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Modeling the Liquidity Gap in a Private Bank

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The present study suggests a model for predicting liquidity gap, based on source and cost of funds approach concerning the daily time series data (25 March 2009 to 19 March 2018), in order to control and manage the liquidity risk. Using the family of autoregressive conditional heteroscedasticity models, the behavior of bank liquidity gap is modeled and predicted. The results show that the APGARCH with the Johnson-SU distribution is the most suitable model for explaining the liquidity gap behavior. Based on the rolling window method the more accurate model has been selected to be the APGARCH model with T-Student distribution which provides the least error in forecasting liquidity gap.

Keywords: Liquidity Forecast, Liquidity Risk, GARCH Family, Rolling Window.
JEL Classification*:* C22, C53, C58, G17, G32

1 Introduction

Liquidity is the capacity of a bank to increase the amount and value of financial assets and to meet expected and unexpected cash and collateral liabilities with reasonable costs and without causing unacceptable damages. Liquidity risk is the bank's inability to meet its maturity obligations without reverse effect on the financial condition of the bank. Effective liquidity risk management is a set of policies that leads to timely maturity of the bank's liabilities and reduce the likelihood of a reversal of the financial situation (Kumar & Yadav, 2013).

Balancing between short-term obligations (deposits) and long-term investments (facilities) is the main strategy for managing the bank's liquidity. The main challenge in the bank's liquidity management is that most of the banks' resources are financed from short-term deposits, while the banks' granting facilities are limited to investing in assets with a low liquidity rating.

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Keeping large amounts of liquidity lowers the ability of the bank's investment, reduces profitability, and ultimately loss of the market, which reflects an inefficient allocation of resources. On the other hand, keeping inadequate liquidity would put the bank at risk of failing to meet its obligations on time, loss of customers, risk of collapse, and ultimately bankruptcy risk (Department of Risk Research and Management of EN Bank, 2008).

Failure to quickly access cash at the right time and with the right cost will put the bank at risk of liquidity. Therefore, determining the amount of liquidity required by the bank to maintain balance between assets and liabilities is one of the most important tasks of the bank's executives. In this regard, the task of the financial manager of the bank is to use a variety of methods and models to predict liquidity with respect to environmental changes. Therefore, the bank's ability to assess and manage liquidity supply and demand in line with the continuation of banking operation, non-exposure to high interest rate risk, capital requirements, high bank reserves and the risk of reputation is necessary (Ismal, 2010).

The Basel Committee is one of the subsidiary committees of the Bank of International Settlement (BIS) and the most important authority in banking supervision; This committee believes that liquidity management in banks is of great significance due to the fact that the most important function of a financial institution is to provide cash to customers with the aim of maximizing returns for the stakeholders. Therefore, banks are required to pay attention to liquidity resolutions, policies and liquidity management approaches to strengthen the financial power of the bank in order to deal with the turbulent market situations. Therefore, in this study, an attempt is made to study more precisely the liquidity gap behavior of the bank, and some of the characteristics observed in the liquidity gap series that has been less considered in previous studies, are well-thought-out in the modeling process.

In order to identify the process of data production and to control and manage the liquidity risk of a private bank, we try modeling and predicting the behavior of the liquidity gap series (the difference of resource and cost of funds) based on cash flow prediction using Generalized Autoregressive Conditional Heteroskedasticity models, In this way, some of the observed characteristics of the liquidity gap series such as Heteroskedasticity, Fat Tails, Volatility Clustering, Leverage Effect, Volatility Feedback and Long Memory in the modeling process are considered. Accordingly, the performance of a number of GARCH family models is compared in normal probability distribution, skewed normal, t-student, skewed t-student, generalized error, skewed generalized error and Johnson-SU distributions. In order to verify the accuracy of the models used, the Likelihood Ratio (LL), as well as the Akaike Information Criteria (AIC) and Schwarz-Bayesian Information Criteria (SBIC) metrics are used. Also, with a goal of selecting the well-anticipating and best forecasting model based on the Rolling Window approach, we use the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Theil's Inequality Coefficient (TIC).

The paper is organized as follows: The second part focuses on theoretical foundations and research background. The third part deals with the methodology of research and description of data. In the fourth section, the model is estimated and the findings are analyzed. Section five summarizes the results of the research.

2 Theoretical Background and Literature Review

2.1 Theoretical Review

Liquidity risk refers to the inability of a financial institution to pay off debt or to provide funds to raise assets. This risk appears in two forms in financial institutions: the liquidity risk of resources and the liquidity risk of assets. The liquidity risk of resources is created when the financial institution is unable to provide the required funds with guarantee at the time of need and at a reasonable level of need. Losses associated with financing are created when short-term and long-term debt (deposits) cannot be made at the time of need. The liquidity risk of an asset, also known as asset market liquidity risk, is the inability of the financial institution to convert assets into cash when cash is needed (Department of Risk Research and Management of EN Bank, 2008).

There are various methods for predicting bank liquidity, which include: 1- Cash flow forecast (sources and costs of funds), 2- Balance-sheet forecast, 3- Income-based forecast, and 4- Forecasts based on the structure of deposits (Department of Risk Research and Management of EN Bank, 2008).

The most commonly used liquidity forecasting method is cash flow forecasting (resources and expenditures). In this way, a liquidity surplus or deficit is predicted by predicting the input and output cash flows over a period of time and calculating the difference between the received and paid funds. After identifying surpluses or deficits, planning for deficits compensation or surplus consumption is required in order to achieve a liquidity balance at the end of the period. In fact, the financial institution's attempt to steer liquidity gap to zero is not the case, since providing liquidity to depositors and investors with the goal of earning money is one of the main functions of the financial institution. In other words, the goal is to adjust the liquidity gap within the acceptable range, considering the ability of the financial institution to convert and sell assets at an appropriate time, in order to replace current assets and liabilities (Pedram, Shirin Bakhsh ~~and~~ & Zavarian, 2008).

