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IMPACT OF LIQUIDITY ON STOCK RETURNS: EVIDENCE FROM SELECTED INDIAN COMPANIES

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ABSTRACT

Purpose- The present study tries to judge the impact of liquidity on stock return in two select Indian companies listed in Bombay Stock Exchange (BSE) by making use of a restructured stock market dataset and financial data for the period from 1 January 2008 to 31March 2025.

Methodology-The study is solely based on secondary daily, monthly, and annual stock market data collected from BSE India. Actual returns calculated using the log difference of previous price and current price R_t= Ln (P_t-P_{t-1}), where P is the price, Ln is natural logarithm and t is the period and R_t is Actual Return. Amihud (2002) measure of illiquidity is applied to arrive at stock illiquidity, single index model (SIM) is used to compute market risk. Several econometric tools like unit root test such as ADF test, PP test, granger causality test, robustness test like multicollinearity, serial correlation (Breusis usedy test), heteroscedasticity test (Breusch-Pagan-Godfrey Test), normality of error terms (Jarque-Bera Test), Ramsey Reset test etc applied. Finally, generalized method of moment has been applied to judge the impact of illiquidity on stock return on select conglomerates.

Findings- The results suggest that the impact of illiquidity on stock returns is diverse in case of select conglomerate industries listed in Indian stock market. More precisely, we observe a reliable positive impact of illiquidity on stock returns in Reliance industry and insignificant negative impact of illiquidity on stock returns in Adani industry. However, we do not find any granger causal connection between fluctuation in liquidity and stock returns in both Indian conglomerate industries. Stock's systematic risk has an insignificant positive effect on stock returns in case of both industries indicating a direct, risk-reward relationship, although existence of insignificantly positive effects.

Conclusion- This research study on the nexus between illiquidity and stock return might be viewed as an effort towards understanding stock return, illiquidity, volatility dynamics in the emerging economy like India.

Keywords: Stock returns, illiquidity, market risk, reliance, Adani.
JEL Codes: G12, G10

1. INTRODUCTION

Investors' decisions are affected by liquidity, market competence or transactions costs. Stock market liquidity is an indispensable market trait whose existence makes certain the smooth operations of the market, while its nonexistence causes restlessness in the market. Researchers appear to agree upon the fact that liquidity is a significant factor in asset pricing. Simply, liquidity is the extent to which one asset can be traded promptly at minimum impact cost. In other words, liquidity relates to trading cost, and it decides how fast the assets can be traded at the normal market price with fractional influence on the stock price movement and is précised by the bid-ask spread known as illiquidity cost. Investors bring upon themselves a systematic liquidity risk, for which they want higher expected return to compensate for the hazard of holding stock whose illiquidity differs with market illiquidity. Additionally, the market microstructure theory (Stoll, 1978) presupposes that higher return volatility enhances illiquidity. Their substantiation on higher return volatility claims that investors holding an asset with high inventory costs increase the bid-ask spread and trading cost.

On the contrary, investors are enthusiastic to accept a lower return on an asset with a higher return in times of market illiquidity. Whilst the market turns down, an investor is prepared to accept a low-priced return on stocks with low illiquidity costs in states of reduced market return. Amihud et al. (2006) designate that market liquidity exposes the existence of keen buyers and sellers who concur to exchange a definite quantity of securities at the stated price without any delay in time. Conversely, illiquidity increases trading costs and unfavorably affects asset return and holding it up until revitalization of liquidity level breeds an extra premium for the investment in the asset. Amihud and Mendelson (1986) exemplify that investors holding stocks characterized by an outsized bid-ask spread accept high costs of positions liquidation, and subsequently they claim compensation for illiquidity.

Hence, one of the factors which investors judge while making investment decisions is the liquidity of a financial asset. Prudent investors need a high premium of risk for holding fewer liquid stocks. So, investors stipulate a higher rate of returns for less liquid stocks than more liquid stocks. Therefore, the risk-adjusted returns of liquid stocks are lower than those of less liquid stocks. Thus, the liquidity risk exhibits explanatory power on the cross-section of stock return (Vu, Chai, & Do, 2015). As higher expected returns are associated with less liquid assets, expected returns and illiquidity are positively related, or conversely, a negative relationship between liquidity and stock returns can be recommended. Ellington (2018) stated that lower liquidity levels cruelly hinder economic growth during catastrophe. Bigger liquidity leads to bigger financial risk-sharing, influencing investors' trading decisions and inspiring portfolio changes. Moreover, deficient market liquidity leads to reducing market competence, incompetent asset allocation, and hindering economic growth. Therefore, liquidity is one factor that investors believe very frequently in the stock market. The existence of market liquidity is significant for a trader as it decides the extent of his returns and in that way, it helps in formulating suitable trading strategies. Many studies (Amihud& Mendelson, 1986; Bradrania et al., 2015; Chang et al., 2010; Lam & Tam, 2011) have tinted the important association between market liquidity and stock returns.

Brief profile of selected conglomerates

Reliance Industries Limited (RIL) was established in 1958 by Dhirubhai Ambani as an unassuming trading firm for spices and polyester yarn. Over the decades, it evolved into an international powerhouse by pioneering the "backward integration" model, expanding from textiles into petrochemicals and refining to control its entire production chain. Now a days, its energy segment remains its financial strength of character, housing the world's largest refining complex in Jamnagar. Under the leadership of Mukesh Ambani, Reliance has pivoted toward a consumer-centric ecosystem, dominating India's digital landscape through Jio Platforms and its AI initiatives, while operating the country's largest retail network through Reliance Retail and a massive media portfolio via JioCinema.

Adani Enterprises Limited (AEL), founded by Gautam Adani in 1988, began as a commodity trading business that shifted focus to the nation's physical infrastructure following the development of Mundra Port in 1995. Functioning as an "in-house incubator," AEL systematically builds and scales capital-intensive ventures before demerging them into independent entities. As of 2026, the group is the primary architect of India's logistics and utilities, managing major gateways through Adani Ports, operating the newly opened Navi Mumbai International Airport, and leading the cement industry through Ambuja Cements. Its portfolio extends into critical "hard" infrastructure, including power transmission, data centers via AdaniConneX, and defense manufacturing.

These companies are termed conglomerates because they administer a vast network of diverse, often unrelated business entities under a single corporate umbrella to diversify risk and leverage internal capital. This structure is particularly evident in their shared pursuit of the Green Energy sector, where both have pledged over $70 billion to lead India's energy transition. While RIL focuses on the manufacturing of solar modules and batteries at its Giga Complex, Adani targets global leadership in renewable generation and the Green Hydrogen ecosystem. By operating across sectors as varied as 5G telecom, city gas distribution, and luxury fashion, these conglomerates make certain that their unwavering cash flows from traditional industries fund to the high-growth technologies of the future.

2. LITERATURE REVIEW

There is a volume of research which substantiates the notion that the liquidity of stock is a crucial aspect for pricing a financial asset. The research endeavor of Amihud and Mendelson (1986) is one of the ground-breaking research projects on the relationship between liquidity and stock returns. Using the bid-ask spread as a proxy for liquidity, this study demonstrates that investors need extra liquidity premium for holding illiquid stocks.

Amihud and Mendelson (1986) opined that investors having a short-term horizon have a propensity to invest more in liquid stocks, even though investors having a long-term horizon tend to invest more in less liquid stocks. Consequently, stock liquidity level is fundamental of motivations differences of investors, more specifically, investments horizon differences, and in equilibrium, the relationship between required return and stock liquidity is non-linear and concave.

Following the research findings, a great deal of studies carries on spotlighting on return–liquidity association from diverse perspectives. Following the move of Amihud and Mendelson (1986), Eleswarapu and Reinganum (1993) deal with this relationship using a restructured database. This finding suggests that the liquidity premium is a recurrent effect as it is consistently positive during the month of January. However, Brennan and Subrahmanyam (1996) found well-built substantiation which is consistent with the conception of a premium for illiquidity. These findings are unwavering over time and strong enough to controlling for Fama and French's (1993) risk factors.

