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A new method for estimating liquidity and stock returns in Indian stock market

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Abstract

Purpose – This study aims to explore the impact of systematic liquidity risk on the averaged cross-sectional equity return of the Indian equity market. It also examines the effects of illiquidity and decomposed illiquidity on the conditional volatility of the equity market.

Design/methodology/approach – The present study employs the Liquidity Adjusted Capital Asset Pricing Model (LCAPM) for pricing systematic liquidity risk using the Fama & MacBeth cross-sectional regression model in the Indian stock market from January 1, 2012, to March 31, 2021. Further, the study employed an exponential generalized autoregressive conditional heteroscedastic (1,1) model to observe the impact of decomposed illiquidity on the equity market's conditional volatility. The study also uses the Ordinary Least Square (OLS) model to illuminate the return-volatility-liquidity relationship.

Findings – The study's findings indicate that the commonality between individual security liquidity and aggregate liquidity is positive, and the covariance of individual security liquidity and the market return negatively affects the expected return. The study's outcome specifies that illiquidity time series analysis exhibits the asymmetric effect of directional change in return on illiquidity. Further, the study indicates a significant impact of illiquidity and decomposed illiquidity on conditional volatility. This suggests an asymmetric effect of illiquidity shocks on conditional volatility in the Indian stock market.

Originality/value – This study is one of the few studies that used the World Uncertainty Index (WUI) to measure liquidity and market risks as specified in the LCAPM. Further, the findings of the reverse impact of illiquidity and decomposed higher and lower illiquidity on conditional volatility confirm the presence of price informativeness and its immediate effects on illiquidity in the Indian stock market. The study strengthens earlier studies and offers new insights into stock market liquidity to clarify the association between liquidity and stock return for effective policy and strategy formulation that can benefit investors.

Keywords Illiquidity, Emerging market, Liquidity adjusted CAPM, WUI, EGARCH

Paper type Research paper

1. Introduction

Sharpe (1964), Treynor (1962), Lintner (1965), Lintner (1965), and Mossin (1966) introduced the Capital Asset Pricing Model (CAPM) and established the asset pricing theory. CAPM looks at the relationship between the expected return and the systematic risk. CAPM involves frictionless markets, and trading activity does not affect asset prices. In contrast, in reality, trading costs and asymmetric information are involved in the stock market, which disrupts the bid-ask spread and price volatility. It is generally acknowledged that asset prices are affected by systematic risk and liquidity risk. Liquidity relates to trading cost, and it determines how quickly the assets can be traded at the usual market price with partial

JEL Classification — G10, G12, G15

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influence on the stock price movement and is measured by the bid-ask spread known as illiquidity cost. Hence, liquidity risk investigation is significant today in the financial market since there needs to be more clarity on the relationship between stock returns and liquidity. It is assumed that higher expected returns are linked to less liquid assets and shows that expected returns and illiquidity are positively related. A strand of research has examined the role and importance of liquidity in the financial market and asset pricing during the last couple of decades. Notion for liquidity measures can influence asset returns (Amihud & Mendelson, 1986). Chordia, Roll, and Subrahmanyam (2001) investigated the cross-sectional relationship between stock returns and liquidity variability and reported that volatile stocks have lower expected returns. Khanna and Sonti (2004) indicated that liquidity improvement leads to increased trade by investors, thereby improving investment decisions. The theoretical model contributed by Acharya and Pedersen (2005) explaining asset prices pretentious by liquidity risk and the commonality of liquidity has attracted numerous studies to explain cross-sectional variations in expected return. Their study claimed that liquidity risk matters for asset pricing. Liquidity is the degree to which one asset can be traded quickly at minimum impact cost. However, illiquidity increases trading costs and adversely affects asset return, and holding it up until recovery of liquidity level generates an extra premium for the investment in the asset. Thus, the liquidity risk exhibits explanatory power on the cross-section of stock return (Vu, Chai, & Do, 2015). Ellington (2018) stated that lower liquidity levels rancorously hinder economic growth during crises. Increased liquidity leads to increased financial risk-sharing, influencing investors' trading decisions and motivating portfolio changes. Furthermore, lacking market liquidity leads to plummeting market efficiency, incompetent asset allocation, and impeding economic progress. Hence, liquidity is one factor that investors consider very often in the stock market. The research study (Holden & Jayoung, 2019; Kazumori, Fang, Sharman, Takeda, & Hong, 2019) provided an adverse opinion on the Liquidity Adjusted Capital Asset Pricing Model. They viewed liquidity risk as insignificant and consistent with the theory. Pástor and Stambaugh (2003) deliberated that investors are cautious about liquidity risk and try to rebalance their portfolios by participating in safer liquid assets, particularly after the 2008 global financial crisis and pandemic crises. Stock market liquidity plays a substantial role in economic progress as well. Acharya and Pedersen (2005) stated that if the liquidity level in the economy worsens, it will increase risk. Further, this study also considers uncertain risk, which is a systematic risk (Su, Pang, Umar, Lobonţ, & Moldovan, 2022), and World Uncertainty Index (WUI) as a proxy for global political and economic uncertainty. It is documented in the literature that emerging markets are more illiquid than developed markets. Several studies on pricing liquidity risk have been conducted in the literature, most from advanced economies. Minimal studies have been attempted in the literature on Emerging Markets (Altay & Çalgıcı, 2019; Donadelli & Prosperi, 2012; Hearn, 2010; Kumar & Misra, 2019). Bekaert *et al.* (2006) stated that liquidity has a greater impact on emerging markets. Emerging markets are normally considered to have low transparency, corporate governance problems, more concentrated ownership, and accessibility of inadequate portfolio choices due to a lack of diversity in securities compared to developed markets. Hence, investors are apprehensive about the liquidity of securities. These factors indicate that liquidity plays a more significant role in emerging markets than in developed ones. Emerging markets (e.g. China, India, Brazil) attract global investors and provide an opportunity for maximizing the benefits of international portfolio diversification. Furthermore, the rapid growth and higher returns in EMs attract investors for international diversification (Domowitz, Glen, & Madhavan, 1997). The contribution of India to global growth is 15.4%, i.e. second highest, followed by China at 34.9%, indicating that both countries had generated more than half of global growth in 2023 [1]. However, these markets are lagging in terms of some key parameters, i.e. institutional strengths, financial liberalization, market efficiency and reforms (Tripathi & Dixit, 2020) and also have some similarity in the stability of macro-environment, size, and strength of the trading structure.

The present study is trying to add to the scant literature on the influential behavior of liquidity on asset return in emerging markets exclusively in the context of India to address the gap and to contribute further to improving the work in the area of stock market liquidity to bring more clarity to the association between liquidity and stock return for effective policy and strategy formulation that can benefit to investors. The motivation behind investigating the liquidity behavior and stock return of Emerging Markets like India is to provide better insights to investors for making investment decisions successfully. Furthermore, higher return volatility reduces stock liquidity (Chan, Hameed, & Kang, 2013; Thomas & Stoll, 1981; Stoll, 1978). The impact of systematic and idiosyncratic volatility on liquidity has been investigated in the literature by Chan *et al.* (2013). However, the illiquidity's reverse impact and decomposed higher and lower illiquidity on conditional volatility are different and have yet to be investigated in the illiquidity time series literature. Additionally, our study differs from others since we have used the World Uncertainty Index (WUI) to measure liquidity and market risks as specified in the LCAPM. WUI as a factor for uncertain risk and examining its impact on the average expected return can help global investors optimize their portfolio in response to the complex and changing international environment. Sanjai, Ghosh, and Srinivasan (2013) stated that India's GDP and corporate investment activity are negatively related to Economic Policy Uncertainty in India. Their study also observed a negative correlation between the stock market and EPU, and predominantly, EPU negatively influenced the stock market during the international financial crisis period. The study can contribute to the literature by considering WUI as a proxy for uncertain risk, e.g. global economic and political uncertainty, apart from systematic market risk and liquidity risk, to explain the cross-sectional expected equity return of the order-driven financial market. To our knowledge, this is probably the first study to examine the impact of uncertain risk on asset pricing.

