Assessment and Explanation of Bank's Liquidity Risk Forecasting Model Using of Liquidity at Risk Case Study: Agricultural Bank

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Abstract

This research studies assessment and explanation of liquidity risk model at danger using of LaR four models which are fluctuation operator or conditional variance. These four models consist of two econometric groups (GARCH and ARCH) and two risk assessment groups (MA and EWMA). Results of the research indicate this fact that possibility of liquidity and liquidity risk forecasting exist in using of liquidity at risk model (LaR) with historical data of bank liquidity, it also shows that studied subset models in 95% confidence level have appropriate performance for liquidity at risk forecasting using of liquidity at risk model (LAR) and confirms that it is possible to predict econometrics liquidity risk and risk assessment in two ways. Liquidity time series of studied bank have very large fluctuation shocks in spread time even to the extent that bank liquidity is negative in some periods. Garch model as a variation operator can be divided the time series into clusters of multiple parts and decrease sudden shocks in both 95% and 99% confidence level is reliable and as a more efficient model than other measurement models presented its fluctuation in this study.

Keywords: risk, value-at-risk, liquidity risk

1. Introduction

Liquidity risk is a risk due to lack of sufficient liquidity to cover short-term obligations and unexpected outputs funds. In such circumstances, banks have to absorb expensive resources (such as interbank loan market) or cash its other assets in less time and with much less price than market price. Another case is when demands for facilities for any reason, is faced with unexpected growth but bank's resources are not enough to meet these high volume of demands. Although in this case the bank has no obligation towards the applicant's facilities and because of the simplest reason, lack of resources avoid loan payments, however, due to lack of required facilities regardless profit from the resources of the bank is robbed. It should be noted that study of the liquidity risk of each bank (which is more originally internal), directly related to the size of the bank, the main activity, internal guidelines.... In this paper, liquidity risk by LaR modeling (liquidity at risk) is calculated by using of four ways of fluctuation estimation which are in two groups of econometric and risk assessment.

It uses Arch and Garch model from econometric group and simple moving average and moving harmonic average from risk assessment group (Radpour, 2008).

1.1 Theoretical and Research Background

Liquidity risk is the result of two factors: (Committee of Basel, 1998)

• Market liquidity has varied over time.

• The Bank's liquidity

Interaction of these two factors could provide condition for bank funds. Cost of providing funds can increase because of the momentary lack of liquidity in the market. Market liquidity has important impacts in the cost of providing funds by all market players. Most banks absorb short-term resources and give long-term loans, this

form (there is a gap in maturity) lead to liquidity risk and produce costly cash flow. Liquidity costs can be expressed as an expense caused by a lack of liquidity for giving facilities.

1.2 Value at Risk (VaR) and Reasons for Its Use

Value at Risk is also called "capital at risk", it identified those amount of the portfolio or asset value which is expected to loose during specific time period and the possible extent. For example, a bank may proclaim that value at daily risk of bank's buy and sale portfolio in 95% confidence level, is 10 billion riyals. Risk calculation in current investments assets include different financial instruments such as stocks, bonds and various derivatives only measure by this index because due to the derivatives specific characteristics, the absence of a linear relationship between the output device and committed original asset, other methods cannot be used to calculate risk (Shahmoradi, 2007).
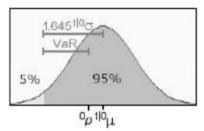

Figure 1. Value at risk at 95% confidence level

1.3 Research Background

There are very different and various ways to calculate value at risk of assets as a single and portfolio assets and financial institutions such as banks and mutual funds are largely used to assess the risk of their asset portfolio (Peziers, 2004).

After G. P. Morgan Corporation introduced risk assessment model in 1994 to measure value at risk, this model was introduced as a method to measure the market risk. International settlement bank in 1996, was introduced the value at risk by the Basel committee banking supervision guidelines format for market risk management. Pascual et al. (2009) in their research with prediction of errors parametric and portfolio variance modeling and Barone-Adesi (1999) in his research examines the simulation model in risk prediction, both of them examine market risk levels (Crouhy et al., 2001). Also Figlewski consider acceptable confidence level in value at risk model prediction.

