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Liquidity Measurement Based on Bid-Ask Spread, Trading Frequency, and Liquidity Ratio: The Use of GARCH Model on Jakarta Stock Exchange (JSX)

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Liquidity Measurement
Based on Bid-Ask Spread, Trading Frequency, and Liquidity Ratio: The Use of GARCH Model on Jakarta Stock Exchange (JSX)

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Abstract

This paper attempts to investigate and clarify previous studies on market liquidity measurement, which involve Bid-Ask Spread, Trading Frequency, and Liquidity Ratio variables. To strengthen our findings, we employ Volatility Models of ARCH and GARCH, as well as JSX daily, weekly, and monthly time series data. Our findings reveal that the observed variables are able to explain volatility magnitude of JSX in terms of liquidity. Volatility model incorporating Trading Frequency variable with monthly data is found the most suitable model for measuring liquidity of JSX.

Keywords: Bid-Ask Spread, Trading Frequency, Liquidity Ratio, and ARCH/GARCH

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1 Introduction

Stock demand and supply are the most significant signal of market power and direction. Magnitude of either side depends on interaction of both in the spot at which they meet. The less the autocorrelation value of stock return, the higher the associated liqudity equilibrium (Grossman and Mille, 1988;1), whereas liquidity is the most crucial factor in capital market growth and assessment. Ability to maintain market liquidity will fundamentally help a capital market become more stable and help accelerate its growth.

There are some approaches to market liquidity measurement, including bid-ask spread time-series assessment, among others. In such an assessment, magnitude of the spread, which can be seen in seconds, shows movement of the whole transactions, so that trading frequency and spread can function as liquidity gauges (Fleming, 2003:85). Greater spread reflects smaller trading volume, and vice versa. In the case of decreased spread, the resulting larger trading volume may lead to more dynamic price movement with small fluctuation, and consequently to a more liquid market.

Meanwhile, market liquidity can also be empirically measured by using liquidity ratio. The ratio is calculated by dividing stock trading volume average by stock price change average in certain period, which can be in days, weeks, or months (Dubofsky dan Groth, 1986). High liquidity ratio reveals that the larger number of stocks traded with small price change in a market, the higher the market liquidity. On the other hand, small liquidity ratio reflects a situation in which only small number of investors interact in the market with small size of transactions resulting in wider spread. In this case, the trasactions are dominated by particularly small number of investors. Market liquidity can also be affected by assymetric information. For instance, when information on company's successful innovation leading to increased sales and profit is accessed by only small number of investors, such investors will conduct massive purchase of the associated stock, leading to an imbalance price formation process. This will further stimulate distortion on the market liquidity in general (Cheung dan Wong, 2000).

From the above description, we can infer that the authorities can manage liquidity to anticipate low liquidity level that may lead to a sharply-fluctuated-individual stock-based fall of composite index. In Indonesian capital market context, JSX Composite Index sometimes fluctuates uncontrollably, triggered by particularly small number of investors. Examining the phenomenon using the aforementioned mechanism of market liquidity creation, we may end up with a conclusion that the uncontrollable fluctuation has to do with the JSX's level of liquidity. However, whether the authorities or competent institutions are able to employ appropriate model, variable, and tool in measuring, and strenthening Indonesian capital market liquidity, is another concern. In this paper, we attempt to investigate whether bid-ask spread, trading frequency, and liquidity ratio can be adequately employed as liquidity measurement means, using JSX historical price data.

2. Research Method

2.1. Data and Sampling

At the very early stage, we conduct a survey on secondary data, which is available on Indonesian Capital Market Directory (ICMD) and other reports published by JSX and *Bapepam* (Indonesian Capital Market Supervisory Agency). The gathered data includes the associated bid-ask spread, trading volume, and stock prices, as well as market capitalization value during the observed periods. We also clarify the captured figures and our preliminary findings by comparing them with materials obtained from relevant academic journals, official publications, and other literatures.

We employ purposive sampling approach to select appropriate data that we include in our assessment. We impose some conditions on the preliminary data, as follows: (i) the stock data should be available in the observed period (1995 – 2005), and (ii) the respective company should never be delisted and suspended in the observed period. At the next stage, we conduct statistical examination on the developed model using the obtained daily, weekly, and monthly data.

