Commonality in liquidity: An empirical examination of emerging order–driven equity and derivatives market

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Abstract

Using a sample of actively traded stocks and options from emerging order-driven market, this study examines and provides satisfactory evidence for the existence of *commonality in liquidity* for both spot and derivatives market. For equities; the market- and industry-wide commonality remain strong even after controlling for market returns and individual firm volatility and for options after accounting for the underlying stock market liquidity and implied volatility. Compared to the stock market, options market exhibit an increased commonality in liquidity with market capitalization. Here information asymmetry acts as an important microstructure related source of commonality in liquidity across markets. The findings are robust across call and put options with negligible evidence of cross-sectional error correlation for all the liquidity measures.

JEL clasificación: G12, G15

Keywords: Microstructure, commonality, liquidity, emerging order–driven market.

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1. Introduction

Liquidity is an important property of any capital market. Liquid markets require market-makers who are willing to buy and sell, and be patient while doing so. A lack of market liquidity may be responsible for inadequate trading in some markets. The liquidity in-turn results in better price discovery, lesser market manipulation and lower transaction cost. The relationship between liquidity and stock market crashes has been one of the central issues in the international corporate finance literature. The level and variability of liquidity in a particular market has direct implication on the portfolio selection strategies of the investors because liquidity risk is a key determinant of asset prices. Prior to seminal work of Chordia et al., (2000), traditional research on liquidity had been primarily focused on individual assets but post Chordia et al., (2000) there was a swift shift of research focus from a single asset to a market-wide phenomenon with respect to liquidity. Chordia et al., (2000) hypothesize that individual market structure phenomenon such as liquidity has common underlying determinants and hence should not be treated in isolation. This phenomenon is termed as *'Commonality in Liquidity'* (CiL hereafter) and is formally defined as the proportion of how much a firm's liquidity is at least partly explained by the market-wide and industry-wide factors (Brockman and Chung, 2002). After Chordia et al., (2000), there has been plethora of research documenting the presence of CiL and the role of common liquidity factors in context with the quote-driven and order-driven markets.

Most of these studies are focused on developed quote-driven markets (Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Coughenour and Saad, 2004; Kamara et al., 2008; Corwin and Lipson, 2011; Karolyi et al.2012) or developed order-driven markets (Brockman and Chung, 2002; Fabre and Frino, 2004; Domowitz et al., 2005). Very few studies are dedicated to understand CiL of order-driven markets (Hong Kong by Brockman and

Chung, 2002, Australia by Fabre and Frino, 2004 and Taiwan by Lee et al., 2006) let alone emerging markets which are highly illiquid (Lesmond, 2005).[1]

Given the evidence that liquidity risk exists in options market, Cetin et al., (2006) show that liquidity risk could impact option prices significantly. Traders use options for hedging and speculative purposes. The amount of liquidity risk (or CiL) present in these markets can significantly impact the trading strategies and profits. Interestingly there is no evidence of CiL for an order-driven derivatives market. Furthermore it is important to address this issue since the evidence on CiL findings from other asset classes and developed markets may not hold true in the case of emerging derivatives markets because emerging markets are highly illiquid (Lesmond, 2005)[2] consequently resulting in high CiL.

The primary objective of this study is to fill an important gap in the literature by documenting the evidence of CiL in an emerging order-driven equity and derivatives market. To the best of our knowledge, ours will be the first study to examine CiL for an order-driven derivatives market. The results of this study will help the market participants to understand liquidity dynamics of these markets and device strategies to overcome the negative impact of CiL. The evidence on commonality in derivatives market may shed some light on the reasons for the under-development of the derivatives markets compared to the equity markets in emerging economies. These findings have a two-fold contribution to the literature in understanding the dynamics of CiL of an order-driven options market because these markets typically do not have any appointed market makers and there are also no voluntary market makers for option trading, therefore order-driven emerging markets can experience significant liquidity risk.

[1] Emerging markets are known to exhibit poor political and legal system and high liquidity cost (Bekaert and Harvey, 2000).

[2] See Tett, (Financial Times, Oct. 31, 2013) – 'If a shock was to hit Brazil, India, Indonesia – or any other emerging market country – tomorrow, how would investors react? Would asset values adjust smoothly, amid an explosion of trading flows? Or would markets instead freeze up, as *liquidity evaporated?* ....'

The importance of liquidity is widely documented in the finance literature. Even though liquidity affects asset prices, the idea that CiL also affects asset prices is not taken into consideration by the conventional models in the asset pricing literature and thus these models have to be modified to incorporate the effect of CiL on asset prices (Acharya and Pederson, 2005). Next the issue of concern for the market participants is to know whether the market liquidity is priced or whether the market risk factor due to CiL enters the stochastic discount factor. If the asset returns are strongly associated with market returns, the determinants of CiL may establish a non-diversifiable risk factor and hence it is an expensive risk factor and investors holding such assets in their portfolio require a risk premium. Besides an additional risk for the investors, it also creates problems for portfolio managers in diversifying their risk who depend on choosing uncorrelated stocks (Domowitz et al., 2005). Therefore CiL is of major concern to government regulators as well as reserve banks because it is a non-diversifiable risk factor and any shocks to CiL may cause market-wide effects and may also impact the smooth working of the financial markets leading to financial crisis or stock market crashes.[3] Therefore what factors impact CiL and identifying their economic effects will help in preventing future market crashes. Also, a detailed examination of commonality may help in understanding how market-wide and industry-wide liquidity movements impact different asset classes and thereby assist the policy makers to formulate better monetary policies.

By using intraday and daily data we estimate six measures of liquidity (Spread, Percent Spread, Depth, Roll’s Spread, Spread_HL, and Amihud) for equity market and four measures of liquidity (Spread, Percent Spread, Depth, and Volume) for the options market for a period of two years from April 01st, 2010 to March 31st, 2012. We find evidence in support of CiL for both

[3] The sudden disappearance of market liquidity across various markets is the major factor causing the Asian financial crisis in 1997-98 as well as the recent 2008 global financial crisis.

equity and options markets of National Stock Exchange (NSE) in India. Our results are consistent with all the liquidity measures used in the study. By using market-model time-series regressions, we report significant market- and industry-wide CiL. Although concurrent industry-wide CiL is higher compared to market-wide CiL for four liquidity measures, nevertheless *Sum* for the previous, current, and next day market-wide CiL dominates the *Sum* coefficient of industry-wide CiL. Besides finding evidence for size effects in CiL, we also find commonality at portfolio level. Furthermore, we document that asymmetric information; as measured by trading frequency is one of the microstructure determinants of CiL for both stocks and options. Lastly we establish that over a contemporary sample period, options market CiL is significantly higher than equity market, which might be driven by the illiquid nature of the options market compared to the equity market in India.

The remainder of this article is organized as follows. The section 2 discusses theoretical background and literature review of the work related to CiL. Section 3 talks in detail about the institutional set-up for NSE, India. In section 4, we explain in detail the data and methodology used in this study. The empirical results on the evidence of CiL on NSE, India are discussed in section 5. Section 6 discusses the existence of CiL under different market settings. Robustness check for asymmetric information and cross-sectional dependence of the error terms are included in section 7. Finally, summary and concluding remarks are presented in the last section 8.

2. Literature Review

2.1 Commonality in liquidity in the equity market

Chordia et al., (2000) is the first study which introduces the idea of CiL. It brings in a new dimension to the existing research and argues that liquidity is not an asset-specific phenomenon but rather there exists a co-movement in liquidity measure across assets. By using

NYSE Transactions and Quotes (TAQ) data for the year 1992 for 1169 stocks, they document the evidence for the existence of CiL even after controlling for individual sources of liquidity such as trading volume, price, and volatility. By employing a market model time series regression, they document circa 35% of the stocks to have positive and significant concurrent slopes while simultaneously detecting a significant industry component of commonality. In line with Chordia et al., (2000); Huberman and Halka (2001), by using a sample of 240 stocks from NYSE TAQ database for 1996 show evidence for the systematic component of liquidity and the variables that are correlated with CiL. They find that the residuals from the time-series market model regression of the average liquidity measure for each of the stocks are positively correlated with and without the inclusion of the explanatory variables which provides evidence for CiL.

Hasbrouck and Seppi (2001) used liquidity measures computed at 15-minute intervals for thirty most actively traded DJI Index firms to document cross-sectional relationship for returns, order flows and liquidity. Principal component analysis and canonical correlation analysis are used to investigate commonality. After controlling for time-of-the-day seasonality, they find significant common factors for quote based proxies of liquidity but contrarily less significant factors for price impact measures of liquidity. There results show that common factors exist in each of the signed order flows and absolute order flows. Next, Coughenour and Saad (2004) argue that liquidity co-variation can arise due to a major NYSE specialist firm supplying liquidity for many different firms as they may share combined capital, profit and loss information and inventory. After adjusting the intercept for intra-day variations in liquidity they find that the liquidity of an individual stock is more susceptible to market portfolio than the specialist portfolio and the liquidity β of the specialist portfolios is slightly higher than those of individual firms.