In relation to the management of liquidity in the banking industry, various theories have been proposed, the most important of which are: 1- The Commercial Loan Theory 2- The Shift Ability Theory 3- The Anticipated Income Theory 4- The Debt Management Theory 5- The Asset-Liability Management Theory. We explain these views (Department of Risk Research and Management of EN Bank, 2008).

2.1.1 The Commercial Loan Theory

The history of this theory dates back to the 18th and 19th centuries in England and the early 20th century in the United States. According to this theory, the best type of investment is short-term facility, which is provided through current deposits, because this type of investment can be liquidated and is appropriate for liquidity needs. The proponents of this theory emphasize only on bank assets and, above all, on the payment of short-term loans with a high degree of liquidation (Roussakis, 1997).

2.1.2 The Shift Ability Theory

The formation of this theory dates back to the 1920s and the expansion of financial markets in the United States. The advocates of this theory believe that banks should hold significant amounts of their funds in short-term, first-class and immediately tradable securities, so that they can sell these securities without loss or with the least harm, in the event of a liquidity problem. Some supporters of this theory, of course, believe that if the size of liquidity is clear, there is no reason for a bank to only hold short-term securities; what matters is the quality of these papers (its liquidity level), not its maturity, that is, all types of cash assets (such as loans and securities available for sale in the secondary market) can be used to offset the outflows (Roussakis, 1997).

2.1.3 The Anticipated Income Theory

In the 1940s, and on the eve of the beginning of the period of installment facilities, the theory of anticipated income was introduced. In this view, the timing of repayment of principal and interest on the facility is based on the repayment power of the borrower and on the basis of his expected earnings. In fact, based on this theory, liquidity needs and, consequently, the payment of banking facilities depends on the borrower's expected revenues (Roussakis, 1997).

2.1.4 The Debt Management Theory

The expansion of the debt management theory from the 1960s was accompanied by the growth and development of money and capital markets. The advocates of this theory believe that they should not keep all the needed liquidity in the bank. Whenever required, debt management can provide liquidity from money and capital markets by purchasing additional reserves of other banks, issuing certificates of deposit, borrowing from central bank, issuing short-term bonds, increasing the bank's normal capital or securing credit from global money markets (Roussakis, 1997).

2.1.5 The Asset-Liability Management Theory

During the 1960s, demand for bank loans grew faster than the growth rates of major deposits and non-sensitive deposits to interest rate fluctuations. The underlying problem in this context was the increased lending capacity of banks, and thus the theory of asset-liability management was formed. In this approach, some of the expected liquidity requirements are held as high-liquidity assets - in the form of holding securities and deposits with other banks. Other expected liquidity requirements are provided through a predetermined order in the credits ceiling, or from counterparty banks and other fund providers. Today, banks are paying attention to both sides of the balance sheet (resources and expenditures) to meet their liquidity needs, and meeting the liquidity needs (costs) with resources is done by the Asset-Liability Management Committee (Rose, Hudgins, 2005).

2.2 Literature Review

Cucinelli (2013) examines the factors affecting bank liquidity risk in the euro area. The results of the research indicate that larger banks are at higher risk of liquidity, while higher capital banks have better long-term conditions for liquidity requirements. Furthermore, the quality and composition of the bank's assets only affects the liquidity risk in the short run. With regard to the specialization, banks more specialized on the lending activity show a more vulnerable funding structure. In addition, liquidity risk management during the crisis will change only in the short run.

In "Unbalanced Liquidity Risk Management: Evidence from Latvian and Lithuanian Commercial Banks", Konovalova and Zarembo (2015) examine and analyze the factors affecting bank liquidity. The results of their research indicate that liquidity provision by the bank in crisis situations is often carried out through the absorption of new deposits at a higher interest rate or through the sale of bank assets. One of the most influential factors on bank liquidity status is fluctuations in interest rates.

Pagratis, Topaloglou, and Tsionas (2017) use the Stress Test approach to assess liquidity risk in US commercial banks. The results of their research indicate that the lack of liquidity in the American banking system appeared in the midst of the financial crisis. They found that banks that hold high-liquidity assets in their assets mix have a high degree of safety against liquidity shocks. Large banks experienced the largest liquidity shock in the first quarter of 2008 (equivalent to $154 billion, equivalent to 14% of their asset value) and small banks in the fourth quarter of 2007 (equivalent to $117 billion, equivalent to 11% of their asset value). Evidence suggests that system vulnerability following a crisis is rooted in maintaining a large part of bank assets in the form of uninsured long-term deposits, while government securities are superior to other assets due to their high liquidity.

Based on the balance sheet data of a bank in India, Mishra and Burns (2017) examine the effect of liquidity shocks on the bank's lending channel. In their research, they use a structured VAR framework, a short-term model for analyzing the dynamic interactions between monetary policy, bank liquidity and bank lending. The results of their study indicate that monetary policy shocks have a rapid, lasting and strong effect on bank lending, while liquidity shocks affect a bank's lending after a 9-month lag. There is also evidence of an indirect feedback channel between monetary policy and bank lending, which acts through the bank's liquidity changes. However, the indirect effect of monetary policy on the bank's facilities (from the bank's liquidity channel) operates with a lag of approximately 6 to 9 months.

DeYoung, Distinguin, and Tarazi (2018) investigate liquidity behavior of commercial banks in response to negative shocks of capital in a study entitled "Joint Rules on Bank Liquidity and Capital." They examine legal liquidity behavior and legal capital, as an alternative, for the US banks with assets under $1 billion, using pre-Basel III data. Looking at exogenous shocks to legal capital ratios, these banks are redirecting their loans, accruals and unprofitable gains, and taking steps to improve capital ratios and increase their liquidity position. This behavior is less observed in large banks. They conclude that the minimum capital limit naturally reduces the risk of liquidity in local banks and justifies the exemption of these banks from the Basel III liquidity standards.

