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Role of Market Liquidity in Sentiment-Based Return Predictions: Evidence from Sri Lanka

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ABSTRACT

Behavioural finance theories contend that market anomalies, driven by human biases and heuristics, link liquidity to investor sentiment in asset markets. The irrational investor underreaction increases liquidity and explains the time-series relationship between liquidity and market returns. Based on data from the Colombo Stock Exchange (CSE), this study examines the extent to which market-wide illiquidity and sentiment proxied by turnover measure can forecast the short-term expected returns of the frontier market Sri Lanka during the period 2010-2021, using OLS time series regression methodology. Research findings show that investor sentiment proxied by turnover is positively related to expected market returns, contrary to the observations based on the US market. Regression estimates indicate that expected illiquidity significantly negatively impacts expected returns in a value-weighted specification. Unexpected illiquidity shocks depress the contemporaneous market returns. Small-cap stock returns show greater sensitivity to market illiquidity indicating that they face greater illiquidity risk compared to large-cap stocks. These findings offer insight into how investor sentiment can influence market liquidity and the impact of liquidity risk pricing on market returns over time in a frontier market.

Keywords: Investor Sentiment, Market Liquidity, Market Anomalies, Asset Pricing, Frontier Markets, Sri Lanka
JEL Classifications: G12, G4, G14

1. INTRODUCTION

The traditional finance theory that assumes frictionless and efficient markets has been challenged by empirical evidence regarding the relationship between liquidity and stock returns. Contemporary research has mainly studied liquidity as a priced risk factor in explaining the cross-sectional variation in share returns yet understanding the causes of time-series variation in market liquidity measure is limited. Even though empirical evidence shows that stock returns increase with bid-ask spread (Amihud and Mendelson, 1986), returns increase with an increase in price impact of trade (Brennan and Subrahmanyam, 1996) and returns decrease when trade volume increases (Brennan et al., 1998), Baker and Stein (2004) state that in each instance, the variation in stock return is too great to be completely explained by the traditional view of liquidity caused by turnover and transaction cost. Behavioural finance suggests that psychological factors, such as investor sentiment, play a role in determining investors' decisions, resulting in fluctuations in stock market liquidity.

Liquidity of stocks is a priced risk factor studied in contemporary literature to explain the cross-sectional variation in share returns (Acharya and Pedersen, 2005; Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). Transaction cost theory states that liquidity risk occurs when investors are unable to find a market for their securities, which would result in higher transaction costs (Baker and Stein, 2004). The volatility of share prices in the market is heavily impacted by its liquidity. Amihud (2002), Datar et al. (1998), and Corwin and Schultz (2012), find that investors demand higher returns for stocks that have higher trading costs and, therefore, lower liquidity. Ex-ante stock excess returns are positively related to expected market illiquidity based on the premise that investors are compensated for an equity's exposure to liquidity risk. Consequently, the expected stock excess return contains an illiquidity premium (Erdinc and Seda, 2019).

The liquidity conditions of securities markets fluctuate over time. Chordia et al. (2000) and Huberman and Halka (2001) demonstrate that the time-series liquidity variation may represent a risk factor that is priced for equities. Amihud (2002) reveals that expected returns across various stocks and over time are positively associated with expected illiquidity. The study contends that the excess stock return also reflects compensation for the expected market illiquidity forecasted based on the previous period's illiquidity. Additionally, unexpected market illiquidity causes a decline in contemporaneous stock prices. Therefore, this research aims to determine if the same illiquidity effect can contribute to explaining aggregate return variation over time in the CSE. If illiquid stocks generate greater returns, institutional investors with long investment horizons, such as life insurance companies and pension funds, could benefit from investing in illiquid stocks as long-term investment could lower the impact of illiquidity costs.

However, the cause for the frequent time-series variation in liquidity metrics is still unclear. Behavioural finance theories suggest that psychological factors, such as investor sentiment, influence investors' decisions, resulting in fluctuations in stock market liquidity. Baker and Stein (2004) and Baker and Wurgler (2006) argue that transaction cost theory cannot fully explain the high predictive power of market liquidity over market returns. The key to understanding why market liquidity varies over time may lie in a behavioural approach that looks at investor sentiment influencing share prices (Liu, 2015). Existing research indicates that investor decisions could be propelled by noise trading instead of fundamental information (Baker and Stein, 2004; Huberman and Halka, 2001), while it could also stem from overconfidence (Statman et al., 2006), where the investor disregards normative rules and make decisions subject to behavioural biases.

Baker and Stein (2004)'s model assumes a market with short-selling restrictions is dominated by irrational, overconfident investors. These investors may underreact to the information in market signals, leading to a lower price impact on order flows and increased liquidity. The increment in liquidity, caused by overconfident investors during high sentiment periods, can be used to measure the variations in equity returns.

There is limited research on the relationship between investor sentiment and liquidity in frontier stock markets. Liquidity driven by investor sentiment may have more significance in predicting market returns in a frontier market like Sri Lanka due to the low transparency and limited diversity in listed equities, resulting in fewer portfolio choices. As investor sentiment can significantly influence decision-making and asset valuation, incorporating it into asset pricing models could enhance our understanding of liquidity pricing of equities over time. Most sentiment measurement research focuses on the US and other developed and emerging stock markets (Pandey and Sehgal, 2019); thus, this study fills a gap in the empirical literature by providing a behavioural theoretical explanation of the relationship between liquidity and share returns in a frontier market.