The initial phase of research on CiL primarily focused on the quote-driven markets but Brockman and Chung (2002) are the first to extend the literature on CiL in the order-driven markets.[4] They document a significantly positive coefficient for 26.1% off the 725 firms from the Hong Kong Stock Exchange (HKSE). Some of their findings were contradictory to the prior research on quote-driven markets whereby they find large firms to be less susceptible to commonality, a significant industry component for depth based measure of liquidity and provided preliminary evidence on trading frequency as the determinant of commonality. Next Fabre and Frino (2004) investigate CiL in the developed order-driven market *i.e.* Australian Stock Exchange (ASX). By taking intraday quotes and trades data for 660 stocks in the year 2000, they show a weaker evidence of CiL on the ASX. Next Kempf and Mayston (2008) examine the CiL in an order-driven market beyond that of best prices.[5] They use a sample of DAX-30[6] stocks listed on the Frankfurt stock exchange (an open limit-order book) from January 2004 to March 2004. After standardizing the liquidity measures, they examine commonality beyond best prices and consider the price impact measure beyond the inside spread. They conclude that CiL increases from 3.71% for the median depth to nearly 10% for the largest depths as they advance deep into the order book which clearly shows that the large investors find it problematic in diversifying the liquidity risk. From the above literature, the evidence on the existence of CiL is mixed in case of order-driven markets and therefore these findings may not be generalized for NSE, India as it is an emerging open electronic order-driven market.

2.2 Commonality in liquidity in the derivatives market

[4] Unlike the quote-driven market system, in an order-driven market, any market participant is free to enter or exit the market at any time and there is no obligation on anyone to supply liquidity to the market.

[5] It is important to understand liquidity commonality beyond best prices because in an order-driven market, generally small orders execute at the inside spread. When a large order arrives beyond the available depth, it immediately moves to the front of the order book until it gets executed resulting in a higher cost of execution.

[6] Deutscher Aktien Index.

While the above literature examines CiL for the equity markets, Cao and Wei (2010) extend the Chordia et al., (2000) methodology on a sample of 1,589 distinct stocks having options listed on them from 1996 to 2004 to investigate CiL in equity options market. Due to absence of intra-day data on options, Cao and Wei (2010) use only proportional bid-ask spread, contract volume, trading volume in dollar terms, and Amihud (2002) illiquidity measure and show a satisfactory evidence for CiL. Their results are robust for call and put options individually while simultaneously finding a significant size effect, with small stocks having higher significance than the large stocks. Following Cao and Wei (2010), Marshal et al., (2013), look into the CiL for the sixteen different commodities which are a part of S&P Goldman Sachs Commodity Index from 1997 to 2009. By implementing the Chordia et al., (2000) and Kamara et al., (2008) methodologies they use proportional effective spread, proportional quoted spread, and Amihud's price impact as proxies for commodity liquidity. Their results show a consistent pattern in liquidity co-movement across all the commodities with commodities exhibiting higher CiL compared to stocks. They also establish a positive relation between stock market systematic liquidity and commodities market commonality which supports the argument that investors consider commodities as alternative asset class to stocks.

The above studies examine CiL in the context of quote-driven derivative markets. Our study is the first to examine CiL for an order-driven options market. Overall, order-driven markets have become more prevalent trading platforms these days due to advancements in information technology and reforms in financial market regulations. Furthermore, recently a significant number of new equity and derivatives markets in emerging countries have been adopting order-driven trading platform (Brazil, China, India, Russia, and Turkey) and hence proper insight is required to comprehend the functionality of these markets to enhance the trading quality. Also, the market structure determines how order submission and subsequent conversion of orders into trades affects the liquidity because there is no designated market maker in an order-driven market and since limit orders are submitted by market participants and therefore how the order submission process affects market liquidity in equity and options market is the main focus of this study.

3. Institutional set-up for National Stock Exchange (NSE), India[7]

Since its establishment in 1992 as an outcome of April 1991 financial liberalization of the Indian economy, NSE has played a prominent role in transforming the Indian capital market to its present state. It operates in three major segments: capital equity market, wholesale debt market, and derivatives market. NSE operates on a completely automated anonymous screen based trading system and follows strict price/time priority. It is an electronic limit order book market with no designated market makers. The exchange operates with an opening call auction and continuous auction throughout the day with a *T+2* rolling settlement cycles. NSE, India has observed a phenomenal growth in the trading volumes over the past few years, contributing up to 83% of the total turnover with an average daily turnover of US$ 1.9 billion in India during financial year 2012–13.[8] According to the recent World Federation of Exchanges statistics (2013),[9] NSE is the market leader in terms of equity trading with 1.40 billion trades followed by NYSE Euronext (US) as a close second with 1.37 billion trades at the end of December 2012.

Trading in equity derivatives on NSE, India commenced in the year 2000 with the index futures. Next, index options started to trade on NSE in June 2001 followed by options on

[7] We would like to thank our anonymous referee for encouraging us in including a section on the working and institutional set-up of NSE, India.

[8] The information and statistics are taken from the "Indian Securities Market Review, 2013" report available on NSE's website www.nseindia.com.

[9] The World Federation of Exchanges (WFE) statistics are available in csv file format and can be accessed at http://www.world-exchanges.org/statistics/annual-query-tool

individual securities in July 2001. The derivatives trading system provides fully automated, screen-based trading platform for all derivative products. It supports an anonymous order-driven market without any designated market makers and operates on strict price-time priority. The individual options used in this study as well as other derivative products are exchange traded. The value of equity derivatives is twice the value of actual equity trading on NSE, India. The total turnover for derivative contracts on NSE in the financial year 2012–13 was *circa* US$ 7 trillion with an average daily turnover of US$ 28.13 billion during this period. According to the Futures Industry Association (FIA) annual volume survey report for 2013,[10] in 2012, NSE, India held fourth position in terms of number of single stock futures contracts traded, second in terms of stock index option contracts traded and fifth in terms of number of stock index futures contracts traded. As per 2013 FIA report, NSE India is the third biggest derivatives exchange with respect to the number of options and futures traded globally (after CME group and Eurex) and biggest among the emerging markets. This exceptional growth of a stock exchange, both in terms of trading volume and turnover within a short span of two-decades since its formation, makes it of first-order importance for the researchers and practitioners to look into the liquidity risk of the contracts being traded on this platform.

4. Data description

We use high frequency daily intraday transactions and order-book snapshot data for equity and options market separately provided by the National Stock Exchange (NSE), India over a period of two years from April 01st, 2010 to March 31st, 2012. The transactions data is recorded for all transactions that took place in our sample period. For the stocks, the trade data comes in a single file with information regarding each and every transaction with time stamp on

[10] The FIA report can be accessed at http://www.futuresindustry.org/downloads/FIA_Annual_Volume_Survey_2013.pdf

a daily basis. NSE collects the snapshot data of the limit-order book at four different time instances during the trading day at 11 A.M., 12 P.M., 1 P.M., and 2 P.M. which gives all the information regarding the quotes (with time stamp) placed by various market participants on that particular day at that specific time instance. Similarly for the options, the trade and snapshot data is obtained for all the option series except that unlike equity, options limit-order book snapshot data is collected at five different time instances of the day by NSE, *i.e.*11 A.M., 12 P.M., 1 P.M., 2 P.M., and 3 P.M. The operating time of stock and options market is synchronized from 9.15 A.M. to 3.30 P.M. for the sample period.

During our sample period, we initially have a stock-level data for 1501 firms traded on NSE over 504 trading days. We construct our final sample of intraday data for the equities in vein with Chordia et al., (2000). Firstly, in order to avoid any contaminating effect of tick size, we filter the top one percent and bottom one percent firms which give us a sample of 1470 firms. Next since stocks with infrequent trades do not provide reliable information we remove infrequently traded stocks, *i.e.* stocks with less than 200 active trading days over our sample period resulting in a sample size of 1404 firms. Finally adopting the criteria followed by NSE to identify illiquid stocks, we delete all those stocks with an average daily trading volume of less than 10,000 shares and number of trades less than 50 in a quarter which gives us a final sample of 960 firms.[11] After the equity dataset, we employ Cao and Wei (2010) approach to screen the options dataset. The total number of options listed on NSE is 256. We eliminate the option data for the firms with observations with zero trading and the one with less than five contracts traded

[11] This criterion is defined by Securities and Exchange Board of India (SEBI) and followed by all major stock exchanges in India to identify illiquid securities. These illiquid securities are reviewed on a quarterly basis by the respective stock exchanges and are traded using a different trading mechanism *i.e.* all the illiquid securities are traded on call auction basis throughout the day as opposed to the liquid securities which have an opening call and continuous trading throughout the day. The daily average number of shares traded in our sample in a quarter is about 300,000 spread over *circa* 700 trades.

on a given trading day. This screening criterion reduces the sample to 201 options. To safeguard the key hypothesis of this study, we eliminate the options with very short (less than seven days) or very long (more than 365 days) maturity thereby giving us a sample size of 194 firm-level option data. Next in order to avoid any pricing related issues caused due to moneyness,[12] we drop the observations with moneyness between 0.9 and 1.1 in our sample which reduces the count to 191. Lastly we filter the sample to include options with at least 300 option observations in a year resulting in a final sample size of 143.

