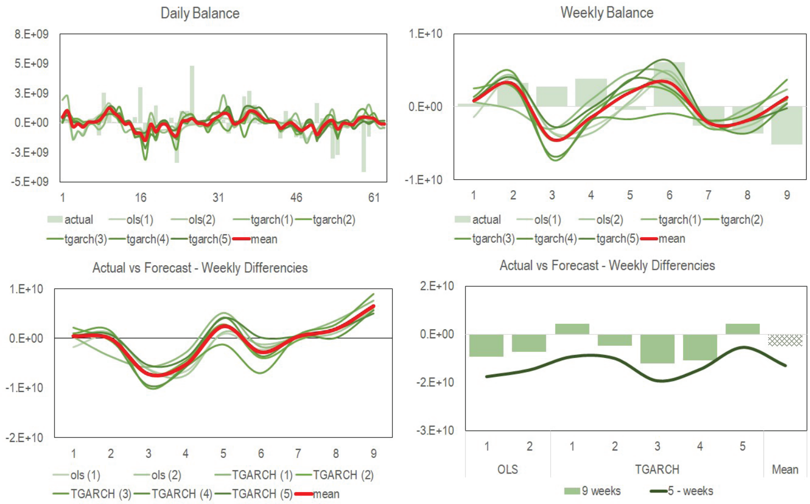
Source: Bank of Albania, Author's Calculations

Figure 25. The Volume of Net Foreign Reserves Bought and Sold by Bank of Albania [in ALL].



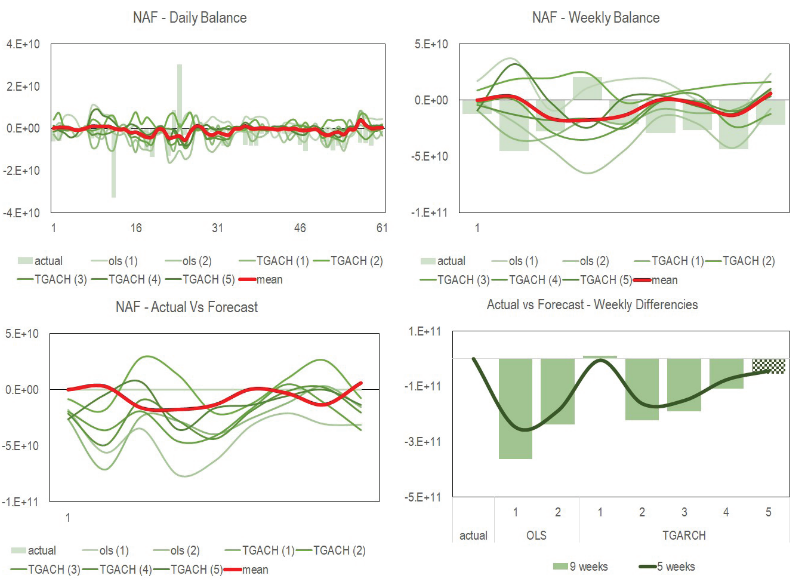
Source: Bank of Albania, Author's Calculations

Figure 26. The Volume of Autonomous Factors [in ALL].



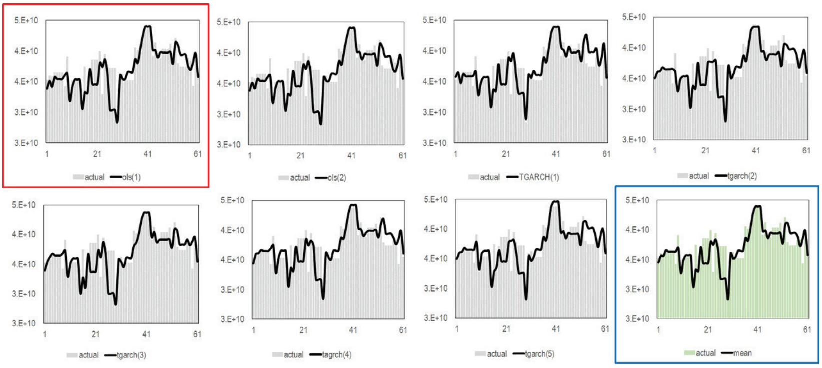
Source: Bank of Albania, Author's Calculations

Figure 27. The Volume of Non-Autonomous Factors [in ALL].