The paper proceeds as follows. Section 2 discusses related literature regarding the impact of liquidity as a risk factor on market returns and the relationship between investor sentiment and price behaviour. Section 3 describes the data used, followed by the methodology employed. Section 4 presents the findings and discussion of their implications while Section 5 concludes the paper and proposes directions for future research.

2. LITERATURE REVIEW

Liquidity factor can explain significant variations in asset returns (Acharya and Pedersen, 2005; Amihud and Mendelson, 1986; Amihud et al., 2012; Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Chordia and Subrahmanyam, 2001; Kyle, 1985; Pastor and Stambaugh, 2003). The illiquidity of a stock is indicated by large trading costs, considerable bid-ask spreads, significant price impacts when trading large volumes, and long position unloading times. Amihud and Mendelson (1986) used bid-ask spreads to study the effect of liquidity on returns, showing that higher risk-adjusted returns correlate with wider spreads. Amihud (2002) applied a price impact measure and showed that excess stock returns increase with expected market illiquidity and contemporaneous returns decrease with unexpected illiquidity over time specifically for small stocks. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), find that equities with higher liquidity risk exposure display higher expected returns. At the same time, Datar et al. (1998) use turnover (Bekaert et al., 2007; Liu, 2015) as a proxy for liquidity. Chordia et al. (2001) examine the variability of liquidity, through dollar trading volume and share turnover as proxies for liquidity and find a negative cross-sectional relationship among variables.

Illiquidity and asset returns have been extensively studied in developed markets, yet evidence from frontier markets is limited and inconclusive. In emerging markets; Bekaert et al. (2007) find that unexpected liquidity is positively related to contemporaneous returns, and Lee (2011) find that liquidity risk is priced differently among countries based on geographic, economic, and political conditions. Batten and Vo (2014) and Phong (2016) found a positive relationship between liquidity and future returns in the Vietnamese market due to minimal integration with global markets.

Behaviouralists argue that investor sentiment influences stock return fluctuations (Berger and Turtle, 2012; Dash, 2016; Stambaugh et al., 2012). Irrational investors under short-sale constraints and limits to arbitrage struggle to distinguish between noise and information. Noise trading is based on irrational cognitive biases, which cause bullish or bearish sentiment, impact equilibrium asset prices and give rise to systematic sentiment risk (Baker and Stein, 2004; Shefrin, 2008). Studies in behavioural equity pricing shows a significant positive link between investor sentiment and stock returns, where optimism leads to overvaluation and vice versa (e.g. Baker and Wurgler, 2006; Baker et al., 2012; Berger and Turtle, 2012; Chue et al., 2019).

Various techniques have been used to quantify investor sentiment. Investor sentiment impact on asset valuation is discussed by Brown and Cliff (2005) using survey-based investor sentiment indices. The results of the study indicate that market is overvalued during periods of high investor optimism, with a significantly positive sentiment coefficient. Baker and Wurgler (2006) produced a composite investor sentiment index and found that investor sentiment acts as a conditional variable in predicting cross-sectional returns.

At the same time, studies use stock liquidity to indicate sentiment. Kyle's (1985) noise trader model shows how the behaviour of noise traders impacts market prices and liquidity. De Long et al. (1990) proposes that higher investor sentiment causes increased noise trading, highlighting how sentiment affects market liquidity, volatility, and price discovery. Combining the insights from both models, it can be deduced that higher investor sentiment can result in higher noise trading and liquidity (Liu, 2015). Lee and Swaminathan (2002) show that trade volume, measured by turnover ratio, reveals investor misperceptions about future earnings based on evidence from the US. Their findings imply that the turnover ratio reflects overconfidence and conservatism biases. Liu (2015) studies the relationship between time-series variation in stock market liquidity and investor sentiment in the US market, using individual and institutional investor sentiment indices along with turnover and Amihud's (2002) illiquidity measure as market liquidity measures. Liu (2015)'s results indicate that market liquidity is high during periods of higher investor sentiment. Low sentiment periods correlate with high illiquidity. This relationship is tested in Debata et al. (2018) concerning emerging markets. They present strong evidence for a positive relationship between domestic investor sentiment and liquidity in 12 emerging stock markets including Brazil, India, China, Mexico, Poland, South Africa, Russia, and Turkey.

Baker and Stein (2004) argue that market liquidity, proxied by the turnover ratio can serve as an indicator of investor sentiment, where high (low) liquidity denotes overvaluation (undervaluation), and Ho and Hung (2009) and Dash (2016) incorporate investor sentiment into conditional asset pricing models. These studies use sentiment indices constructed from various previously tested sentiment proxies. Still, they do not specifically focus on the turnover ratio as a sole indicator of sentiment or the time series impact of sentiment on expected returns.