Datar et al. (1998) employ the turnover ratio as a proxy for liquidity to examine the return–liquidity nexus. The result showed that liquidity had significant effect on analyzing returns on assets. The effect of the liquidity risk factor is well-built in comparison with the size risk factor on asset returns. This study inferred that the size effect could be an indication of liquidity impact. This might partially be owing to the reason that institutional investors have well-built command of large and liquid stocks, and this demand seems to pay no attention to the relative performance of small stocks.

Huberman and Halka (1999) found a momentous connection between liquidity instability of diverse stocks. The result presents the subsistence of common factors of liquidity across stocks and elucidates those factors by the existence of liquidity traders.

Jacoby et al. (2000) restructured CAPM model by reassessing excess returns over one-period of both stock and market by captivating liquidity costs and demonstrate that the measurement of systematic risk obviously connects the alteration of the spread of security.

Chordia et al. (2001) found an adverse unenthusiastic connection between volatility of liquidity and cross-sectional equity returns, in contrast of the perception on risk–return affiliation. These findings are solidified in presence of a variety of controls for the size, momentum, book-to-market ratio, dividend yield effects, price level.

Jun et al. (2003) observed an encouraging affirmative association between market-wide liquidity and stock returns applying statistics for promising equity markets. Pastor and Stambaugh (2003) appraise whether market-wide liquidity is priced and observed that returns of stocks with high sensitivity to market liquidity surpassed those with lesser sensitivity.

Acharya and Pedersen (2005) modify the liquidity-adjusted CAPM model by incorporating three additional risk factors associated with liquidity risk like proxy for commonality in liquidity of stock and market, return sensitivity to market liquidity and liquidity sensitivity to market return. The result indicates that investors have need of higher expected future asset returns to pay off the contemporary liquidity's shocks. The effect is corroborated by Chien and Lustig (2010) who assert that liquidity risks resulted by diverse business cycles should be satisfied by higher expected stock return. Liu (2006) made use of a new proxy for liquidity and the liquidity-augmented CAPM model. The study suggested that liquidity explicates cross-sectional stock return better than CAPM and the Fama–French three-factor models (1993).

Amidst controversies upon whether the prevailing asset-pricing models with well-known factors such as market premium, size, book-to-market, Nguyen et al. (2007) carry out both time-series and cross-section tests upon the three-moment CAPM and four factor model based on Fama–French and Pastor–Stambaugh factors as well as the mix of these two models. The result on empirical study displayed that all the factors do not include the characteristic liquidity premium. The characteristic liquidity should take part in its important role in elucidating stock returns jointly with further recognized risk factors.

Hearn (2010) observed in his study that liquidity is one of the significant determinants for asset evaluation in a bigger market, mostly in less competitive stock markets because these markets are distinguished to have a high cost of equity. Loukil et al. (2010) observed a positive consequence of both present and past illiquidity on expected stock returns wherein the return of small size stocks was highly affected by illiquidity over some time.

Lee (2011) found an optimistic and important effect of liquidity on the expected return while considering the International financial liquidity factor. Lam and Tam (2011) advocated that the liquidity augmented Fama–French model elucidates better stock returns in the Hong Kong stock market which corroborates the concept that illiquidity capitulates superior stock returns. Narayan and Zheng (2011) established that liquidity has an unconstructive consequence on Chinese expected stock returns, and the result is not vigorous due to asymmetric information and unwarranted government control. Lam and Tam (2011) found that liquidity is the most significant issue influencing stock returns even after controlling other determinants of stock returns.

Mazouz, Alrabadi, and Yin (2012) established that the less systematic risk responds to positive and negative shocks, while the high systematic risk does not respond to shocks. Donadelli and Prosperi (2012) affirmed that the international liquidity factors, i.e. VIX and open interest, have envisaged surplus returns. Shieh et al. (2012) observed that any alteration in liquidity levels of stock results in a gigantic impact on stock returns.

Papavassiliou (2013) showed substantiation on liquidity pricing in the Greek stock market and informed that the shocks occur as liquidity has noteworthy implications on portfolio diversification.

Batten and Vo (2014) concluded that liquidity did not have influence on asset return owing to the dearth of integration of emerging markets into the global market. Cao and Petrasek (2014) deal with the query of whether liquidity risk is priced in stock returns applying an event study framework and observed that abnormal stock returns for the duration of liquidity crises are strappingly and negatively associated with liquidity risk. Using Vietnamese firm level data, Batten and Vo (2014) too presented a positive affiliation between stock market and stock turnover as a measure of stock liquidity.

Chiang and Zheng (2015) emphasized that the excess stock returns of the G7 countries are optimistically connected with market illiquidity risk and found that market-level illiquidity considerably impacts large-cap stock excess return, and firm-level illiquidity sturdily affects small-cap stock excess return. Hung et al. (2015) found the analogous results of a constructive link between the illiquidity measures and stock returns in the Chinese stock markets.Vu et al. (2015) substantiated the LCAPM (Acharya & Pedersen, 2005) and established that liquidity affects anticipated stock returns. Bradrania et al. (2015) proved that liquidity persuades the expected returns since it significantly determines the association between expected returns and expected volatility.

Shih and Su (2016) demonstrated an encouraging association between liquidity and expected cross-sectional return for the duration of the market downturn in Taiwan. Arjoon et al. (2016) observed that the existence of institutional ownership establishes positive association between liquidity and stock returns.

Fong, Holden, and Trzcinka (2017) and Goyenko, Holden, and Trzcinka (2009) substantiated the Amihud (2002) illiquidity measures as the most excellent substitute for global research and Ahn, Jun, and Yang (2018) and Amihud (2002) affirmed that illiquidity measures are the most efficient price impact using high-frequency data in emerging Markets.

Harris and Amato (2019) presented conflicting confirmation against (Amihud, 2002) illiquidity measures for asset pricing. Kumar and Misra (2019) substantiated the economic implication of the LCAPM (Acharya&Pedersen, 2005) in the Indian stock market and reported the covariance of individual security return with combined liquidity as a authoritative effect on expected return even after controlling idiosyncratic risk. Altay and Çalgıcı (2019) found the identical experiential results supporting the LCAPM theory and the opposing confirmation on positive and significant covariance of individual security return with aggregate liquidity. Their conclusions may be owing to microstructure differences in Asian Economics and Emerging Markets.

Xu, Taylor, &Lu (2018) observed that illiquidity shocks are an indispensable conduit for transmitting shocks in the equity market There is a feedback connection between illiquidity shocks and volatility shocks (Zhang & Han, 2022). Wang, Cohen, and Glascock (2022) examined the asymmetric impact of frequency and measured shocks on return volatility across assets and markets.

Kao et al. (2020) studied the association between return and trading volume and between return volatility and trading volume by explaining the asymmetric relations of contemporaneity and lead-lags between these factors for the S&P 500 VIX Futures Index using the threshold model with the GJR-GARCH framework. The result suggests that with trading volume, which is above the threshold, it guides to higher returns, but at below the threshold limit, it led to lower returns.

Zhang Y, Ding S(2021) strived to examine the liquidity upshot on commodity prices and return movements based on daily stock data. The result suggests that daily price co-movements across different commodity futures are mostly determined by cross-sectional liquidity spillover rather than exclusively by macroeconomic factors. While daily liquidity shocks depressingly impact instant commodity returns, these influences smooth out over time, leaving monthly co-movements subjugated by global indices.

Seo-Yeon Lim & Sun-Yong Choi (2022) examined liquidity spillovers among industry sectors in the S&P 500 index to explain the interconnection dynamics in the US stock market using the spillover model as well as sectoral liquidity measure based on the Amihud liquidity measure. The result demonstrates that liquidity associations became sturdy during both crises-GFC period and COVID-19 pandemic period. The result also found that net liquidity spillovers between all sectors fluctuated remarkably during the GFC, whereas the industrial, consumer staples, and healthcare sectors had the biggest net liquidity spillovers during the COVID-19 crisis.

Cheng, Liu, Jiang, and Cao (2023) investigated the stock liquidity effects on accrual irregularity, and their findings pointed out that stock liquidity is pessimistically associated with the accrual irregularity and that there is a causal connection between the effect of stock liquidity and accrual irregularity.