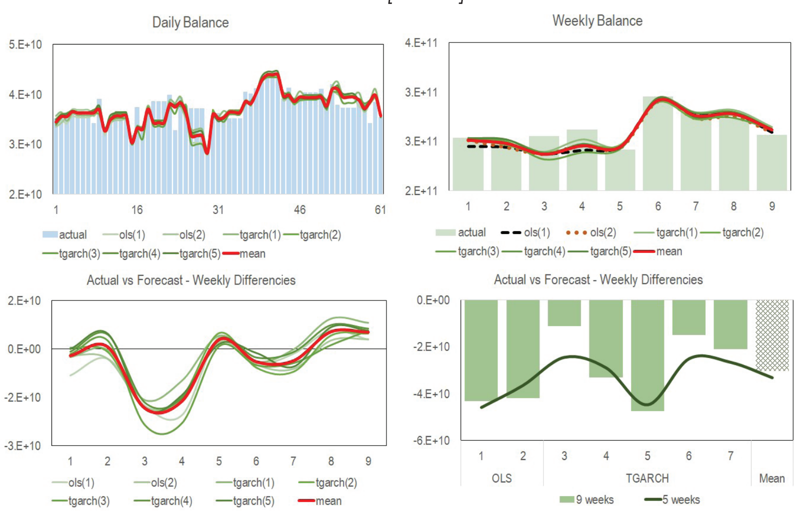
Source: Bank of Albania, Author's Calculations

Figure 28. The Volume of Market Liquidity Situation: Excluding Net BoA REPO [in ALL].



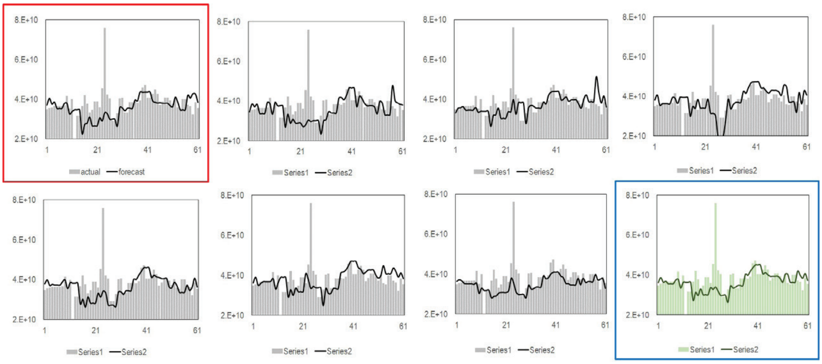
Source: Bank of Albania, Author's Calculations

Figure 29. The Volume of Market Liquidity Situation: Excluding Net BoA REPO [in ALL].



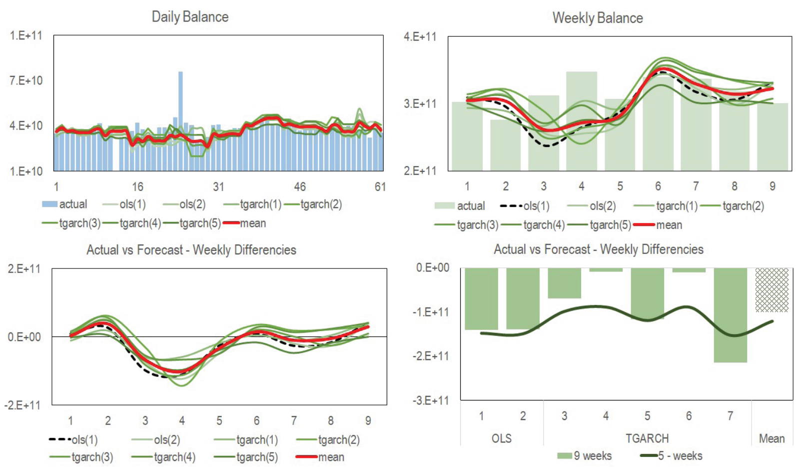
Source: Bank of Albania, Author's Calculations

Figure 30. The Volume of Market Liquidity Situation Including Net BoA REPO [in ALL].