Researchers highlight the importance of understanding the country-specific impact of investor sentiment on stock returns. Although an overall negative correlation between sentiment and future stock returns is observed using consumer confidence as a proxy for investor sentiment, Schmeling observed that cross-sectionally, the impact of sentiment is greater for countries with lower market integrity and are culturally more influenced by herd behaviour and overreaction. Baker et al. (2012) provide further international evidence that sentiment acts as a contrarian predictor of country-level market returns. Considering developing and emerging markets, Anusakumar et al. (2017), using trade volume as a proxy for sentiment, also find that market-wide sentiment has varying impacts on stock returns based on country. A high level of country-specific heterogeneity is visible in the effect that investor sentiment has on stock returns, which highlights the need for more localized studies.

While there are studies regarding the role of investor sentiment in predicting market returns in developed and emerging markets, there is a notable gap in the literature which examines this relationship based on data from frontier markets, specifically the Colombo Stock Exchange (CSE). Since these studies use alternate proxies for investor sentiment, applying Baker and Stein's (2004) turnover ratio can either support or dispute the applicability of turnover as a strong sentiment indicator, providing fresh empirical evidence on these relationships in a new context. By studying data from the CSE, this research can provide valuable comparative insights on how investor sentiment, particularly through liquidity measures like turnover, influences market returns in a different economic and cultural context.

3. METHODOLOGY

This study examines the relationship between investor sentiment and future stock returns from January 2010 and December 2021, considering all the 296 CSE-listed firms as of December 31, 2021. Due to companies listing and delisting, the sample size may fluctuate over 142 months. Outliers, defined as stocks in the highest or lowest 1% of the estimated illiquidity, have been omitted following Amihud (2002). Market-related information for sentiment proxies is extracted from the Colombo Stock Exchange and DataStream platform. The risk-free rate was based on the 91-day Treasury bill auction rates from the Central Bank of Sri Lanka.

3.1. The Market Liquidity Measure

Following Amihud (2002), this study first looks at the time series impact of market liquidity, as an indicator of the price impact of trade, on predicting excess expected market returns. Amihud's (2002) illiquidity measure has been used in several recent studies on market liquidity, such as Acharya and Pedersen (2005), Avramov et al. (2006), Hasbrouck (2009), and Liu (2015).

To obtain Amihud's (2002) illiquidity measure, the average ratio of daily absolute stock return to its traded volume is calculated as shown in equation (1), where R^i_{td} represents stock i's absolute return on day d of month m and is the trading volume of the same date. R^i_{md} is calculated by dividing stock price of day d by stock price of day d-1 and taking the natural logarithm to convert to absolute terms. VOL^i_{md} is calculated by multiplying the share price in Sri Lankan Rupees with the trade volume of that stock on that day.

$$\text{ILLIQ}_i = \frac{\left|R^i_{md}\right|}{VOL^i_{md}} \tag{1}$$

By averaging the daily ILLIQ measures within a single month, the monthly AILLIQ measure for each security can be calculated as shown in equation (2) where D^i_m represents the number of days in month m.

$$AILLIQ^i_m = \frac{1}{D^i_m}\sum_{d=1}^{D^i_m}\frac{\left|R^i_{md}\right|}{VOL^i_{md}} \tag{2}$$

For the time series regression, aggregate market illiquidity is calculated using equal-weighted and value-weighted methods to observe whether large-cap stocks will cause the illiquidity factor to have a lesser impact on expected excess returns.

Equal weighted average monthly market illiquidity (MILLIQ1) is the average illiquidity values of all the firms ($\sum AILLIQ$) and the value-weighted illiquidity (MILLIQ2) requires $AILLIQ_m^i$ to be multiplied by the ratio of the average monthly market value of each company *i* by total monthly market capitalisation and taking the sum of all the monthly value-weighted AILLIQ. Following Amihud (2002), this study applied a logarithmic transformation to market illiquidity.

Amihud (2002) identifies that the illiquidity's effect on stock returns can be broken down into expected and unexpected illiquidity.

RM_m is the annual market return for month *m*, Rf_m is the risk-free monthly rate, and $\ln AILLIQ_m^E$ is the expected market illiquidity for month *m* based on information in *m-1*. Investors are presumed to predict illiquidity for month *m* from information available in month *m-1* and then forecast prices to produce the expected return they desire in month *m*. Market illiquidity, $AILLIQ_m$, is the value-weighted or equal-weighted average illiquidity of all the stocks in month *m*.

An autoregressive model is used to estimate expected market illiquidity.

$$ln\ MILLIQ_m = c_0 + c_1\ MILLIQ_{m\text{-}1} + v_m \qquad (3)$$

At the beginning of month m, investors determine the expected illiquidity for the coming month, $\ln MILLIQ_m^E$, based on the information in month m-1 that has just ended. Therefore, by substituting the coefficients in Tables 1 and 2 into equation 4, the expected market illiquidity values were calculated.

$$\ln MILLIQ_m^E = c_0 + c_1 \ln MILLIQ_{m-1} \qquad (4)$$

Equal-weighted expected market illiquidity model:

$$\ln MILLIQ1_m^E = -1.2546 + 0.9061 \ln MILLIQ_{m-1} + v_m \qquad (5a)$$

Value-weighted expected market illiquidity model:

$$\ln MILLIQ2_m^E = -1.4621 + 0.9032 \ln MILLIQ_{m-1} + v_m \qquad (5b)$$

Amihud (2002) postulated that in the US market, investors predict illiquidity for the next month, taking into consideration information available in the previous month, and then use this forecast to set prices that will produce the expected return they desire in the next month. Ex-ante excess stock returns increase with expected illiquidity because rational investors anticipate higher returns if they expect market illiquidity to increase. Therefore, this study empirically tests whether, in the frontier market of Sri Lanka, the ex-ante excess market return increases as the level of expected market illiquidity increases through hypothesis 1 (H_1) below:

H_1: Ex-ante excess stock market returns increase with expected market illiquidity.