Campbell et al. (2001) determine the optimal weighting of assets in the portfolio, considering the limitations of the model at risk. Also Billio and Pelizzon (1998) used semi-parametric methods to predict the value at risk. One of the most important challenges that prediction models of value at risk faced with was conditional variance in return distribution of financial data. It resulted to design regression conditional dissimilar variance models. This model, first was introduced in 1982 by Engle (Engle, 1982). Bollerslev generalized Angel model and offered group of models which are known as generalized models (GARCH). Akgiray (1989) also consider conditional dissimilar variance (conditional heteroscedasticity) in time series of stock returns. After other conditional spread models emphasizing on different characteristics of financial data, such as FGARCH, EGARCH, IGARCH models, other recent researches about market risk assessment can mention Hafner and Romboust and also, Yu researches. Hafner and Romboust in order to predict their researches, compared Monte Carlow's simulated model, and value at risk model and the results of their study showed more performance of the model in market risk prediction.

So, Yu also considered GARCH models in calculation of value at risk in equity portfolio in New York exchange. Their findings suggest that in most cases, returns distribution in stock market follow normal distribution with thicker sequence. Which assumes normal distribution of returns, as a result such models have less performance in market risk prediction. Their results also indicate that due to the asymmetric behavior of investors in the market, among GARCH models, IGARCH model have better performance in market risk prediction. (Risk Metrics Group, 1996)

2. Methodology and Research Applied Methods

This study is time series correlation analysis. This paper attempts using of the risk assessment model (Simple Moving Average and Moving Harmonic Average) and Arch and Garch econometric Value at Risk—which are the

most important measure in liquidity risk, estimate Agricultural bank liquidity of two years ago. And then performance of the two models in value at risk measurement are compared and select the best model. In general, the basic steps in the procedure are as follows:

1) To collect time-series and doing normal and viable tests on being liquidity data in 1387 and 1389 of the Agricultural Bank in Iran.

2) Anticipate 1389 liquidity using1387 to 1388 liquidity data by Aryma model.

3) Describes Arch and Garch econometric model and risk assessment moving harmonic average and simple harmonic oscillation index as an important measure to estimate the value at risk

4) Estimate fluctuations index using mentioned models

5) Estimate the value at risk using Arch and Garch models and risk assessment

6) Estimate the model validity using test ratio to Kopic possibility failure, evaluating two fitted models and select more efficient model.

2.1 Liquidity Forecasting Model

In this research for forecasting everyday liquidity net we use autoregressive process- integrated moving average (ARMA) that contains p amount of autoregressive and q amount of waste interruptions:

To calculate the value at risk at specific confidence level of liquidity, should multiply conditional fluctuation index $(\sigma^2_{t+1|t})$ in critical quantity of the normal distribution at specified error level and net amount of liquidity:

$$LAR = -Z_\alpha.\sigma^2_{t+1|t}.L$$

Z_α: critical quantity of the normal distribution

$\sigma^2_{t+1|t}$: fluctuation index

L: liquidity

So the next step to calculate the conditional fluctuations index, on ARMA waste model GARCH & ARCH models are estimated.

2.2 GARCH & ARCH Econometric Model (Autoregressive Conditional Dissonance Variance and Generalized Autoregressive Conditional Dissonance)

GARCH model is presented as follows:

$$\varepsilon_t|\Psi_{t-1}\sim N(0,h_1$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i\varepsilon^2_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} \quad = a_0 + A(L)\varepsilon^2_t + B(L)h$$

$$p \geq 0, q \rangle 0$$

$$a_0 > 0, a_i \geq 0 \qquad i = 1,2,\ldots,q$$

$$\beta_i \geq 0 \qquad\qquad i = 1,2,\ldots,p$$

For the ARCH (q) p=0 process will be and if p=q=0 it is easily seen that ε_t is a white noise sentence. In ARCH (q) process, conditional variance is a linear function of the past variance but in the GARCH (q) process, interruption conditional variances are also entered in the model. Regression Model of GARCH (p, q) is from the wastes get from the fit y_t on the X_t vector. If the following equation is satisfied:

$$\varepsilon_t = y_t - X'_t\beta$$

As y_t is a dependent variable, X_t is a vector of explanatory variables and β is a vector of unknown parameters GARCH (p, q) process can be r revealed in other forms:

$$h_t = a_0 + \sum_{i=1}^{q} a_i\varepsilon^2_{t-j} + \sum_{j=1}^{p} \beta_j \varepsilon^2_{t-j} - \sum_{j=1}^{p} \beta_j V_{t-j} + V_t$$

$$V_t = \varepsilon_t^2 - h_t = (\eta_t^2 - 1)h_t$$

$$\eta_t \sim N(0,1)$$

2.3 Risk Assessment Model for Measuring EMWA and SMA Fluctuations (Simple Moving Average and Moving Harmonic Average)

One of the models which is used to measure and predict the risk is risk metrics model, of Metrics risk group J. P. Morgan Corporation.