Divandari, Lucas and Mousavi (2004) design a prediction model for liquidity management of financial institutions within the framework of a usury-free banking system in order to control liquidity risk. In the first step, in order to design the operational model of the research, they sought to identify and model all liquidity items based on the resource-expenditure approach using the financial data of Mellat Bank in 2004. In the next step, in order to predict daily liquidity components (resources and expenditures), the method of neural networks with three-layer perceptron structure and post-release error training algorithm are used.

In a study (2008), Pedram, Shirinbakhsh and Zavarian predict the liquidity of the bank and determine the liquidity gap in order to control the liquidity risk of one of the private banks of Iran. In this regard, they used the resource and expenditure funds approach to predict liquidity. In addition to daily prediction of liquidity flows from the bank's operations, they predict liquidity gap with regard to the impact of macroeconomic variables and financial market conditions as well as calendar effects for the next period. In this way, they use a structural approach to explain resource-expenditure changes and a time-series method to predict the flow of liquidity gap.

Yazdanpanah and Abbasi (2009), predict liquidity resources of EN Bank in order to control and reduce liquidity risk. To this end, they design a model to predict the liquidity of the EN Bank, which includes the current account, and the account between banks and the fund. In this regard, they use prediction based on cash inflow during this period, so that in order to meet the goals and strategies of the bank, the necessary planning for the deficit recovery (surplus consumption) with the aim of liquidity equilibrium will be prepared at the end of the period. The model is based on ARIMA, and the forecast based on this model is for the next 52 weeks, which indicates the excess liquidity of the bank.

Poursherafatan et al. (2014) investigate the liquidity risk management in the banking system using a Stochastic Optimal Control method. In order to determine the optimal strategy to reduce liquidity risk of the bank by increasing the liquidity coverage ratio, they propose a method based on the stochastic dynamics of the liquidity parameters such as cash assets and net cash outflow. In order to predict liquidity behavior of the bank, they present a dynamic system to explain liquidity behavior by observing the same type of credit, operational, market and liquidity behavior in the past.

Esmaeilzadeh and Javanmardi (2017) present a liquidity modeling and forecasting to obtain a liquidity risk management model of Saderat Bank. In their research, using liquidity data from 2011 to 2014, they predict bank liquidity for the year 2015 using the ARIMA model. In order to model liquidity risk, they estimate Liquidity at Risk based on ARCH and GARCH models. The results of their research indicate that the ARIMA model is an appropriate model for predicting liquidity, with econometric models, it is possible to model liquidity risk.

3 Methodology and Data Description

The survey of volatility in financial markets, which is used as a risk measurement criterion, plays a fundamental role in investing, valuing securities, market rules and controlling and managing risk. Therefore, modeling and estimating the turbulence of financial-economic time series, has become the focus of numerous studies in finance.

Among the approaches proposed in modeling the turbulence of financial-economic data, time series modeling (parametric approach) methods, including Historical Standard Deviation, Stochastic Volatility models and ARCH class models, are the most widely employed methods. All of these models are capable of explaining characteristics such as volatility clustering and fat tails of probability distribution, while some of these models also take into account asymmetry of volatility. The efficient performance of such models in capturing the dynamic properties of turbulence in financial-economical time series, makes them a proper tool for modeling of turbulence. These models formulate the conditional variance of time series through the Maximum Likelihood method. (Poon and Granger, 2003).

3.1 Autoregressive Conditional Heteroskedasticity Model (ARCH)

The ARCH model was proposed by Engel in 1982, and has become a well-known category of nonlinear models for modeling financial time series. This model is one of the most common approaches to variability modeling, which is done by examining the variance structure of the error sentence, in which the conditional variance is a function of the second power of the residual lags. In general, an ARCH model with q lags is specified as follows:

$$v_t \sim i.i.d(0,1) \qquad y_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i y_{t-i} - \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \ , \ \varepsilon_t = \sigma_t v_t \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad , \quad i > 0 \ , \ \alpha_i \geq 0 \ , \ \alpha_0 > 0 \quad (2)$$

It has the capability of modeling fat tails as well as clustering phenomena of volatilities.

3.2 Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH)

Taylor (1986) and Bollerslev (1986) have tried to resolve some of the disadvantages of the ARCH model, such as determining the number of lags in errors terms, as well as violating the non-negative assumption of conditional variance. With the aim of long memory process modeling and more flexible lag structure than the ARCH model, they proposed the generalized ARCH process, referred to as GARCH in the financial econometric literature. The structure of a GARCH (p, q) model with a fixed general form of the mean equation (the mean equation is given in the form of equation (1)), is formulated as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad , \quad \alpha_0 > 0 ,\ \alpha_i \geq 0 ,\ \beta_j > 0 \qquad (3)$$

This model can explain the characteristics of the fat tails and kurtosis more than the normal distribution, as well as the volatility clustering phenomenon of financial time series.

3.3 IGARCH Model

Engel and Bollerslev (1986) presented the Integrated GARCH model (IGARCH) to investigate the persistence of shock effects. This model has the same structure as the GARCH model, with the difference that if the conditional variance equation in the GARCH model has a unit root, then the GARCH model becomes IGARCH. The equation of variance in the IGARCH(1,1) model is written as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + (1 - \alpha_1)\sigma_{t-1}^2 \quad , \quad 0 < \alpha_1 \leq 1 \qquad (4)$$

3.4 TGARCH Model

A review of financial time series suggests that negative shocks (bad news) have a greater effect in comparison with similar positive shocks (good news) on fluctuations. For this purpose, GARCH models have been developed with the aim of considering the effects of positive and negative shocks on conditional variance asymmetrically in the form of leverage effect. The TGARCH model, which is an asymmetric GARCH model, was presented by Zakoian (1994). The variance equation in this model is formulated as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{r} \gamma_i \varepsilon_{t-i}^2 I_{t-i} \qquad (5)$$

Where $\varepsilon_{t-i} \geq 0$ represents good news and $\varepsilon_{t-i} < 0$ indicates bad news. If γ_i is not meaningful, the model will be symmetric. Also, if $\gamma_i > 0$, the effect of negative shocks is more than the effect of positive shocks.