The model that shows this relationship is

$$(RM - Rf)_m = f_0 + f_1 \ln MILLIQ_m^E + u_m = g_0 + g_1 \ln MILLIQ_{m-1} + u_m. \qquad (6)$$

The expected illiquidity estimates from (5a and 5b) were used to calculate unexpected illiquidity for each month. Unexpected illiquidity is the difference between observed liquidity at the end of the current month and expected illiquidity based on the observed illiquidity of the previous month. u_m is the residual representing the unexpected excess market return. Unexpected market illiquidity decreases contemporaneous unexpected stock returns. Since c1 >0 (as shown in equation [4]) indicates that more illiquidity in 1 month predicts high illiquidity in the next, higher expected illiquidity results in an increase in ex-ante stock market returns. Based on results from Amihud's (2002) study, we hypothesize that the relationship between unexpected illiquidity and contemporaneous stock market returns in the CSE should be negative.

H_2: Contemporaneous excess stock market returns have a negative relationship with unexpected market illiquidity.

As the next step, the two hypotheses discussed above are tested in the model (7) using a time-series regression. The output is provided in the results and findings chapter.

$$(RM - Rf)_m = g + hlnMILLIQ_m^E + j \ln MILLIQ_m^U + w_m \qquad (7)$$

Where $\ln MILLIQ_m^U$ is the unexpected illiquidity in month *m* and $\ln MILLIQ_m^U = v_m$, the residual from equation (13).

3.2. Market Illiquidity and Size-based Portfolio Returns

As expected market illiquidity increases, investors shift to stocks with higher liquidity. An unexpected surge in market illiquidity adversely impacts stock prices, further increasing demand for liquid stocks. This preference can be attributed to the ease of converting liquid stocks into cash, ensuring a quick exit from the market during market uncertainty.

Accordingly, Amihud (2002) finds that impact of illiquidity is greater on small, illiquid stocks. We hypothesise the same relationship is present in the CSE as shown in hypothesis three (H_3):

H_3: Illiquidity effect is stronger for smaller, illiquid stocks.

This effect is tested through equation (8) below:

$$(RSZ_p - Rf)_m = g^p + h^p lnMILLIQ_m^E + j^p \ln MILLIQ_m^U + w_{pm}, \qquad (8)$$

Where, RSZ_p is the return of a particular-sized portfolio, and *p* represents large-cap, medium-cap or small-cap portfolios. The three portfolios are formed by splitting the data into three groups using two tertiles so that the companies with the highest 1/3 average monthly market capitalization are grouped into the large-cap portfolio, the middle 1/3 are grouped into the medium-

Table 1: Results of autoregressive function for prediction of equal-weighted monthly average illiquidity ($lnMILLIQ1_m$)

$lnMILLIQ1_m$	R^2: 0.8203 Adj R^2: 0.8190 F: 639.14 (0.0000)		
	Coefficients	**t Stat**	**P-value**
C_O	−1.2546	−2.6150	0.0099
C_1	0.9061	25.2813	0.0000

Table 2: Results of autoregressive function for prediction of value-weighted monthly average illiquidity ($lnMILLIQ2_m$)

$lnMILLIQ2_m$	R^2: 0.8166 Adj R^2: 0.8153 F: 623.48 (0.0000)		
	Coefficients	**t Stat**	**P-value**
C_O	−1.4621	−2.6696	0.0085
C_1	0.9032	24.9696	0.0000

cap portfolio, and the lowest 1/3 are grouped into the small-cap portfolio. Logarithmic transformation of the illiquidity of the portfolio is used in the autoregressive model to obtain expected ($lnMILLIQ_m^E$) and unexpected ($\ln MILLIQ_m^U$) illiquidity figures as before.

3.3. Market Turnover

In this study, the impact of aggregate market sentiment on ex-ante market excess returns is tested. The share turnover rate has been recommended as an indicator of investor sentiment as a measure of liquidity (Baker and Stein, 2004). Several researchers, including Baker and Wurgler (2006), Liao et al. (2011), Chen et al. (2013), and Anusakumar et al. (2017), have proposed turnover as a reliable and readily available sentiment measure in frontier markets.

Daily Turnover is calculated by dividing the rupee trade volume by the market value of each stock on a particular date following Baker et al. (2012). Monthly turnover ($ATurnover_m^i$) for each stock (i) each month (m) is calculated by taking the average of all the daily turnovers. To calculate the equal-weighted market turnover measure (Turnover1), the sum of all the average turnover values ($\bullet\ ATurnover_m^i$) of the companies for that month are divided by the number of firms present in that month. Value-weighted monthly average market turnover (Turnover2) requires to be $ATurnover_m^i$ multiplied by the ratio of the average monthly market value of each company *I* by total monthly market capitalisation and taking the sum of all the value-weighted *ATurnover* of all the companies for each month.