For our analysis of the equity market, we estimate six liquidity proxies; Absolute Spread (Spread), Percentage Spread (Pspread), Quoted Depth (Depth), Roll's Spread (Roll) following Roll (1984), High Low Spread Estimator (Spread_HL) in line with Corwin and Schultz (2012) and Amihud (2002) illiquidity measures (Amihud). First four measures are constructed using intraday data while the latter two (Spread_HL and Amihud) use daily data. The snapshot files containing the limit order book information lists all outstanding orders which are identified as buy or sell at the time when the snapshot is recorded. We estimate the spread and depth measures by extracting the highest ask price (and associated quantity) and the lowest bid price (and associated quantity) at each of the snapshot record time on a given trading day. For the options market, we construct four liquidity measures; Absolute Spread (Spread), Percentage Spread (Pspread), Quoted Depth (Depth), and Trading Volume (Volume). To overcome intraday idiosyncrasies and to conveniently manage the data, following Chordia et al., (2000) and Brockman and Chung (2002), each liquidity proxy for each stock is constructed as an equally weighted average of intraday liquidity measure. Thus for each of the 960 stocks, the sample consists of at most 504 observations *i.e.* one each for each trading day during the sample period.

[12] Following Cao and Wei (2010), we define moneyness as exercise price divided by stock price for both put and call.

In case of options, we follow Cao and Wei (2010) and use the volume-weighted average of intraday liquidity measure for all the option series on a stock to arrive at a daily liquidity measure for each option (we also do this individually for call and put options). By doing this, each of the 143 listed options in the sample has at most 504 observations for the full sample.

5. Empirical results for commonality in liquidity

5.1 Summary Statistics

Table 1 presents our main sample descriptive statistics across all the liquidity parameters used for the equities and the options in the study. In case of equities, we report six different proxies for liquidity for 960 stocks in our sample, off which four are constructed using intraday data (Spread, Pspread, Depth and Roll) while the remaining two use daily data (Amihud and Spread_HL). Similarly, three liquidity parameters for 143 firm-level option contracts *i.e.* Spread, Pspread and Depth use intraday tick-data while the fourth is the daily trading Volume. In panel A of table 1 we present the summary statistics – mean, standard deviation, median, 5th, 25th, 75th and 95th percentile, minimum and maximum values and the number of firm intraday tick-data observations for all the liquidity parameters for NSE equities and options. In panel A1 and A2 it can be observed that the average spread on NSE equity (options) market is INR 1.34[13] (INR 3.22) with a range of INR 0.05 (INR 0.01) to INR 30.00 (INR 1307.53) from 2010 to 2012. The numbers for percentage spread are comparable to the spread for both the equities and options. Next the average depth for the sample stocks (options) is 376 (3897) shares with a standard deviation of 1191 (5754) shares and a range from 6 (125) shares to circa quarter million shares for both stocks and options. A higher value for the option contracts over equities clearly shows

[13] In order to avoid any form of exchange rate bias, in this study we report all our findings in local currency numéraire i.e. Indian Rupee (INR). For the convenience of the readers – the average daily exchange rate for the sample period between Indian Rupee and US$ is 46.84. The minimum and maximum for the same period was 44.24 and 54.07 respectively.

the sign of illiquidity in the option market in the Indian set-up. The remaining three liquidity variables for equities show similar pattern as the three discussed above with Amihud exhibiting the maximum variation (320.44) with a range of 0 to 32495 with an average (median) value of 16.72 (22.13). Besides the standard summary statistics we also report the 5th, 25th, 75th and 95th percentile value for all the liquidity parameters in order to show the significant variability in our sample. Lastly, our estimation for the CiL in subsequent tables is based on a rich sample of *circa* 2.2 million intraday observations for six equity-level liquidity proxies and 220,932 intraday observations for four option liquidity proxies in total.

Panel B of table 1 shows the cross-sectional means of pair-wise time-series correlations of different liquidity proxies used in the study. Panel B1 presents the correlation for the equity market followed by the options market in panel B2. It can be observed that all the liquidity measures are significantly correlated at 1% significance level with only few exceptions which are then correlated at 5% level. As expected, Spread and Pspread shows highest correlation level for both equity (0.84) and option (0.45) markets alike. Next Roll factor also shows significantly high correlation and so do Amihud and Spread_HL which have a correlation coefficient of 0.31. This establishes that Spread_HL as a reliable measure for liquidity as shown by Corwin and Schultz (2012).

[Please insert table 1 about here]

5.2 Market-wide stock market commonality in liquidity

To examine market-wide CiL for equity market for the firms listed on the NSE, India, we run firm by firm market model time series regressions. We regress the percentage change in individual stock liquidity measures on the percentage change in market liquidity measure. The market liquidity measure is an equally weighted average liquidity of all stocks in the market excluding the stock under examination in order to eliminate any cross-sectional dependence in the estimated coefficients. The market model time series regression is given as:

$$DLIQ_{j,t} = \propto_J + \beta_{1,j} DLIQ_{M,t} + \beta_{2,j} DLIQ_{M,t+1} + \beta_{3,j} DLIQ_{M,t-1} + \delta_{1,j} Return_{M,t} + \delta_{2,j} Return_{M,t+1} + \delta_{3,j} Return_{M,t-1} + \delta_{4,j} Volatility_{j,t} + \varepsilon_{J,t} \quad (EQ1)$$

Where, j = 1, 2, 3………, 960, t = 1, 2, 3………., 504.

Here $DLIQ_{j,t} = (LIQ_{j,t} - LIQ_{j,t-1})/LIQ_{j,t-1}$ denotes the percentage change in each of the six liquidity measures used in the study on a given day t for a firm j. $DLIQ_{M,t}$ is the concurrent percentage change in the corresponding average market liquidity measure. We also include a lag and lead market liquidity variables in *EQ1* to capture any non-synchronous change in liquidity due to thin trading while the concurrent, lag and lead market return along with idiosyncratic firm volatility act as control variables. The rationale for including the control variables is to help segregate the impact of changes in market-wide liquidity on an individual firm's liquidity after accounting for market-wide price changes and idiosyncratic volatility. Following Fama–MacBeth (1973) we report the cross-sectional means of time-series slope coefficients with the t-statistics to test the null hypothesis that there is no market-wide CiL for stocks listed on NSE, India. The description and construction of six firm-level liquidity factors for equities and options used in this study are as follows:

(a) Absolute Spread (Spread): It is estimated as the difference between highest bid and lowest ask price quoted by the market participants at each snapshot record time. It is one of the high-frequency liquidity measures used in most of the liquidity studies to measure the liquidity of a stock.

$$Spread = P_{Ask} - P_{Bid}$$

Where, P_{Ask} is the lowest asked price quoted and P_{Bid} is the highest bid price quoted in the interval concerned. The absolute quoted spread is in rupee units.

(b) Percentage Spread (*Pspread)*: This high frequency liquidity measure is computed as the ratio of absolute quoted spread to the average of asked price and bid price in a given interval.

$$Pspread = \frac{P_{Ask} - P_{Bid}}{P_{Mid}}$$

Where P_{Mid} is the average of *ask* and *bid* prices.

(c) Quoted Depth (*Depth)*: This high frequency liquidity measure signifies a stock's capability to take in the demand for buy and sell orders without much price impact. It is computed as the average quantity of asked shares and the bid shares.

$$Depth = (Q_{Ask} + Q_{Bid})/2$$

Where, Q_{Ask} is the quantity of asked shares and Q_{Bid} is the quantity of bid shares. It is quantified by number of shares.

(d) Roll's Spread (*Roll)*: The Roll's spread is based on the assumption that there would not be any serial correlation in observed price changes when trading costs are zero. It is given by

$$Roll = 2\{-Cov(\Delta P_t, \Delta P_{t-1})\}^{1/2}$$

Where, P_t is the trade price at time t, and $Cov(\Delta P_t, \Delta P_{t-1})$ is the serial covariance between successive price changes.

(e) High Low Spread Estimator (*Spread_HL)*: This measure is a recent measure proposed by Corwin and Schultz (2012) to estimate the spread from daily low-high prices. It is given by

$$Spread\_HL = \frac{2(e^{\propto} - 1)}{1 + e^{\propto}}$$

Where, $\propto = (\sqrt{2\beta} - \sqrt{\beta}/(3 - 2\sqrt{2})) - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$

$$\beta = (Ln\left(\frac{H_t}{L_t}\right))^2 + (Ln\left(\frac{H_{t+1}}{L_{t+1}}\right))^2$$

$$\gamma = (Ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right))^2$$

Here, H_t and L_t are the daily high and low prices.

(f) Amihud's Illiquidity (*Amihud*): Amihud (2002) compute liquidity measure which captures the daily price impact associated with a stock per one dollar of trading volume and it is defined as follows:

$$Amihud_t = \frac{|Return_t|}{Volume_t}$$

Where, Amihud's liquidity measure on day t is calculated as the ratio of absolute return of a security on day t to the total traded volume of that security on that day.

