On The Relationship between Illiquidity, Aggregate Market Return and Conditional Volatility of the NIFTY Index

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Abstract
This study investigated the relationship between daily returns and illiquidity of the NIFTY Index (one of the broad based market indices of the National Stock Exchange of India). In this paper, illiquidity was used as an exogenous variable in the EGARCH (1, 1) framework. The empirical results clearly indicate the presence of a liquidity premium in the National Stock Exchange of India, as evidenced by the positive relationship between illiquidity and returns of the NIFTY Index. They also imply a relationship between liquidity and volatility since illiquidity was used as an exogenous variable in estimating the mean equation and hence it influenced the values of the residuals. The lags of residuals, lags of conditional standard deviation, and lags of conditional variance in turn were inputs in the determination of (the natural logarithm of) conditional variance in the EGARCH framework.

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Keywords: Illiquidity; Return; Conditional Volatility

INTRODUCTION

Market liquidity may be defined as the ability to trade large volumes of securities in a market quickly and without heavy discounting of the prevailing security prices. It is an important factor which affects the functional efficiency of the market. Given that market liquidity is an indicator which represents market depth and signifies the extent to which the seller's discount perpetuates demand in an illiquid stock, the condition of market liquidity can be considered as one of the factors affecting the price discovery function of capital markets.

There may be lack of liquidity (illiquidity) in a security market due to various reasons. Amihud, Mendelson and Pederson (2005) opined that due to the presence of exogenous trading costs (e.g., brokerage cost or fees), order processing costs, and transaction taxes, a security might face liquidity risk through its entire life. They suggested that illiquidity might also arise due to information asymmetry between the buyer and seller, difficult in locating a counterparty, and lack of friction-less trading. If an investor does not find a buyer for his security in a timely

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manner, he may be compelled to sell it to a market maker. The market maker, in turn, faces the risk of an adverse price change while holding the security in his inventory and, as such, should be compensated for this risk. This compensation is known as the liquidity risk premium.

The "clientele effects" theory (Amihud et al., 2005) might also be used to justify the liquidity premium concept. This theory signifies that different groups of investors have different expected holding periods. On one hand, there are investors who buy-and-hold securities (with no immediate needs for liquidity) while on the other hand; there are mark-to-market investors who are interested in trading their assets in the short term. Investors with the shortest holding periods will therefore tend to hold the assets with the lowest trading costs and investors with the longest holding periods will hold assets with the highest trading costs. Correspondingly, illiquid assets must offer higher returns relative to more liquid assets. This implies that one should expect investors with long horizons to earn a liquidity premium by holding relatively illiquid assets.

It is now well established that the liquidity premium exists and therefore it is necessary to move from the commonplace two-dimensional (risk – return) framework to a novel three-dimensional framework (which incorporates illiquidity) of formulating asset pricing models. Bodie, Kane, Marcus and Mohanty (2006) proposed that trading costs (the surrogate of the liquidity premium) should be added to the CAPM when estimating the required rate of return on illiquid assets; thus accounting for the increase in the required rate of return occasioned by an increase in the liquidity risk.

It can be readily observed that most of the studies regarding the subject matter of this paper deal with cross sectional data. Although many of the previous studies have tried to figure out the time varying property of liquidity, this research utilizes a different approach by incorporating illiquidity as an exogenous variable in modeling the conditional volatility of market returns in an EGARCH (1, 1) framework. In the backdrop of the Indian Stock Market this area remains scantily researched. This paper is therefore an attempt at filling this research gap, particularly in the Indian context by investigating the relationship between returns, conditional volatility, and illiquidity in an Indian Stock Market Index: the NSE NIFTY index.

REVIEW OF LITERATURE

A number of studies have shown that the liquidity of financial assets has a significant bearing on their prices. There is evidence of a negative liquidity-return relationship in the literature, and this result has been yielded using a variety of liquidity measures. This has shown that the level of liquidity is an important characteristic of individual securities (Amihud and Mendelson, 1986, Brennan and Subrahmanyam, 1996). Amihud and Mendelson (1986) proposed that illiquidity (foregone liquidity) is a risk and investors require more return to compensate for their loss of liquidity. According to them, investors anticipate that at a future date they will have to sell their assets and at that time they will have to incur transaction costs. This implies therefore that a positive relationship between prospective future returns and illiquidity prevails.