The study's contributions are five-fold: first, it uses the (Acharya & Pedersen, 2005) LCAPM model to investigate the impact of systematic liquidity risk on equity return variation in the Indian stock market by considering the large-cap stocks listed in the S&P BSE SENSEX. This model helps to determine how liquidity risks affect expected asset returns and explain how liquidity affects the excess return by the risk price coefficients. This model also estimates the pricing of systematic risk factors and idiosyncratic volatility in examining the asset pricing to assist investors in decision-making by assessing the possible level of risk.

Second, the study employed Fama and MacBeth (1973) cross-sectional regression model to explore whether liquidity risks are priced individualistically of market risk and investigate which risk type is essential for asset pricing. This study also investigates the robustness of the (Acharya & Pedersen, 2005) model to provide information about individual asset and market liquidity.

Third, the study considered illiquidity time series analysis to examine the return-volatility-liquidity relationship using the OLS model to provide information on price informativeness and its immediate impact on illiquidity in the Indian stock market. The result of our study is consistent with the notion of asymmetric information, suggesting that the higher illiquidity associated with negative return is more than the lower illiquidity associated with positive return in the same magnitude.

Fourth, the study employed the EGARCH model to test the relationship between illiquidity and conditional volatility and find the presence of an asymmetric effect of shocks on conditional volatility in the Indian stock market to deliver information to investors while making an investment decision.

Fifth, the study used the Granger Causality Model to observe the relationship among return, illiquidity, and return volatility in the Indian market to provide information to investors that Market efficiency is increased in the existence of liquidity, and hence the market capability to rivetted shocks is enhanced.

The findings may be helpful to regulators in determining the optimum level of liquidity in the market. The study may benefit investors in considering risk while making investment decisions. It also provides valuable information to individual investors and institutional investors for portfolio diversification.

2. Institutional background

The stock market provides business capital and allows individuals to invest in companies and is an integral part of a nation's economy. The Indian stock market is more internationalized, all-inclusive, market-oriented, and older than China (Dong, 2019). India has two stock exchanges, the Bombay Stock Exchange (BSE) and the National Stock Exchange of India (NSE). The Bombay Stock Exchange was established in 1875 and is the oldest in Asia. It is considered as the world's fastest stock exchange, with a median trade speed of six microseconds. In 2012, it also joined the United Nations Sustainable Stock Exchange initiative. The National Stock Exchange of India (NSE) was founded in 1992 and occupies the eleventh-largest stock exchange in the world in terms of market capitalization. The NSE was the first Indian stock exchange to provide traders with fully computerized electronic trading facilities. Both exchanges follow the same trading mechanism, trading hours, and settlement process and are regulated by the Securities Exchange Board of India (SEBI). The BSE had 5,657 listed firms as of June, 2023, while the NSE had 2,137 as of March, 2023. The Indian stock market is booming and attracting global investors and companies. It is more market-oriented, with higher levels of both de-listings and listings. India is open to foreign investments, and two foreign companies are listed on India's stock market. In December 2023, the Nifty Index recorded a 7.9% increase, outperforming other emerging economies. Factors such as infrastructure investment, foreign funds, and retail investors have contributed to the outperformance of Indian stocks, which have risen 63% compared to an 18% return in the Chinese market over five years (Gujar, 2023). Optimism about India's growth projections augmented liquidity and greater domestic participation, which contributed to the progress in the performance of stock markets. Supplementary to this, India's growth is due to strong corporate earnings, a growing retail investor base, sustained foreign institutional investments (FII), and stable domestic macroeconomic fundamentals (India Beats Hong Kong To Become 4th Largest Stock Market, 2024). According to HSBC, the banking sectors, health care, energy, autos, retailers, real estate, and telecoms are best positioned for 2024. (Sanyal, 2023).

China's stock market started later than India. The Shanghai Stock Exchange (SSE) was established in November 1990 and operated by the China Securities Regulatory Commission (CSRC), the world's third-largest stock market by market capitalization. The Shanghai Stock Exchange is only partially open to foreign investors. It is also one of Asia's biggest stock exchanges. The Shenzhen Stock Exchange (SZSE) was established on December 1, 1990, as a self-regulated legal entity under the supervision of the China Securities Regulatory Commission (CSRC). It is the world's eighth-largest stock exchange by market capitalization of $3.90tn in July 2021. (SSE, 2021) The Shanghai Stock Exchange had 2273 listed companies, whereas the Shenzhen Stock Exchange had 1,930 listed companies as of June 2023 (Slotta, 2023). However, China accomplished the progress within three decades, while the India took over a century to attain. If the Chinese stock market is compared with the Indian stock market, in that case, its system lags in terms of the number of listed companies, market system, stock market structures, stock market supervision, the corporate structure of listed companies, the market development pattern, and the market operation mechanism. One of the most prominent features of the stock market of India is that the law of India endows the administration segment with countless supervision and management rights, usually making Indian-listed companies of high quality. There are five important laws such as Securities and Exchange Board of India Act, 1992, Securities Contracts (Regulation) Act, 1956, Companies Act, 2013, SEBI (Listing Obligations and Disclosure Requirements) Regulations, 2015 and SEBI (Prohibition of Insider Trading) Regulations, 2015 which control the Indian stock market to ensure transparency in transactions and the protection of shareholder rights. Securities and Exchange Board of India Act authorizes SEBI as a regulatory and enforcement authority over the securities market. Securities Contracts (Regulation) Act of 1956 provides the legal framework for the regulation of stock exchanges and the listing of securities. The Companies Act 2013 governs the issuance and transfer of securities. SEBI (Listing Obligations and Disclosure Requirements) Regulations prescribe the listing requirements for listing companies. It also contains provisions related to corporate governance, disclosures and shareholder rights. SEBI (Prohibition of Insider Trading) Regulations prevent insider trading in securities. Further, all listed companies in India take initiatives to intensify the corporate system, soothe the corporate structure, and strengthen corporate governance. On the other hand, in China, many parties with their interest keep relations directly or indirectly with the company, leveraging extensive scopes that have led to the structure of governance of listed Chinese companies becoming more complicated. Furthermore, the shareholding pattern of China is subjugated by non-mainstream common shares, which makes the shareholding structure unreasonable. In addition, most of the board of directors are internal directors, which leads to a disproportionate power. The Chinese listed companies are pigeonholed by single-large shareholders that make them firm stockholders, while those listed in India have diversified shareholdings. The Indian market offers diverse companies with good fundamentals that can take advantage of the untapped growth potential. India has the highest number of companies listed on the stock market, and the United States has the highest number of companies listed after India. The Indian stock market has shown impressive growth, especially regarding market capitalization, the number of listed companies, and the turnover rate. India is one of the largest recipients of foreign direct investment (FDI) in significant sectors.