Table 2 reports the results for the existence of market-wide CiL for the equity market by employing six different liquidity measures. The main parameter of interest *i.e.* concurrent mean coefficient (t-statistics) - β_1 is 0.707 (27.1) for the spread measure. Spread is positive (and significant) for 89.81% (32.23%) of the 960 time series regressions while negative and significant for 0% of firms in the sample. The sum of all liquidity coefficients ($\beta_1 + \beta_2 + \beta_3$)[14] is also positive (0.547) and significant (10.69). These results provide preliminary support for the existence of CiL in an order-driven emerging equity market. Simultaneously a higher β_1 coefficient in the case of NSE compared to HKSE (Brockman and Chung, 2002) show that CiL has relatively higher effect on spread of emerging market stocks. Next, for percentage spread the mean estimated coefficient (t-statistics) of interest β_1, is 0.728 (28.61) which is positive (positive and significant) for 90.48% (35.44%) and negative and significant for 0% of the firms. The sum of all liquidity coefficients (t-statistics) is 0.527 (11.17) which are comparable to our findings for spread. The depth measure has a mean coefficient (t-statistics) of 0.225 (5.07) but it is positive and significant for only 12.40% of sample firms, a significantly low proportion compared to the quote-driven and prior (developed) order-driven market studies. The Roll's measure has the highest coefficient across the four liquidity parameters based on the snapshot data. It has a mean estimated slope coefficient (t-statistics) of 0.882 (19.76) and a sum

[14] concurrent + lag + lead

of 0.960 (11.12). This coefficient is positive (positive and significant) for 90.72% (45.18%) of the sample firms.

[Please insert table 2 about here]

These results give enough evidence for the existence of CiL in the context of NSE equity market using intraday liquidity measures. Similar to the intraday measures, liquidity variables constructed using daily data also show high degree of CiL. For instance, the concurrent (β_1) coefficient (t-statistics) for the Spread_HL and Amihud measure is 0.920 (75.65) and 0.462 (5.72) while it is positive (and significant) for 99.46% (48.91%) and 86.47% (45.99%) of the sample-firms respectively. The sum of ($\beta_1 + \beta_2 + \beta_3$) is also highly significant for these daily data liquidity proxies which shows that CiL is highly pervasive in the context of emerging order-driven equity market.

5.3 Market-wide options market commonality in liquidity

We analyze the methodology used by Chordia et al., (2000) and Cao and Wei (2010) to study the CiL for the NSE, India options market; nevertheless, we make some modifications to *EQ1* for it to accommodate the requirements and of the options market. The revised time-series market model regression in the case of options market is given as:

$$DOPLIQ_{j,t} = \propto_J + \beta_{1,j}\, DLIQ_{j,t} + \beta_{2,J} DOPLIQ_{M,t} + \beta_{3,J} DOPLIQ_{M,t-1} + \beta_{4,J} DOPLIQ_{M,t+1} + \beta_{5,J}\, DLIQ^{res}{}_{M,t} + \beta_{6,J}\, DLIQ^{res}{}_{M,t-1} + \delta_{1,J}\, Return_{j,t} + \delta_{2,J}\, ImpVol_{j,t} + \varepsilon_{j,t} \quad \textit{(EQ2)}$$

where, j = 1, 2, 3………, 143, t = 1, 2, 3………., 504.

Here $DOPLIQ_{j,t} = (OPLIQ_{j,t} - OPLIQ_{j,t-1})/OPLIQ_{j,t-1}$, denotes each of the four option market liquidity measures used in the study on a given day t for a firm j. $DOPLIQ_{j,t}$ is the percentage change in the option's liquidity measure and $DLIQ_{j,t}$ is the percentage change in the liquidity measure of the stock corresponding to the option which controls for the positive association between liquidities of the equity and options market due to hedging demand of the later. $DOPLIQ_{M,t}$ is the option market's liquidity measure and, $DLIQ^{res}{}_{M,t}$ is the residual from the regression equation given below:[15]

$$DLIQ_{M,t} = \propto_0 + \propto_1 DOPLIQ_{j,t} + \varepsilon_t \qquad (EQ3)$$

$DLIQ^{res}{}_{M,t}$ is included in *EQ2* to make sure that the coefficients estimated are purely for the options market. The underlying firm's return $(Return_{j,t})$ and option's implied volatility $(ImpVol_{j,t})$ are additional control variables. Next, as discussed above for the equity market, we run firm by firm time-series regression for the model stated in *EQ2* for all the options in our sample and use Fama-MacBeth (1973) methodology to estimate the cross-sectional mean of time series slope coefficients and associated t-statistic.[16] Table 3 presents the time-series regression results for the liquidity model discussed in *EQ2*. The findings in the table show satisfactory evidence for the existence of CiL on the NSE, India options market. The regression coefficients (t-statistics) for the key parameter of interest viz. concurrent option market liquidity - β_2 is 0.654 (19.11) while the numbers are qualitatively similar for the percentage spread and significant at 1% level for the remaining three liquidity proxies for the options used in this study.

The coefficient is positive (positive and significant) for 97.9% (79.02%), 100% (87.41%) and 99.3% (78.32) of the total 143 option contracts for spread, percentage spread and trading volume measures while shows no sign of significance when the desired coefficient is negative.

[15] As our liquidity measures are free of transaction prices and effective bid-ask spreads (this is a data availability issue because currently NSE, India does not disseminate continuous order book data and hence it is difficult to estimate effective spreads), we do not include the market returns in EQ3 as there won't be a problem with the correlation between liquidity measures and market returns.

[16] We also report the percentage of firms having a positive (positive and significant) and negative (negative and significant) coefficients for the concurrent option market liquidity (β_2), its lag (β_3), the stock market liquidity (β_1) and the concurrent residual (β_5). We also report the mean R^2 and mean adjusted R^2 along with the sum of the concurrent and lagged variables. For brevity, though the coefficients of other control variables are not reported here, but are available from the authors on request.

Furthermore, we can easily see that the spread based mean coefficients for the option contracts in table 3 are comparable with the stock market mean coefficients for spread (as reported in table 2 above), even after controlling for the underlying stock market liquidity; thereby establishing clear sign of CiL for option contracts listed on NSE, India. Next we find mixed results for the options market lagged liquidity parameter - β_3 which is not only small and negative in terms of magnitude but only significant for three of the four proxies (Spread, Pspread and Depth). Whatsoever the case maybe, the sum of the lagged and the concurrent proxies is positive and significant across all the four variables. The mean coefficient for the concurrent stock market liquidity measure (β_5) is positive and significant for all the four measures. Finally the evidence for co-variation between options and lagged equity market liquidity are mixed as even though the mean coefficient (β_6) is positive for all liquidity measures, it is significant only for spread and percentage spread.

[Please insert table 3 about here]

Overall, our results are consistent with the findings with respect to the quote-driven market study by Cao and Wei (2010). For a deeper analysis, we individually perform the similar analysis for call and put options. Here we employ the model specification similar to *EQ2* with one minor modification, *i.e.* market liquidity measure for the call and put options – $DOPLIQ_{M,t}$ ($DOPLIQ_{M,t-1}$) is the equally weighted average of only call and put options respectively. Appendix A1 and A2 reports the results for call and put options respectively. The results are qualitatively similar to the one discussed above for all the option contracts in terms of CiL. Nevertheless, the mean estimated option liquidity coefficient is higher for call options compared to put options. This evidence reveals that call options are more susceptible to CiL and thus should be priced accordingly.[17]

6. Commonality in liquidity under different settings

6.1 Industry-wide stock market commonality in liquidity

In this sub-section, we study the impact of industry-level liquidity on the individual firm-level liquidity measures for equity while simultaneously controlling for the impact of market liquidity. To examine industry-wide liquidity on firm-level liquidity we use the following time-series regression model coined by Chordia et al., (2000):

$$DLIQ_{j,t} = \propto_j + \beta_{1,j} DLIQ_{M,t} + \beta_{2,j} DLIQ_{M,t+1} + \beta_{3,j} DLIQ_{M,t-1} + \beta_{4,j} DLIQ_{Ind,t} + \beta_{5,j} DLIQ_{Ind,t+1} + \beta_{6,j} DLIQ_{Ind,t-1} + \delta_{1,j} Return_{M,t} + \delta_{2,j} Return_{M,t+1} + \delta_{3,j} Return_{M,t-1} + \delta_{4,J} Volatility_{j,t} + \varepsilon_{j,t} \qquad (EQ4)$$

where, *j* = 1, 2, 3………, 960, *t* = 1, 2, 3………., 504, *Ind* = 1, 2, 3………., 17

Here $DLIQ_{j,t} = (LIQ_{j,t} - LIQ_{j,t-1})/LIQ_{j,t-1}$ represents each of the six liquidity measures used in the study on a given day *t* for a firm *j*. $DLIQ_{M,t}$ is the concurrent change in the corresponding average market liquidity measure and $DLIQ_{Ind,t}$ is the corresponding change in the industry liquidity measure. We classify all the stocks into 17 broad industries based on 2 digit NIC classification. Table 4 presents the results for industry-wide CiL on the individual stock liquidity. We witness that four of the six proxies viz. spread, percentage spread, Roll and Spread_HL with an exception of depth and Amihud factor for industry-wide liquidity in our study are not only significant but also dominate market-wide measures in terms of magnitude. Therefore it will not be wrong to conclude that industry-wide CiL significantly explains the individual stock-level liquidity even after controlling for the market-wide liquidity in the model.