2.2. Dynamic Model and Symptom on Stock price

2.2.1. AR, MA, ARMA and ARIMA Models

In statistical analysis stage, we compare constant means models with some other models, i.e. comparing time series model with Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). In this case, the employment of estimation model, except for ARIMA, includes Ordinary Least Square (OLS), Weghted Least Square (WLS), Generalized Least Square (GLS), as well as Maximum Likelihood Estimation (MLE). To ensure suitability of the model with the data, we conduct model validation test, which reveals whether a model fulfills the assumption of no autocorrelation, and no heterocedasticity (Diebold, 2000). If the assumptions are satisfied, the model can be said efficient and unbiased.

2.2.2. Autocorrelation Test

For one or more regressor variables in lags of dependent variable, we can employ the following general model, where the residual is p^{th} autoregressive process order (AR(p)):

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \ldots + \rho_p u_{t-p} + \varepsilon_t$$

We can perform statistical test on residual with more than one lag. The test, introduced as Godfrey's Lagrange Multiplier (LM) Tests in 1978, is carried out in two stages. Firtsly, the model is estimated using OLS, resulting in residual value. At the second stage, the resulting residual is then used as dependent variable, while the lag value of the residual is used as the independent variable. Then we measure the associated R^2 statistics. Godfrey's test statistic is sum of TR^2, where T is number of sample in the preliminary regression. In this test, TR^2 is asymptotically distributed with chi-square. The null hypotheses is that all AR coefficients are zero. Godfrey's test allows multiple p^{th} autoregressive order process with $u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + ... + \rho_p u_{t-p} + \varepsilon_t$ or moving average p^{th} autoregressive order process with white noise error (ε) as $u_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + ... + \phi_p \varepsilon_{t-p}$. In practice, it is common to select maximum value of p by counting from p-max to p =1. The maximum p is usually 3 for annual data, and 6 for quarter data. Significant statistics indicates serial correlation exists in the resulting residual.

2.2.3 Heteroscedasticity

Stock price data assessment frequently reveals violations on econometric assumption, such as heteroscedasticity and autocorrelation. This is possible since the data frequency is pretty high, accordingly inducing high volatility. A particular econometric model is therefore required to overcome such problems. A study done by Black (1992) has proven that GARCH Model can alleviate problems related to high correlation on stock price and stock return data.

Other studies try to explain rationales behind the above stock price data tendency. Rosenberg (2003) investigates anomalies on stock price movement at month ends and the potential correlation with macroeconomic indicator movement. He finds that the anomaly appears at the end of month when macroeconomic indicator contraction occurs. Using daily data, Peter and Wessel (2004) show that heteroscedasticity symptoms exist when return covariance among stocks changes asymmetrically. Hughes and Winter (2005) find that U-shape on volatility of daily data is good in both short and long period. Jeff, Jirby, and Ostdiek (2006) show that GARCH model is able to detect volatility magnitude on stock trading volume. Stephen and Zang (2006) reveal that prices of both newly listed stocks and stocks listed earlier are negatively correlated with their respective ROEs and have high volatilities.

Capital market analysts frequently use ARCH and GARCH models to estimate daily, weekly, and monthly stock price movements. Michael and Gulan (2006) prove that historical data they employ to develop the prediction model is as consistent as the out-of-sample data.

2.2.4. Unit Root Test

Stationary state is crucial pre-condition in time-series econometric model. Stationary data is data which confirms that the associated mean, variance, and auto-covariance on lag variation remain the same whenever it is used, meaning that such a data will result in stable time series model. If the data is not stationary, the resulting model will end up with spurious regression. Therefore, validity and stability of such a data should be re-assessed. In this study, we employ Unit Root Test (The Augmented Dickey-Fuller Test) to examine whether our data is stationary or not. The regression model of the test is as follows: $Y_t = \rho Y_{t-1} + u_t$. Conclusion is derived from comparison between the test result value and the predetermined critical value. If IτI is higher than the absolute value of MacKinnon Critical Value, the null hypothesis is rejected, meaning that the data is stationary.