The Indian stock market emphasized strengthening market liquidity, upholding market stability, improving risk management, and broadening the market foundation in the circulation market. The bidding pricing method is prevalent in Indian IPO pricing, which enhances the efficacy of the stock issuance system. On the other hand, china follows the examination and approval system. Hence, the issuer needs to keep accurate information about security issuance private before issuing securities. Further, it is essential to fulfill the essential conditions stipulated in the Company Law and the Securities Law while issuing securities. In China, the issue price is usually negotiated between the lead underwriter and the issuer to set a lower price to expose a low possible risk and also to confirm the achievement of the offering. Hence, the price gap is vast amid the secondary and primary markets. The information disclosure system, law and regulation system, unified market supervision system, and strict market supervision rules of India created robust stock market management. In contrast, China's stock market administration system still needs to improve the market system, regulations and processes, and the unified supervision system.

China is the second and third largest stock and bond markets globally (Arora, 2024). China's stock markets are deeply associated with the individual and corporate levels, not the economy, and are dominated by retail investors. Furthermore, Chinese companies profoundly trust retained earnings and bank loans. Companies remain limited in financing opportunities; hence, China's economy remains relatively protected from disruptive ups and downs in the stock market. Over recent years, India's market capitalization has passed the UK and France and is predicted to become the third-largest economy by 2028, overtaking Japan and Germany. Its stocks have been one of the strongest performers in emerging markets. India's economy is fundamentally driven by domestic consumption and currently accounts for around 60% of India's economy, while the large emerging economies such as China are mainly export-led (Dzmitry, 2023). India is the fifth-highest stock market in the world, and it only ranks behind the United States, China, and Japan. (Hindustan Times, 2023). However, India was outpacing Hong Kong and became the world's fourth-largest stock market by market capitalization, leveraging its robust performance and reaching new highs in 2023. India's market cap stood at \$4.33tn, slightly ahead of Hong Kong's \$4.29tn (Mint, 2024). India's market growth was the toughest in 2023. India has joined the ranks of superpowers in the financial world. India and the U.S. witnessed an enrichment in their stock exchanges by over 20% each, while China cut by around 9% in 2023. This may be attributed to struggling to cope with the COVID-19 pandemic.

So far, in the market-making system in India, market makers provide liquidity to the markets by continuously buying and selling securities with their two-way quote offering. Market makers typically maintain a minimum level of liquidity and provide two-sided quotes for a specified number of securities. Since they provide two-way quotes, they reduce the basis and trading risks for the market players. Market makers gave the quotes so that the liquidity would automatically be created. In the process, the market makers take the risk of market volatility, improve the stocks' liquidity and trade volume, and provide liquidity in the market. The stock becomes highly illiquid without the market makers, and traders may not be too keen on trading it. In a nutshell, the market markets play a crucial role in supplying liquidity to the stock. In India, there are no official market-makers in the stock markets. Due to the absence of a Designated Market Maker (DMM), the *de facto* market maker is the High-Frequency Trader (HFT), which infers information at an ultra-fast speed (milliseconds) from institutional investors, retail investors, etc., and makes their investment decisions. Though *de facto* market makers are not obliged to provide liquidity during a period of high information asymmetry and stress (Tripathi & Dixit, 2020; Tripathi & Dixit, 2021), they can swiftly withdraw liquidity from the market because of free entry and free exit hypothesis (Brockman & Dennis, 2002). So, they prefer to go for market order (liquidity consumption) instead of limit order (liquidity supply), which makes the market informationally efficient in the dominance of private information, which supports the asymmetric information hypothesis of market microstructure theory.

Our study investigates the liquidity aspect of the stock market of India, which is considered a prominent emerging market in the world, has some similarities with China (the world's largest emerging market), and follows a driven market microstructure. The market, with a high level of segmentation and substantial restrictions, prohibits foreign investors. This market is also dominated by retail investors (more than 99% of total investors), a state-controlled market economy (more than 43% of total market share), restricted trading rules with disallowed short selling, and the presence of unfavorable policies increases investors' fear and causes illiquidity (Su, Lyu, & Yin, 2022). In the U.S. market, high liquidity volatility leads to increased market liquidity (Engle, Fleming, Ghysels, & Nguyen, 2013). This is consistent with the inventory consideration hypothesis of market microstructure theory by enhancing liquidity provisioning in quote-driven financial markets. However, in an order-driven economy like India, information asymmetry significantly affects market liquidity (Tripathi & Dixit, 2021). The influence of liquidity as a risk factor in asset pricing is becoming a topic of interest for regulators, portfolio investors, policymakers, and researchers today. Therefore, it is necessary to understand the association between liquidity and stock return, which is fundamental to pricing, valuation, risk management, and speculation.

The organization of the study is as follows: section 2 presents the past literature reviews while data and methodology are described in section 3. The results and discussion are elucidated in section 4. The concluding remarks and managerial implications are illuminated in section 5.

3. Review of literature

The influence of liquidity as a risk factor in asset pricing has received attention in recent years. Brennan and Subrahmanyam (1996) showed a positive relationship between liquidity risk premium and transaction cost (fixed and variable). Datar, Narayan, and Robert (1998) reported the explanatory power of liquidity premiums to explain average stock returns by supporting the original notion (Amihud & Mendelson, 1986). Chordia, Roll, and Avanidhar (2000) conveyed a negative and significant relationship between liquidity levels and expected stock return. Pástor and Stambaugh (2003) described that the cross-sectional expected return is related to the aggregate liquidity variability. Acharya and Pedersen (2005) presented a theoretical model called the Liquidity Adjusted Capital Asset Pricing Model (CAPM) for pricing different components of liquidity risk. The study was applied to NYSE and AMEX stocks for 1963–1999. Their study reported commonality in liquidity due to the covariance of individual security liquidity and market liquidity and the covariance between security return and market liquidity. Their study indicated that the covariance between individual security liquidity and market return contributes 0.82% to the average cross-sectional return. Their study also claimed that LCAPM is better than standard CAPM and the Three-Factor Model (Fama & French, 1993). Liu (2006) developed and tested a two-factor model based on market and liquidity factors. The study reported that liquidity explains cross-sectional stock return better than CAPM and the Three-Factor Model (Fama & French, 1993). Hearn (2010) reported that liquidity is one of the important determinant factors for asset valuation in a larger market. Narayan and Zheng (2011) found that liquidity has a negative effect on Chinese expected stock returns, and the result is not robust due to asymmetric information and excessive Government control. Mazouz, Alrabadi, and Yin (2012) found that the lower systematic risk reacts to positive and negative shocks, whereas the higher systematic risk does not react to shocks. Donadelli and Prosperi (2012) stated that the global liquidity factors, i.e. VIX and open interest, have predicted excess returns.