Cuong Nguyen Thanh and Hai Phan Thanh (2024) investigate the effect of market liquidity on the stock returns of non-financial companies listed on the Vietnam Stock Market during the COVID-19 pandemic phase from January 30, 2020, to December 31, 2021, for 647 non-financial companies listed on the Vietnamese stock market using a fixed-effects panel data regression model. The result suggests a statistically significant and negative affiliation between market tightness and stock returns. Moreover, market depth exhibits a remarkable optimistic affiliation with stock returns. The result also demonstrates that stocks with lower liquidity tended to succumb high returns during the COVID-19 phase which gradually was heightened during periods of lockdown.

Prem Bahadur Budhathoki, Ganesh Bhattarai and Arjun Kumar Dahal (2024) evaluate the influence of liquidity, trading volume, market capitalization, book-to-market ratio, asset growth, size, profitability financial and asset risk on stock returns in Nepalese commercial banks for the study period from 2009-10 to 2019-20 using pooled ordinary least squares regression model. The research findings demonstrate that trading volume as a substitute of liquidity, optimistically influences stock returns in Nepalese commercial banks. On the contrary, asset growth and return on assets display an insufficiently constructive linkage with stock returns in Nepal. On the other hand, the result recommends an irrelevant contrary association between book-to-market and stock returns and also Market capitalization is found to have a very small effect on stock returns in Nepal.

Garg, Rakesh (2025) investigates the impact of stock market liquidity on firm value by utilizing secondary data from a sample of 150 firms listed on the National Stock Exchange (NSE) for the period 2015– 2025. The result exhibits a statistically noteworthy optimistic connection between stock market liquidity and firm value, indicating that firms with higher liquidity be likely to benefit from better-quality valuation in the capital market.

In contrast, research studies (Lischewski&Voronkova, 2012; Nguyen & Lo, 2013) have not observed any empirical substantiation supporting the effect of liquidity on expected stock returns. In frontier markets, Stereńczak et al. (2020) found that liquidity does not influence returns because they are less internationally integrated. Also, Garleanu (2009) suggested that liquidity does not have any effect upon stock returns because diverse traders utilize different trading strategies in view of their different trading objectives.

2.1. Research Gap

From the literature, it has been recognized that liquidity is a vital factor influencing stock returns, but the literature on liquidity–stock returns offer contradictory results. Asset-pricing theories advocate that liquidity is priced in asset-pricing models as investors claim higher returns to compensate for less liquid stocks. Based on asset-pricing theories, the matter of whether liquidity is priced is extensively investigated in developed countries which have established stock markets. From the above literature review, it has also been found that most of the studies on illiquidity and stock return made use of data taken from the US stock market. Furthermore, the greater part of studies of Illiquidity and liquidity risk linked with asset returns are in US market which has been normally documented as the prominent liquid market in the universe with a little impact of liquidity than those of other markets, particularly the promising markets. The result might be prejudiced because equity markets in diverse countries have diverse market structures. In common parlance, while the hypothetically explained scheme seems to be corroborated by experiential confirmation employing data from developed stock markets, most of the research endeavors employing emerging markets data endow with opposite results (Jun et al., 2003; Geert et al., 2005; Batten and Vo, 2014). In a nutshell, the increasing body of research studies on liquidity typically centered around the developed markets while research on emerging stock market liquidity is still very scanty.

Emerging markets are normally considered to have stumpy transparency, problems of corporate misgovernance, highly intense ownership, and ease of use of insufficient portfolio choices owing to dearth of diversity in securities as compared to developed markets. Moreover, as emerging markets are distinguished by the dearth of liquidity, it is imperative to endow with additional investigation into this subject matter in the perspective of emerging market like India. Consequently, investors are worried about the liquidity of securities. These factors mean that liquidity plays a more crucial role in emerging markets than in developed ones. Emerging market like India generates a center of attention to worldwide investors and affords a chance for maximizing the benefits of international portfolio diversification. There is not much research work done applying emerging market data and emerging market perspective. Facts suggest that negligible studies have been attempted in the literature on Emerging Markets (Altay &Çalgıcı, 2019; Donadelli&Prosperi, 2012; Hearn, 2010; Kumar & Misra, 2019). So, the dearth of research work on the effect of liquidity volatility on stock returns in emerging markets highlights the significance of this work. In view of the above research gap, other emerging markets like Indian stock market need to be examined in order to avoid the data-dredging problem. This paper deepens the literature considering the liquidity–stock returns nexus in the Indian context. Therefore, it is imperative to empirically investigate the proliferation of illiquidity shocks on return volatility across assets and markets in India as an Emerging Market.

2.2. Objective of the Study

The present study tries to judge the impact of liquidity on stock return in two select Indian companies listed in Bombay Stock Exchange (BSE) to bring more transparency in the relation between liquidity and stock return. The impetus behind probing the liquidity performance and stock return of Emerging Markets like India is to endow with improved insight to investors for making investment decisions effectively.

3. METHODOLOGY

The study used the daily historical return and volume data (Total Turnover) of 2 large-cap Stocks of Reliance and Adani Ltd listed in the Bombay Stock Exchange (BSE) and obtained data fromwww.bseindia.com. The study period covers from 1 January 2008 to 31March 2025. The reason for taking this period is that the study period observed the first two years as a coalition Government. The residual period covers a steadfast government followed by enormous structural reforms in India's economy, i.e. the introduction of GST, demonetization, etc. The last part of the study period covers the COVID-19 Pandemic.

This period had a vibrant impact on the liquidity of India's stock market and exposed both high liquidity and low liquidity scenarios.

Before applying the most suitable regression method for studying a relationship between a dependent (endogenous) variable and several independent (exogenous) variables, we first assume that the model is linear in parameters, the regressed (dependent variable) is considered in a linear function by a specific set of regressors (independent variables) with residual. Other assumptions such as absence of multicollinearity (variable inflation factor), absence of serial correlation (by Durbin Watson test and Breusch-Godfrey LM test), homoscedasticity or absence of heteroskedasticity (by Breusch-Pagan-Godfrey test**)**, normality of error terms (by Jarque-Bera test**)** and model specification (by Ramsey RESET Test**)** must be observed before applying appropriate regression to achieve Best Linear Unbiased Estimator (BLUE) properties.

3.1. Dependent Variable

MRT: The yearly stock returns represent a dependent variable. In the estimations, we take the natural logarithm of each price data point to reduce the observed skewness in the stock price data distribution. We use logarithm of stock return because most studies estimate that stock return follows a log normal distribution. The stock return data used in this research consists of the logarithmic first difference of closing stock prices, which is defined symbolically as follows:

To calculate the return, the following formula has been used:

$$R_t = lnP_t - lnP_{t-1} \quad (1)$$

R_t= daily stock return, P_t= closing price of the stock at time t, and P_{t-1} = previous day's closing price at time t-1while ln symbolizes the natural log.

3.2. Independent Variables

ILIQ: Petersen and Fialkowski (1994), and Brennan and Subrahmanyam (1996) denigrate that the quoted spread is a meager substitute for liquidity as smaller equity trades are frequently executed inside the quoted prices, while larger trades often face prices far less to those quoted. As such, many substitute proxies for liquidity have been used for additionally investigating the relationship between asset returns and liquidity, such as trading volume (Brennan et al., 1998), turnover ratio (Datar et al., 1998; Howard and Robert, 2005), zero return (Lesmond et al., 1999), price impact of trading (Breen et al., 2002), Amihud's illiquidity ratio (Amihud, 2002), the Pastor and Stambaugh (2003) liquidity measure and the Liu (2006) liquidity ratio. Nonetheless, most of these papers corroborate Amihud and Mendelson (1986).

Amihud (2002) proposes a measure of illiquidity, which is the daily ratio of absolute stock return to its currency volume, and argues that this can be interpreted as "the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact." This measure only needs daily data on returns and volume to calculate and can be calculated for longer time periods than we have microstructure data for.

Let D_{iy}be the number of days with available data for stock *i*in year *y*, R_{iyd}be the stock return for stock *i*in day *d* of year *y*, and $VOLD_{ivyd}$be the daily volume [in units of currency(rupee)]. Amihud (2002)'s measure is calculated as:

$$ILR_y = 10^6 \frac{1}{D_{iy}} \sum_d \frac{|R_{iyd}|}{VOLD_{ivyd}} \quad (2)$$

This measure is multiplied by 10^6. This ratio has a daily impact on order flow on prices (Amihud, 2002). Investors are averse to illiquidity, and they require a premium of return for holding illiquid stocks.