This model is formed base on the assumption that the returns distribution follow a normal distribution. Forecasting equation output fluctuations for a set of data (with a T) with equal weights or same simple moving average are as follows:

$$\sigma_t = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2}$$

For fluctuations forecasting, we use "harmonic moving average" method as follows:

$$\sum_{T=0}^{\infty} \lambda^t r_{t-T}^2 = (1 - \lambda)\,\sigma_{t+1|t}^2$$

Using harmonic moving average method causes the fluctuations dynamic characteristics to be preserved because last observations carry more loader in predicting fluctuations.

3. Data and Measurement Ways

Survey data are weekly liquidity net of Agriculture bank for 2 years, which use of longitudinal sectional cutting method during 87 to 89 of Agriculture bank.

4. Research Hypotheses

1) The possibility of forecasting liquidity risk exists using of historical data of the banks by Aryma model.

2) The possibility of forecasting liquidity at risk exists using of LAR model based on ARCH and GARCH.

2-1) The possibility of forecasting one day liquidity at risk exists using of LAR model based on ARCH and GARCH.

2-2) The possibility of forecasting three days liquidity at risk exists using of LAR model based on ARCH and GARCH.

3) The possibility of forecasting liquidity at risk exists using of LAR model based on (MA) and (EWMA) (Simple and Moving Harmonic Average).

3-1) The possibility of forecasting one day liquidity at risk exists using of LAR model based on (MA) and (EWMA) (Simple and Moving Harmonic Average).

3-2) The possibility of forecasting three days liquidity at risk exists using of LAR model based on (MA) and (EWMA) (Simple and Moving Harmonic Average).

4) There is no significant difference between effectiveness of risk assessment models and Arch and Garch econometric models.

5. Research Findings

5.1 Data Time-Series

Basic data of this research include time series related to Agriculture bank liquidity. It is for the period of 01.01.1387 to 28.12.1389 it is seen in the following schematic diagram.
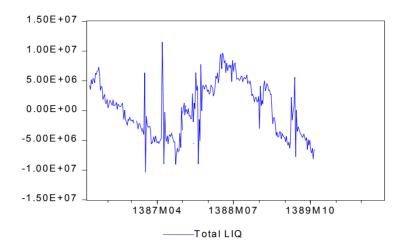
Figure 2. Liquidity net process of agricultural bank during of 87–89

5.2 Test of Data Normality

As many parametric tests are based on the normality of data distribution with these assumptions that data distribution follow a normal distribution therefore using the Jag test were examined for variables normality. According to the initial test primary data statistic are less than 005/0.The result shows that the data distribution is not normal. To make data normal, we use convert operation and data research is converted from x to 1/x3, after that data's normality are examined again.

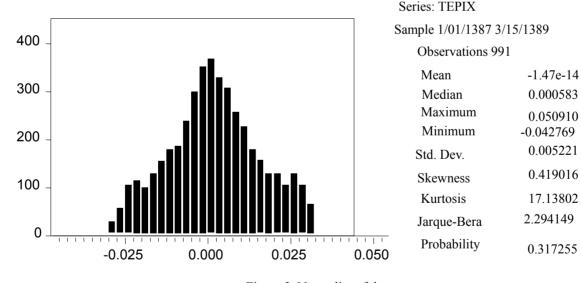| Series: TEPIX	
Sample 1/01/1387 3/15/1389	
Observations 991	
Mean	-1.47e-14
Median	0.000583
Maximum	0.050910
Minimum	-0.042769
Std. Dev.	0.005221
Skewness	0.419016
Kurtosis	17.13802
Jarque-Bera	2.294149
Probability	0.317255

Figure 3. Normality of data

Again test shows statistic possibility of Jarque-Bera is 0/317 and H hypothesis is accepted as a normality of time series distribution.