Similarly, Lee (2011) and Liu (2006) observed a positive and significant impact of liquidity on the expected return when considering the International financial liquidity factor. Papavassiliou (2013) presented evidence on liquidity pricing in the Greek stock market and reported that the shocks happen since liquidity has significant implications on portfolio diversification. Vu *et al.* (2015) supported the LCAPM (Acharya & Pedersen, 2005) and confirmed that liquidity affects expected stock returns. Batten and Vo (2014) stated that liquidity does not impact asset return due to the lack of integration of Emerging Markets into the global market. Chiang and Zheng (2015) observed that market-level illiquidity substantially impacts large-cap stock excess return, and firm-level illiquidity strongly affects small-cap stock excess return. Akbas, Armstrong, and Ralitsa (2011), and Bradrania, Maurice, and Stephen (2015) stated that systematic liquidity risk captures the average cross-sectional stock return variation before and after eliminating microstructure-induced noise from the closing price. There is a significant correlation between illiquidity shocks and return and volatility across assets and markets (Andrikopoulos, Timotheos, & Vasiliki, 2014). The illiquidity multiplier theory (Cespa & Foucault, 2014) indicates that illiquidity shocks of an asset may provide information to the liquidity provider of related assets. Illiquidity multiplier theory also observes a slight drop in the liquidity of one asset, which contains the price informativeness of another asset and, in turn, significantly reduces market liquidity. Their empirical evidence of a positive relationship between liquidity and price informativeness supported the underlying theory. Shih and Su (2016) showed a positive relationship between Liquidity and expected cross-sectional return during the market downturn in Taiwan. Fong, Holden, and Trzcinka (2017) and Goyenko, Holden, and Trzcinka (2009) supported the Amihud (2002) illiquidity measures as the best proxy for global research. Ahn, Jun, and Yang (2018) and Amihud (2002) Stated that illiquidity measures are the most effective price impact using high-frequency data in Emerging Markets.

In contrast, Harris and Amato (2019) have given contradictory evidence against (Amihud, 2002) illiquidity measures for asset pricing. Kumar and Misra (2019) supported the economic significance of the LCAPM (Acharya & Pedersen, 2005) in the Indian stock market and reported the covariance of individual security return with aggregate liquidity as a commanding effect on expected return even after controlling idiosyncratic risk. Altay and Çalgıcı (2019) reported the same empirical results supporting the LCAPM theory and the contrary evidence on positive and significant covariance of individual security return with aggregate liquidity. Their findings may be because of microstructure differences in Asian Economics and Emerging Markets.

Illiquidity shocks are an essential channel for propagating shocks in the equity market (Xu, Taylor, & Lu, 2018). There is a feedback relationship between illiquidity shocks and volatility shocks (Zhang & Han, 2022). Wang, Cohen, and Glascock (2022) examined the asymmetric impact of frequency and magnitude shocks on return volatility across assets and markets. Cheng, Liu, Jiang, and Cao (2023) explored the stock liquidity effects on accrual anomaly, and their findings indicated that stock liquidity is negatively related to the accrual anomaly and that there is a causal relationship between the effect of stock liquidity and accrual anomaly. Therefore, it is imperative to empirically investigate the propagation of illiquidity shocks on return volatility across assets and markets in India as an Emerging Market. Further, the market microstructure theory (Stoll, 1978) assumes that higher return volatility increases illiquidity. Their evidence on higher return volatility insists that investors holding an asset with high inventory costs increase the bid-ask spread and trading cost.

4. Data and methodology

The study used the daily historical return and volume data (Total Turnover) of 30 large-cap stocks listed in the Bombay Stock Exchange Sensex Index (BSE) and obtained data from www.bseindia.com. The BSE is the oldest and Asia's first exchange, which was established in 1875. It provides an efficient and transparent trading platform for equity, derivatives, bonds, etc. The BSE SENSEX is considered to be India's leading economic indicator. It depicts the nation's growth consisting of 30 major listed companies, traded internationally on the EUREX and the leading exchange of BRCS nations (Brazil, Russia, China, and South Africa). The BSE plays a vital role in the global economy and is considered the most widely tracked stock market benchmark index. Chiang and Zheng (2015) document that market illiquidity significantly impacts the excess return of large-cap stocks. Chiang and Zheng (2015) document that market illiquidity significantly impacts the excess return of large-cap stocks. The 91-Treasury Bill is extracted from the official RBI website to consider a proxy for a Risk-free interest rate. The study period covers from 1 January 2012 to 31 March 2021. The reason for taking this period is that the study period has witnessed the first two years as a coalition Government. The remaining period covers a stable government followed by massive 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 dynamic impact on the liquidity of India's stock market and exposed both high liquidity and low liquidity scenarios.

The study has taken the data from highly liquid large-cap stocks of blue-chip companies during the unstable Government and the COVID-19 pandemic, which may be considered a high level of political and economic uncertainty. World Uncertainty Index (WUI) is a GDP-weighted average considered one of the most important macroeconomic indicators that ranks the level of uncertainty in a nation's economy. WUI data are collected from www.policyuncertainty.com. We have considered WUI as a control variable in our study to capture economic and political uncertainty, which allows us to explore the effect of uncertain risk on equity return variation in India. The reason for taking WUI is that uncertainty affects the economy, market consumption, production, economic growth, and company investments. When facing economic uncertainty, companies will likely defer capital investments, slowing the economy down. Stock prices are responding dramatically to divergences in the economic policy uncertainty index. The higher the uncertainty level, the more volatile the stock market, contributing to the long swings trend and the variability of stock prices that tend to illiquidity problems. Secondly, economic policy uncertainty reduces investors' hunger to trade securities and perverts their trading competence in the securities market. Thirdly, high EPU increased the firm value uncertainty, intensifying the withdrawal of securities traders from the stock market and leading to a drying up of liquidity. Fourthly, firms are highly cautious during the EPU period and reluctant to disclose more information to the market if the news is unfavorable, since information about the firm may have a negative impact on investors, which leads to encouraging investors to pull out securities and create liquidity problems. Since security performance and traceability are affected by two crucial market innovations, i.e. market downturn and liquidity dry-up, it is becoming essential to price the factors associated with liquidity, which involves the cost of liquidity and uncertainty related to liquidity, which increases liquidity risk. Acharya and Pedersen (2005) incorporated liquidity-associated betas in the CAMP model and contended that liquidity shocks are negatively related to stock returns and positively associated with future stock returns.

The liquidity-adjusted Capital Asset Pricing Model (LCAPM) proposed three forms of liquidity: Commonality in liquidity, stock liquidity sensitivity to market returns and stock return sensitivity to market liquidity. Acharya and Pedersen (2005) suggested that liquidity risk measured by the stock liquidity sensitivity to market returns significantly affects stock returns among all three. Our study tested the theory Acharya and Pedersen (2005) advocated based on the liquidity-adjusted Capital Asset Pricing Model. The conditional equilibrium asset pricing model with liquidity risk is:

$$E_t(r_{it+1} - c_{it+1}) = r_f + \lambda_t \frac{Cov_t(r_{it+1} - c_{it+1}, R_{Mt+1} - C_{Mt+1})}{Var(R_{Mt+1} - C_{Mt+1})} \tag{1}$$

$r_{it+1} - c_{it+1}$ denotes liquidity adjusted return of individual security i while $R_{Mt+1} - C_{Mt+1}$ signifies liquidity adjusted market return, and r_f represents risk-free rate.

$$\begin{aligned} E_t(r_{it+1} - c_{it+1}) = E_t(c_{it+1}) + \lambda_t \frac{Cov_t(r_{it+1}, R_{Mt+1})}{Var(R_{Mt+1} - C_{Mt+1})} + \lambda_t \frac{Cov_t(c_{it+1}, C_{Mt+1})}{Var(R_{Mt+1} - C_{Mt+1})} - \\ \lambda_t \frac{Cov_t(r_{it+1}, C_{Mt+1})}{Var(R_{Mt+1} - C_{Mt+1})} - \lambda_t \frac{Cov_t(c_{it+1}, R_{Mt+1})}{Var(R_{Mt+1} - C_{Mt+1})} \end{aligned} \tag{2}$$

In equation (2), market risk and liquidity risk factors can predict the required excess return of security i. Then, total liquidity risk decomposed into three covariances (Acharya & Pedersen, 2005). These are as follows:

Cov_rR: Market or CAPM Beta comovement between individual security return and market return.