3.4. Advance and Decline Ratio

The advance and decline ratio is a market sentiment measure used by technical analysts to provide an overview of market activity by gauging the direction in which most shares are moving (Zaremba et al., 2021). When the number of advancing shares is greater than the number of declining shares, the advance and decline ratio rises, indicating positive market sentiment (Brown and Cliff, 2004). High (low) advance and decline ratio shows a positive (negative) relationship with expected returns (Zaremba et al., 2021). Dash and Maitra (2018) also use Advance and Decline ratio to predict relationship between sentiment and expected returns.

Following Brown and Cliff (2004), the number of companies with advancing shares each month has been divided by the number of companies with declining shares for that month to obtain the advance and decline ratio for the market on a monthly frequency.

Hypothesis four (H_4) examines the relationship between advance and decline ratio as a sentiment indicator and ex-ante excess aggregate market return,

H_4: Ex-ante excess stock market returns have a positive relationship with advance and decline ratio.

3.5. Dividend Yield

The impact of dividends and announcements on stock returns has been well-documented (Blume, 1980; Fama and French, 1988; Samarakoon, 1999). The constant dividend growth model by Gordon (1962) shows that the dividend yield equals the interest rate less the dividend growth rate. Amihud (2002) posits that for the investors to be compensated for the greater dividend taxes relative to the capital gains tax, dividends should have a positive impact on returns. Nonetheless, dividend yield could have a negative impact on stock returns if it is negatively associated with an unobserved risk factor, i.e., if stocks with a greater dividend are considered less risky. Therefore, following Baker and Stein (2004), this study uses monthly dividend yield data obtained from CSE data publications to control general valuation levels.

3.6. Model Specification

Under a short-sale constraint, Baker and Stein (2004) argue that a higher number of irrational investors in the market reduces the price impact of trade, resulting in increased trading volumes, increased liquidity, and a subsequent decrease in expected returns. Hypothesis five (H_5) examines the relationship between market turnover as a sentiment indicator and expected market return in the CSE,

H_5: Ex-ante excess stock market returns have a negative relationship with market turnover.

To test the stationarity of the variables, the Augmented Dickey-Fuller test has been used. The following model is used to predict the 1-month-ahead returns while using turnover as a sentiment indicator and controlling for the general valuation influence of the dividend yield:

$$(RM - r_f)_m = a + b\,lnTurnover_{m-1} + c\,ln\frac{ADV}{DEC}_{m-1} + \\ + d\,lnMILLIQ_m^E + e\ln MILLIQ_m^U + k\,DIVY_{m-1} + \mu_m, \quad (11)$$

Where, $(RM-r_f)_m$ is expected excess market return of month m, $lnTurnover_{m-1}$ is the logarithm of turnover rate at the end of the preceding month *(m-1)*, $ln\frac{ADV}{DEC}_{m-1}$ is the logarithm of advance and decline ratio at *m-1*, $lnMILLIQ_m^E$ is logarithm of expected average market illiquidity based on the previous month's value, $lnMILLIQ_m^U$ is unexpected illiquidity and $DIVY_{m-1}$ is dividend yield at *m-1*.

4. FINDINGS AND DISCUSSION

4.1. The Impact of Market Illiquidity on Ex-ante Excess Market Return

Using the expected and unexpected illiquidity variables, a time series regression is performed according to the model in equation (7) in the methodology section. Two separate regression models have been executed for equal-weighted and value-weighted variables. The results are summarized in Table 3.

The results indicate firstly that the significance of the impact of expected illiquidity ln $MILLIQ_m^E$ on expected return is greater for the value-weighted model. Equal-weighted CSE market expected returns do not include a premium for expected illiquidity. The estimated coefficient, h, with the equal (value) weighted model, is −0.023 (−0.027) with a P = 0.112 (0.024). The relationship between ln $MILLIQ_m^E$ and expected returns is negative. This finding contradicts Amihud's (2002) results from US market where expected market illiquidity leads to higher expected returns.

Results from the CSE's value-weighted model suggest that, even in situations where high illiquidity is anticipated in the market, investors do not demand larger expected returns from large-cap equities. The reason may be that large-cap stocks are less sensitive to illiquidity and can be traded quickly with little price impact, reducing the need for higher returns to compensate for the risk.

The lack of evidence for significant illiquidity premium was also encountered by Stereńczak et al. (2020) for frontier markets. When examining the mean returns of the zero investment portfolios formed based on Amihud's illiquidity measure, they observe that only Jordan and Lebanon show significantly positive payoffs. All the other 20 frontier markets show an insignificant return-illiquidity relationship, but in the case of Sri Lanka, it is negative at a 10% significance level. Stereńczak et al. (2020) claim that findings support the notion that for countries that are not fully integrated into the global economy, diversification's benefits outweigh illiquidity's disadvantages, making the latter less significant. Similar to the present study, Yaakoubi (2024) also fails to find a significant explanatory power of expected illiquidity for stock returns for an equal-weighted market portfolio, based on data from New York Stock Exchange.