3.5 EGARCH Model

Nelson (1991) presented the Exponential GARCH model to take into account the asymmetric effects of positive and negative shocks on the conditional variance of series and with the aim of considering the leverage effect. This model also has the ability to model the shock persistence. The structure of the EGARCH model is formulated as follows:

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{q} \left[\gamma_i \left[\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right] + \alpha_i \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \right] + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 \qquad (6)$$

In which γ_i expresses the effect of positive and negative shocks. If $\gamma = 0$, the model is symmetric and otherwise is asymmetric. Also, if $\gamma < 0$, then the effect of negative shocks is greater than the effect of positive shocks.

3.6 GARCH-M Model

The GARCH-M model, presented by Kim and Kon (1994), introduces the conditional variance (as an explanatory variable) in the conditional mean equation, examining the positive correlation between risk and returns. Positive and significant variance coefficient in the conditional mean equation implies that more risk premium will lead to higher returns. The GARCH-M model is formulated as follows:

$$y_t = \mu + c\sigma_t^2 + \varepsilon_t \quad , \varepsilon_t = \sigma_t v_t \quad , \; v_t \sim \text{i.i.d}(0,1) \qquad (7)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (8)$$

Where c is called the Risk Premium, and if it is significant, it indicates the relationship between efficiency and risk.

3.7 APGARCH

Taylor (1986) and Schwert (1989) used standard deviations instead of variance in modeling the GARCH model. Later, Ding et al. (1993) developed the Asymmetric Power GARCH model (APGARCH) as a category of asymmetric volatility models. In this model, conditional variance is formulated as follows:

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q} \alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j\sigma_{t-j}^\delta \quad (9)$$

For all values $i = 1,2, \dots, r$ if $\gamma_i = 0$, the APGARCH model becomes the GARCH model.

3.8 CGARCH Model

Engle and Lee (1993) proposed Component GARCH (CGARCH) model to investigate short-run and long-run volatilities, by modeling the return to mean property of time series. In other words, the effects of any changes (shocks) that is created, will be lost after a while and conditional variance returns to a constant level. In this model, the conditional variance is specified as follows:

$$\sigma_t^2 - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \quad (10)$$
$$q_t = \omega + \rho(q_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (11)$$

Equations (10) and (11) represent the short-term (temporary) component and the long-term (permanent) component in uncertainty, respectively. This model is also used to evaluate the asymmetric effects of positive and negative shocks.

3.9 Nonlinear Generalized Autoregressive Conditional Heteroskedasticity (NGARCH)

To investigate the effect of asymmetric volatility, Engle and NG (1993) introduced another form of GARCH model in the form of non-linear heteroskedastic model (NGARCH). In addition to features such as clustered volatility and fat tails of series, it can model the asymmetric volatility response to good and bad news in the form of leverage effect. In this model, conditional variance is formulated as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\sigma_{t-1}^2 + \beta_1(\varepsilon_{t-1} - \gamma_1\sigma_{t-1})^2 \quad (12)$$

If $\varepsilon_{t-1} < 0$, bad news increases the variability and vice versa. Also, if γ_1 (Leverage effect parameter) is not significant, the model will be symmetric, that is, the effect of good and bad news is the same.

4 Data and Empirical Results

In this study, the daily data of resources (deposits) and expenditures (facilities and receivables) of a private bank (based on the national currency, IRR) as an inflow and outflow of funds during the period from 25 March 2009 to 19 March 2018 are used. Resources consist of all outstanding deposits (current and savings), term investment deposits (short-term and long-term), as well as

Certificate of Deposit (CD). Expenditures include the total balance of current grant facilities plus claims (non-current facilities). In this way, the liquidity gap is created by the difference in resources (inflow) and expenditures (outflow). The aforementioned time range includes 2,180 observations, which are divided into two parts: an inside sample of 1,180 primitive observations for creating and estimating models and the remaining 1,000 observations for outside sample forecasting using a Rolling Window and also for measuring the accuracy of predictions. Statistical analysis is done using R software. The liquidity gap of the bank during the time period studied is shown in Fig. 1. As we can see, daily changes in the liquidity gap have an incremental and swinging trend that can be attributed to factors such as increased deposits (subsidy transfers, payrolls of social security organizations, etc.), increased deposit checks, deposits from big customers, etc. which can strengthen the inflow to the bank. On the other hand, the withdrawal of big customers from their accounts, the payment of large facilities, the effect of certain days (calendar effects), etc., can lead to an increase in the outflow of the bank.

Table 1 shows descriptive statistics related to the daily liquidity gap of the bank in the period under consideration. The average liquidity gap in the reviewed period is 29,210,548 million Rials (IRR) and its standard deviation is 16,694,895 million Rials (IRR). The positive and small skew indicates that the right side of the data distribution is long tail and the left side is peaked, and the positive gaps are above average compared with the negative gaps (the mean is on the right of the peak value). The statistic for skewness (0.522) indicates that the distribution of data is somewhat symmetrical. The Kurtosis is smaller than the normal value (3), indicating that the tails are wider than the normal distribution. The Jarque-Bera test statistic used to verify the normal distribution of data is 123.77, which rejects the null hypothesis of normal distribution of data,. This indicates that errors can have a distribution other than normal distribution.

Table 1

Descriptive Statistics

Mean	**Median**	**Mode**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**	**Jarque-Bera**
29,210,548	27,166,176	1,025,048	16,694,895	0.522	2.478	4,275,591	87,231,637	123.7741

Source: Research Findings.

One of the basic assumptions in the modeling of volatility is stationarity of the time series data. The existence of a unit root denotes the non-stationarity of the time series, which indicates the absence of constant moments for data, that can undermines the validity of the tests performed. In order to investigate the stationarity of the liquidity gap series, two Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP) tests are used. Based on the results of both tests depicted in Table 2, the Null Hypothesis of the unit root cannot be accepted. In other words, the liquidity gap time series data is stationary.