According to Amihud and Mendelson (1988), an improvement in stock liquidity decreases the firm's cost of capital. The cost of capital incorporates a proportionate risk premium for the magnitude of each risk that the investors' funds are exposed to and therefore an increment in liquidity will decrease the liquidity risk premium leading to a corresponding decrease in the required rate of return. In the three dimensional framework, taking into account returns, liquidity and risk, the required rate of return decreases proportionately with decrease in liquidity risk. This increases the firm's set of viable investment opportunities because with a lower cost of capital, managers are likely to accept projects which previously had negative net present values (NPV). Improvements in stock liquidity expand the investment opportunity set and therefore, influence subsequent corporate investment activity. By increasing liquidity, firms reduce their cost of capital and increase their value. Amihud and Mendelson (1988) further analyzed the role of some financial management policies and institutional mechanisms in enhancing the secondary market liquidity of firms. The implication of their findings is that there is a need to move from the two dimensional risk/return framework to a three dimensional risk/return/liquidity framework in appraising the firm's required rate of return.

In their study, Eleswarapu and Reinganum (1993) raised some doubts regarding the findings of Amihud and Mendelson (1986). Using bid-ask spreads as the illiquidity measure for 1961-1990, they reported positive and seemingly seasonal association between bid-ask spreads and returns, i.e. this effect was confined to the month of January only. Later, Brennan et al (1996) contradicted Eleswarapu and Reinganums' (1993) observation. They found out that the regression coefficients of indicator variables for price impact groups increase monotonically from low (more liquid) to high (less liquid) portfolios, suggesting that excess returns are higher for less liquid stocks. Haugen and Baker (1996) also found a statistically significant negative relationship between return and liquidity. Brennan et al (1996) re-established Amihud and

Mendelson (1986) by applying the methodology of Fama and French (1993). Their results suggested a positive relationship between illiquidity and return.

Using Turnover Ratio as the proxy for liquidity, Datar et al (1998) reported that liquidity plays a significant role in explaining the cross-sectional variation in stock returns. After controlling for firm size, book to market ratio, and firm beta they concluded that liquidity is not restricted to the month of January, as suggested by Eleswarapu and Reinganum (1993), but it persists throughout the year. They reported that on average, a decrease of 1% in turnover increased the required rate of return by 4.5 basis points per month.

Brennan et al. (1998) reported strong evidence on the importance of trading activity in forecasting stock returns. Using dollar volume as a proxy for liquidity, they posited a significant negative effect of volume on returns. However, they added that this effect is robust to the choice of risk-adjustment model. For a sample covering 1966-1995, and after controlling for the usual non-risk factors, a one standard deviation increase in dollar volume led to a decrease in excess returns of 0.11% per month.

Using NYSE data, Chordia, Roll and Subrahmanyam (2000) concluded that liquidity, trading costs, and other specific microstructure components have common determinants. This study also reported that individual stock liquidity and industry liquidity move together. Chordia et al (2001) reported that daily changes in market averages of liquidity are highly volatile and negatively serially correlated. This study also observed that both long term and short term interest rates influence liquidity. Pastor and Stambaugh (2003) found out that cross-sectional variations in expected returns are explained by the sensitivities of returns to fluctuations in aggregate liquidity. Liquidity was measured in this study by order flow-induced price fluctuations of daily data for the 1966 to 1999 time-period. Stocks with higher sensitivity to liquidity were found to outperform stocks with low sensitivity by 7.5 percent per year.

Jones (2002) used the proportional spread of Dow Jones stocks and the share turnover of NYSE stocks over the 1900 - 2000 century and concluded that both spread and turnover predict annual excess market returns up to three years ahead. Amihud (2002), using Fama and MacBeth (1973)'s methodology, explored the effect of illiquidity on stock returns for NYSE stocks over the period between 1963 and 1977. This study reported that the ex-ante excess return of a stock is an increasing function of expected illiquidity and unexpected stock returns.