[17] From hereafter, in the subsequent sections, we report the results of combined options *i.e.* call and put together because the properties of both the options are same except for magnitude *i.e.* commonality properties are same for all liquidity measures except that they may vary in terms of magnitude.

The mean industry coefficient (t-statistics) is 0.967 (3.94) for the spread measure, 0.993 (4.34) for the percentage spread, 1.458 (9.33) for Roll measure and 1.641 (9.03) for the Corwin and Schultz (2012) liquidity proxy. However, when we turn to the sum of concurrent, lag and lead we find industry-wide CiL is weaker than the market-wide CiL for the sum of all coefficients except in the case of Roll (1984) and Corwin and Schultz (2012) variables. In simple terms we can say that the presence of commonality within the same industry increases in magnitude compared to existence of CiL within the same market *i.e.* industry-wide liquidity has a higher effect on the firm-level CiL. Clearly our findings are robust across different liquidity measures whereby we are able to establish the existence of industry-wide and market-wide CiL in the order-driven equity market.

[Please insert table 4 about here]

6.2 Commonality in liquidity based on size effect

Chordia et al., (2000) and Cao and Wei (2001) found a significant size effect when CiL coefficients are sorted by firm size for the equity and options market respectively. Although the strategy of exploring the liquidity effect by segregating based on the size effect may result in lower explanatory power of the model due to non-inclusion of some systematic factors in *EQ1* or due to variation in firm-specific liquidity or both.[18] To overcome this problem, we use size-based portfolios and construct the quintiles (for equities) and terciles (for options). We start by constructing five size based quintiles with 192 firms each for the equity market and three size based terciles of circa 48 firms each for the options dataset.[19] To assign a quintile (tercile) for each stock (option), we use the average number of outstanding shares and share price for each

[18] Cao and Wei (2010) run an error dependence test to check for this issue and find that the explanatory power is in fact lower due to the firm-specific liquidity variation over time.
[19] Unlike Cao and Wei (2010), we construct terciles rather than quintiles because of the limited sample for the listed options contract on NSE, India.

firm in a year and assign a firm to a quintile or tercile based on the market capitalization of the firm. For each quintile (tercile) portfolio, the regression in *EQ1 (EQ2)* is run for each proxy of liquidity by modifying *EQ1 (EQ2)* to make it quintile (tercile) specific model. This is done by constructing an equally weighted liquidity measure for all the equities (options) in the quintile (tercile) and calculating the mean market liquidity by excluding all those firms in the quintile (tercile) under examination. Also, the control variables are computed to be quintile-specific (tercile-specific). Once the quintiles (terciles) are constructed, we calculate the statistics in exactly the same way as we did for market-wide CiL reported in table 2 (table 3) for the stocks (options).

Table 5 panel A presents the evidence for size effect on the coefficient of mean market liquidity variables for the equities. The results show a significant CiL both for the intraday and daily measures of liquidity across all the five quintiles. Overall in vein with Chordia et al., (2000), we document that large firms have relatively higher mean market liquidity compared to their counterparts. For instance, if we closely observe the mean concurrent coefficient (t-statistics) for the largest quintile, it is not only highest across all the six liquidity measures but also significant at 1% level – spread 0.836 (10.91) percentage spread 0.841 (11.56), depth 0.535 (3.15), Roll measure 0.840 (35.18), Spread_HL 1.022 (36.09) and Amihud factor 0.739 (3.42). Results for the sum ($\beta_1 + \beta_2 + \beta_3$) coefficient for the highest quintile are qualitatively similar and highly significant to the concurrent coefficient. Next in vein with Brockman and Chung (2002) we find mixed results with either no impact or asymmetric behavior in terms of the concurrent and sum coefficient for the lowest and intermediate quintiles. The dominance of the Foreign Institutional Investors and their correlated trading activity in the Indian market can be a possible explanation of the strong sign of CiL for the larger firms.

Table 5 panel B reports the results for size effects on options portfolios. Unlike the equity quintiles, all the liquidity proxies besides depth exhibit a statistically significant size-effect and increase monotonically, but like the equity market, largest portfolio exhibits relatively higher commonality with a mean concurrent coefficient (t-statistics) being 0.891 (14.06) for spread, 0.844 (19.19) for percentage spread and 2.09 (6.08) for the volume based liquidity variables. The sum of market liquidity for option contracts also shows consistent size effect. Our findings are contradictory to those for developed quote-driven market by Cao and Wei (2010) who state that the smallest quintile firms exhibit significantly higher commonality compared to largest quintile firms. Main rationale for these contradictory results might stem from a higher information asymmetry and thereby lower liquidity among smaller firms in emerging markets (Bekaert and Harvey, 2000).

[Please insert table 5 about here]

6.3 Portfolio commonality in liquidity

Until now, even though we are able to establish an existence of CiL for both equity and options market among NSE, Indian firms, we consistently fail to achieve results with high explanatory power proxied by the average adjusted R^2 statistic. In our sample over two years duration which uses both intraday and daily data, the average adjusted R^2 ranges from a mere one percent (for depth) to as high as fourteen percent (for Amihud proxy).[20] Chordia et al., (2000) argue that the explanatory power of the time-series regression may improve if we incorporate changes in individual liquidity proxies in our model. They hypothesize that the unexplained variation may be due to random noise or omitted variables and hence to overcome the problem of low explanatory power and thereby implement a more parsimonious model Chordia et al., (2000)

[20] These results have been reported in table 2.

suggest the use of portfolio liquidity measures instead of individual equity–level liquidity measures in *EQ1*.

Table 6 panel A provides some solution to this problem by examining CiL at portfolio level. We commence by dividing the sample into size quintiles based on the average market capitalization over the sample period, and thereafter an equally weighted mean liquidity measure is calculated for each of the five quintiles (called quintile portfolio) for each trading day. Next we estimate the daily percentage change in quintile liquidity in our portfolio but exclude daily quintile specific liquidity from the market liquidity measure. Lastly to account for error correlations; following Chordia et al., (2000) we estimate the model as system of seemingly unrelated regressions (SUR). In panel A of table 6, all concurrent quintile liquidity coefficients are positive and significant at 1% level across six liquidity measures. But the parameter of primary interest in this new setup is the system weighted R^2. Besides Amihud factor the explanatory power of the regressions has improved dramatically for all the five other liquidity measures. For example, the spread, depth and Roll measure have an improved average system-weighted R^2 of 0.382, 0.6052 and 0.3123 from a low R^2 of 0.0287, 0.012 and 0.072 respectively. However, the explanatory power of percentage spread show modest improvement (from 0.021 to 0.1023) while Amihud measure declined by two percentage points. These results clearly depict that when risk component of the unexpected changes in the market-wide factors affect firm-level liquidity, portfolio managers may face more challenges in rebalancing their portfolios because even though two portfolio managers may arbitrarily choose their holdings with completely different assets, but still their portfolios may show similar liquidity pattern overtime.

Similar to the explanatory power of stock market commonality, the explanatory power of options market is also drastically low. The average adjusted R^2 ranges from one percent (for depth) to five percent (for trading volume)[21] even though the mean concurrent coefficient is highly significant. The logic behind the low explanatory power is possibly either omitted variables or random noise. Henceforth to show that this low explanatory power is indeed due to the firm specific variation of individual option liquidity overtime, we follow Cao and Wei (2010) and undertake the regression analysis at portfolio level similar to stock market analysis. The tercile construction for the option portfolios is directly in vein with the approach used for the equity market. The firm by firm market model time-series regression in *EQ2* is run for each liquidity measure and portfolio with the following modifications: (1) the market liquidity of each portfolio is the average liquidity over all the sample options sans the current portfolio; (2) the control variables are constructed at the portfolio level; and (3) to permit error correlations among portfolios, we run a system of three SUR.

[Please insert table 6 about here]

The results are reported in table 6, panel B and for brevity; we only report the concurrent and lag coefficients of the market liquidity measure. Apart from the fact that the t-statistic for the concurrent mean coefficient is highly significant for all the liquidity measures, in this model, the system weighted R^2 is of primary interest and significantly improves revealing the fact that at option level, firm specific behavior is prominent for individual option liquidity. The system weighted R^2 of percentage spread measure shows the biggest improvement from 0.031 to 0.8438 closely followed by spread, trading volume and to some extent depth. Simultaneously, the lagged market mean coefficient shows mixed signs which is either positive with high significance (Spread and Pspread) or no significance (Volume) and in some cases even negative significant value (Depth) is observed showing that the lagged coefficients do not exhibit market-wide movement.

[21] These results have been reported in table 3.