Cov_cC: A commonality in the liquidity of individual assets with market liquidity should have a positive relationship with an expected return. The Covariance between individual security illiquidity and market illiquidity is expected to increase the returns. This may be due to investors getting a premium for market illiquidity.

Cov_cR: Comovement between individual security liquidity and market return. It negatively affects expected return since investors prefer lower expected return on illiquid security in downturn markets (Acharya & Pedersen, 2005; Chordia *et al.*, 2000).

Cov_rC: Comovement between individual security returns and market liquidity. It also affects the expected return because investors prefer lower returns on individual security with high returns during market illiquidity (Amihud, 2002).

The daily return is calculated using the closing price:

$$r_{id} = \frac{P_1 - P_0}{P_0} * 100 \tag{3}$$

The impact of daily price on order flow using the (Amihud, 2002) illiquidity measure:

$$c_{id} = \frac{|r_{id}|}{dvol_{id}} \tag{4}$$

Where, r_{id} is the individual security return i and $dvol_{id}$ is the rupee trading volume of security i at day d expressed in crores.

Akbas *et al.* (2011) suggest the time-varying liquidity risk and indicate that stocks with small value have higher liquidity revelations than small growth stocks in the nastiest times. On the contrary, small growth stocks have higher liquidity exposures in good times. We have applied the cross-sectional regression model of Akbas *et al.* (2011) to compute Cov_cC, Cov_cR, Cov_rC, and Cov_rR:

$$c_{id} = \alpha_i + \beta_{ci}^{C} \Delta C_{Md} + \beta_{ci}^{R} (R_{Md} - R_{fd}) + u_{id} \tag{5}$$

$$r_{id} - r_{fd} = \alpha_i + \beta_{ri}^{C} \Delta C_{Md} + \beta_{ri}^{R} (R_{Md} - R_{fd}) + \nu_{id} \tag{6}$$

where Cov_rR: Market or CAPM Beta is the Covariance between individual security return and market return,

Cov_cC: Commonality in liquidity of individual assets with aggregate liquidity.

Cov_cR: Covariance of individual security liquidity and market return.

Cov_rC: Covariance of individual security return and aggregate liquidity.

To empirically validate the theory of LCAPM by Acharya and Pedersen (2005), the study used the regression model of Fama and French (1993) to capture the quarterly-averaged cross-sectional return variation:

$$r_{it+1} - r_{ft+1} = \gamma_0 + \gamma_1 \beta_{rit}^{R} + \gamma_2 \beta_{cit}^{C} + \gamma_3 \beta_{rit}^{C} + \gamma_4 \beta_{cit}^{R} + \varepsilon_{it+1} \tag{7}$$

Finally, to check our result's robustness, we further augment the World Uncertainty Index (WUI) in the regression model (Fama & MacBeth, 1973). Fama and MacBeth (1973) model was employed to capture the impact of the World Uncertainty Index (WUI) on stock returns:

$$r_{it+1} - r_{ft+1} = \gamma_0 + \gamma_1 \beta_{rit}^{R} + \gamma_2 \beta_{cit}^{C} + \gamma_3 \beta_{rit}^{C} + \gamma_4 \beta_{cit}^{R} + \gamma_5 WUI_{it} + \varepsilon_{it+1} \tag{8}$$

Further, this study has considered illiquidity time series analysis to examine empirically the return-volatility-liquidity relationship in the Indian context.

The OLS model is applied to estimate the asymmetric impact of price change on illiquidity in the Indian context.

$$Illiquidity_t = \alpha + \beta_1 Illiquidity_{t-1} + \beta_2 r_t + \beta_3 D_1 r_{t-1} + \varepsilon_t \tag{9}$$

α = Intercept

β_1 = Parameter to be estimated for autoregressive

β_2 = Measures the slope of return irrespective of directional change in stock price.

β_3 = Measures the asymmetric effect of directional change of return on market illiquidity.

EGARCH (1, 1) Model without illiquidity:

We employ the EGARCH model developed by Nelson (1991) to test whether the return series exhibits volatility asymmetry. The estimated model has been specified as follows:

$$\log\left(h_t\right) = \beta_0 + \beta_1\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta_2 \log\left(h_{t-1}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) \tag{10}$$

On the left-hand side, the log of the conditional variance denotes that the asymmetric effect is exponential rather than quadratic. The forecast of conditional variance is to be nonnegative; however, the coefficients can be negative. In this model, if ε_t is positive and represents good news, it contributes $\beta_1(1+\gamma)|\varepsilon_{t-1}|/\sqrt{h_{t-1}}$ to the log volatility. If ε_t negative denotes bad news contributes $\beta_1(1-\gamma)|\varepsilon_{t-1}|/\sqrt{h_{t-1}}$. If $\gamma \neq 0$, it signifies the support of volatility of asymmetry in the data-generating process. If γ coefficient is negative, negative shocks stimulate more volatility than positive shocks. This supports the leverage effect hypothesis. When $\beta_1 > 0$, the $\beta_1|\varepsilon_{t-1}|/\sqrt{h_{t-1}}$ the log variance increases when the scale of market movement is hefty. β_2 coefficient indicates the degree of volatility.

EGARCH (1, 1) Model with Augmented illiquidity:

The inclusion of illiquidity as an exogenous variable in the conditional volatility equation:

$$\log\left(h_t\right) = \beta_0 + \beta_1\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta_2 \log\left(h_{t-1}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta_3 Illiquidity_{t-1} \tag{11}$$

EGARCH (1,1) Model with decomposed illiquidity:

The inclusion of decomposed illiquidity as an exogenous variable in the conditional volatility equation. Where, D_1 indicates the higher illiquidity (more than median value) and D_2 shows the lower illiquidity (less than the median value of the illiquidity series).

$D_1 = 1$, If illiquidity > median value of illiquidity or 0 otherwise.

$D_2 = 1\text{-}D_1$ or 0 otherwise.

$$\log h_{t(X)} = \beta_0 + \beta_1\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta_2 \log\left(h_{t-1}\right) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \beta_3 D_1 Illiquidity_{t-1} + + \beta_4 D_2 Illiquidity_{t-1}. \tag{12}$$

β_1 : Assess the reaction of volatility to change in news.

β_2 : Measures the volatility persistency.

γ: Explains the asymmetry or Leverage effect.

β_3: Higher Illiquidity.

β_4: Lower Illiquidity.

4.1 Granger causality model

The estimated Granger Causality Model has been represented in a Vector Autoregression (VAR) framework employed to check the existence of a causal relationship between two variables:

$$Y_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i Y_{t-1} + \sum_{j=1}^{2} \beta_j X_{t-j} + \varepsilon_t \tag{13}$$

$$X_t = \omega_0 + \sum_{i=1}^{2} \gamma_i Y_{t-1} + \sum_{j=1}^{2} \beta_j X_{t-j} + v_t \tag{14}$$

Where, α_0 and ω_0 are the intercepts, X_t *and* Y_t are the returns of markets and ε_t and v_t are the white noise error terms are assumed to be uncorrelated.

5. Results and discussion

Table 1 depicts the descriptive statistics of variables used in the regression model and LCAPM. It shows that the mean and standard deviation of aggregate illiquidity are higher and lower in the case of a change in aggregate illiquidity. Table 2 presents the descriptive statistics of various systematic risk factors, i.e. CAPM market risk and decomposed liquidity risk. It shows that the mean value of commonality between security liquidity and market liquidity is higher, and the co-movement between security liquidity and market return is lower except for excess stock return. The covariance between security liquidity and the market return (Cov_cR) shows a higher standard deviation, whereas CAPM Beta (Cov_rR) exhibits a significantly lower standard deviation.