Gibson and Nicholas (2004) inferred that the liquidity risk premium varies significantly over time. Chordia, Sarkar and Subrahmanyam (2005) explored the causes of daily liquidity movements of NYSE stocks for the January 1, 1988 to December 31, 2002 period. Their study revealed that volatility shocks in a market are informative of shifts in liquidity. Salehi et al. (2011), using monthly data for the 2002 to 2009 time period, confirmed a negative relationship between stock returns and liquidity at the Tehran Stock Exchange.

Sen and Ghosh (2006) investigated the relationship between market liquidity and volatility at the NSE by taking impact cost as the proxy of liquidity. This study reported a negative relationship between monthly volatility of NIFTY returns and monthly liquidity, while Sen (2009) analyzed the nature and properties of monthly illiquidity data at the NSE. His study concluded that there was no month effect on mean illiquidity.

DATA AND VARIABLES

The time series data used in this study comprises the daily closing values and Rupee volume of the CNX NIFTY index for the March 3, 2003 to October 31, 2013 period - a total of 2664 observations. The data was obtained from the National Stock Exchange of India website (www.nseindia.com).

Variables

Daily Market Returns. The values for daily Market Returns (R_t) were computed as follows:

$$R_t = \ln(I_t) - \ln(I_{t-1}) \tag{1}$$

Where:

I_t is the closing value of the CNX NIFTY for day *t*

I_{t-1} is the closing value of the CNX NIFTY for day *t-1*

Log transformation was done to obtain the continuously compounded rate of return.

Illiquidity. Amihud (2002) developed a measure of illiquidity which can be interpreted as the daily stock/index price impact per unit currency of trading volume. This measure defines illiquidity as the ratio of the daily absolute returns of a stock/index to its daily unit currency trading volume (Turnover):

$$Illiquidity = \frac{|R_t|}{VOL_t} \times 10^5 \tag{2}$$

Where:

$|R_t|$ is the absolute value of returns (in Rupees) of a stock/index on day *t*.

VOL_t, is the trading volume (in Rupees) of stock/index on day *t*.

Here, illiquidity for NIFTY index on day 't' gives the absolute return per Rupee traded. Thus, illiquidity represents the absolute returns (in terms of decimals of the rupee) corresponding to a trading volume of one rupee. In order to get meaningful results, 10^5 is multiplied with this very ratio. If a stock/index is illiquid, then it will have lesser depth and more resilience. Therefore, for an illiquid stock/index, the estimated daily illiquidity should be higher than for a liquid stock/index.

METHODOLOGY

Since the study dealt with time series data, we tested whether the data had goodness of fit for the desired model. First, the Unit Root Test was applied to test for stationarity. Next, using an AR (1) process, an initial model was built to test the time series data for ARCH effects. The EGARCH (1, 1) model was then utilized to investigate a possible relationship between returns and illiquidity under the conditional volatility framework. The logic behind incorporating illiquidity as an exogenous variable in the mean equation was to investigate whether illiquidity was a significant regressor and therefore a plausible determinant of the residuals of the mean equation. The residuals of the mean equation in turn determined the inputs of the EGARCH (1, 1) model, i.e. their own lags, lagged conditional standard deviations, and lagged conditional variances.

Diagnostic Testing

Unit Root Test. To test for stationarity, the Phillips-Perron Unit Root Test (PP Test) was used. Phillips and Perron (1988) proposed a nonparametric method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented DF test equation

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \varepsilon_t \tag{3}$$

and modifies the t-ratio of the coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic

$$\tilde{t}_{\alpha} = t_{\alpha}\left(\frac{\gamma_0}{f_0}\right)^2 - \frac{T\left(f_0 - \gamma_0\right)\left(se\left(\hat{\alpha}\right)\right)}{2 f_0^{1/2} s} \tag{4}$$

Where:

$\hat{\alpha}$ is the estimate

t_{α} is the t ratio of α

$se\left(\hat{\alpha}\right)$ is the coefficient of standard error

s is the standard error of the test regression

γ_0 is a consistent estimate of the error variance in (3) (calculated as $(T-k)s^2 / T$ where k is the number of regressors)

f_0 is an estimator of the residual spectrum at frequency zero.