2.2.5. GARCH Model

Econometric models are quite accurate in predicting liquidity and its associated volatility (Tsuji, 2005:163). One of the models is Generalized Autoregressive Conditional Heteroscedasticity (GARCH), which is the advancement of Autoregressive Conditional Heteroscedasticity (ARCH) model firstly introduced by Engle (1982). GARCH model is focused on observations of different variance. In other words, the model examines fluctuation of time-series data not based on the constant mean, rather based on the variance. This model has significant advantage over preceding econometric models, especially in short-term prediction (Engle dan McFadden, 1994; 2966). ARCH(q) process equation is as follows (Greene, 2000:800):

$$\sigma^2{}_t = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \alpha_2 \varepsilon^2{}_{t-2} + \ldots + \alpha_q \varepsilon^2{}_{t-q}$$

The above model is a process of MA(q). To develop the model into GARCH, Engle and Bollerslev (1986) utilize the following equation:

$$\sigma^2{}_t = \alpha_0 + \delta_1 \varepsilon^2{}_{t-1} + \delta_2 \varepsilon^2{}_{t-2} + \ldots + \delta_q \varepsilon^2{}_{t-q} + \alpha_1 \varepsilon^2{}_{t-1} + \alpha_2 \varepsilon^2{}_{t-2} + \ldots + \alpha_q \varepsilon^2{}_{t-q}$$

2.2.6. Estimating GARCH Model

In estimating GARCH (*p,q*) model parameters, we utilize Maximum Likelihood Estimation (MLE) through several iterations. GARCH is somewhat non-linear, so we take up algorithm by finding optimum parameter and maximizing log likelihood function:

$$Log\ Lik = \sum_{t=1}^{T} \log\ f\langle y_i \,|\, \Omega_{t-1} \rangle$$

where $f\langle y_i \,|\, \Omega_{t-1} \rangle$ is density function

All the aforementioned models are implemented on time series data of Bid-Ask Price, Trading Frequency, and Liquidity Ratio with consideration on the preliminary hypothesis test results. When the null hypotesis is resjected, then there is a change in liquidity magnitude and the liquidity measurement model is valid.

When there is more than one valid and suitable model, we choose the best model based on the resulting respective Akaike Information Criterion (AIC) or SIC. Model with the least AIC or SIC is the best model.

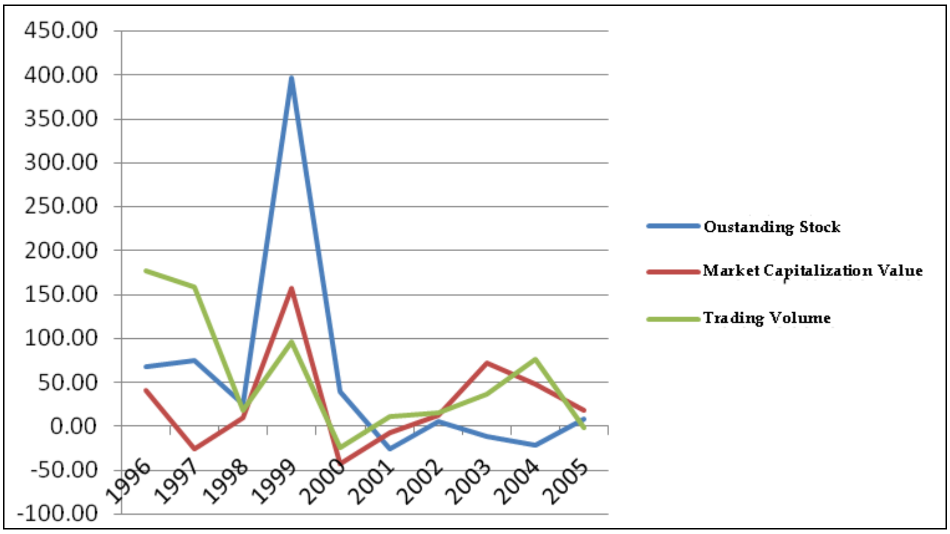
3. Result and Discussion

Our quantitative process starts from revealing descriptive data of respective statistical test periods, by which we know data uniqueness, data pattern, volatility measure, and mean-compared volatility. We then analyse the data and test GARCH model's ability to result in volatility. At the end, we conclude the study based on the test results and the associated comparison with the prior similar studies.

3. 1. Descriptive Data

As mentioned earlier, data utilized in this study includes daily, weekly, and monthly data of Bid-Ask Spread, trading frequency, and liquidity ratio of stocks in JSX in period of 1995-2005. To review volatility of stock price movement and trading volume, we employ natural logarithm of stock return (growth) data, so that we can avoid spurious regression and autocorrelation.