7. Robustness test

7.1 Asymmetric information and commonality in liquidity

The existing literature on market microstructure signals the presence of inventory risk and information asymmetry;[22] which are mutually inclusive, as potential sources of CiL in the equity and options market alike. Therefore we test for the impact of information asymmetry on CiL. Furthermore Barclay and Warner (1993) empirically found that informed traders mask their identity by initiating *medium-sized* orders while Jones et al. (1994) stated that individual firm-level information asymmetry is signaled by *number of trades* and not *trade size*. Therefore to study the importance of transaction frequency in order to address information asymmetry as one of the possible explanations of the market-wide and industry-wide CiL, we employ following time-series regression model:

$$\begin{aligned} DNTrades_{j,t} = \propto_J + \beta_{1,j}\, DNTrades_{M,t} + \beta_{2,j} DNTrades_{M,t+1} + \beta_{3,J} DNTrades_{M,t-1} \\ + \beta_{4,j} DNTrades_{I,t} + \beta_{5,j} DNTrades_{I,t+1} + \beta_{6,j} DNTrades_{I,t-1} + \delta_{1,j}\, Return_{M,t} \\ + Return_{M,t-1} + Return_{M,t+1} + \varepsilon_{J,t} \qquad (EQ5) \end{aligned}$$

Where $DNTrades_{j,t}$ measures the percentage change in the transaction frequency of overall trades for the firm j on a given day t. $DNTrades_{M,t}(DNTrades_{I,t})$ measures the equally-weighted transaction frequency of all the firms in the sample for the market (industry) except firm (industry) being regressed.[23] For the options market, the specification is similar to *EQ5* other than the transaction frequency is calculated for the options. We run firm by firm time-series regressions and the average coefficients are reported in table 7.

In panel A of table 7, the mean concurrent coefficient (t-statistics) for the market-wide transaction frequency for equities is 1.058 (20.39). The 85% (56%) of firms have a positive (and

[22] Chordia et al., 2000, Brockman and Chung, 2002, and Cao and Wei, 2010.

[23] We include the trading frequency at the industry level too in *EQ5* because Chordia et al., (2000) argue that information asymmetry may be present at the industry or market level in the form of technological advancements.

significant) concurrent coefficient which is *circa* 100% improvement from the figures known for the HKSE (Brockman and Chung, 2002). The sum of $\beta_1 + \beta_2 + \beta_3$ coefficients is 1.052 and significant at 1% level. When the analysis is performed for market and industry, market-wide concurrent coefficient (t-statistics) of 0.773 (7.22) is *circa* three times higher than the industry-wide concurrent coefficient of 0.281 (3.37) which undoubtedly suggests that asymmetric information at the market-level is stronger than that at the industry-level. Also, the percentage of firms with a positive and significant concurrent coefficient for the market and industry is 42.37% and 37.71% respectively. Thus we can infer that since transaction frequency is a reliable proxy for asymmetric information and also one of the possible explanations for CiL, there very well may exist a common underlying source of commonality in the form of transaction frequency both at the market- and industry-level in the order-driven emerging market.

In table 7 panel B we observe that the trading frequency has a 63 percent higher effect on the market-wide commonality for the options market with a concurrent mean coefficient (t-statistics) of 1.72 (5.49) compared to the equity market. The number of firms with positive (and significant) concurrent coefficient is 87% (56%) but interestingly none of the 143 firms in the sample has a negative and significant coefficient. This clearly supports our hypothesis that information asymmetry proxied by the number of transactions is a significant source of CiL for the options market.[24] Hence asymmetric information is a significant contributor of CiL in the emerging options market.

[Please insert table 7 about here]

7.2 Reliability of t-statistics

[24] When we examine the asymmetric information as a source of CiL for call and put options individually, the estimated coefficients for the call options is qualitatively and (almost quantitatively) in vein with the numbers reported for all the options. The results are also (marginally) significant for the put options.

The t-statistics reported in all the commonality tables (tables 2–7) are used to deduce the null hypothesis – if mean commonality coefficient is significantly different from zero. The t-statistics will be valid only if the residuals from *EQ1* and *EQ2* are not correlated with each other for stocks and options respectively. Since the dependence of the residuals in the time-series cross-section regressions results from the omission of common variables in the model specification, in line with Chordia et al., (2000) and Cao and Wei (2010), we inspect the cross-sectional dependence of the error terms and perform pair-wise time-series regression analysis on the residuals for stocks and options separately. We start by sorting the stocks based on the NSECODE (Ticker symbol) and regress the residuals of the first stock / option on those of second stock / option, and so on:

$$\varepsilon_{j+1,t} = \vartheta_{j,0} + \vartheta_{j,1}\varepsilon_{j,t} + \rho_{j,t} \qquad (j = 1, 2, 3\ldots\ldots959 \text{ (equities) / 142 (options)}) \qquad (EQ6)$$

Where, n is the number of stocks / options that have residuals from *EQ1 / EQ2*. The methodology described above generates n-1 pair-wise time-series regressions. We report the mean slope coefficient of $\vartheta_{j,1}$, and the mean and the median t-values for the slope coefficient besides the percentage of absolute t-values at the 5% significance. From Table 8, we conclude that very little cross-sectional error correlation is present among the stocks and options across all the six and four liquidity variables respectively with a Spread_HL measure in case of equities and Spread for options turning up with the highest sign of cross-sectional dependence in about 6% cases. The mean slope coefficient and the mean and median t-value are both close to zero for both stocks and options for different liquidity measures.

[Please insert table 8 about here]

8. Summary and conclusion

There has been relatively little attention given to the idea of CiL in the literature on emerging market which are becoming of increasing importance to investors worldwide. Following the model coined by Chordia et al., (2000) our empirical findings are based on a rich sample of intraday data over 504 trading days for 960 equities and 143 options listed on Indian National Stock Exchange from 2010 to 2012 and employ six different liquidity measures for the equities and four measures for the options market to examine the CiL in the emerging order-driven market set-up. Our results for market-wide CiL provide enough evidence for the existence of CiL in the context of NSE equity market using intraday as well as daily data based liquidity measures. For the options market, the CiL is higher than the equity market even after controlling for the factors affecting liquidity. The results are consistent across both call and put options, however the mean estimated option liquidity coefficient is higher for calls. In brief, our findings for the order-driven market are contradictory to the quote-driven derivatives market study (Cao and Wei, 2010) with respect to the size and the portfolio effects on CiL.

In case of industry-wide commonality, except for depth and Amihud illiquidity measures industry-wide liquidity significantly explains the individual stock liquidity even after controlling for the market-wide liquidity. For all the liquidity proxies, industry liquidity dominates market liquidity in explaining individual stock liquidity; however, the impact of industry-wide CiL is weaker than the market-wide CiL for the sum of the coefficients. Consistent with the prior literature findings, there is significant evidence in favor of size and portfolio effects on CiL among NSE equities and options. Furthermore information asymmetry at the market-level is stronger than industry-wide asymmetric information for stocks, but an important contributing factor in explaining CiL. Similarly, for the options market, market-wide CiL is also significantly high with call options exhibiting higher CiL. Lastly we find negligible evidence of cross-sectional error correlation in our sample of liquidity measures used in this study.

In summary, our study presents some interesting and contrasting results to those reported in CiL literature. Market- and industry-wide CiL in order-driven market is comparable with the quote-driven market. Next, the effect of size on CiL for quote-driven market increases with size for equity, and *vice-versa* for the options. However, for an emerging order-driven market like India, the equity and options market commonality increases simultaneously with size. Nevertheless, within the order-driven market setup, our findings are markedly different from the developed exchanges since we find higher CiL in an emerging market compared to developed market (Brockman and Chung, 2002; Fabre and Frino, 2004) and similarly positive and higher size effects on CiL for the derivatives market over the equity market.

In brief, this study provides strong evidence in favor of CiL for both equity and option market in the Indian set-up. The results reported here are of interest to the academics, regulators and policymakers alike who foresee emerging markets like India with immense growth potential since it is the third biggest market-based economy based on purchasing power parity. We conclude that whatsoever the case maybe, variation in CiL is not idiosyncratic and exists at both market- and industry-level.

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Table 1

Table 1 presents the descriptive statistics. Panel A presents the summary statistics for the six liquidity factors for the 960 stocks (Panel A1) and four liquidity factors for the 143 option-listed firms (Panel A2) used in this study using daily intraday tick-data for the firms listed on NSE, India from April 01st, 2010 to March 31st, 2012. Mean is the average, Median is the median, Std. dev. is the standard deviation, 5%, 25%, 75% and 95% is the 5th, 25th, 75th and 95th percentile. Min and Max are the minimum and maximum values for the factors and N is the number of firm-days for liquidity parameters used in this study. Panel B presents the pair-wise correlation matrix of liquidity variables for stocks and options. We first estimate the time-series correlations for each stock and option for a pair of liquidity measures and then average across all stocks and options in the sample.