The MacKinnon (1996) critical values are compared with the computed t value and if the p value is significant, it is deduced that there is no unit root in the series.

Testing for ARCH Effects. Before estimating a GARCH-type model, one should first compute the Engle (1982) test for ARCH effects to make sure that this class of models is appropriate for the data. Specifying the mean equation is usually the first step in testing for ARCH effects. In this paper, the following AR (1) model was the mean equation:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 Illq_t + \varepsilon_{i,t} \tag{5}$$

Where:

R_t is the NIFTY return for day 't',

R_{t-1} is the NIFTY return for day 't-1',

$Illq_t$ is illiquidity for day 't', computed in line with Amihud (2002) as discussed above.

Next, the regression for the mean equation is run and the residuals saved. The squared residuals are then run through a second regression on *p* lags. In our case, *p* was taken as 5 as there are at most five trading days in a week.

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{s=1}^{p} \beta_s \varepsilon_{t-s}^2 \right) + \nu_t \qquad (6)$$

The number of observations multiplied by the R-squared statistic gives Engle's LM test statistic, which is asymptotically distributed as $\chi^2(p)$. If the LM statistic is significant, then it is concluded that there is an ARCH effect.

The GARCH Model

It is unlikely in the context of financial time series data that the variance of the errors will be homoscedastic, and hence it makes sense to consider a model that assumes that the variance is heteroscedastic and which describes how the variance of the errors evolves. The GARCH (1, 1) model (Bollerslev, 1986) is one of the most popular frameworks for modeling heteroscedastic data.

Estimation of the GARCH (1, 1) Model. The estimation of the GARCH (1, 1) model involves joint estimation of both mean equation (equation 5) and a conditional variance equation (equation 7).

The conditional variance σ_t^2 is stated as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (7)$$

Where:

α_0 = mean

${\varepsilon}^2_{t-1}$ = volatility from the last period, measured as the lag of the squared residuals from the mean equation. It is also called the ARCH term.

${\sigma}^2_{t-1}$ = last period's forecast variance. It is also called the GARCH term.

For non negativity, $\alpha_1 \geq 0$ and $\beta \geq 0$ and $\alpha_1 + \beta \leq 1$

A large GARCH lag coefficient (β) indicates that shocks to conditional variance take a long time to die out and so volatility is 'persistent', while a large GARCH error coefficients (α_1) means that volatility reacts quite intensely to market movements. So, if α_1 is relatively high and β is relatively low, volatilities tend to be more 'spiky'.

The EGARCH Model

GARCH models enforce a symmetric response of volatility to positive and negative shocks and the conditional variance in equation (7) is a function of the magnitudes of the lagged residuals and not their signs (by squaring the lagged error in (7), the sign is lost). However, it has been observed that a negative shock to stock market return time series is likely to cause volatility to rise by more than a positive shock of the same magnitude (Black, 1976).This is called the leverage effect. The EGARCH (Exponential GARCH) model was proposed by Nelson (1991) to remedy this problem.

Estimation of the EGARCH (1, 1) Model. The estimation of this model also involves the estimation of mean and conditional variance equations. For the EGARCH Model the mean equation is similar to equation (5) but the conditional variance specification is:

$$\ln \sigma_t^2 = \omega + a\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln \sigma_{t-1}^2 \tag{8}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential, and that forecasts of the variance are non-negative. The asymmetry effect is highlighted by γ. This estimated parameter must be significant and lower than zero.

There is a difference between the EViews specification of the EGARCH model and that of the original Nelson model in that the Nelson specification assumes that the error terms follow a Generalized Error Distribution (GED) while EViews gives a choice of the GED, Students' t or normal distributions. Estimating the Nelson model yields identical estimates to those reported by EViews except for the intercept term ω. For example if the error terms are normally distributed the difference will be $\alpha_1\sqrt{2/\pi}$. In this study, it was assumed that error terms follow the student t distribution. All computations were carried out using the EViews 7 software.