Unexpected illiquidity, ln $MILLIQ_m^u$ and contemporaneous market return premiums are significantly negatively related. The estimated coefficient, j, with the equal-(value-) weighted model, is −0.084 (−0.097) with a $P < 0.05$ significance level. The second hypothesis of the study is accepted with this empirical outcome. This result is in line with the findings of Amihud (2002), who showed a negative correlation between unexpected illiquidity and the excess returns in the market contemporaneously. In the face of unexpected illiquidity shocks, CSE investors become more risk-averse, demanding higher returns and decreasing demand and causing a decline in the price of assets. In frontier markers, for expected illiquidity not to have a significant impact on market returns, but unexpected illiquidity effect of being significant is likely if individual investors are believed to have a relatively simple and passive trading strategy. These investors typically employ the trading strategy of buying winners and selling losers. They react to market performance rather than anticipating market developments (Chu et al., 2016).

4.2. Illiquidity on Ex-ante Excess Return of Size-based Portfolios

According to the proposition made by Amihud (2002), returns of small, illiquid stocks are more affected by illiquidity. To test hypothesis 3, the differences in the effects of illiquidity on the expected returns of various size-based portfolios are estimated through the regression model provided in equation (8). The results are displayed in Table 4.

The estimated coefficient, j^p, of the large-cap portfolio (−0.060) is greater than that of the small-cap portfolio (−0.071). This suggests that the impact of unexpected illiquidity is less for larger, more liquid equities than for smaller, illiquid stocks. The greater sensitivity of small-capitalization stock returns to market liquidity shows that small-cap stocks face greater illiquidity risk, proving hypothesis 3 for CSE. As Pastor and Stambaugh (2003) demonstrate, stocks with greater illiquidity risk should earn a higher illiquidity risk premium.

The large-cap stocks don't show a significant positive premium for expected illiquidity, similar to the findings of the previous model. The significant negative relationship between expected illiquidity and sized-based portfolio returns may signify that investors pay a premium to buy large-cap stocks when expected future illiquidity is high. A possible explanation is that investors consider large companies less risky, so they are willing to accept lower returns. However, this possible explanation requires further study in the CSE.

4.3. The Impact of Market Sentiment on Ex-ante Excess Market Return

The second part of this study examines the pricing of aggregate liquidity as a sentiment proxy using a linear time series regression model shown by equation (11). The regression results are shown in Table 5 are all variations of equation (11), although in some cases, the univariate versions of the specifications are considered, effectively setting subsets of the coefficients *b, c, d, e,* and *k* to zero.

The results of the regression shown in Table 5 indicate that turnover for the CSE positively and significantly affects 1-month-ahead equal-weighted and value-weighted market returns. The coefficient of aggregate turnover for the equal- (value) weighted market portfolio is 0.007 (0.017) with a P = 0.024 (0.004). This positive coefficient signifies that an increase (decrease) in market turnover is associated with an increase (decrease) in stock returns. Therefore, evidence from CSE does not support hypothesis 5.

This study's findings, based on data from frontier market Sri Lanka, do not agree with Baker and Stein's (2004) argument that market returns should have a negative relationship with turnover. The relationship between expected returns and turnover could vary depending on the stock market and the underlying sources of heterogeneity among market participants. It has occasionally been shown that turnover and expected returns are positively related. Schmeling's (2009) study supports a country-specific heterogeneity in the impact of investor sentiment on market returns. Schmeling examines potential determinants of the degree

Table 3: Regression results for effects of market illiquidity on expected excess return

Expected excess market return	g	h	j	R^2	Adj R^2	DW
Equal Weighted	−0.071	−0.023	−0.084	0.226	0.214	2.076
t-stat	[−12.863]	[−1.600]	[−6.280]			
P-values	(0.000)	(0.112)	(0.000)			
Value weighted	−0.070	−0.027	−0.097	0.362	0.353	2.015
t-stat	[−16.431]	[−2.28]	[−8.807]			
P-values	(0.000)	(0.0241)	(0.000)			

$(RM - Rf) = g + h\, lnMILLIQ + j \ln MILLIQ + w$ Where, $(RM-r_f)_t$ is expected excess market return, lnMILLIQ is logarithm of expected aggregate illiquidity based on the previous month's value and is lnMILLIQ unexpected illiquidity. is only stationary at the first difference, so monthly changes in the logarithm of equal-weighted and value-weighted expected illiquidity were used in the regression. t-statistics are mentioned within square brackets [], and *P* values are mentioned within parentheses ()

Table 4: Regression results of the excess returns on size-based portfolios as a function of expected and unexpected illiquidity

Size-based portfolio excess returns	g^p	h^p	j^p	R^2	Adj R^2	DW
Large-cap Portfolio	−0.066	−0.030	−0.060	0.174	0.162	1.921
	[−13.177]	[−2.427]	[−5.295]			
	(0.000)	(0.017)	(0.000)			
Medium-cap portfolio	−0.070	−0.014	−0.089	0.321	0.311	2.056
	[−13.648]	[−1.197]	[−8.076]			
	(0.000)	(0.233)	(0.000)			
Small-cap portfolio	−0.074	−0.012	−0.071	0.160	0.148	2.091
	[−11.560]	[−0.770]	[−5.129]			
	(0.000)	(0.442)	(0.000)			