Table 3 presents the correlation matrix of the systematic liquidity risk, which is decomposed into Commonality in liquidity with aggregate liquidity (Cov_cC), liquidity

Table 1. Descriptive statistics of variables

Variables	Mean	Std. Deviation	Median
Amihud illiquidity (C_{id})	0.568936	0.96777	3.478517
Security return (R_{id})	0.065011	0.112031	1.059354
Market return (R_m)	0.56547	0.075241	1.081979
Risk free return (R_f)	0.026746	0.026733	0.006529
Excess security return ((R_i-R_f)	0.03731	0.088384	1.039923
Excess market return ($R_m - R_f$)	0.034884	0.108654	0.964309
Aggregate illiquidity (C_{md})	2.289374	1.577845	2.460285
Change in aggregate illiquidity (ΔC_{md})	7.51E-05	6.65E-05	8.71E-05

Source(s): Authors

Table 2. Descriptive statistics of variables (LCAPM)

Variables	Mean	Std. Deviation	Median
Excess stock return (R_i-R_f)	7.674093	3.817721	15.12187
CAPM beta (Cov_rR)	0.934982	0.898105	0.115938
Liquidity commonality beta (Cov_cC)	1.866345	1.640785	1.720076
Covariance od security liquidity and market return (Cov_cR)	−2565.81	−1913.75	1818.986
Covariance of stock return and aggregate liquidity (Cov_rC)	−1.26E-05	−7.31E-06	2.48E-05

Source(s): Authors

Table 3. Correlation matrix

Variables	Cov_cC	Cov_cR	Cov_rC	Cov_rR
Cov_cC	1			
Cov_cR	0.495478	1		
Cov_rC	0.600069	−0.054753	1	
Cov_rR	0.29984	0.176981	0.133423	1

Source(s): Authors

sensitivity to market return (Cov_cR), return sensitivity to aggregate liquidity (Cov_rC), and CAPM market risk (Cov_rR). The study finds a very low correlation among the variables.

Table 4 reports the pricing of liquidity risks, i.e. Commonality in liquidity with market liquidity (Cov_cC), liquidity sensitivity to market return (Cov_cR), return sensitivity to market liquidity (Cov_rC), along with market beta (Cov_rR). Table 4 shows that the expected return is positively affected by the Covariance of asset and market illiquidity. This is due to

Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
Full Sample period (Q1–Q37)				
C	−54.7491	19.17098	−2.85583	0.1039
Cov_cC	4.325811	1.342079	3.223216	0.0843***
Cov_cR	−0.00611	0.001095	−5.58438	0.0306***
Cov_rC	47803.22	92819.23	0.515014	0.6578
Cov_rR	42.17366	19.59485	2.152283	0.1643
Diagnostic result				
Adjusted *R*-squared			0.939352	
Durbin-Watson statistics			1.916857	
J-B statistics			0.649993	0.72253
Wald Test			Chi-Square	
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			96.93168	0.0000
1st sub-sample period covers coalition govt. (Q1–Q13)				
Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
C	0.007761	0.033388	0.232449	0.8179
Cov_cC	−111.3584	61.81777	−1.801398	0.0828*
Cov_cR	2.62E+33	1.84E+33	1.426865	0.1651
Cov_rC	4.65E-35	2.12E-35	2.195561	0.0369**
Cov_rR	2.198640	1.204327	1.825616	0.0790*
Diagnostic result				
Adjusted *R*-squared			0.032286	
Durbin-Watson statistics			2.304690	
J-B statistics			52.52779	0.0000
Wald test			Chi-square	
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			5.034245	0.2838
2nd sub-sample period covers COVID-19 (Q33–Q37)				
Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
C	0.004055	0.019415	0.208874	0.8360
Cov_cC	311.9925	48.70856	6.405291	0.0000***
Cov_cR	3.91E+36	6.76E+36	0.578502	0.5672
Cov_rC	4.03E-42	8.15E-43	4.942505	0.0000***
Cov_rR	−5.157793	0.799318	−6.452739	0.0000***
Diagnostic result				
Adjusted *R*-squared			0.565285	
Durbin-Watson statistics			2.158476	
J-B Statistics			0.124596	0.939603
Wald test			Chi-square	
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			48.21219	0.0000

Note(s): *, ** and ***represent statistical significance at 1, 5 and 10% respectively
Source(s): Authors

Table 4.
Systematic risk factors

the risk premium associated with Commonality in liquidity stemming from the affluence effect of illiquidity. It is also noticed from the table that individual security illiquidity and market return covariance negatively influence the expected return of the stock market in India. This indicates that the investors prefer to accept a lower return on an asset with a higher return in market illiquidity. The result of both the estimated parameter Cov_cC, positive and significant, and Cov_cR, negative and significant, delivers a robust signal to support the theory (Acharya & Pedersen, 2005).

The results of the first sub-sample period covering the coalition Government in India are reported in Table 4. It shows the Covariance of the asset. The aggregate market liquidity (Cov_cC) represents the liquidity commonality, which shows negative and significant results, indicating that the expected return will decrease with the Covariance of asset liquidity and market liquidity. The covariance of asset return and market liquidity positively and significantly affects the average expected return. However, the results contradict the evidence of the theory (Acharya & Pedersen, 2005) in the Indian context during the coalition Government period. This may be because the investors demand more return when the market becomes less liquid. The result also reports that apart from systematic liquidity factors, the systematic market risk factor also positively affects the average expected return. Similarly, this study reported the results during the 2nd sub-sample period covering COVID-19. The systematic liquidity and market risk factors significantly affect the expected return during this period. The Covariance of asset liquidity and market liquidity is positive and significantly affects expected return, indicating that when both market and individual security become less liquid, the investors demand more return for holding the asset until the market recovers from illiquidity. Correspondingly, the Covariance of asset return and market liquidity is positively related to expected return, indicating that the investors demand more return in a less liquid market. The systematic risk factors are significantly related to expected return in both full and sub-sample periods, and the result is robust. The diagnostic result confirms that the ordinary least square regression model is well-fitted to the data. The Wald test confirms the inequality by rejecting the null hypothesis, and finally, the JB statistics accept the null hypothesis that residuals are normally distributed.

Table 5 presents the results of the asset pricing model when the study introduced the World Uncertainty Index (WUI) as a control variable in the (Fama & MacBeth, 1973) regression model to examine the robustness of the empirically verified (Acharya & Pedersen, 2005) model. The estimated Beta coefficient of Commonality in liquidity of individual assets with market liquidity Cov_cC is positive and significant. This indicates that the covariation of individual assets liquidity and market liquidity positively explains the average equity return variation in the Indian stock market, particularly in large-cap stocks. Secondly, the covariation of individual security illiquidity and market return Cov_cR negatively affects the expected return of the Indian stock market. Investors accept a lower return on an asset with a higher return in times of aggregate illiquidity. This is consistent with the theory, which is expected to be negative and significant.