RESULTS AND DISCUSSION

Preliminary Statistics of Time Series Data

Descriptive statistics of the daily CNX NIFTY returns and illiquidity time series data were reported in Table 1. The return series was negatively skewed but the illiquidity series was positively skewed. Kurtosis was in excess of 3 in both cases, indicating heavy tails and implying that the two distributions were leptokurtic. Moreover, highly significant & large JB statistics confirmed that both series were not normally distributed.

Unit Root Test Results

The PP test results were reported in the Table 2. The computed values of the PP test statistic were -48.20576 and -51.55389 for the return and illiquidity series respectively. These statistics are far greater (in absolute term) than the critical value of -3.4363 at 1% significant level, implying therefore that the time series used in this study were stationary.

Table 1
Descriptive Statistics

	RETURN	ILLIQUIDITY
Mean	0.000669	3.036616
Median	0.001346	1.785142
Maximum	0.163343	1432.960
Minimum	-0.130539	0.002669
Std. Dev.	0.016298	27.85307
Skewness	-0.259787	50.84325
Kurtosis	11.86615	2610.452
Jarque-Bera	8752.231	7.56E+08
Probability	0.000000	0.000000
Observations	2663	2663

Table 2
Unit Root Test Results

Variable	Computed PP
Daily NIFTY Return Series	-48.20576*
Daily illiquidity	-51.55389*

* Significant at 1% level

ARCH Effects Test Results

In conducting the ARCH effects test, the mean equation was first estimated using illiquidity and the first lag of returns as the predictor variables of returns. The residuals of this regression were then squared and regressed on five lags of their own. The R-Squared from this second regression was multiplied with the number of observations to give a test statistic for the ARCH – LM test, which was compared with the tabulated chi square statistic at 1% level of significance and *p* (5) degrees of freedom.

Regression Results of the Mean Equation. The regression results of the AR (1) model (equation 5) were reported in Table 3. It is clear from the above table that illiquidity was positively related with return as the coefficient of illiquidity was positive and highly significant. The F statistic was also significant and the D-W statistic was quite satisfactory.

Table 3
Estimation of the Mean Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000297	0.000312	0.951748	0.3413
RETURN(-1)	0.065184	0.019003	3.430270	0.0006*
$Illq_t$	0.000110	1.11E-05	9.883410	0.0000*
R-squared	0.039847	Mean dependent var		0.000674
Adjusted R-squared	0.039125	S.D. dependent var		0.016299
S.E. of regression	0.015977	Akaike info criterion		-5.434175
Sum squared resid	0.678770	Schwarz criterion		-5.427541
Log likelihood	7235.887	Hannan-Quinn criter.		-5.431774
F-statistic	55.17556	Durbin-Watson stat		1.990433
Prob (F-statistic)	0.000000			

* Significant at 1% level; Dependent Variable: RETURN

ARCH-LM test Results. The ARCH LM test results (equation 6) were reported in Table 4. From the above Table, both the *F*-statistic and the *LM*-statistic were very significant, suggesting the presence of ARCH effects in the daily NIFTY return series.

Table 4
ARCH-LM test Results

Heteroscedasticity Test: ARCH				
F-statistic	100.2326	Prob. F(5,2651)		0.0000*
Obs*R-squared (Engle's LM test Statistic)	422.4369	Prob. Chi-Square(5)		0.0000*
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000107	1.46E-05	7.372469	0.0000
RESID^2(-1)	0.245476	0.019379	12.66708	0.0000
RESID^2(-2)	0.134464	0.019781	6.797614	0.0000
RESID^2(-3)	-0.003143	0.019953	-0.157520	0.8748
RESID^2(-4)	0.136232	0.019782	6.886759	0.0000
RESID^2(-5)	0.066492	0.019380	3.430945	0.0006
R-squared	0.158990	Mean dependent var		0.000255
Adjusted R-squared	0.157404	S.D. dependent var		0.000714
S.E. of regression	0.000655	Akaike info criterion		-11.82060
Sum squared resid	0.001139	Schwarz criterion		-11.80731
Log likelihood	15709.67	Hannan-Quinn criter.		-11.8158
F-statistic	100.2326	Durbin-Watson stat		1.9978
Prob (F-statistic)	0.0000			

* Significant at 1% level

Estimated Results of the EGARCH (1, 1) Model

The estimated EGARCH (1, 1) mean and variance equations were reported in Table 5. From the table, it can be readily observed that the coefficient of the $Illq_t$ variable (0.000116) in the mean equation was positive and highly significant. This suggests that, there existed a positive return-illiquidity relationship in Indian stock market at an aggregate level during the study period. Note that the estimated EGARCH mean equation differs slightly from the one in Table 3 because EViews computes both mean equation and variance equation simultaneously and the number of iterations is different for different models.