Many researchers use the price impact or the price response to sign order flow as a measure of stock liquidity, using intra-day continuous data on transactions. These fine measures of illiquidity require for their calculation microstructure data on transactions and quotes that are unavailable in most markets around the world for long time periods of time. In contrast, liquidity measures based on transaction volume are more available. We expect a positive effect of the illiquidity ratio on stock returns.

SIZE: The size of firm is represented by the logarithm of market capitalisation (outstanding shares multiplied by the last transaction price of the month). Size is related to liquidity since a larger stock issue has smaller price impact for a given order flow. Thus, stock expected returns are negatively related to size (Banz, 1981; Reinganum, 1981; Fama and French, 1992).

MRISK(β **)**:The systematic risk of stock is included in the model as a measure of risk. we calculate portfolios returns and market returns (NSE return is taken as proxy market return), and we estimate the following market model for each portfolio:

$$R_{pt} = \alpha_{pt} + \beta_{pt} MR + \varepsilon_{pt} \quad (3)$$

where MR is the market return and β is the slope estimated by Sholes and Williams (1977). p is the index of portfolio (p = 1,2,….5), t is the index of day. We expect a positive association between systematic risk and stock return.

STRISK: The stock total risk is computed by the logarithm of the standard deviation of the daily returns on stock i in month t multiplied by 10^2. As proposed by Stoll (1978), liquidity is associated negatively with stock risk. Constantinides (1986) proposes that stock total risk affect positively the return required by investors. Indeed, this risk imposes higher trading costs on them due to the need to engage more frequently in portfolio rebalancing. We expect in this study a positive effect of total risk on stocks returns.

RET2_3: The cumulative returns over the second through the third month prior to the end of current year (Jegadeesh and Titman, 1993; Chordia et al., 2001; Chang et al., 2010)

RET4_6: The cumulative returns over the fourth through sixth month prior to the end of current year (Jegadeesh and Titman, 1993; Chordia et al., 2001; Chang et al., 2010)

RET7_12: The cumulative returns over seventh through 12th month prior to the end of current year (Jegadeesh and Titman, 1993; Chordia et al., 2001; Chang et al.,2010)

The 2 months, 3 months or 6 months cumulative return is a measure of the total gain or loss of a stock over 60 days, 90-day or 180-day period. It is an absolute, non-annualized figure that acts as a short-term momentum indicator, showing how the stock price has recently behaved. The lagged return variables serve as proxies for momentum effects. Jegadeesh and Titman (1993) advance that stock preserve their characteristics in short term. Lee and Swaminathan (2000) suggest that liquidity and stocks return depend on previous performance.

We have included in this analysis year dummy variables in order to eliminate effects of macroeconomics variables associated to following years.

YR 20-21. A dummy variable that takes on the value of 1 in 2020-21 and 0 in other years.

YR 21-22. A dummy variable that takes on the value of 1 in 2021-22 and 0 in other years.

3.3. Model Specification

We model portfolio return as a function of several exogenously related factors–such as Illiquidity, market risk, portfolio stock risk, size, relative changes in volume and return, cumulative returns over several prior months before end of relevant years.

The regression model is represented as follows:

MRT= f(ILR, MRISK, STRISK, SIZE, RCV, RCR, RET2_3, RET4_6, RET7_12)

The regression equation is depicted below:

$$MRT_t = \beta_0 + \beta_1 \mathrm{ILR} + \beta_2 \mathrm{MRISK} + \beta_3 \mathrm{STRISK} + \beta_4 \mathrm{SIZE} + \beta_5 \mathrm{RCV} + \beta_6 \mathrm{RCR} + \beta_7 \mathrm{RET2\_3} + \beta_8 \mathrm{RET4\_6} + \beta_9 \mathrm{RET7\_12} + \varepsilon$$

Unit root test - When dealing with time series data, a number of econometric issues can influence the estimation of parameters using OLS. Regressing a time series variable on another time series variable using the Ordinary Least Squares (OLS) estimation can obtain a very high R^2, although there is no meaningful relationship between the variables. This situation reflects the problem of spurious regression between totally unrelated variables generated by a non-stationary process.

Therefore, prior to testing and implementing the Granger Causality test, econometric methodology needs to examine the stationarity; for each individual time series, most macro-economic data are non-stationary, i.e., they tend to exhibit a deterministic and/or stochastic trend. Therefore, it is recommended that a stationarity (unit root) test be carried out to test for the order of integration. A series is said to be stationary if the meaning and variance are time-invariant.

A non-stationary time series will have a time dependent meaning or make sure that the variables are stationary, because if they are not, the standard assumptions for asymptotic analysis in the Granger test will not be valid. Therefore, a stochastic process that is said to be stationary simply implies that the mean [(E(Y_t)] and the variance [Var (Y_t)] of Y remain constant over time for all t, and the covariance [covar (Y_t, Ys)] and hence the correlation between any two values of Y taken from different time periods depends on the difference apart in time between the two values for all t≠s.

Since standard regression analysis requires that data series be stationary, it is obviously important that we first test for this requirement to determine whether the series used in the regression process is a difference stationary or a trend stationary.

ADF Test - To test the stationary of variables, we use the Augmented Dickey Fuller (ADF) test which is mostly used to test unit root. Following equation checks the stationarity of time series data used in the study:

$$\Delta y_t = \beta_1 + \beta_1 t + \alpha\, y_{t-} + \gamma_1 \Sigma \Delta y_{t-1} + \varepsilon_t \qquad (4)$$

where: ε_t is white nose error term in the model of unit root test, with a null hypothesis that variable has unit root.

The ADF regression test for the existence of unit root of y_t that represents all variables (in the natural logarithmic form) at time t. The test for a unit root is conducted on the coefficient of y_{t-1} in the regression. If the coefficient is significantly different from zero (less than zero) then the hypothesis that y contains a unit root is rejected. The null and alternative hypothesis for the existence of unit root in variable y_t is:

H_0; $\alpha = 0$ versus H_1: $\alpha < 0$. Rejection of the null hypothesis denotes stationary in the series.

If the ADF test-statistic (t-statistic) is less (in the absolute value) than the Mackinnon critical t-values, the null hypothesis of a unit root cannot be rejected for the time series and hence, one can conclude that the series is non-stationary at their levels. The unit root test tests for the existence of a unit root in two cases: with intercept only and with intercept and trend to take into the account the impact of the trend on the series.

PP Test - The PP tests are non-parametric unit root tests that are modified so that serial correlation does not affect their asymptotic distribution. PP tests reveal that all variables are integrated of order, one with and without linear trends, and with or without intercept terms.

Phillips–Perron test (named after Peter C. B. Phillips and Pierre Perron) is a unit root test. That is, it is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis δ = 0 in $\Delta y_t = \delta y_{t-1} + u_t$, here Δ is the first difference operator.

Like the augmented Dickey–Fuller test, the Phillips–Perron test addresses the issue that the process generating data for y_t might have a higher order of autocorrelation than is admitted in the test equation - making y_{t-1} endogenous and thus invalidating the Dickey–Fuller t-test. Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of Δy_t as regressors in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

Granger Causality Test - Causality is a kind of statistical feedback concept which is widely used in the building of forecasting models. Historically, Granger (1969) and Sim (1972) were the ones who formalized the application of causality in economics. Granger causality test is a technique for determining whether one time series is significant in forecasting another (Granger. 1969). The standard Granger causality test (Granger, 1986) seeks to determine whether past values of a variable help to predict changes in another variable.

The definition states that in the conditional distribution, lagged values of Y_t add no information to explanation of movements of X_t beyond that provided by lagged values of X_t itself (Greene, 2003). We should take note of the fact that the Granger causality technique measures the information given by one variable in explaining the latest value of another variable. In addition, it also says that variable Y is Granger caused by variable X if variable X assists in predicting the value of variable Y. If this is the case, it means that the lagged values of variable X are statistically significant in explaining variable Y. The null hypothesis (H_0) that we test in this case is that the X variable does not Granger cause variable Y and variable Y does not Granger cause variable X. In summary, one variable (X_t) is said to granger cause another variable (Y_t) if the lagged values of X_t can predict Y_t and vice-versa.