The third estimated parameter for systematic liquidity risk is Cov_rC, the Covariance of individual security return and aggregate illiquidity. The result indicates that Cov_rC is positive and significant in contradiction with the empirically validated theory of Acharya and Pedersen (2005). It is expected to be negative and significant because investors are inclined to acknowledge a lower expected return on liquid security in a down market. The results of our study are consistent with those of other studies (Altay & Çalgıcı, 2019; Kumar & Misra, 2019) studies. This is due to the microstructure of emerging markets being different from the developed stock markets like the U.S., and the market microstructure-induced noise in Emerging Markets. The CAPM market Beta Cov_rR is the Covariance of the individual security return and market return, which is positive and significant. The estimated coefficient of the World Uncertainty Index is negative and significant, indicating that it negatively

Full sample period (Q1–Q37)				
Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
C	−43.65182	2.082014	−20.96616	0.0303
Cov_cC	2.860152	0.170528	16.77236	0.0379***
Cov_cR	−0.005691	0.000114	−49.91241	0.0128***
Cov_rC	108914.0	10291.48	10.58293	0.0600***
Cov_rR	44.97731	1.978838	22.72916	0.0280***
WUI	−8.25E-05	5.88E-05	−14.04011	0.0453***
Diagnostic result				
Adjusted R-squared			0.999388	
Durbin-Watson statistics			2.651971	
J-B statistics			0.582263	0.747417
Wald test (Chi-square)				
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			9799.409	0.0000
(Cov_cC + Cov_cR + Cov_rC + Cov_rR) = 0			112.1166	0.0000
(Cov_cC + Cov_cR + Cov_rC + Cov_Rr) = WUI = 0			223.4571	0.0000
WUI = 0			197.1248	0.0000
1st sub-sample period covers coalition govt. (Q1–Q13)				
Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
C	0.009037	0.032708	0.276283	0.7845
Cov_cC	−145.8221	64.93448	−2.245681	0.0334**
Cov_cR	3.30E+33	1.86E+33	1.776761	0.0873*
Cov_rC	5.78E-35	2.21E-35	2.611960	0.0148**
Cov_rR	2.857969	1.262090	2.264472	0.0321**
WUI	−0.001271	0.000866	−1.467411	0.1543
Diagnostic result				
Adjusted R-squared			0.071928	
Durbin-Watson statistics			2.469097	
J-B statistics			28.85721	0.0000
Wald test (Chi-square)				
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			7.149715	0.1282
(Cov_cC + Cov_cR + Cov_rC + Cov_rR) = 0			3.156879	0.0756
(Cov_cC + Cov_cR + Cov_rC + Cov_Rr) = WUI = 0			4.276204	0.1179
WUI = 0			2.153295	0.1423
2nd sub-sample period covers COVID-19 (Q33–Q37)				
Variables	Coefficient	Std. Error	*t*-statistic	*p*-value
C	0.003977	0.019284	0.206220	0.8381
Cov_cC	289.1589	48.09775	6.011901	0.0000***
Cov_cR	−3.91E+37	9.84E+36	−3.974941	0.0004***
Cov_rC	1.16E-41	3.76E-42	3.099367	0.0043***
Cov_rR	−5.105861	0.821207	−6.217505	0.0000***
WUI	−0.005480	0.002089	−2.623130	0.0137***
Diagnostic result				
Adjusted R-squared			0.571149	
Durbin-Watson statistics			2.127945	
J-B statistics			0.143232	0.930889
Wald test (Chi-square)				
Cov_cC=Cov_cR=Cov_rC=Cov_rR = 0			50.28166	0.0000
(Cov_cC + Cov_cR + Cov_rC + Cov_rR) = 0			15.80016	0.0001
(Cov_cC + Cov_cR + Cov_rC + Cov_rR)=WUI = 0			16.46680	0.0003
WUI = 0			6.880811	0.0087

Note(s): *, ** and *** represent statistical significance at 1, 5 and 10% respectively
World Uncertainty Index as control variable
Source(s): Authors

Table 5.
Systematic risk factors

affects the expected return on individual security. We found a contemporaneous negative and significant relationship between expected return and WUI.

Further, the study reports the results of the first sub-sample period, which covers the coalition Government in India. It depicts that all systematic liquidity and market risk factors are significantly related to the expected return. The results also report a decrease in the expected return of asset and market liquidity covariance. Furthermore, the Covariance of security liquidity with market returns and security return with market liquidity positively affects the expected return, implying that the investors need more return when the market is uncertain and less liquid, respectively. At the same time, the World Uncertain Index as a proxy for global economic and political uncertainty does not significantly impact expected returns during the period of the coalition government in India. Finally, our study reports the results of LCAPM augmented with the World Uncertainty Index (WUI), where all the systematic liquidity and market risk factors along with WUI significantly affect expected returns during COVID-19. The liquidity commonality, i.e. the Covariance of security and market liquidity, is positively linked to expected return because the investors demand extra return for bearing illiquidity risk. The covariance of security liquidity and market return negatively influences expected return, indicating that the investors accept lower returns in uncertain markets, which is consistent with the theory. In contrast, our study reports contradictory evidence of Covariance of security return and market liquidity positively affecting expected return, implying that the investors claim more return while the market is less liquid. The result also shows that the market risk factor is negative and significant. Finally, Table 5 shows that the WUI negatively affects the expected return. The consistency in the significant relationship of systematic risk factors with an expected return in full and sub-sample periods improves the robustness of the results. After introducing the WUI in the OLS regression model, the model's predictability has undoubtedly improved as the adjusted R-square value is 99% and DW statistics is more than 2. The JB statistics indicate that the residuals are normally distributed by accepting the null hypothesis in diagnostic results. Similarly, the Wald test confirms the inequality of coefficients in explaining the expected return. Firstly, the individual impact of all Beta coefficients for systematic risk is not equal, the combined effect of all Beta is not identical with the coefficient of WUI, and finally, the individual impact of the coefficient of WUI is also different from Zero.

The result shows that the positive and significant deterministic dummy variable for negative change in return has more impact on illiquidity than the positive change in return in the same magnitude. Table 6 uses the OLS Model to present the Contemporaneous Relationship between Illiquidity and Stock Return. The estimated coefficient β_1 of autoregressive one lag illiquidity, which is positive and significant, indicates that the past

Variables	Coefficient	Standard error	t-ratio	p-value
Intercept	0.00015	9.26E-06	16.17692***	0.0000
β_1	0.477710	0.017901	26.68688***	0.0000
β_2	−0.002250	0.000708	−3.178392***	0.0015
β_3	0.002328	0.001107	2.102864**	0.0356
Diagnostic result				
Adjusted R-squared			0.240250	
Log likelihood			14860.73	
F-statistics			240.9612	
D/W statistics			2.169016	
Wald test (Chi-square): $\beta_1 = \beta_2 = \beta_3 = 0$			722.8837	0.0000

Note(s): *, ** and *** represent statistical significance at 1, 5 and 10% respectively. OLS model ($ILLIQ_t = \alpha + \beta_1 ILLIQ_{t-1} + \beta_2 r_t + \beta_3 D_1 r_{t-1} + \varepsilon_t$)

Table 6.
Contemporaneous relationship between illiquidity and stock return

illiquidity data is informative and has the power to explain current illiquidity. Then, β_2 the measures of the return slope, irrespective of directional change, are negative and significant, indicating a contemporaneous relationship between return and illiquidity. The positive change in return reduces illiquidity and increases liquidity level in a market, consistent with (Chan *et al.*, 2013). Finally, β_3 the measures asymmetric impact of directional change of return on market illiquidity. The outcome of our study corroborates with the study of Hameed *et al.* (2010) that a decrease in liquidity associated with a negative return is more than the increase in liquidity associated with a positive return in explaining the asymmetric impact of asset prices in stock market illiquidity. While interpreting the asymmetric result of this model, the study confirms the presence of price informativeness and its immediate impact on illiquidity in the Indian stock market, supporting the empirical evidence of the illiquidity multiplier theory (Cespa & Foucault, 2014). The diagnostic result confirms the robustness of the model where the adjusted R-squared value is more than 24%, and D/W statistics is more than 2. Finally, the Chi-square value of the Wald test confirms the inequality. The result shows that the positive and significant deterministic dummy variable for negative change in return has more impact on illiquidity than the positive change in return of the same magnitude.