Table 2

Unit Root Test Results

Test	**ADF**	**Philips-Peron**
Value	-3/663 [0.027]	-62/782 [0.01]

Note: The p-values associated with the statistical tests are presented in brackets. Source: Research Findings.

We use the correlation coefficient graph and Q Ljung-Box (Q_{LB}) statistics to test whether any of a group of autocorrelations of liquidity time series are different from zero. The results of this test for various lags, shown in Table 3, indicate the autocorrelations in the liquidity gap series, which is an endorsement for using ARMA models. Also, the Ljung-Box test statistic on the squared liquidity gap series implies the rejection of the null hypothesis, which in fact represents non-linear effects and also confirms the heteroskedasticity and the use of the ARCH model for the series.

Table 3

Q Ljung-Box Statistics for Various Liquidity Gap Lags and Their Squares

Liquidity Gap	2137 [0.000]	8344 [0.000]	16208 [0.000]	23718 [0.000]	31042 [0.000]	38221 [0.000]
Squared Liquidity Gap	2110 [0.000]	8152 [0.000]	15653 [0.000]	22690 [0.000]	29516 [0.000]	36172 [0.000]

Note: The numbers of lags are reported in parentheses and the p-values associated with the statistical tests are presented in brackets. Source: Research Findings.

The conditional mean equation is chosen based on the Box-Jenkins methodology. According to the ACF and PACF charts of the liquidity gap series, different models of ARMA (p,q) are fitted for the data series. Based on the Akaike Criterion (AIC) and Schwarz-Bayesian Criterion (SBIC) and the

Log Likelihood (LL) provided that error terms are not correlated, the appropriate model is chosen. Accordingly, the best model is ARMA (2.1).

In order to use the ARMA models, the variance of the error term must be known. For this purpose, ARCH Engle test (1982) with the Lagrange Multiplier (LM) criterion on the conditional mean equation is tried, with the null hypothesis of the absence of the effects of ARCH (Homoskedasticity). Based on the results of this test, shown in Table 4, the null hypothesis of constant variance over the sample is rejected, so the liquidity gap series has ARCH effects.

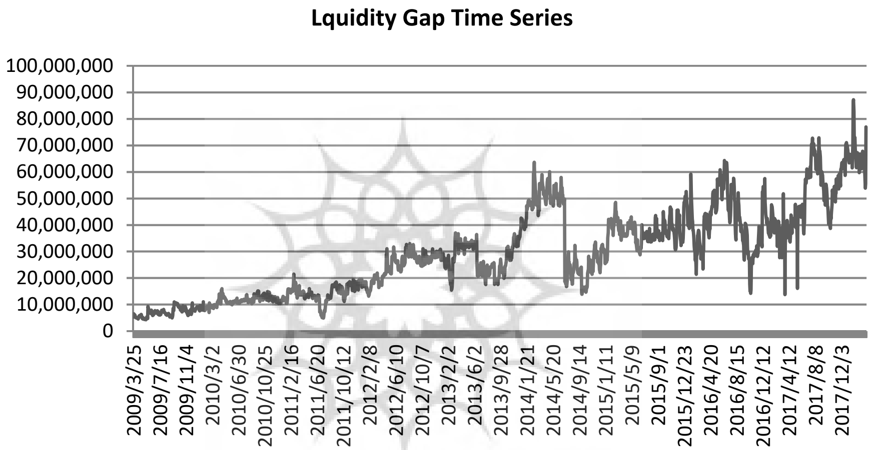

Figure 1. Liquidity Gap Series. Source: Research Findings.

Table 4

Results of ARCH Effects Test

LM Test Statistic	(4)=7152 Q [0.000]	(8)=3463 Q [0.000]	(12)=2088 Q [0.000]	(16)=1517 Q [0.000]	(20)=1160 Q [0.000]	(24)=957 Q [0.000]

Note: The numbers of lags are reported in parentheses and the p-values associated with the statistical tests are presented in brackets. Source: Research Findings.

The Q Ljung-Box statistics is used to investigate the auto-correlation of error terms in the ARCH process. The values of Ljung-box statistics for various lags, depicted in Table 5, indicate that there is no correlation between error terms and the proper specification of the conditional mean model. Also, the Ljung-Box test statistic on the squared residual of the conditional mean regression indicates that there is a correlation between the squares of the conditional mean model which is the confirmation of the effects of ARCH in the liquidity gap series.

Table 5

Ljung-Box Test for the Residual Series and the Squared Residuals of the Conditional Mean Model

Residual	1)=0.521 Q([0.470]	4)=0.836 Q([0.934]	8)=6.607 Q([0.580]	12)=18.393 Q([0.104]	16)=19.040 Q([0.267]	20)=31.269 Q([0.052]
Squared Residual	(1)=26.9 Q [0.000]	(4)=30.1 Q [0.000]	(8)=41.5 Q [0.000]	Q(12)=48.9 [0.000]	Q(16)=52.2 [0.000]	Q(20)=78.0 [0.000]

Note: The numbers of lags are reported in parentheses and the p-values associated with the statistical tests are presented in brackets. Source: Research Findings.

Based on the results of the diagnostic tests in the previous section, the performance of various GARCH family models including GARCH, IGARCH, EGARCH, TGARCH, NGARCH, APGARCH, GARCH-M and CGARCH with the ARMA model (2.1) as a conditional mean equation are compared, assuming that the shock liquidity gap series has a Normal Distribution (N), Skewed Normal (sN), t-student (t), skewed t-student (st), Generalized Error Distribution (GED), Skewed Generalized Error Distribution (sGED) and Johnson-SU (JSU). The study of the Long Memory feature in the liquidity gap series using R/S (Rescaled Range) and GPH (Geweke & Porter Hudak) tests suggests that this feature does not exist in the data. Furthermore, the results of the fitting tests of the models used indicate that the coefficients of NGARCH, GARCH-M and CGARCH models are not significant. In order to rank the models used and select the optimal model, the Akaike (AIC) and Schwarz-Bayesian (SBIC) criteria and the Log Likelihood (LL) are used. The most suitable model is the one that maximizes the logarithm of likelihood and minimizes the AIC and SBIC criteria. Based on the AIC criterion and the Log Likelihood, depicted in Table 6, the APGARCH model with Johnson-SU distribution is the best model for describing the correlation in skedastic function (conditional variance). Therefore, in order to describe the behavior of bank liquidity gap volatilities, the APGARCH model with the Johnson-SU distribution can be applied.