Panel A: Summary statistics

Variable	**Mean**	**Std. dev.**	**Min**	**5%**	**25%**	**Median**	**75%**	**95%**	**Max**	**N**
Panel A1: Stocks										
Spread (INR)	1.340	1.920	0.050	0.113	0.325	0.763	2.075	8.675	30.000	370215
Pspread (%)	1.200	1.290	0.002	0.254	0.529	0.959	2.028	5.864	50.182	370215
Depth (Shares)	376.44	1191.09	6.00	28.13	77.63	168.63	350.00	1122.50	253527.75	370215
Roll (INR)	1.720	10.550	0.000	0.130	0.411	0.901	2.840	11.568	180.230	370215
Amihud (x 10^{-6})	16.720	320.440	0.000	0.216	3.535	22.133	124.451	1440.901	32495	370215
Spread_HL (%)	1.940	1.560	0.000	0.011	0.311	0.922	2.563	4.563	21.830	370215
Panel A2: Options										
Spread (INR)	3.22	9.17	0.01	0.093	0.311	0.922	3.371	11.889	1307.530	55233
Pspread (%)	0.35	0.33	0.01	0.069	0.128	0.22	0.407	1.122	2.000	55233
Depth (Shares)	3897	5754	125	457.4	1125	2347.37	4671.5	13853	246263	55233
Volume (Shares)	998693	3395556	125	1500	13500	81000	387250	2396000	164838968	55233

Panel B: Pair-wise correlation matrix

Panel B1: Stocks

Variable	**Spread**	**Pspread**	**Depth**	**Roll**	**Amihud**	**Spread_HL**
Spread	*1*					
Pspread	*0.84****	*1*				
Depth	*-0.19****	*-0.18****	*1*			
Roll	*0.55****	*0.51****	*-0.16****	*1*		
Amihud	*0.29****	*0.37****	*-0.17****	*0.20****	*1*	
Spread_HL	*0.21****	*0.25****	*-0.12****	*0.22****	*0.31****	*1*

Panel B2: Options

Variable	***Spread***	***Pspread***	***Depth***	***Volume***
Spread	*1*			
Pspread	*0.45****	*1*		
Depth	*-0.13***	*-0.15***	*1*	
Volume	*-0.24****	*-0.31****	*0.28****	*1*

Note: **, *** show the significance of the mean correlations at 5% and 1% respectively.

Table 2

Table 2 presents the market-wide CiL for 960 stocks *(EQ1)* used in this study using daily intraday tick-data for the firms listed on NSE, India from April 01st, 2010 to March 31st, 2012. Market-wide CiL for 960 stocks is estimated by regressing percentage change in the individual stock liquidity measure on the percentage change in equally-weighted market liquidity measure on a daily basis. The equally-weighted market average measure excludes the liquidity of the dependent variable stock. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, lag, and lead coefficients.

	Spread	**Pspread**	**Depth**	**Roll**	**Spread_HL**	**Amihud**
Concurrent	0.707 (27.10)	0.728 (28.61)	0.255 (5.07)	0.882 (19.76)	0.920 (75.65)	0.462 (5.72)
% Positive	89.81	90.48	55.26	90.72	99.46	86.47
%Positive Significant	32.23	35.44	12.40	45.18	48.91	45.99
% Negative	10.19	9.52	44.74	9.28	0.54	13.35
% Negative Significant	0.00	0.00	0.44	0.00	0.00	0.00
Lag	-0.170 (-5.91)	-0.185 (-7.05)	-0.24 (-0.54)	-0.022 (-0.59)	0.014 (-1.97)	0.143 (1.32)
% Positive	37.10	36.32	44.85	33.27	45.09	29.58
%Positive Significant	1.66	1.11	3.54	6.13	7.66	3.43
% Negative	62.90	63.68	55.15	66.73	54.82	70.42
% Negative Significant	6.53	6.20	0.66	32.01	10.64	0.54
Lead	-0.003 (-0.17)	-0.015 (-0.72)	-0.39 (-1.23)	0.100 (2.69)	-0.028 (-4.30)	0.194 (1.64)
% Positive	47.62	46.84	44.52	33.45	44.00	33.54
%Positive Significant	2.77	3.10	3.88	5.55	6.04	4.15
% Negative	52.38	53.16	55.48	66.55	55.91	66.46
% Negative Significant	2.66	2.99	1.00	20.29	10.01	0.63
Sum	0.547 (10.69)	0.527 (11.17)	0.191 (2.31)	0.960 (11.12)	0.906 (20.14)	0.799 (3.12)
R-Squared Mean	0.045	0.044	0.0251	0.077	0.066	0.142
Adj. R-Squared Mean	0.029	0.021	0.012	0.072	0.061	0.137

Table 3

Table 3 presents the market-wide CiL for all the options (both call and put) for 143 firms *(EQ2)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Market-wide CiL for all options is estimated using the firm time series regression of percentage change in option liquidity and its lag measure for the corresponding firm on the equally-weighted average of the option market liquidity, stock market liquidity, the residual from the regression of stock market liquidity measure on the option market liquidity measure and its lag for 143 option listed firms. The time-series regression also includes control variables. The equally-weighted market average measure excludes the liquidity of the dependent variable stock. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent and lag coefficients. For brevity, we report the coefficients of concurrent and lag of option market liquidity, stock market liquidity, and the residual liquidity measures.

	Spread	**Pspread**	**Depth**	**Volume**
Concurrent Option Market Liquidity	0.654 (19.11)	0.710 (27.88)	0.008 (4.98)	1.583 (12.21)
% Positive	97.90	100	65.03	99.30
%Positive Significant	79.02	87.41	21.68	78.32
% Negative	2.10	0.00	34.97	0.70
% Negative Significant	0.00	0.00	2.80	0.00
Option Market Liquidity Lag	-0.1 (-5.50)	-0.083 (-4.44)	-0.002 (-2.64)	0.008 (0.09)
% Positive	28.67	35.66	39.16	41.26
%Positive Significant	1.40	2.10	1.40	6.29
% Negative	71.33	64.34	60.84	58.74
% Negative Significant	7.69	9.79	6.99	2.80
Stock Market Liquidity	0.11 (7.24)	0.15 (10.12)	0.01 (3.63)	0.18 (9.12)
% Positive	72.03	78.32	69.23	69.23
%Positive Significant	55.94	68.53	34.97	53.15
% Negative	27.97	21.68	30.77	30.77
% Negative Significant	0.70	1.40	2.10	1.40
Residual Liquidity	0.558 (4.92)	0.128 (2.76)	0.021 (1.58)	0.518 (1.34)
% Positive	81.12	55.94	56.64	55.24
%Positive Significant	9.09	8.39	9.09	13.99
% Negative	18.88	44.06	43.36	44.76
% Negative Significant	0.70	0.70	2.80	2.10
Sum	0.553 (16.54)	0.637 (23.85)	0.005 (3.57)	1.59 (10.26)
R-Squared	0.034	0.036	0.017	0.054
Adj. R-Squared	0.031	0.031	0.012	0.049

Table 4

Table 4 presents the market-wide and industry-wide CiL for 960 stocks *(EQ4)* used in this study using daily intraday tick-data for the firms listed on NSE, India from April 01st, 2010 to March 31st, 2012. Market-wide and industry-wide CiL is estimated for a sample of 960 stocks by regressing the percentage change in the stock liquidity measure on the percentage change in market and industry liquidity measure. Market and industry liquidity measure excludes the corresponding stock liquidity measure. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, lag, and lead coefficients. The coefficients are reported separately for the market and industry. Ind represents the industry coefficient.

	Spread		**Pspread**		**Depth**		**Roll**		**Spread_HL**		**Amihud**	
	Market	**Ind**	**Market**	**Ind**	**Market**	**Ind**	**Market**	**Ind**	**Market**	**Ind**	**Market**	**Ind**
Concurrent	0.835 (10.98)	0.967 (3.94)	0.876 (11.09)	0.993 (4.34)	0.351 (3.92)	0.077 (0.23)	0.651 (24.71)	1.458 (9.33)	0.671 (23.14)	1.641 (9.03)	0.511 (6.91)	-1.132 (-0.76)
% Positive	76.75	69.45	77.27	70.39	51.93	50.16	84.42	65.49	81.79	62.68	81.88	43.93
%Positive Significant	14.49	9.59	15.95	10.11	5.94	5.21	51.99	18.03	42.39	16.94	50.82	11.23
% Negative	23.25	30.55	22.73	29.61	48.07	49.84	15.13	34.06	17.75	36.78	17.57	55.53
% Negative Significant	0.31	1.15	0.21	1.25	0.21	0.52	1.09	4.89	1.00	3.17	2.08	12.23
Lag	-0.117 (-2.0)	-0.339 (-1.71)	-0.112 (-1.90)	-0.344 (-1.86)	-0.061 (-0.97)	0.002 (0.01)	-0.216 (-8.91)	0.435 (2.90)	0.006 (0.24)	0.097 (0.66)	-0.067 (-0.92)	-0.851 (-0.53)
% Positive	43.48	43.80	43.38	43.17	43.69	45.67	32.34	58.79	48.19	50.82	30.25	52.36
%Positive Significant	2.40	1.25	2.19	1.25	3.75	3.65	1.18	9.33	6.34	6.61	5.71	9.60
% Negative	56.52	56.20	56.62	56.83	56.31	54.33	67.12	40.67	51.27	48.73	69.20	47.10
% Negative Significant	3.44	3.86	3.86	3.86	0.83	0.52	14.49	3.17	7.97	6.34	29.26	10.51
Lead	0.082 (1.43)	0.073 (0.47)	0.080 (1.37)	0.078 (0.50)	0.022 (0.43)	0.086 (0.76)	-0.073 (-3.24)	0.557 (3.32)	0.027 (1.09)	-0.185 (-1.24)	0.138 (2.04)	1.285 (1.05)
% Positive	49.95	47.34	49.64	47.55	45.26	44.53	41.39	56.79	46.74	48.55	44.38	54.80
%Positive Significant	3.34	3.34	3.34	3.23	4.07	3.34	2.17	6.25	6.43	5.71	6.97	9.33
% Negative	50.05	52.66	50.36	52.45	54.74	55.47	58.06	42.66	52.72	51.00	55.07	44.66
% Negative Significant	2.19	2.19	2.29	1.98	0.52	1.15	6.52	2.54	6.52	6.70	8.06	6.52
Sum	0.800 (6.37)	0.701 (2.12)	0.844 (6.43)	0.727 (2.82)	0.312 (2.53)	0.129 (-0.21)	0.362 (12.51)	2.45 (7.20)	0.704 (11.56)	1.553 (5.66)	0.582 (2.34)	-0.698 (-0.23)
Adj. R-sq Mean	0.0179		0.0220		0.0034		0.0009		0.0007		0.0006	