The asymmetry effect is highlighted by γ. Because this parameter was significant and lower than zero (-0.109431), it can be inferred that the daily volatilities of the NIFTY returns were characterized by asymmetry. This is consistent with the notion that new negative information elicits a higher volatility relative to new positive information. The large β coefficient (0.965552) implies that volatility persists over a long period of time in the pertinent market.

Table 5

Regression Results of EGARCH (1, 1) Mean and Variance Equations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000709	0.000239	2.970825	0.0030*
RETURN(-1)	0.077717	0.020369	3.815460	0.0001*
$Illq_t$	0.000116	2.64E-05	4.398878	0.0000*
	Variance Equation			
ω	-0.461588	0.060060	-7.685387	0.0000*
a	0.210697	0.023275	9.052384	0.0000*
γ	-0.109431	0.014950	-7.319533	0.0000*
β	0.965552	0.006156	156.8547	0.0000*

* Significant at 1% level

AC, PAC, and Box-Pierce Q Statistics of Squared Residuals

To test whether any ARCH effects were still present in the mean equation, the AC and PAC functions & the Q statistics of the standardized residuals were calculated. The results are reported in Table 6. Since none of the AC functions, PAC functions or Q statistics at any lag were significant, we can conclude that there was no ARCH effects remaining.

CONCLUSION

This study sought to investigate the relationship between daily NIFTY return and illiquidity time series data. The EGARCH (1, 1) model was applied to model conditional volatility and illiquidity, following Amihud (2002), was used as an exogenous variable in the mean equation. After diagnostic testing, the model was deemed a good fit. The estimated results clearly showed that illiquidity was positively related to aggregate returns and therefore a liquidity premium existed in the Indian Stock Market during the study period. The empirical results also indicated a relationship between liquidity and volatility since illiquidity was used as an exogenous variable in estimating the mean equation and hence it influenced the values of the residuals. The lags of residuals, lags of conditional standard deviation, and lags of conditional variance in turn were inputs in the determination of (the natural logarithm of) conditional variance in the EGARCH framework.

Table 6
AC, PAC, and Box-Pierce Q Statistics of Squared Residuals

Lag	AC	PAC	Q-Stat	Prob
1	0.007	0.007	0.1272	0.721
2	-0.023	-0.023	1.5668	0.457
3	0.027	0.028	3.5459	0.315
4	0.020	0.020	4.6638	0.324
5	-0.026	-0.025	6.5126	0.259
6	-0.019	-0.018	7.4615	0.280
7	0.024	0.022	8.9392	0.257
8	0.004	0.004	8.9931	0.343
9	0.029	0.032	11.207	0.262
10	0.021	0.020	12.438	0.257
11	-0.031	-0.032	15.055	0.180
12	0.006	0.007	15.160	0.233
13	0.022	0.020	16.490	0.224
14	0.027	0.029	18.460	0.187
15	-0.012	-0.009	18.861	0.220
16	-0.003	-0.005	18.886	0.275
17	0.036	0.032	22.412	0.169
18	-0.000	0.000	22.412	0.214
19	-0.016	-0.013	23.115	0.232
20	-0.022	-0.022	24.359	0.227

In conclusion, it can be noted that the liquidity-return relationship deserves further investigation because of a number of factors: First, since the identification of factors that predict market returns has been an interest to academicians and practitioners, a study that examines the robustness of past empirical findings using different liquidity measures is important. It is also desirable to examine the return-liquidity relationship using various liquidity measures. This is because, unlike other financial variables such as price and volume, liquidity (illiquidity) is unobservable and has many facets that cannot be captured in a single measure.

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