In order to investigate the asymmetry of variability, the nonlinear ARCH analysis of Engle and NG (1993) is used. In fact, this test seeks to ascertain whether positive or negative shocks, or unequal shocks have different effects on conditional variance. In this direction, we use Sign Bias Test (SB), Negative Size Bias Test (NSB), Positive Size Bias Test (PSB) and Joint Test. The results of this test, shown in Table 7, indicate the insignificance of sign bias test and negative size bias test, but positive size bias test and joint test are significant at 1% and 5% levels, respectively. Therefore, the effects of asymmetric shocks on variability cannot be rejected.

According to the estimation results of APGARCH model in terms of Johnson-SU distribution for the volatility of liquidity gap, depicted in Table 8, the coefficients of ARCH and GARCH (β and α) are positive and significant at high level of confidence. The lagged variance coefficient (β) indicates the rate of stability of the oscillation shock whose high value ($\beta = 0.96$) indicates that the shocks created in the oscillation process have a slight tendency to return to the mean oscillation. The forecasted error factor (α) shows the adaptive speed rate of volatility with new market shocks, the low value of which ($\alpha = 0.05$) indicating that the predictions are not susceptible to new information. The leverage effect parameter (γ) is negative in the model at a high significant level, which indicates that positive and negative shocks (good and bad news) have a different effect on liquidity gap volatilities, so that the effect of positive shocks on liquidity gap is greater than negative shocks; this is confirmed by the impact curve of the news (Pagan and Schwert) as well. The estimated parameter δ is 0.4003, which is significant at the high level. The significance of the skewness and kurtosis coefficients confirms the use of the Johnson-SU distribution, which takes into account the kurtosis and skewness in the liquidity gap series modeling.

The results of the diagnostic statistics indicate that the template is appropriately arranged, so that the ARCH test indicates the constant variance of the residual values obtained from the model estimation. The Q Ljung-Box statistic for lag (14) indicates a lack of serial correlation between error terms. In addition, the Q^2 Ljung-Box test (9) on the squared of the residuals generated from the model estimation indicates that there is no serial correlation between the squared of the residuals.

Table 6

Ranking of Models Based on Akaike, Schwartz-Bayesian Criteria and Logarithms Likelihood

Model	Criteria					
	Log Likelihood	AIC	SBIC	Rank LL	Rank AIC	Rank SBIC
APGARCH-norm	830.1343	-1.3918	-1.3531	27	27	27
APGARCH-snorm	837.6829	-1.4029	-1.3599	26	26	26
APGARCH-std	985.3458	-1.6531	-1.6101	5	5	5
APGARCH-sstd	988.3247	-1.6565	-1.6092	2	3	7
APGARCH-ged	977.5127	-1.6399	-1.5969	11	11	10
APGARCH-sged	979.3093	-1.6412	-1.5939	10	10	11
APGARCH-jsu	988.9801	-1.6576	-1.6103	1	1	3
EGARCH-norm	806.6388	-1.3536	-1.3192	31	31	31
EGARCH-snorm	813.0141	-1.3627	-1.324	30	30	30
EGARCH-std	986.4337	-1.6567	-1.618	3	2	1
EGARCH-sstd	980.4767	-1.6449	-1.6019	8	8	8
EGARCH-ged	966.5168	-1.6229	-1.5842	17	18	19
EGARCH-sged	969.407	-1.6261	-1.5831	14	15	20
EGARCH-jsu	979.9468	-1.644	-1.601	9	9	9
GARCH-norm	795.3287	-1.3362	-1.3061	34	34	35
GARCH-snorm	800.3119	-1.3429	-1.3085	32	32	33
GARCH-std	963.0303	-1.6187	-1.5843	21	21	18
GARCH-sstd	965.6385	-1.6214	-1.5827	19	19	21
GARCH-ged	956.8095	-1.6082	-1.5738	24	25	24
GARCH-sged	960.0918	-1.612	-1.5733	22	23	25
GARCH-jsu	968.1347	-1.6257	-1.587	16	16	17
IGARCH-norm	792.2344	-1.3326	-1.3068	35	35	34
IGARCH-snorm	798.16	-1.3409	-1.3109	33	33	32
IGARCH-std	963.2555	-1.6208	-1.5907	20	20	15
IGARCH-sstd	965.85	-1.6235	-1.5891	18	17	16
IGARCH-ged	956.4598	-1.6093	-1.5792	25	24	22
IGARCH-sged	959.8225	-1.6133	-1.5789	23	22	23
IGARCH-jsu	968.2436	-1.6275	-1.5931	15	14	12
TGARCH-norm	824.1717	-1.3833	-1.3489	29	29	29
TGARCH-snorm	828.8355	-1.3896	-1.3509	28	28	28
TGARCH-std	982.0997	-1.6493	-1.6106	7	7	2
TGARCH-sstd	984.9482	-1.6525	-1.6095	6	6	6
TGARCH-ged	971.437	-1.6312	-1.5926	13	13	13
TGARCH-sged	974.3838	-1.6345	-1.5916	12	12	14
TGARCH-jsu	985.3724	-1.6532	-1.6102	4	4	4

Source: Research Findings

Table 7
Asymmetry Test Results

Description	Sign Bias Test (SB)	Negative Size Bias Test (NSB)	Positive Size Bias Test (PSB)	Joint Test
Liquidity Gap	1.31 [0.190]	0.11 [0.915]	3.26 [0.001]	10.67 [0.014]

Note: The p-values associated with the statistical tests are presented in brackets.