Source: Bank of Albania, Author's Calculations

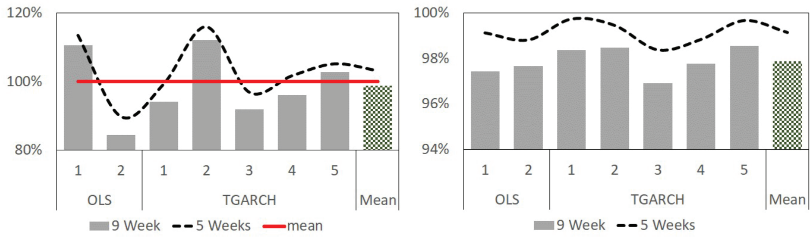
Figure 31. The Volume of Market Liquidity Situation: Including Net BoA REPO [in ALL].



Source: Bank of Albania, Author's Calculations

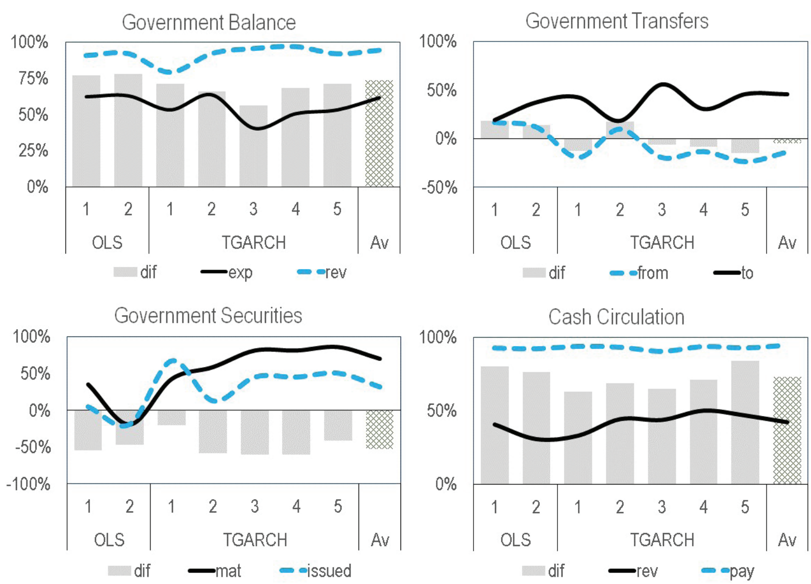
Figure 32. Bank Liquidity Situation: Actual as a Percentage of Estimated Level.

[including Net Bank of Albania REPO Component] *[excluding Net Bank of Albania Repo Component]*



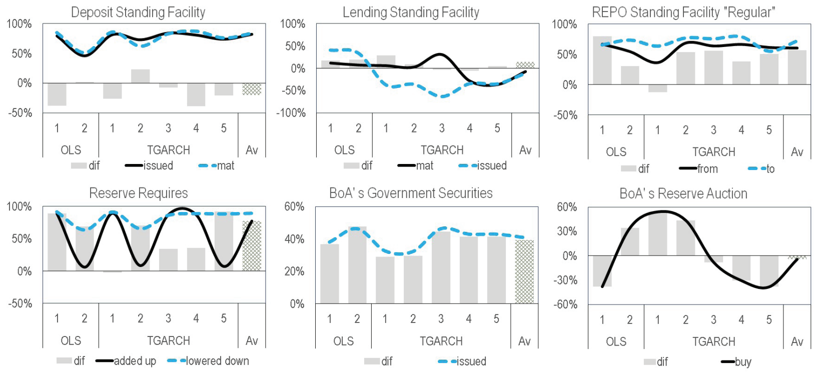
Source: Bank of Albania, Author's Calculations

Figure 33. Correlation Test Results: Autonomous Factors [9 Weeks Approach].



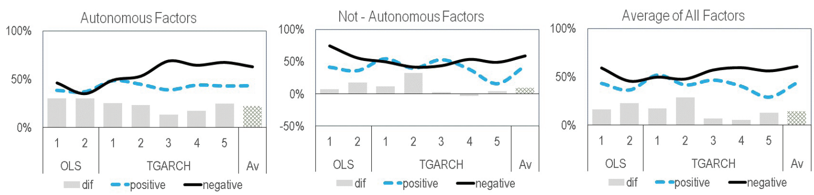
Source: Bank of Albania, Author's Calculations

Figure 34. Correlation Test Results: Non – Autonomous Factors [9 Weeks Approach].



Source: Bank of Albania, Author's Calculations

Figure 35. Correlation Test Results: Non – Autonomous Factors [9 Weeks Approach].



Source: Bank of Albania, Author's Calculations

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