Table 7 presents the EGARCH (1,1) model to estimate the asymmetric impact of return shocks on its conditional volatility and illiquidity as an exogenous variable. The EGARCH (1,1) model (Nelson, 1991) is augmented with illiquidity and decomposed illiquidity, where market illiquidity is segregated into higher and lower illiquidity. In the mean equation component, we found that the estimated autoregressive parameter of market return is positive and significant in all three models, indicating that past one lag return is the important explanatory variable. In the variance equation of these models, the positive and significant α indicates that the most recent news significantly impacts conditional volatility. Secondly, the negative and significant γ confirms the asymmetric effect of shocks on conditional volatility in the Indian stock market, where the negative return shocks have more effect on conditional volatility than the positive return shocks. The positive and significant β in all three conditions, i.e. without illiquidity, with illiquidity, and with decomposed illiquidity, indicates high volatility persistency. However, it starts decreasing, i.e. 97.36, 97.23, and 96.99%,

Parameters/variables	Without illiquidity	With illiquidity	With illiquidity decomposed
Mean equation			
μ	0.0003(1.9476)*	0.0003(1.7609)*	0.0003(1.9134)*
R_{t-1}	0.0706(3.1899)***	0.0676(2.9842)***	0.0698(3.0843)***
Variance equation			
ω	−0.3518(-8.882)***	−0.367(-9.0)***	−0.3745(-9.58)***
α	0.1376(9.8683)***	0.1337(8.9022)***	0.1355(9.2225)***
Γ	−0.108(-13.493)***	−0.1112(-13.812)***	−0.114(-13.909)***
β	0.9736(258.03)***	0.9723(259.4)***	0.9699(263.31)***
Θ		22.877 (3.5585)***	
Θ_1			3.0408(0.395)***
Θ_2			−162.68(-2.625)***
Log likelihood	7533.264	7536.715	7539.242
Durbin-Watson stat	2.156062	2.149987	2.154451
Akaike info criterion	−6.57403	−6.57617	−6.577504
Schwarz criterion	−6.559	−6.558636	−6.557464
H-Q criterion	−6.568549	−6.569776	−6.570196
J/B statistics	335.2215	354.4676	341.7514

Note(s): *, ** and ***represent statistical significance at 1, 5 and 10% respectively,
Source(s): Authors

Table 7.
EGARCH (1,1)

respectively. The in the illiquidity augmented model is positive and significant, indicating that illiquidity has a direct and positive relationship with conditional volatility in the Indian context and can be treated as an important factor to be taken into consideration while making the investment decision. Finally, when we introduced both decomposed higher and lower illiquidity in a variance equation, the study found that (Θ_1) for higher illiquidity does not significantly impact conditional volatility. However, Θ_2 for lower liquidity is negative and significant, indicating that conditional volatility decreases with lower illiquidity. The model is appropriate and well-fitted to the time series data of the Indian stock market after satisfying all the AIC, SIC, and H-Q criteria. It also shows that the D/W statistics are more than 2.

Finally, in Table 8, we have applied the Granger causality model to investigate the causal relation between return, illiquidity, and return volatility in the Indian context. The study found the presence of unidirectional causality between these variables, i.e. the causality runs from a return to illiquidity, illiquidity to volatility, and finally, from a return to volatility, but the study does not find any reverse causality, and also reports that the return has the power to affect both illiquidity and volatility. Thus, it implies that when the expected return increases, it leads to a decreased illiquidity.

6. Concluding observation and managerial contribution

The study examined the influence of systematic liquidity risk on averaged equity return variation in the Indian stock market using the LCAPM model (Acharya & Pedersen, 2005) for a period from January 1, 2012 to March 31, 2021, considering the return and volume data of Large-cap stocks listed on the BSE and S&P BSE SENSEX. For pricing of liquidity risks, i.e. Commonality in liquidity with aggregate liquidity, liquidity sensitivity to market return, and return sensitivity to aggregate liquidity, along with market beta, the (Fama & MacBeth, 1973) cross-sectional regression model is applied in the study. World Uncertainty Index (WUI) is used as a control variable in the model to check the robustness of the result. The study found that the covariance of individual security liquidity with aggregate liquidity has an optimistic and substantial influence on the expected return. The Covariance of individual security liquidity and the market return has a negative and significant impact on the expected return. In contrast, the Covariance of individual security return and aggregate liquidity has a positive and substantial influence on expected return, which should be negative and significant, as per theory. The study also reports a contemporaneous negative and significant relationship between expected return and WUI. This contrary evidence may be because the market microstructure noise in Emerging Markets needs further study to include multiple nations. The outcomes of our study indicate that liquidity is a significant concern in the illiquid markets when investors rebalance their portfolios. Further in the time series set up, we found the presence of an asymmetric directional change in return on illiquidity; return is affecting both illiquidity and volatility, and finally, EGARCH (1,1) model confirms that

Table 8. Pairwise granger causality test (lag 2)

Null hypothesis	F-Statistic(*p*-value)	Decision
Return does not granger cause illiquidity	4.53308(0.0109)	Rejected
Illiquidity does not granger cause return	1.46912(0.2304)	Cannot Reject
Volatility does not granger cause illiquidity	0.30070(0.7403)	Cannot Reject
Illiquidity does not granger cause volatility	*66.4739(2. E-28)*	*Rejected*
Volatility does not granger cause return	1.05930(0.3469)	Cannot Reject
Return does not granger cause volatility	*150.346(2. E-60)*	*Rejected*

Source(s): Authors

illiquidity has direct and positive impact on conditional volatility but in specification our study found lower illiquidity reduces volatility.

The study supports the empirical validation of the theory except for the covariance between individual security return and market liquidity. This may be because of market microstructure-induced noise in Emerging Markets. Finally, one of the most important macroeconomic indicators, such as the World Uncertainty Index (WUI), is used to control the impact of global forces in the (Fama & MacBeth, 1973) cross-sectional regression model. Finally, the study reported the robustness in results after considering macroeconomic indicators in the cross-sectional regression model, which improves the model's predictability. The study results suggest that an investor demands a premium over the systematic market and liquidity risk. Further, the study findings signpost that the flow of funds amid markets disturbs illiquidity; hence, it impacts asset prices and risk premiums required by an investor.

The findings also deliver important implications to the regulators. The study's findings may attract the policymakers in investment strategy development to determine the optimum level of liquidity in the market. Since, liquidity is one of the most important factors in asset pricing and provides valuable information to individual and institutional investors for portfolio diversification, the study's outcome would have significant insinuation for investors to consider systematic and idiosyncratic liquidity risk while making investment decisions. Further, the study may be helpful for portfolio allocation strategy and the decision-making process of investors. The analysis could be extended further by spreading the study period, the number of nations, and multiple proxies for measuring Liquidity.

Note

1. https://www.imf.org/en/Blogs/Articles/2023/05/01/asia-poised-to-drive-global-economic-growth-boosted-by-chinas-reopening

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