Table 8
Estimation Result of the APGARCH-JSU Model for Liquidity Gap

Mean Equation	μ	0.53	[0.000]	**Diagnostic Statistics**	Log Likelihood	988.9801	
	ar1	1.57	[0.000]				
	Ar2	-0.56	[0.000]		AIC	-1.66	
	ma1	-0.67	[0.000]		SBIC	-1.61	
Variance Equation	ω	0.01	[0.002]		H-Q	-1.64	
	α	0.05	[0.000]		Shibata	-1.66	
	β	0.96	[0.000]				
	γ	-0.71	[0.000]		ARCH-LM	1.05	[0.906]
	δ	0.40	[0.000]				
	skew	0.15	[0.006]		Q(14)	7.041	[0.552]
	shape	1.11	[0.000]		$Q^2(9)$	4.56	[0.497]

Note: The p-values associated with the statistical tests are presented in brackets.

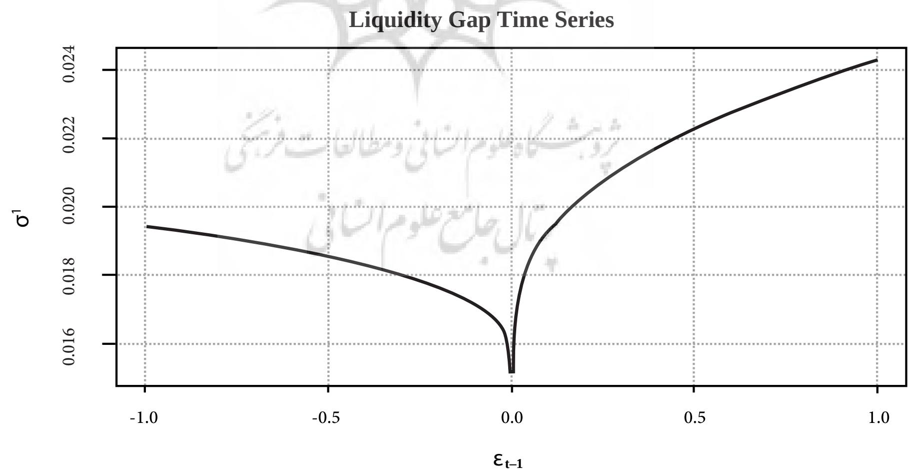

Figure 2. The Effect of the News Curve

Table 9
Evaluation of Out-of-Sample Volatility Forecasts

Model	Criteria					
	RMSE	MAE	TIC	Rank RMSE	Rank MAE	Rank TIC
APGARCH-norm	0.2804	0.1883	0.0629	34	9	34
APGARCH-snorm	0.2807	0.1889	0.063	35	13	35
APGARCH-std	0.2779	0.1865	0.0624	1	1	1
APGARCH-sstd	0.2793	0.1885	0.0627	14	11	14
APGARCH-ged	0.2791	0.1876	0.0626	10	4	10
APGARCH-sged	0.28	0.1899	0.0628	28	26	28
APGARCH-jsu	0.2792	0.1883	0.0626	12	10	12
EGARCH-norm	0.2798	0.19	0.0628	24	28	24
EGARCH-snorm	0.2801	0.1899	0.0628	29	27	29
EGARCH-std	0.2781	0.1873	0.0624	2	2	2
EGARCH-sstd	0.2796	0.1893	0.0627	19	18	19
EGARCH-ged	0.2789	0.1879	0.0626	7	6	7
EGARCH-sged	0.2797	0.1896	0.0628	22	22	22
EGARCH-jsu	0.2799	0.1896	0.0628	27	23	27
GARCH-norm	0.2793	0.1914	0.0627	13	33	13
GARCH-snorm	0.2797	0.192	0.0628	23	35	23
GARCH-std	0.2785	0.1881	0.0625	3	8	3
GARCH-sstd	0.2793	0.1896	0.0627	16	21	16
GARCH-ged	0.2789	0.1891	0.0626	6	15	6
GARCH-sged	0.2802	0.1903	0.0629	32	30	32
GARCH-jsu	0.2795	0.1898	0.0627	17	24	17
IGARCH-norm	0.2791	0.1912	0.0626	11	32	11
IGARCH-snorm	0.2796	0.1919	0.0627	21	34	21
IGARCH-std	0.2785	0.1881	0.0625	4	7	4
IGARCH-sstd	0.2793	0.1895	0.0627	15	20	15
IGARCH-ged	0.279	0.1893	0.0626	9	17	9
IGARCH-sged	0.2804	0.1906	0.0629	33	31	33
IGARCH-jsu	0.2795	0.1898	0.0627	18	25	18
TGARCH-norm	0.2799	0.1888	0.0628	25	12	25
TGARCH-snorm	0.2801	0.1892	0.0629	30	16	30
TGARCH-std	0.2787	0.1876	0.0625	5	3	5
TGARCH-sstd	0.2796	0.1891	0.0627	20	14	20
TGARCH-ged	0.279	0.1878	0.0626	8	5	8
TGARCH-sged	0.2802	0.19	0.0629	31	29	31
TGARCH-jsu	0.2799	0.1895	0.0628	26	19	26

Source: Research Findings

For the modeling and prediction of the liquidity gap series based on the models used in this research, from the 2,180 observations, a rolling window of 1,180 observations is created to build the models. Then the rank and unknown parameters of the model are determined using a preliminary observation of 1,180 and based on this, the liquidity gap is predicted for the period of 10, 20 and 30 stages ahead. By moving the rolling window at a level of one observation, the orders of parameters are re-set according to the best fit, and using it, the prediction is resumed at the specified time intervals; this procedure is repeated 1,000 times for the whole 2,180 available observations. Finally, for estimating the accuracy of prediction of each model, the estimated Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Taylor Inequality Coefficient (TIC) are used. The results of the prediction error measuring criteria for the 10-day period are presented in Table 9. Only the results for the 20th and 30th day periods are mentioned to avoid the prolongation of the article.