Multicolliearity- Before running the regression, investigation into the multicollinearity problem must be conducted using the pairwise correlation matrix. First, bivariate (pairwise) correlations among the independent variables were examined to find out the multicollinearity problem. The existence of correlation of about 0.90 or larger indicates that there is problem of multicollinearity. When independent variables are highly correlated in a multiple regression analysis, it is difficult to identify the unique contribution of each variable in predicting the dependent variable because the highly correlated variables are predicting the same variance in the dependent variable. Some statisticians say correlations above 0.70 indicate multicollinearity and others say that correlations above 0.90 indicate multicollinearity.

Multicollinearity is assessed by examining tolerance and the Variance Inflation Factor (VIF) which are two collinearity diagnostic factors that can help to identify multicollinearity. If a low tolerance value is accompanied by large standard errors and no significance, multicollinearity may be an issue. The variable's tolerance is indicated by $1-R^2$. A small tolerance value indicates that the variable under consideration is almost a perfect linear combination of the independent variables already in the equation and that it should not be added to the regression equation. The Variance Inflation Factor (VIF) measures the impact of collinearity among the variables in a regression model. The Variance Inflation Factor (VIF) is 1/Tolerance, it is always greater than or equal to 1. There is no formal VIF value for determining presence of multicollinearity. A commonly given rule of thumb is that multicollinearity exists when Tolerance is below 0.1 and values of VIF that exceed 10 are often regarded as indicating multicollinearity. When those R^2 and VIF values are high for any of the variables in regression model, multicollinearity is probably an issue.

Serial Correlation (Breusch-Godfrey Test) - In Ordinary Least Squares (OLS) regression, time series residuals are often found to be serially correlated with their own lagged values. Serial correlation means (a) OLS is no longer an efficient linear estimator, (b) standard errors are incorrect and generally overstated, and (c) OLS estimates are biased and inconsistent. This test is an alternative to Q-Statistic for testing for serial correlation. It is available for residuals from OLS, and the original regression may include autoregressive (AR) terms. Unlike the Durbin-Watson Test, the Breusch-Godfrey test may be used to test for serial correlation beyond the first order and is valid in the presence of lagged dependent variables. The null hypothesis of the Breusch-Godfrey test is that there is no serial correlation up to the specified number of lags. The Breusch-Godfrey test regresses the residuals on the original regressors and lagged residuals up to the specified lag order. The number of observations multiplied by R^2 is the Breusch-Godfrey test statistic. The statistic labelled'Obs*R-squared' is the LM test statistic for the null hypothesis of no serial correlation. The high probability values indicate the absence of serial correlation in the residuals.

Normality of Error Terms (Jarque-Bera Test) - The Jarque-Bera test, a type of Lagrange multiplier test, was developed to test normality of regression residuals. The Jarque-Bera statistics are computed from skewness and kurtosis and asymptotically follow the chi-squared distribution with two degrees of freedom. While testing for normality, it was found that Jarque-Bera statistics where p values for all variables are lower than 0.05 imply that variables under our consideration are normally distributed.

Ramsey Reset Test - The Ramsey Reset Test, popularly known as Regression Equation Specification Error Test, is a statistically analytical device applied in econometrics to confirm for functional form misspecification in a linear regression model, such as the existence of omitted variables or incorrect relationships. It works by adding powers of the predicted values from the original regression as new explanatory variables in a second regression; if these added terms are statistically significant, it suggests the original model's functional form is incorrect. The null hypothesis is that the model is correctly specified, and a rejection indicates misspecification.

4. ANALYSIS OF RESULTS

The diagrammatic presentation in Fig-1&2 shows the trend of illiquidity and stock return in both select conglomerates-Reliance and Adani Ltd which can be explained and corroborated analytically through subsequent econometric presentation in the study.

Figure 1: Graphical Presentation of the Trend of Illiquidity and Stock Returns of Adani Ltd

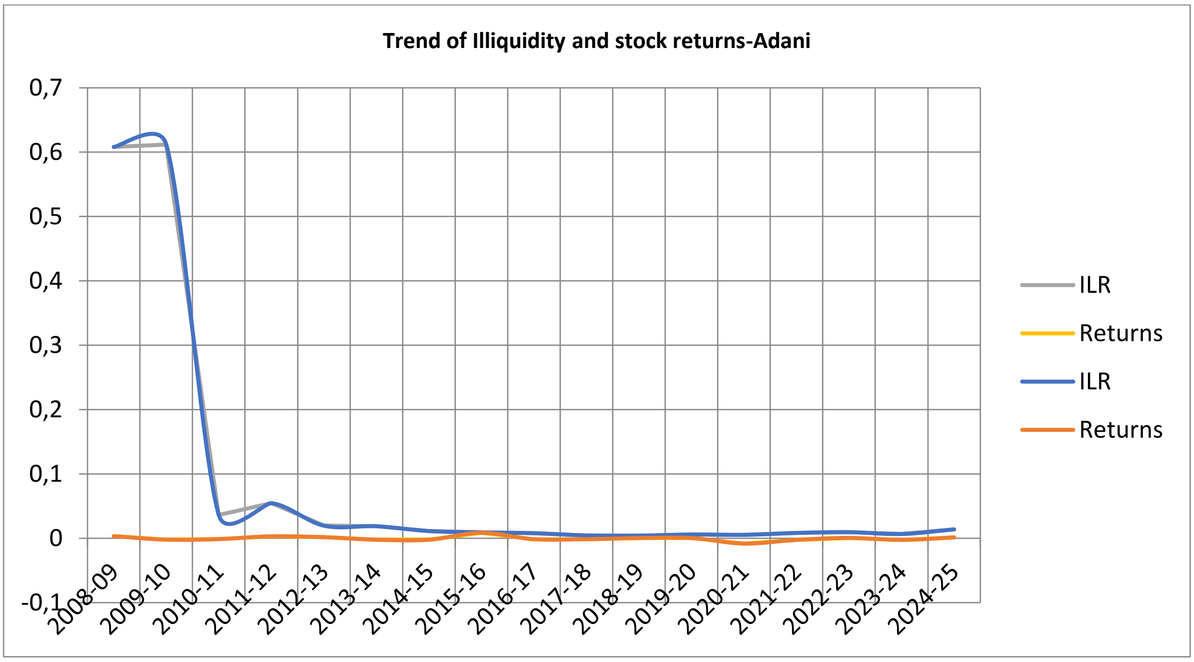
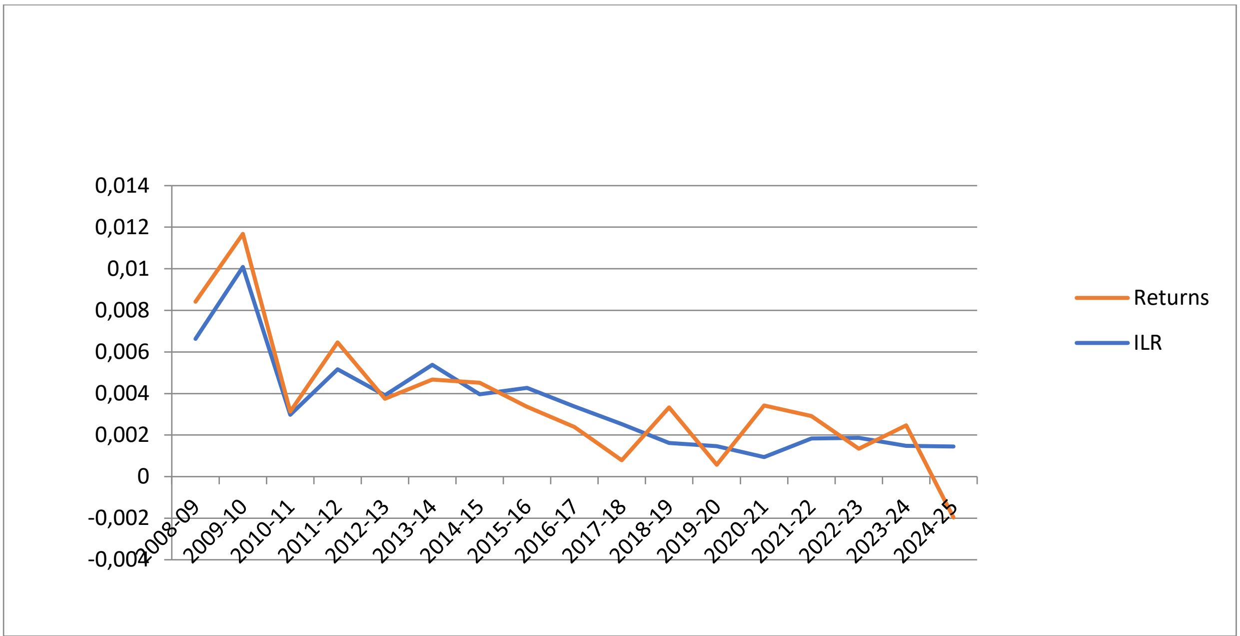


Figure 2: Graphical Presentation of the Trend of Illiquidity and Stock Returns of Reliance Ltd



Descriptive statistics in Table 1 reveal following results. The mean distribution of variable measuring illiquidity is 0.00346 and 0.084426 in case of Reliance Ltd and Adani Ltd respectively, and their respective standard deviations are moderately low (0.00236 and 0.198231 respectively) and significant, which demonstrates that liquidity level does not vary much from firm to other. The meaning of size (SIZE) is 15.5309 and 14.61915and the standard deviation of these variables is significant and positive.