5.3 Time Series Durability Test

In methodologies and GARCH arch, reliability of applied time series is extremely important. In this study test it is used of the generalized Dickey-Fuller (ADF) and Phillips Brown at a significance level of 5% for testing the reliability of the time series.

Be noted that the modulus of ADF and PP computing statistics are more than critical quantities modulus in thier table (means DF modulus) and null hypothesis will be rejected and accept the other hypothesis that the time

series is durability. And also the null hypothesis related to the reliability is rejected as a result time series is stationary.

5.4 Calculation of Liquidity Forecasting Model by Using Aryma Model by Box-Jenkins

In this research in order to calculation of Aryma forecasting model it is used of Box-Jenkins approach. Using this method, based on Schwartz and Akaeik information criteria and according to things, such as the camera—watson statistics, Standard deviation errors, and adjusted for appropriate model is selected, which is shown in Table 2–4.

Table 1. Summarizes of dickey fuller and phillips-brown test results

PP Test Statistic			ADF Test Statistic		
-30.75657			-12.44825		
%1 Critical valu	%5 Critical value	Critical value %10	%1 Critical value	Critical value %5	Critical value %10
- 3.43137	- 2.86442	- 2.56359	-3.43711	- 2.86476	-2.56854

Table 2. Data summary of appropriate model calculation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.031136	0.345333	0.090163	0.9282
AR(2)	0.987515	0.004951	199.4546	0.0000
MA(2)	-0.606542	0.025235	-24.03572	0.0000
R-squared	0.859484	Mean dependent var		0.001049
Adjusted R-squared	0.859223	S.D. dependent var		0.956805
S.E. of regression	0.358995	Akaike info criterion		0.791756
Sum squared resid	138.9301	Schwarz criterion		0.805593
Log likelihood	-424.9444	F-statistic		3296.863
Durbin-Watson stat	1.239277	Prob(F-statistic)		0.000000

The final parameters of the final model were estimated as follows.

$$\emptyset_1(\beta) \ \nabla\nabla_{11}y_t = \theta_1 \ \beta\Theta_1(\beta)^{11}\alpha_t$$

$$\emptyset_1 = 0.051 \qquad \theta_1 = 0620 \qquad \Theta_1 = 0658$$

After developing the model and the final placement of the forecasting model was estimated as follows.

$$y_t = y_{t-1} + 0.051y_{t-1} - 0051y_{t-2} + y_{t-5} + y_{t-8} - 005y_{t-11} - 0.051y_{t-13} + \alpha_t - 0.620 \ \alpha_{t-1} - 0.6258\alpha_{t-11} + 0.408\alpha_{t-12}$$

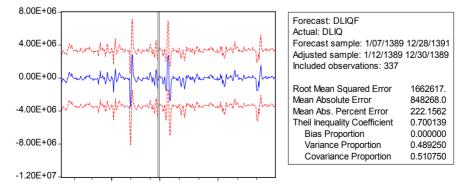In the following chart Aryma's forecasting is:

Figure 4. Prediction diagram belong to aryma model

Statistic of t-student for autoregressive interruptions and moving average interruptions, respectively—are 60.85 and 21.94447.

Estimation results indicate that autoregressive intervals coefficients are significant and moving average interval with a 5% significance level is constantly significant. To evaluate the suitability of the estimated models, autocorrelation functions (ACF) and partial Autocorrelation) (PACF were considered for waste series, resulted from estimation).

All of these charts, are small and do not follow any particular pattern therefore, it is concluded that the estimated model is a good model and can use of this model for a period beyond the estimation period.

5.5 ARCH and GARCH Calculation Model

E-views7 software output to find the best interval of GARCH & ARCH is shown below.