Comparison of the models based on all three MAE, RMSE and TIC criteria suggests that the APGARCH model with t-student distribution provides a better prediction of the liquidity gap in the 10-day period. The results of the values of the predictive error measuring criteria for the 20-day period show that based on the two criteria of MAE and RMSE, APGARCH model with t-student distribution, and based on the TIC criterion, APGARCH model with skewed t-student provide better predictions. Also, comparing the accuracy of prediction of oscillation of research models for a 30-day period indicates that the APGARCH model with t-student distribution provides the least error in predicting liquidity gap based on all three criteria of MAE, RMSE and TIC. The results of the predicted error statistics for the mean time series and the volatility of the liquidity gap, applying the rolling window, indicate that the APGARCH model with t-student distribution has a better performance in predicting the liquidity gap of the bank in periods of 10, 20 and 30 days.

In order to test the models used, we use the Diebold & Mariano (1995) test with null hypothesis of the predictive power equality of the two competing models. Since the APGARCH-std model has the best performance in predicting volatilities in 10, 20, and 30-day horizons, we compare other research models against this model based on the Diebold & Mariano test. The probability values of this test based on the Root Mean Square Error (RSME), depicted in Table 10, indicate that the predictive powers are not equal and the difference between the mean squared errors of the competing models at the 5% level is meaningful; in other words, the difference in prediction accuracy of the APGARCH-std model volatilities in comparison with other research models is statistically verified.

Table 10
Results of the Diebold-Mariano Test

Model	Statistic	P-Value Less	P-Value Greater
APGARCH-norm	-0.963	0.168	0.832
APGARCH-snorm	-3.196	0.001	0.999
APGARCH-sstd	-0.802	0.211	0.789
APGARCH-ged	-3.379	0.000	1.000
APGARCH-sged	-2.914	0.002	0.998
APGARCH-jsu	-1.454	0.073	0.927
EGARCH-norm	-1.659	0.049	0.951
EGARCH-snorm	-1.934	0.027	0.973
EGARCH-std	-0.975	0.165	0.835
EGARCH-sstd	-2.022	0.022	0.978
EGARCH-ged	-1.503	0.067	0.933
EGARCH-sged	-3.218	0.001	0.999
EGARCH-jsu	-2.382	0.009	0.991
GARCH-norm	-2.178	0.015	0.985
GARCH-snorm	-14.668	0.000	1.000
GARCH-std	-2.054	0.020	0.980
GARCH-sstd	-15.172	0.000	1.000
GARCH-ged	-0.610	0.271	0.729
GARCH-sged	-2.574	0.005	0.995
GARCH-jsu	-3.392	0.000	1.000
IGARCH-norm	-16.019	0.000	1.000
IGARCH-snorm	-12.886	0.000	1.000
IGARCH-std	-2.065	0.020	0.980
IGARCH-sstd	-17.148	0.000	1.000
IGARCH-ged	-0.863	0.194	0.806
IGARCH-sged	-2.711	0.003	0.997
IGARCH-jsu	-3.401	0.000	1.000
TGARCH-norm	-4.111	0.000	1.000
TGARCH-snorm	-5.054	0.000	1.000
TGARCH-std	-1.104	0.135	0.865
TGARCH-sstd	-1.917	0.028	0.972
TGARCH-ged	-4.424	0.000	1.000
TGARCH-sged	-2.878	0.002	0.998
TGARCH-jsu	-1.977	0.024	0.976

Source: Research Findings

5 Conclusion and Discussion

Liquidity risk is one of the most important types of financial risk, and refers to the inability of a financial institution to pay off debt, or providing funds to raise assets. In the process of financial institutions' operations, the maturity of the grant facilities is usually longer than the maturity of deposits. This discrepancy in the maturity of payments and receipts increases the likelihood of payment failure of the financial institution in the prescribed period, and creates a time gap between facilities and deposits, in such a way that the financial institution is not prepared to provide the funds needed in the short term and with a reasonable cost.

Therefore, in the present study, in order to identify the liquidity behavior of the bank with the aim of managing and controlling liquidity risk, we aim to model and predict the liquidity gap based on cash flow forecasts (resources and expenditures). In this way, using the Generalized Autoregressive Conditional Heteroskedasticity, the GARCH model family, considering the effects of ARCH in the liquidity gap series, we examine the liquidity gap of the bank during the period from March 26, 2009 to March 19, 2018.

In order to recognize the data production process, the performance of the GARCH family models (8 models) with some of the characteristics observed in the liquidity gap series, such as heteroskedasticity, fat tails, clustered volatilities, leverage effect, fluctuation feedback and long memory are compared with the assumption that the error component has normal, skewed normal, t-student, skewed t-student, generalized error, skewed generalized error and Johnson-SU distributions. The results of the fitting test of the applied models suggest that the coefficients of the NGARCH, GARCH-M and CGARCH models are insignificant. The most suitable model for explaining the liquidity gap based on the Akaike and Schwarz-Bayesian information criteria, as well as the logarithm likelihood (LL), is the APGARCH model with the Johnson-SU distribution.

The results of the estimation of the APGARCH model with the Johnson-SU distribution indicate persistence in volatilities, so that the shocks created in the oscillation process are reluctant to return to the mean oscillations. Significant leverage effect parameter indicates the asymmetry of positive and negative shocks on volatility. The significance of the coefficients of kurtosis and skewness indicates that there is excess kurtosis and skewness in the distribution of the data series, which is considered by the Johnson-SU distribution in the liquidity gap series modeling.

In line with the prediction of the liquidity gap series based on the research models, we use the rolling window method and predict over the windows of 10, 20 and 30 days. Furthermore, in order to compare the prediction accuracy of the applied models, the mean absolute error, mean squared error and Taylor's inequality coefficient are used. The results of this comparison indicate that the APGARCH model with the t-student distribution has the least error in the prediction of liquidity gap in the time horizons of research based on all three MAE, RMSE and TIC criteria. The results of post-test using the Diebold-Mariano test is suggesting a difference in prediction accuracy of volatilities in APGARCH-std model compared to other research models.

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