Table 1: Descriptive Statistics

RELIANCE										
	RETURNS	ILR	MRISK	STRISK	SIZE	RCV	RCR	RET2_3	RET4_6	RET7_12
Mean	0.00013	0.00346	-0.02255	0.75930	15.5309	-0.15817	-3.69897	-0.01348	-0.01154	0.03662
Median	0.00015	0.00297	-0.00258	0.54772	15.4183	-0.12376	-3.21392	0.02338	0.00514	0.00579
Maximum	0.00248	0.01008	0.08943	1.66800	16.6810	-0.06493	-1.56691	0.11448	0.41851	0.72657
Minimum	-0.00341	0.00094	-0.35366	0.21196	14.9437	-0.38633	-6.10552	-0.13062	-0.88775	-0.86272
Std. Dev.	0.00151	0.00236	0.09449	0.4766	0.47318	0.07893	1.36283	0.08405	0.27622	0.30911
Skewness	-0.519384	1.35301	-2.62472	0.84071	0.79029	-1.43006	-0.45919	-0.14364	-1.62352	-0.82233
Kurtosis	2.85597	4.5668	10.208	2.2494	3.0704	4.9952	2.1043	1.5825	7.4109	6.46109
ADANI										
Mean	-0.000266	0.084426	-0.01618	1.253703	14.61915	-0.36568	-2.96969	0.025004	-0.08558	0.019413
Median	-0.001305	0.009584	-0.01161	1.154450	15.05494	-0.2013	-2.60226	0.018211	-0.13846	0.020503
Maximum	0.008602	0.611821	0.007476	2.460800	16.01802	-0.13818	-1.79031	0.898346	0.560729	2.028508
Minimum	-0.008230	0.004119	-0.05393	0.837476	11.25763	-2.18248	-5.70855	-0.55025	-0.64254	-0.86272
Std. Dev.	0.003535	0.198231	0.016440	0.376722	1.269329	0.495346	1.085152	0.329792	0.342458	0.642768
Skewness	0.352977	2.354247	-0.71786	2.055099	-1.4047	-3.16218	-1.33396	0.807364	0.572285	1.629502
Kurtosis	4.519092	6.579827	2.937246	7.308785	4.300148	12.05538	3.796043	4.203165	2.548811	6.835602

The variability of size exhibit that our sample is heterogeneous and it includes large and small firms. The standard deviation of measures of risk stock's own risk (STRISK), and market risk (MRISK) are positive significant and indicate that the variability of level of risk between firms of sample is high. The means of cumulated lagged returns (RET2_3), (RET7_12) are negative and significant and for (RET7_12), means of cumulated lagged returns is positive for both industries and their dispersions are high and significant.

Negative skewness of return series notices in case of Reliance but it shows positive in case of Adani. A left tail event is highly undesirable as it highlights the black swan event, i.e. a negative event, the occurrence of which is highly unpredictable. A negative skewness is highly undesirable from investors' point of view as it indicates frequent small gain but few large losses. A fat-tailed or thick-tailed distribution has a value for kurtosis that exceeds 3. That is, excess kurtosis is positive. This is called leptokurtosis. The distribution is also leptokurtic in nature i.e. for the return series for Adani only (not Reliance), the indices display the thicker tail than normal distribution indicating many prices fluctuation positive or negative away from average return. In Indian Context, these movements were typically product of "euphoria to despondency cycles" (Gupta,1997, p. 3).

In other words, stock returns irrespective of the regime when standardized by their scale exhibit more probability mass in the tails than distributions like the standard normal distribution. This means that extremely high and low realizations occur more frequently than under the hypothesis of normality.

Table 2: Test of Multicollinearity

Variable	Reliance	Adani
	Centered VIF	Centered VIF
ILR	8.511465	7.93853
STRISK	2.638307	8.28169
MRISK	1.741244	6.817622
SIZE	3.858506	7.32177
RCR	1.721915	4.956413
RCV	3.283259	3.325043
RET2_3	1.611223	2.987441
RET4_6	2.957969	3.088638
RET7_12	2.734254	8.118127

All the variable under consideration of the study is free from multicollinearity as those are within the permissible general rule of thumb of VIF range [1-10] in table-2.

To confirm that the regression model used in the analysis is correctly specified, Ramsey's RESET test has been applied in the above model. Result of the Ramsey's RESET has been given in Table3.

Moreover, we reject null hypothesis when the p-value for the model is less than the significance level of 0.05, otherwise do not reject the null hypothesis. According to the generated result, p-value is always greater than 0.05. Thus, we fail to reject null hypothesis of no functional misspecification in the series and model is specified and there is enough evidence to conclude that the regression model is specified correctly at significance level of 0.05. In our study, Ramsey's test statistic indicates no functional misspecification in the series and therefore, model is well specified as shown by F-statistics provided by Ramsey Reset Test.

Table 3: Ramsey's RESET Test

	Reliance			Adani		
Parameters	Value	df	Probability	Value	df	Probability
t-statistic	0.232438	4	0.8276	0.329113	4	0.7586
F-statistic	0.054028	(1, 4)	0.8276	0.108316	(1, 4)	0.7586
Likelihood ratio	0.228080	1	0.6330	0.454219	1	0.5003

$H_{0:}$ There is no functional misspecification in the series and model is specified; $H_{1:}$ There is functional misspecification in the series and model is non-specified

An important assumption of the classical linear regression model is that the disturbance (residual) term u_i is homoscedastic; that is, they all have the same variance. For the validity of this assumption, Breusch-Pagan-Godfrey Test are applied in the regression equation, and the result is given in Table-4. We can define heteroscedasticity as the condition in which the variance of error term or the residual term in a regression model varies.

The Breusch-Pagan-Godfrey Test in table-4 do not reject the null hypothesis of no heteroscedasticity because the p-value is larger than 0.05. [p>0.05]. So, we fail to reject null hypothesis of no heteroscedasticity and the *F*-statistic and the LM test statistics both indicate that the residuals are not heteroscedastic and therefore variances for the errors are equal.

Table 4: Heteroscedasticity Test

Breusch-Pagan-Godfrey Test							
	Reliance			Adani			
F-statistic	0.358697	Prob. F(11,5)	0.9273	F-statistic	0.830941	Prob. F(11,5)	0.6309
Obs*R-squared	7.498193	Prob. ChiSq.(11)	0.7574	Obs*R-sq.	10.98883	Prob. Chi-q.(11)	0.4442
Scaled expl. SS	0.782578	Prob. ChiSq.(11)	1.0000	Scaled expl. SS	1.429939	Prob. Chi-Sq.(11)	0.9997

$H_{0:}$ There is no heteroscedasticity i.evariance for the errors are equal. In math terms, that's: $H_0 = \sigma^2{}_1 = \sigma^2$;$H_{1:}$ There is heteroscedasticity i.evariance for the errors are not equal. In math terms, that's:$H_{1=}\, \sigma^2{}_1 \neq \sigma^2$

In Table5, the test rejects the null hypothesis of no serial correlation up to order 2[p<0.05]. The *Q*-statistics and the LM test both indicate that the residuals are serially correlated. Also, Durbin Watson test result in table-8 confirms that there is autocorrelation in regression model as the D-W value is 2.496879 and 2.861481[(>2) for both industries].