$(RSZ_p - Rf)_m = g^p + h^p lnMILLIQ_m^E + j^p \ln MILLIQ_m^U + w_{pm}$. *RSZp* is the monthly return of a particular-sized portfolio; *P* represents large-cap, medium-cap, or small-cap portfolios formed based on each company's average monthly market capitalization. $lnMILLIQ_m^E$ is the expected illiquidity and $\ln MILLIQ_m^U$ is the unexpected illiquidity of the size-based portfolio. The model is robust to heteroskedasticity, autocorrelation, and multicollinearity. $lnMILLIQ_m^E$ is stationary at the first difference, while other variables are stationary at levels. t-statistics are mentioned within square brackets [], and *P* values are mentioned within parentheses ()

Table 5: Regression results for effects of market sentiment, dividend yield, and market illiquidity on expected excess return

Coefficient	Equal Weighted			Value Weighted		
	1	2	3	1	2	3
a	−0.015	−0.070	−0.025	0.107	−0.069	0.065
	[−0.487]	[−11.493]	[−1.201]	[1.624]	[−11.145]	[1.340]
	(0.627)	(0.000)	(0.232)	(0.107)	(0.000)	(0.183)
b	0.008		0.007	0.022		0.017
	[1.852]		[2.292]	[2.806]		[2.902]
	(0.066)		(0.024)	(0.006)		(0.004)
c		0.012	0.010		0.013	0.008
		[2.247]	[1.011]		[3.332]	[1.070]
		(0.026)	(0.314)		(0.001)	(0.287)
d			−0.032			−0.031
			[−2.189]			[−1.989]
			(0.030)			(0.049)
e			−0.094			−0.102
			[−4.873]			[−5.538]
			(0.000)			(0.000)
k			−0.017			−0.018
			[−0.312]			[−0.474]
			(0.756)			(0.636)
R^2	0.024	0.035	0.251	0.083	0.062	0.418
Adj R^2	0.017	0.028	0.223	0.077	0.055	0.397
DW	1.620	1.886	1.984	1.811	1.945	2.091

$(RM - r_f)_m = a + b\, lnTurnover_{m-1} + c \ln \frac{ADV}{DEC}_{m-1} + d\, lnMILLIQ_m^E + e \ln MILLIQ_m^U + k\, DIVY_{m-1} + \mu_m$, where, $(RM-r_f)_m$ is expected excess market return, is the natural logarithm of the turnover rate at the end of the preceding month *(m-1)*, is the advance and decline ratio at *m-1*, is logarithm of expected average market illiquidity based $ln \frac{ADV}{DEC}_{m-1}$ on the previous month's value, $lnMILLIQ_m^U$ is unexpected illiquidity and $DIVY_{m-1}$ is dividend yield at *m-1*. Two regressions were run for the model's equal-weighted and value-weighted specifications. Turnover, expected illiquidity, and dividend yield data series were only stationary at the first differences. Therefore, monthly changes in these variables were applied in the regression. t-statistics are mentioned within square brackets [], and *P* values are mentioned within parentheses ()

of influence sentiment has on returns and concludes that the impact of noise traders on markets is variable due to country-specific factors such as overconfidence, herd behaviour, efficiency of regulatory institutions, and level of market integrity.

Jun et al. (2003) analyse the liquidity behaviour in emerging markets and discover that returns in developing nations have a positive relationship with market turnover. Dey (2005) also finds supporting evidence from emerging markets regarding a positive turnover expected return relationship. He states that investors expect higher returns from high-turnover markets and that the sources and pricing of risks in emerging markets are different from those in developed markets. Their findings are consistent with the high liquidity return premium theory put forth by Ying (1966) and empirically extended by Gervais et al. (2001), which states that high levels of turnover provide insight into the future direction of stock prices. They discover that stocks that experience abnormally high (low) trade volume over the course of a day or a week tend to increase (decline) over the course of the subsequent month. They contend that this high-volume return premium is in line with the theory that fluctuations in a stock's trading activity have an impact on its visibility, which in turn has an effect on demand and price.

Urooj et al. (2019) find a positive relationship between aggregate turnover and market returns. They explain that the findings support the existence of an overconfidence bias among Pakistani investors, which makes them trade more aggressively with positive returns. Anusakumar et al.'s (2017) empirical research on a sample of emerging Asian markets also finds a significant positive relationship between market turnover and returns in the Indian, South Korean, and Taiwan stock exchanges.

In the univariate regressions, the advance and decline ratio has a positive and significant effect on equal-weighted and value-weighted market returns, with coefficients of 0.012 (P = 0.026) and 0.013 (P = 0.001), respectively. This finding is in line with the results of Zaremba et al. (2021) which show that high (low) advance and decline ratio shows a positive(negative) relationship with expected returns. They conclude that the advance and decline ratio has a predictive ability for future stock performance in developed, emerging and frontier equity markets. Dash and Maitra (2018) also identified it as a sentiment indicator positively related to returns. However, in multivariate regression with turnover and illiquidity, the ratio's effect on returns becomes insignificant, similar to Brown and Cliff's (2004) findings.