Table 3. Results of the Box—Jenkinz test in selecting the best model is viewed

Panel A: Parameter Estimates (Robust Standard Error)					
Parameter	MLE ARCH (1,0)	MLE ARCH (2,0)	MLE GARCH (1,1)	MLE GARCH (2,1)	MLE GARCH (1,2)	MLE GARCH (2,2)
μ	0.041	0.044	0.047	0.047	0.047	0.047
α	(0.011)	(0.011)	(0.016)	(0.017)	(0.017)	(0.016)
β_1	0.628	0.610	0.002	0.002	0.003	0.004
β_2	(0.047)	(0.054)	(0.001)	(0.001)	(0.003)	(0.003)
γ_1	0970	0.975	0.980	0.982	0.527	0.010
γ_2	(0.047**)**	(0.054)	(0.001)	(0.001)	(0.003)	(0.003)
Panel B: Diagnostics					
Log Likelihood	-2440.90	-2439.30	-2311.62	-2310.45	-2310.94	-2311.22
BIC	4912.125	4916.499	4661.135	4666.378	4667.369	4675.501
AR	0.057	0.015	0.124	0.133	0.130	0.096
LM ARCH	0.959	0.994	0.998	0.980	0.000	0.000
Sign Test	0.583	0.566	0.52 1	0.470	0.539	0.610

ARCH (2) and GARCH (2,2) models have significant coefficients and also have less Akaic (AIC) and Schwarz (SC) information criteria, are suggested for fluctuation forecasting. Increase the output according to coefficients output by the software, fluctuations index equation for the two models is as follows. Fluctuations index for ARCH (2) model:

$$\varepsilon_{t-1}^2 0.0009475 + (0.011245) = \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2$$

fluctuations index for GARCH (2,2) model

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} = 0009475 + (0.016544)\varepsilon_{t-1}^2 + (0.003456)h_{t-1}$$

As you will see in the attachment, fluctuations index forecasting for 1389 is done by the software which has been calculated by the liquidity at risk at the end.

5.6 Estimation of MA, EWMA Model

This model in order to forecasting the fluctuations variance use of moving harmonic average and simple moving average methods, moving harmonic average method is superior to the simple moving average.

Using moving harmonic average causes fluctuations dynamics characteristics are preserved. Calculation of conditional variance in moving harmonic average model (EMWA) is:

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1 - \lambda) r_t^2$$

We considered y parameter recommended by J.P.Morgan corporation in risk assessment methodology for the daily data 94 0. Empirical studies also confirm this amount to estimate the fluctuations index simple moving average can also be used:

$$\sigma_{t+1|t}^2 = \frac{1}{T} \sum_{t=1}^{T} (r_t - \bar{r})^2$$

Then, by considering the output variance and output squared at T time fluctuations index were estimated for a next period.

Table 4. Summary information of risk assessment effectiveness

	γ	LR Statistics	P-values	LOG
MA	-	7.3486	(0.0000)	5804.3378
EWMA	0.9476	2.6983	(0.0000)	5802.9887

Due to the significant of coefficients and significant of Laghood criteria than the values in Table 4 selected equations are reliable.

Table 5. Kopic test results for one-day liquidity at risk

model	confidence level	LR Statistics	$\chi^2(x)$	Result
	% 99	6.862	6.635	Valid
ARCH(2)	%95	2.6452	3.841	Valid
	%99	3.338	6.635	Valid
GARCH(2-2)	%95	1.386	3.841	Valid
	%99	7.029	6.635	not valid
MA	%95	3.233	3.841	Valid
	%99	6.971	6.635	not valid
EWMA	%95	4.623	3.841	not valid

5.7 Model Validation

In order to test the research hypothesis we use of feedback tests for liquidity at risk. To check the hypothesis it is used of the statistical tests of kopic and christophersen.

5.8 Kopic Test

An important criterion in this context is the number or proportion of failures (deviation from the expected value). Liquidity real results compared with calculated Liquidity at risk lead to a binomial distribution.

As it is seen in the above table for the one-day liquidity at risk model, ARCH (2) model at the 95% confidence level, the test confirms Kopic possible failure, but for higher confidence levels of (99%), mentioned models are not valid. For the GARCH (2, 2) at all confidence levels, the test results is approved. In reviewing of risk assessment models is also observed EWMA and MA models is rejected at 99% and at 95% level test results are approved.

Table 6. Kopic test for three days liquidity at risk

model	confidence level	LR Statistics	$\chi^2(x)$	Result
	% 99	9.862	6.635	not valid
ARCH$_{(2)}$	%95	1.535	3.841	Valid
	%99	4.536	6.635	Valid
GARCH$_{(2-2)}$	%95	.865	3.841	Valid
	%99	11.213	6.635	not valid
MA	%95	5.621	3.841	not valid
	%99	5.857	6.635	not valid
EWMA	%95	2.362	3.841	Valid

According to the above table you can see for the three days liquidity at risk, ARCH (2) model in all levels test confidence rejects Kopic's probability failures ratio.