Table 5: Breusch-Godfrey Serial Correlation LM Test

Reliance				Adani			
F-statistic	4.413688	Prob. F(2,3)	0.1277	F-statistic	2.515321	Prob. F(2,3)	0.2283
Obs*R-sq.	12.68797	Prob. Chi-Sq.(2)	0.0018	Obs*R-sq.	10.64932	Prob. Chi-Sq.(2)	0.0049

H_0: There is no serial correlation in the residuals up to the specified order; H_1: There is serial correlation in the residuals up to the specified order

In Jarque-Bera test of normality, if the p-value is smaller than significance level which is 0.05, the null hypothesis will be rejected. It means that the error terms in the model are not normally distributed. Here, in table-6, in all the sample years, p-values of Jarque-Bera Test statistic of all variables under consideration are not greater than 0.05 level. Therefore, all the variables do not satisfy normality conditions.

Table: 6: Jarque-Bera Test-Normality of Error Terms

Reliance										
	RETURNS	**ILR**	**MRISK**	**STRISK**	**SIZE**	**RCV**	**RCR**	**RET2_3**	**RET4_6**	**RET7_12**
Jarque-Bera	0.779013	6.925775	56.32238	2.401669	1.773133	8.614289	1.165609	1.481669	21.2500	10.40126
Probability	0.677391	0.031339	0.000000	0.300943	0.412068	0.013472	0.558330	0.476716	0.00002	0.005513
Observations	17	17	17	17	17	17	17	17	17	17
Adani										
Jarque-Bera	1.987591	24.78110	1.462905	25.11705	6.788073	86.41486	5.490651	2.872257	1.07214	17.94417
Probability	0.370169	0.000004	0.481210	0.000004	0.033573	0.000000	0.064227	0.237847	0.58504	0.000127
Observations	17	17	17	17	17	17	17	17	17	17

Ho: series are normal; H_1: series are not normal.

Table 7 presents the results of the unit root test. The results show that all variables in our study attain stationarity at level I(0), using both ADF and PP tests. The results indicate that the null hypothesis of a unit root can be rejected for the all given variables as all the ADF statistic value and PP statistic value are smaller than the critical t-value at 1%, 5% and 10%level of significance for all variables and, hence, one can conclude that the variables under consideration attained stationary at their levels in both ADF and PP test.

Table 7: Unit Root Test

Variables name	Reliance				Adani			
	ADF test		PP test		ADF test		PP test	
	Level	Conclusion	Level	Conclusion	Level	Conclusion	Level	Conclusion
RETURNS	-3.6527	I(0)	-3.6224	I(0)	-4.3764	I(0)	-4.4643	I(0)
ILR	-3.5042	I(0)	-9.8363	I(0)	-12.363	I(0)	-9.7856	I(0)
MRISK	-3.3331	I(0)	-3.3233	I(0)	-3.3987	I(0)	-3.4205	I(0)
STRISK	-3.7883	I(0)	-3.7885	I(0)	-5.4108	I(0)	-6.0186	I(0)
SIZE	-3.8573	I(0)	-3.8575	I(0)	-4.4641	I(0)	-4.4642	I(0)
RCV	-4.8028	I(0)	-4.6962	I(0)	-13.079	I(0)	-9.5064	I(0)
RCR	-5.8570	I(0)	-6.7180	I(0)	-5.240	I(0)	-5.242	I(0)
RET2_3	-3.5731	I(0)	-3.5821	I(0)	-4.8438	I(0)	-6.4953	I(0)
RET4_6	-4.6407	I(0)	-3.3530	I(0)	-4.4048	I(0)	-5.8549	I(0)
RET7_12	-4.1651	I(0)	-4.1595	I(0)	-3.5538	I(0)	-3.5587	I(0)
Critical value	1% level	-3.9203		-3.9203	1% level	-3.9203		-3.9203
	5% level	-3.0655		-3.0655	5% level	-3.0655		-3.0655
	10% level	-2.6734		-2.6734	10% level	-2.6734		-2.6734

Note: *MacKinnon critical values for rejection of hypothesis of a unit root.

Ho: series has unit root; H_1: series is trend stationary

All conditions for applying OLS technique have been fulfilled except absence of serial correlation and normality. So, in presence of autocorrelation, Newey West HAC consistent covariance matrix estimator (this model is useful in situations where the standard assumptions of regression analysis do not appear be valid) is more efficient than OLS technique unless the sample is large. Moreover, one of the primary advantages of GMM over other methods is that it does not require strong assumptions about the probability distribution of the data or the errors. GMM handles non-normal data (like skewed or heavy-tailed distribution) well, particularly in time series with heteroscedasticity. Newey and West (1987b) propose a covariance estimator that is consistent in the existence of both heteroskedasticity and autocorrelation (HAC) of unknown form, under the assumption that the autocorrelations between distant observations die out. NW advocates using kernel methods to form an estimate of the long-run variance, $E(X'\varepsilon'\varepsilon' X/T)$.

Table 8: Determinants of Stock Returns [Generalized Method of Moment]

Dependent Variable: RETURNS
Method: Generalized Method of Moments
Included observations: 17
Sample: 2008-09 to 2024-25
Estimation weighting matrix: HAC (Bartlett kernel, Newey-West fixed Bandwidth=3.0000

Reliance					Adani				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-0.049521	0.009317	-5.315218	0.0011	C	-0.001827	0.005812	-0.314425	0.7624
ILR	0.792270	0.209104	3.788870	0.0068	ILR	-0.000543	0.003017	-0.180078	0.8622
MRISK	0.000720	0.002651	0.271614	0.7938	MRISK	0.013356	0.028278	0.472306	0.6511
STRISK	-0.002413	0.000563	-4.282565	0.0036	STRISK	0.000600	0.001403	0.427818	0.6816
SIZE	0.003090	0.000594	5.198999	0.0013	SIZE	0.000130	0.000459	0.282831	0.7855
RCV	-6.44E-05	0.003550	-0.018135	0.9860	RCV	-0.000234	0.000471	-0.495877	0.6352
RCR	-0.000191	0.000209	-0.912983	0.3916	RCR	0.000215	0.000201	1.071108	0.3197
RET2_3	0.000989	0.003063	0.322966	0.7562	RET2_3	0.003078	0.000854	3.604577	0.0087
RET4_6	0.001842	0.001387	1.327767	0.2259	RET4_6	0.005114	0.001006	5.086125	0.0014
RET7_12	0.002182	0.000625	3.489263	0.0101	RET7_12	0.003510	0.000777	4.514527	0.0028
Durbin-Watson	2.496879				Durbin-Watson	2.861481			

Results in Table 8 demonstrate that investors evaluate stock illiquidity, given that the coefficient associated with (ILIQ) variable is positive and statistically significant. This indicates that more illiquid the stock is, the more the expected return on portfolio in case of reliance but found no significant impact of illiquidity on returns in case of Adani Ltd.

By observing the significance of risk measures, we find that in Reliance, return volatility (STRISK) is associated negatively and significantly with stock returns, which is contrary in case of Adani Ltd. It indicates that stocks' own volatility in Reliance has an unenthusiastic consequence on its return, meaning that higher volatility relates to lower future returns**.** This event is generally frequently described as the "low-volatility anomaly" or "low-risk effect" which contradicts traditional financial theory (CAPM), which induces that higher risk should be rewarded with higher returns.

This might be due to spiky turn in stock price, leading to increase in a firm's debt-to-equity ratio. It results in increase in its volatility. This result reflects that high volatility not only causes low returns, but also low returns (price drops) increase volatility but in case of Adani, both these effects are absent on stock returns. But stock systematic risk (BETA) has an insignificant positive effect on stock returns in case of both industries.

In Reliance, the positive effect of size on stock return is beyond expectation, but it might be viewed or judged under specific crisis period where large cap companies regularly demonstrate better flexibility than small-cap firms because intending Investors are likely to congregate unwavering companies, leading to higher returns for large firms during these periods. Moreover, smaller firms being characteristically riskier having more unstable returns, larger firms might put forward a better risk-adjusted return during specific market phases. Whereas in Adani Ltd, no size effect on stock return is prominently found.