Graph 3.1
Growth of Oustanding Stock, Market Capitalization Value, and Trading Volume in The Jakarta Stock Exchange (JSX) During Period of 1995-2005



Source: JSX (processed data)

On Graph 3.1, we can see that market capitalization starts to increase sharply in 1999, indicated by growth rate of 156.8% year on year. Number of listed outstanding shares also increases by 396% in 2000. However, these increases degree is not in line with that of trading volume, meaning that there are significant amount of idle stocks (not traded stocks).

Table 3.1
Descriptive Statistics of the Observed Stocks in JSX (1995-2005)

Statistics	Daily	Weekly	Monthly
Mean	0.0017	0.0124	0.0232
Standard Deviation	0.0951	0.0345	0.0145
Max	0.2343	0.2133	0.2602
Min	-0.2432	0.2322	-0.1232
Skew	0.145	0.234	0.232
Kurtosis	6.356	5.243	4.435
JB	421.432	325.335	210.234
Probability	0.00000	0.000	0.000
Observations	2691	547	132

Source: JSX (processed data)

On Table 3.1, we can see that the daily data shows the smallest mean, i.e. 0.0017, compared with that of weekly and monthly data, which means that daily stock trading results in less return than do weekly and monthly trading in JSX. Nevertheless, contrarily, daily data reveals the highest standard deviation, i.e. 0.0951, meaning that daily trading bears more risk than do weekly and monthly trading in JSX. Meanwhile, none of the time series data is normally distributed, which is indicated by their skewness values far from the symmetric value of 3 and probabilities far below any significance level.

On Table 3.2 shows the descriptive statistics of the time series in three different periods. This reveals data structure of JSX stock prices in different economic cycle.

Table 3.2
Descriptive Statistics of the Observed Stock prices in JSX in Different Periods

Statistics	1995-2005			1995-2000			2000-2005		
	D	W	M	D	W	M	D	W	M
Mean	0.0017	0.0124	0.0232	0.012	0.0432	0.0411	0.020	0.0322	0.1333
Standard Deviation	0.0951	0.0345	0.0145	0.0345	0.0145	0.0145	0.0332	0.0034	0.0045
Max	0.2343	0.2133	0.2602	0.2133	0.2602	0.2241	0.2341	0.2010	0.2013
Min	-0.2432	-0.2322	-0.1232	-0.2322	-0.1232	-0.2032	-0.2321	-0.2111	-0.0123
Skew	0.1452	0.234	0.232	0.234	0.232	0.3232	0.3333	0.3454	0.2452
Kurtosis	6.3562	5.243	4.435	5.243	4.435	4.4123	4.2344	5.3234	4.3456
JB	421.432	325.335	210.234	525.335	510.234	501.221	623.342	543.234	542.347
Prob	0.00000	0.000	0.000	0.000	0.000	0.000	0.0000	0.0000	0.0000
Observations	2691	547	132	1474	298	72	1456	298	72

Source: JSX (processed data)

On the Table 3.2, we can see that none of the time series data is normally distributed, with probabilities far below any significance level. The associated skewness values are also far from the normal standard of 3. The table also shows that in period of Asian Financial Crisis (1995-2000), daily, weekly, and monthly stock trading at JSX record the highest risk as well as the highest return.

Table 3.3
Descriptive Statistics of JSX's
Bid-Ask Spread, Trading Frequency, and Stock Liquidity Ratio

Statistics	Bid-Ask Spread			Trading Frequency			Liquidity Ratio		
	D	W	M	D	W	M	D	W	M
Mean	0.0011	0.0133	0.0321	0.0345	0.0443	0.0543	0.0100	0.0123	0.1333
Standard Deviation	0.0666	0.0643	0.0345	0.0986	0.0723	0.0407	0.0832	0.0453	0.02045
Max	0.2343	0.2133	0.2602	0.3452	0.4531	0.4344	0.5455	0.3454	0.5555
Min	-0.2432	-0.2322	-0.1232	-0.3452	-0.3433	-0.3432	-0.3321	-0.7341	-0.6123
Skew	0.2452	0.3342	0.4322	0.3444	0.5467	0.4543	0.4333	0.3422	0.4355
Kurtosis	7.3562	6.243	4.5135	9.243	8.4351	8.4123	5.2346	7.3234	8.3456
JB	821.432	625.335	310.234	767.335	657.234	567.221	714.342	777.234	644.347
Prob	0.00000	0.000	0.000	0.000	0.000	0.000	0.0000	0.0000	0.0000
Observations	2691	547	132	1474	298	72	1456	298	72