For the GARCH (2, 2) at all levels to confidence the test results are confirmed. In reviewing of risk assessment models is also observed that MA model is rejected at all levels of Kopiv test and in the EWMA model is only approved for the 95% of test result.

5.9 Christophersen Test

In Kopic test acceptance or rejection of a model is only based on the number of failures and successes, there is no attention to failure independent.

Christophersen combined independent test with Kopic test and invented another test which was care about both sides of the number of failures and their independence of each other. Christophersen test is more stronger than Kopic's test and may have different results, test statistic is calculated as follows.

If the statistic LRcc model is less than amount of critical part at confidence level, the model will be accepted at that confidence level.

The above table shows the Arch and Garch econometric model at 99% and 95% at confidence level has been successfully passed the test, and risk assessment models MA at 95% level and

EWMA at 95% and 99% of confidence level were accepted in this test.

Table 7. Christophersen test for one day liquidity at risk

model	confidence level	LR Statistics	$\chi^2(x)$	Result
	% 99	9.862	6.635	not valid
ARCH$_{(2)}$	%95	1.535	3.841	not valid
	%99	4.536	6.635	not valid
GARCH$_{(2-2)}$	%95	.865	3.841	Valid
	%99	11.213	6.635	not valid
MA	%95	5.561	3.841	not valid
	%99	5.854	6.635	not valid
EWMA	%95	2.362	3.841	Valid

Table 8. Christophersen test for three days liquidity at risk

model	confidence level	LR Statistics	$\chi^2(x)$ d=2	Result
	% 99	8.233	6.635	Valid
ARCH$_{(2)}$	%95	3.964	3.841	Valid
	%99	5.234	6.635	Valid
GARCH$_{(2-2)}$	%95	2.109	3.841	Valid
	%99	15.153	6.635	Not valid
MA	%95	4.466	3.841	Valid
	%99	8.698	6.635	Valid
EWMA	%95	5.407	3.841	Valid

As it is seen in the above table, Arch, and simple moving average and moving harmonic average at 99% level and simple moving average model at 95% level is still not confirmed and the conclusion may be by increasing the time period model`s accuracy is reduced.

6. Conclusion

This research study assessment and explanation of liquidity risk model at danger using of LaR four models which are fluctuation operator or conditional variance. These four models consist of two econometric groups (GARCH and ARCH) and two risk assessment groups (MA and EWMA). Results of the research indicate this fact that possibility of liquidity and liquidity risk forecasting exist in using of liquidity at risk model (LaR) with historical data of bank liquidity, it also shows that studied subset models in 95% confidence level have appropriate performance for liquidity at risk forecasting using of liquidity at risk model (LAR) and confirms that it is possible to predict econometrics liquidity risk and risk assessment in two ways.

With the reasons that except Garch model, results from other three models of fluctuations estimation at 99%

level were not reliable.

Liquidity time series of studied bank have very large fluctuation shocks in spread time even to the extent that bank liquidity is negative in some periods. Garch model as a variation operator can be divided the time series into clusters of multiple parts and decrease sudden shocks in both 95% and 99% confidence level is reliable and as a more efficient model than other measurement models presented its fluctuation in this study. Another important result of the calculation of the liquidity at risk, is related to the time range of risk calculation that test results show that by increasing time period, accuracy of risk forecasting will decrease. And this confirms the calculated Basel Committee in liquidity risk calculation in the shortest timeframe (One to three days) consider that for measuring the liquidity risk we need to liquidity daily data, it is recommended that banks separately register their daily liquidity reports.

It is also proposed to quantify the risk by LAR managers are aware of shortage and surplus of their liquidity and plan for liquidity management.

On of the problems and errors of the LaR modelis:

It does not consider external variables, In response to this error can be noted that past trends are repeated in future, for example, each year in the end of Shahrivar customers need to cash for traveling ,This is repeated every year, but we should accept this fact that LaR model does not measure separately external variable. It views this fact in side itself and in the processes, so it is recommended to increase accuracy in managers decision-making can use this model alongside scenario analysis model.

The model for the liquidity external variables such as exchange rates, share rates, government regulations, unexpected events design different scenarios and determine need to liquidity and lack of liquidity based on the external variables.

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