When firm size has an optimistic positive influence on stock returns, larger sized firms produce higher returns for investors as compared to smaller sized firms which contradict the conventional "small-firm effect." This classically suggests that larger, deep-rooted companies with better asset quality, superior reputations, and less risk are privileged by the market. From investors perspective, they may recognize bigger, reputable firms as safer investments destination, nevertheless, they are satisfied with elevated returns, often owing to superior effectiveness in terms of profitability position and greater economies of scale. While early research showed small firms outperforming larger ones (Banz, 1981), our study suggest this premium has vanished in case of Adani industry, with findings of Reliance industry showing encouraging positive size effects during our study period. It indicated that there's no authoritative accord that small firms constantly outperform larger ones.

The predictable consequence of relative changes in a company's trade volume on its stock return is usually having an optimistically positive correlation between volume and price momentum (trend persistence), despite the fact that the causality is intricate and frequently provisional on market conditions whether it is bull market or bearish market condition. But, in both industries under our consideration, Reliance and Adani Ltd, relative changes in trading volume (RCV) have insignificantly negative impact on stock returns. It indicates that trading volume affects future stock returns negatively for low return quartiles. In bearish market, a considerable boost in trading volume in times of a price slump indicates sturdy selling pressure which can be termed as 'panic selling' or 'institutional dumping'. High volume associated with a fall in stock price frequently predicts additionally, sustained turn downs. Therefore, in low-return or bear markets, volume-return causality can be pessimistic, as panic-induced high volume frequently leads to more declines.

A relative enhancement in a company's return is generally expected to have a positive, significant effect on stock returns.This might be due to the fact that a company improves its profitability relative to the market or historical benchmarks; investor confidence typically increases, driving up the stock price. Result shows insignificant negative impact of relative changes in return on stock return in Reliance and insignificant positive impact on stock return of Adani industries respectively.

By examining the significance of cumulated lagged returns, table 7 demonstrates that the cumulated return (RET2_3) and RET4_6 do not affects significantly the stock returns in Reliance but cumulated return RET4_6 affects significantly and positively in Adani Ltd; RET7_12 affects significantly and positively in both Reliance and Adani Ltd.

A positive relationship between a company's 3 months or 6-month cumulative returns prior to end of any current year and its subsequent stock return implies that the stock is exhibiting a momentum effect. This means that if the stock has performed well over the past six months, it is more likely to continue performing well in the immediate future, while a poor performance over the past six months suggests continued underperformance.

Investors can potentially generate higher returns by employing a strategy that buys "winner" stocks (those with high 6-month cumulative returns) and avoids or shorts "loser" stocks (those with low 6-month returns). Indeed, strategy of buying stocks with high past performance and of selling stocks with low past performance induce a significant excess return for a period of holding of six months. This often results from a delayed market reaction to information, where investors react to news, allowing prices to drift upwards (or downwards) over the 6-month period. While this positive relationship can be effective, it is often more pronounced in rising markets (up markets) and may reverse over longer periods (13-60 months).

In Table 9, the OLS technique in addition is applied to judge the impact of other macroeconomic variables not considered here as well as covid impact during specified time point of time (2020-21&2021-22).

Table 9: Determinants of Stock Returns by OLS

Dependent Variable: RETURNS
Method: Least Squares
Included observations: 17
Sample: 2008-09 to 2024-25

Reliance					Adani				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-0.071258	0.020734	-3.436804	0.0185	C	-0.036499	0.025700	-1.420185	0.2148
ILR	1.056943	0.305954	3.454582	0.0181	ILR	-0.005064	0.005698	-0.888777	0.4148
MRISK	-0.002857	0.000789	-3.621802	0.0152	MRISK	0.031406	0.041686	0.753406	0.4851
STRISK	-0.000454	0.002854	-0.159197	0.8797	STRISK	0.001236	0.002003	0.616864	0.5643
SIZE	0.004426	0.001294	3.420619	0.0188	SIZE	-0.000141	0.000766	-0.183736	0.8614
RCV	-0.000319	0.000208	-1.533339	0.1858	RCV	-2.40E-05	0.001146	-0.020936	0.9841
RCR	5.23E-05	0.004529	0.011543	0.9912	RCR	-0.000709	0.000589	-1.202425	0.2830
RET2_3	0.001204	0.002948	0.408347	0.6999	RET2_3	0.001938	0.001371	1.413508	0.2166
RET4_6	0.001406	0.001246	1.127852	0.3106	RET4_6	0.004999	0.001268	3.941183	0.0109
RET7_12	0.003232	0.001364	2.369383	0.0640	RET7_12	0.003217	0.001054	3.051635	0.0284
YR20_21	-0.002304	0.001793	-1.2850	0.2551	YR20-21	-0.004231	0.002388	-1.77223	0.1366
YR21-_22	-0.000427	0.000904	-0.47236	0.6566	YR21-_22	-0.001647	0.001148	-1.43438	0.2109

The COVID-19 dummy years variables (YR20_21), (YR21-_22), have a negative effect on stocks returns but not so significant. Thus, macroeconomic variables associated to COVID-19 years do not affect stock return.

It suggests the firm's stock performance is firm-specific, driven more by internal factors (management, products, operations) or industry trends, rather than broad economic shifts, or that macroeconomic effects are already captured by other variables in the model, implying the firm is less sensitive to aggregate cycles or that macro variables work indirectly. The company's stock price is more influenced by its own earnings, competitive position, innovation, and management quality than by overall GDP, inflation, or interest rates. Macro factors influence the overall market (aggregate returns), but individual stock returns might deviate significantly.

Table 10: Granger Causality Test

RELIANCE				Decision
Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**	
ILR does not Granger Cause RETURNS	15	0.29547	0.7505	Cannot Reject
RETURNS do not Granger Cause ILR		0.14422	0.8675	Cannot Reject
ADANI				
ILR does not Granger Cause RETURNS	15	0.29547	0.7505	Cannot Reject
RETURNS do not Granger Cause ILR		0.14422	0.8675	Cannot Reject

H_0: Return does not granger cause illiquidity; H_1: Return granger causes illiquidity

There is no causal connection between illiquidity and returns and vice versa. Unfortunately, the study found no causal connection between illiquidity and returns and vice versa, i.e. the causality neither runs from a return to illiquidity, nor from illiquidity to return.

5. CONCLUSIONS

The present study investigated the influence of illiquidity on stock returns of select conglomerate industries like Reliance and Adani Ltd in India for the period from 1 January 2008 to 31March 2025. The results endow with confirmation on the consequence of illiquidity in explaining the deviation of stock returns in the select conglomerate industries which administer a enormous network of varied, frequently discrete business entities under a solitary corporate umbrella to diversify risk and leverage internal capital. The result suggests that the impact of illiquidity on stock return is prominent in Reliance industry but negligible in case of Adani industry. In Reliance, stock's own return volatility is associated negatively and significantly with stock returns implying higher volatility connected with lower future returns which contradicts traditional financial theory (CAPM)**.** But the result is contrary to Adani Ltd signifying insignificant positive impact of illiquidity on stock return. Positive effect of size on stock return in Reliance industry, although beyond expectation, indicates larger firms having a better risk-adjusted return during specific market phases, particularly under specific crisis period. This effect is prominently absent from Adani Ltd.

Stock's systematic risk (BETA) has an insignificant positive effect on stock returns in case of both industries indicating a direct, risk-reward relationship, although insignificantly positive. This is supportive of the capital asset pricing model (CAPM) implying that investors get rewarded for bearing higher systematic risk. In both industries under our consideration, Reliance and Adani, relative changes in trading volume (RCV) have insignificantly negative impact on stock returns. The result obtained indicates that approach of buying stocks with high past performance and selling stocks with low past performance stimulates a considerable excess return for a period of holding of six months. The granger causality test confirms no causality between illiquidity and stock return in any direction.

Prominently, by using Amuhud's measure of liquidity, we find that investors stipulate higher returns by holding illiquid stocks in select industries in emerging market of India. We, furthermore, came across with the fact that market risk effect is undersized and insignificant in elucidating stock returns in select conglomerate industries in India. The current study can be additionally broadened to appraise the research endeavor on illiquidity in diverse financial markets over a longer time frame.

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