When looking at the multivariate regression that includes both sentiment and illiquidity variables simultaneously (along with dividend yield), the coefficient, d, on expected illiquidity ln $MILLIQ_m^E$ shows a slight decrease compared with the model tested with only illiquidity factors against expected market returns. The estimated coefficient, d, with the equal (value) weighted model, is −0.032 (−0.031) with a P = −0.030 (0.049). In both instances, the relationship between expected market return and illiquidity is negative and significant. Therefore, the hypothesis that ex-ante excess stock market returns increase with expected market illiquidity must also be rejected.

These results may signify a unique feature of the CSE that was not captured in Amihud's (2002) study. This could mean that the relationship between expected market return and expected illiquidity may not be universal and could vary across different markets, as was indicated by the heterogenous illiquidity-return relationships observed by Stereńczak et al. (2020) for frontier markets.

Unexpected illiquidity, ln $MILLIQ_m^u$ and contemporaneous market return premiums are significantly negatively related. The estimated coefficient, e, with the equal- (value-) weighted model, is −0.094 (−0.102) with high statistical significance. As with the results of the previous model, this empirical outcome is consistent with the findings of Amihud (2002), who demonstrated a negative correlation between unanticipated illiquidity and simultaneous market excess returns. In the Sri Lankan market context, the impact of unexpected illiquidity on market returns appears to be more significant than the effect of expected illiquidity, which investors anticipate based on past market illiquidity. This finding underscores the importance of considering unexpected illiquidity as a crucial factor in predicting market returns.

The dividend yields variable, which acts as a control variable representing the general valuation impact of dividends on returns in the current study, does not indicate a significant predictive power over expected returns within a forecast horizon of 1 month, similar to the findings of Samarakoon (1999). The OLS coefficient for equal- (value) weighted specification of the model is −0.017 (−0.018) with a P = 0.756 (0.636). Over a short-term horizon, such as 1 month, dividend yield's impact on returns may be diluted, as short-term market sentiment and liquidity conditions have a greater influence on stock prices than fundamental considerations, such as dividends, in a frontier market like the CSE.

5. CONCLUSION

The market turnover acting as a sentiment proxy affects aggregate market returns, providing evidence from a frontier market. While the time variation of the illiquidity-return relationship has been extensively investigated in the developed markets, frontier market research is limited. In this study, the impact of aggregate expected and unexpected Amihud's (2002) illiquidity on time series variation in excess expected market returns of the CSE has also been closely examined.

This study finds that expected market illiquidity significantly impacts returns in the value-weighted model but not in the equal-weighted model, suggesting that future stock returns are influenced by illiquidity when large-cap stocks are emphasised. In contrast to the expectation that stock returns include a positive premium for illiquidity, this study finds that ex-ante returns decrease in expected illiquidity. This indicates that investors do not demand higher returns for holding large-cap stocks even when the market is illiquid, possibly because these stocks carry lower risk.

Unexpected market illiquidity has a significant negative effect on contemporaneous returns, as hypothesized based on the theoretical underpinnings of Amihud (2002). Therefore, in the CSE, unexpected illiquidity shock significantly depresses contemporaneous market returns. The effect of unexpected illiquidity on contemporaneous returns is weaker for large, more liquid stocks than for small, illiquid stocks. The greater sensitivity of small-capitalisation stock returns to market illiquidity indicates that they face greater illiquidity risk.

In summary, expected and unexpected market illiquidity has an impact on the CSE's market returns over time. While excess returns include compensation for illiquidity costs, the expected illiquidity-return relationship is reversed in the Sri Lankan market compared with Amihud's (2002) findings in the US market. This suggests that the relationship between expected return and illiquidity may vary depending on the market conditions and regulations. Further research is needed to understand these unique aspects of the Sri Lankan market.

Aggregate turnover positively and significantly affects 1-month-ahead equal-weighted and value-weighted market returns. This finding suggests that higher market sentiment, measured by turnover, correlates with an increase in expected market returns in the CSE, opposing the sentiment-based model of Baker and Stein (2004), which proposes a negative relationship. Depending on the stock market and the underlying sources of heterogeneity among market participants, the relationship between expected returns and turnover could vary, as supported by Schmeling's (2009) findings of country-specific heterogeneity. The positive turnover-return relationship is consistent with the high liquidity returns premium theory studied by Ying (1966) and Gervais et al. (2001), which states that high trading activity signals greater interest in stocks by making them more visible to investors, increasing demand and impacting price changes in the near term. Jun et al. (2003), Dey (2005), and Anusakumar et al. (2017) also find supporting evidence from emerging markets regarding a positive turnover expected return relationship.

The results highlight the importance of liquidity and investor sentiment in influencing market returns, providing insights into investor behaviour and the potential risks and opportunities in the market. Understanding the influence of investor sentiment on equity prices in Sri Lanka is vital as it can influence short-term market fluctuation without fundamental support, potentially leading to significant devaluations and risks to market stability. The remarkable negative illiquidity premium observed in the CSE warrants further investigation, along with the long-term effects of market sentiment on returns. This study contributes a foundational understanding of the role of liquidity and investor sentiment in the CSE, paving the way for future research.

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