Source: JSX (processed data)

From Table 3.3, we can infer that logarithm of trading frequency mean and standard deviation are the highest, in daily, weekly, and monthly forms. Meanwhile, none of the data is normally distributed, as their respective skewness values are far from the standard of 3. Nevertheless, this is not really weird since getting normal time series data is pretty rare.

3. 2. Data Analysis

We then conduct regression on the data using volatility models (ARCH and GARCH) to measure liquidity level of JSX. We start from to observation using ACF and PACF indicators to check the stationary state of the data, followed by hypothesis test on the stationarity using ADF (Augmented Dickey Fuller) Unit Root Test. In the next stage, we carry out trial and error measurement using AR, MA, ARMA, ARIMA, ARCH and GARCH models. The results can be seen on Table 3.4.

GARCH (1,1) model is standard model. However, we can test other combinations involving figures ranging from 1 to 4 to find the best combination for GARCH. A condition that must be fulfilled in this model is that TR of the regression should have value of asymptotic distribution χ^2_p. The tested hypothesis is that $\phi_1 = \ldots = \phi_p = 0$, meaning that there is no persistent level from the variance.

Table 3.4
ARCH/GARCH Model for Variables of Bid-Ask Spread, Trading Frequency, and Liqudity Ratio Using JSX Daily Stock Price Data

STOCK	ARCH / GARCH				SIC	LM-TEST
	Conditional Mean		Conditional Variance			
Bid-Ask Spread	C	0.00656	C	0.0001***	**-3.7023**	**0.2767**
			ARCH(1)	0.3296***		
			GARCH(1)	0.4230***		
Trading Frequency	C	0.00767	C	0.0029***	**-8.4992**	**0.8296**
			ARCH(1)	0.4295***		
			GARCH(1)	0.4910***		
Liquidity Ratio	C	0.00443	C	0.0020***	-7.872	**0.5433**
			ARCH(1)	0.4211***		
			GARCH(1)	0.4730***		

Source: JSX (processed data)
Note : This table shows 3 models of Volatility equations with conditions of Mean and Variance of stocks listed in JSX. Total Observations is 2691.
* Significant at Confidence Level of 10%
** Significant at Confidence Level of 5%
*** Significant at Confidence Level of 1%

Table 3.4 shows results of the use of ARCH and GARCH (1,1) volatility models that have passed autocorrelation test. This table further reveals that variable of Trading Frequency comes up with the largest mean, i.e. 0.00767 or 0.77 %. This means that liquidity of JSX is dominantly explained by Trading Frequency.

All the regression coefficients of ARCH and GARCH models are significant at any level of confidence. Combination of the above models also proves to have the largest absolute SIC values and be the best resulting model. The model using Trading Frequency variable for measuring JSX liquidity has SIC value of -8.4992, of which absolute value is 8.4992.

On Table 3.5, we can see that the largest conditional mean consistently comes from ARCH/GARCH models using trading frequency variable, i.e. 2.54%. All the regression coefficients of ARCH and GARCH models are significant. Volatility model using Trading Frequency variable is again proven to be best the best regression model, since it has the highest absolute SIC value, i.e. 27.4992. It is worth to note that all the volatility models have passed the conditional autocorrelation tests at any confidence level, as indicated by the LM-test figures which exceed 0.1, 0.05, and 0.01.

Table 3.5
ARCH/GARCH Model for Variables of Bid-Ask Spread, Trading Frequency, and Liqudity Ratio Using JSX Weekly Stock price Data

STOCK	ARCH / GARCH				SIC	LM-TEST
	Conditional Mean		Conditional Variance			
Bid-Ask Spread	C	0.01656	C	0.0021***		
			ARCH(1)	0.3296*		
			GARCH(1)	0.5132**	**-17.7023**	**0.6788**
Trading Frequency	C	0.02542	C	0.0037***		
			ARCH(1)	0.3545***		
			GARCH(1)	0.2910**	**-27.4992**	**0.9296**
Liquidity Ratio	C	0.01243	C	0.0010***		
			ARCH(1)	0.2221*		
			GARCH(1)	0.3730*	-7.872	**0.3433**

Source: JSX (processed data)
Note : This table shows 3 models of Volatility equations with conditions of Mean and Variance of stocks listed in JSX. Total Observations is 2691.
* Significant at Confidence Level of 10%
** Significant at Confidence Level of 5%
*** Significant at Confidence Level of 1%

The next observation can be seen on Table 3.6. Based on monthly data, model using Trading Frequency variable records the highest conditional mean of 7.42 %. The models also show significant regression coefficients at varied confidence levels. They have passed autocorrelation test with LM-test values exceeding 10%, 5% and 1%. We can infer from the table that the best model for liquidity measurement is volatility model using Trading Frequency variable, which records the highest absolute SIC value of -90.5.

Table 3.6
ARCH/GARCH Model for Variables of Bid-Ask Spread, Trading Frequency, and Liqudity Ratio Using JSX Monthly Stock price Data

STOCK	ARCH / GARCH				SIC	LM-TEST
	Conditional Mean		Conditional Variance			
Bid-Ask Spread	C	0.05552	C	0.0044***		
			ARCH(1)	0.3296**		
			GARCH(1)	0.5132**	**-66.6755**	**0.8481**
Trading Frequency	C	0.07415	C	0.0073***		
			ARCH(1)	0.5535***		
			GARCH(1)	0.3881***	**-90.4992**	**0.9966**
Liquidity Ratio	C	0.05422	C	0.0011***		
			ARCH(1)	0.4454***		
			GARCH(1)	0.3444**	-10.882	**0.2322**

Source: JSX (processed data)
Note : This table shows 3 models of Volatility equations with conditions of Mean and Variance of stocks listed in JSX. Total Observations is 2691.
* Significant at Confidence Level of 10%
** Significant at Confidence Level of 5%
*** Significant at Confidence Level of 1%

On Table 3.7, we can see brief summary of the best volatility models that have been developed through the study. The best model to measure liquidity in JSX is the model that utilizes Trading Frequency variable, which consistently records the highest absolute SIC values.

Furthermore, from observations on the three volatility models, we can infer that the best model for measuring JSX liquidity is ARCH/GARCH model that utilizes Monthly Trading Frequency data. Therefore, in the case of JSX, it is recommended to measure the market liquidity using monthly data, as it allows minimization of data volatility. These results are consistent with those of the prior study carried out by Fleming (2003;94). He finds that utilization of trading frequency provides higher significance level than do other variables. Similar results are also proven by Huang, Cai, and Wang (2002).

Tabel 3.7
ARCH/GARCH Model for Variable of Trading Frequency Using JSX Daily, Weekly, and Monthly Stock price Data

STOCK	ARCH / GARCH		SIC	LM-TEST
	Conditional Mean	Conditional Variance		
Trading Frequency (Daily)	0.00767	C 0.0029*** ARCH(1) 0.4295*** GARCH(1) 0.4910***	**-8.4992**	**0.8296**
Trading Frequency (Weekly)	0.02542	C 0.0037*** ARCH(1) 0.3545*** GARCH(1) 0.2910**	**-27.499**	**0.9296**
Trading Frequency (Monthly)	0.07415	C 0.0073*** ARCH(1) 0.5535*** GARCH(1) 0.3881***	**-90.499**	**0.9966**

Source: JSX (processed data)
Note : This table shows 3 models of Volatility equations with conditions of Mean and Variance of stocks listed in JSX. Total Observations is 2691.
* Significant at Confidence Level of 10%
** Significant at Confidence Level of 5%
*** Significant at Confidence Level of 1%

4. Concluding Remark

Data processing and analysis in this study end up with a conclusion that from the three variables, Trading Frequency is the best and the most suitable variable incorporated in volatility model to measure market liquidity in JSX. The authorities and competent institutions can therefore use this model to measure JSX liquidity and issue relevant policies accordingly to maintain the appropriate liquidity level and to accelerate the market development. It is also recommended to use monthly data to avoid more volatile time series data.

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