Table 5: Panel A

Table 5 panel A presents market-wide CiL by size quintiles for 960 stocks *(EQ1)* used in this study using daily intraday tick-data for the firms listed on NSE, India from April 01st, 2010 to March 31st, 2012. Market-wide CiL is estimated for five size quintiles of 192 firms each by regressing percentage change in equally weighted market liquidity measure on stock liquidity measure. In each of the regressions, the equally weighted market liquidity measure excludes the corresponding stock liquidity measure. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. For brevity, we report concurrent slope coefficient along with Sum which represents the sum of concurrent, lag and lead coefficients.

		Quintile				
		Smallest (N=192)	**2 (N=192)**	**3 (N=192)**	**4 (N=192)**	**Largest (N=192)**
Spread	Concurrent	0.671	0.771	0.715	0.609	0.836
		(8.39)	(14.59)	(11.11)	(12.20)	(10.91)
	Sum	0.396	0.658	0.560	0.440	0.668
		(2.17)	(8.50)	(6.53)	(6.41)	(5.28)
	Adj. R-Sq Mean	0.012	0.0176	0.0192	0.017	0.021
Pspread	Concurrent	0.706	0.802	0.737	0.639	0.841
		(8.91)	(14.15)	(12.21)	(12.94)	(11.56)
	Sum	0.433	0.692	0.576	0.456	0.666
		(2.51)	(7.67)	(6.59)	(6.79)	(5.63)
	Adj. R-Sq Mean	0.016	0.0229	0.0242	0.0225	0.0251
Depth	Concurrent	0.237	0.188	0.322	0.117	0.535
		(2.82)	(1.84)	(1.63)	(1.28)	(3.15)
	Sum	0.181	0.291	0.193	-0.157	0.348
		(1.22)	(2.05)	(1.38)	(-0.9)	(1.16)
	Adj. R-Sq Mean	0.002	0.003	0.006	0.006	0.002
Roll	Concurrent	0.559	0.696	0.672	0.670	0.840
		(2.57)	(6.77)	(18.36)	(11.22)	(35.18)
	Sum	1.121	0.762	0.762	0.494	0.761
		(1.35)	(2.34)	(4.12)	(3.80)	(5.67)
	Adj. R-Sq Mean	0.0003	0.0004	0.0006	0.0007	0.0017
Spread_HL	Concurrent	0.795	0.874	0.971	0.991	1.022
		(28.50)	(37.41)	(37.97)	(34.32)	(36.09)
	Sum	0.722	0.823	0.925	0.985	0.999
		(5.34)	(6.78)	(8.11)	(7.76)	(4.12)
	Adj. R-Sq Mean	0.0004	0.0005	0.0006	0.0008	0.0008
Amihud	Concurrent	0.163	0.113	0.376	0.490	0.739
		(3.49)	(3.60)	(3.25)	(2.09)	(3.42)
	Sum	0.423	0.165	0.411	0.695	1.359
		(0.90)	(1.34)	(2.01)	(1.25)	(1.98)
	Adj. R-Sq Mean	0.0003	0.0005	0.0016	0.0023	0.0026

Table 5: Panel B

Table 5 panel B presents market-wide CiL by size effects for all options (both call and put) for 143 firms *(EQ2)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. CiL for the options markets is estimated for three option portfolios based on market capitalization. The equally-weighted market liquidity measure in each portfolio excludes the liquidity of the dependent variable firm. Cross-sectional mean of the time-series slope coefficients are reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistics in the parentheses. Concurrent and lag refers to the same and previous trading day market liquidity measures. For brevity, we report concurrent and lag coefficients of options market CiL along with the sum (Sum) of concurrent and lag coefficients.

		Smallest (N=47)	**Medium (N=48)**	**Largest (N=48)**
Spread	Concurrent	0.660	0.739	0.891
		(11.57)	(9.59)	(14.06)
	Lag	-0.127	-0.106	-0.06
		(-3.87)	(-2.58)	(-2.73)
	Sum	0.530	0.633	0.667
		(7.58)	(9.96)	(13.67)
	Adj. R-Sq Mean	0.026	0.034	0.029
Pspread	Concurrent	0.588	0.707	0.844
		(16.29)	(14.6)	(19.19)
	Lag	-0.041	-0.123	-0.077
		(-1.13)	(-3.38)	(-2.64)
	Sum	0.547	0.584	0.767
		(11.90)	(13.22)	(16.87)
	Adj. R-Sq Mean	0.026	0.028	0.039
Depth	Concurrent	0.001	0.007	0.002
		(4.54)	(2.63)	(1.19)
	Lag	-0.002	-0.002	-0.001
		(-1.52)	(-1.77)	(-0.75)
	Sum	0.0007	0.0004	0.0001
		(2.95)	(1.79)	(0.62)
	Adj. R-Sq Mean	0.009	0.008	0.007
Volume	Concurrent	1.20	1.457	2.09
		(11.63)	(8.4)	(6.08)
	Lag	0.077	0.140	-0.194
		(1.66)	(0.47)	(-1.65)
	Sum	1.27	1.598	1.90
		(11.26)	(4.48)	(6.07)
	Adj. R-Sq Mean	0.058	0.051	0.038

Table 6: Panel A

Table 6 panel A presents portfolio CiL by size quintiles for 960 stocks *(EQ1)* used in this study using daily intraday tick-data for the firms listed on NSE, India from April 01[st], 2010 to March 31[st], 2012. Portfolio CiL is estimated by regressing percentage change in portfolio liquidity measure on the proportional change in the equally weighted market liquidity measure which excludes the quintile specific liquidity measure. The model is estimated as SUR to account for the correlations in error terms across the five quintiles under examination. Concurrent, lag, and lead are the coefficients of the same, previous and next trading day market liquidity measures. The corresponding t-statistics are reported in the parentheses.

		Smallest (N=192)	**2 (N=192)**	**3 (N=192)**	**4 (N=192)**	**Largest (N=192)**
Spread	Concurrent	0.53 (5.20)	0.883 (12.40)	1.012 (12.85)	0.897 (8.53)	1.135 (24.59)
	Lag	0.046 (1.09)	0.042 (1.40)	-0.105 (-2.77)	-0.005 (-0.13)	-0.016 (0.90)
	Lead	-0.01 (-0.24)	0.041 (1.38)	-0.090 (-2.37)	0.029 (0.69)	0.003 (0.16)
	SystemWeighted R-sq	0.3820				
Pspread	Concurrent	0.128 (2.45)	0.345 (11.68)	0.819 (4.92)	0.092 (2.12)	1.308 (26.77)
	Lag	0.004 (0.14)	-0.059 (1.22)	-0.065 (-0.99)	-0.025 (-0.53)	0.011 (0.55)
	Lead	-0.082 (-2.17)	0.105 (2.17)	-0.005 (-0.09)	-0.082 (-1.73)	-0.003 (-0.18)
	SystemWeighted R-sq	0.1023				
Depth	Concurrent	0.991 (15.68)	0.683 (7.05)	1.209 (19.95)	0.973 (11.57)	0.957 (14.65)
	Lag	0.028 (1.16)	0.013 (0.35)	-0.042 (1.80)	-0.014 (-0.45)	0.024 (1.01)
	Lead	-0.009 (0.38)	-0.015 (-0.41)	-0.010 (0.46)	-0.034 (-1.06)	0.030 (1.26)
	SystemWeighted R-sq	0.6052				
Roll	Concurrent	0.671 (47.91)	0.993 (40.88)	0.83 (50.49)	1.11 (39.63)	0.929 (35.58)
	Lag	-0.137 (-9.79)	0.023 (0.99)	-0.018 (-1.13)	0.022 (0.80)	0.072 (2.83)
	Lead	0.139 (-9.94)	-0.00 (-0.04)	-0.012 (-0.74)	-0.037 (-1.35)	0.146 (5.65)
	System Weighted R-Sq	0.3123				
Spread_HL	Concurrent	0.729 (25.18)	0.812 (30.81)	0.83 (50.49)	0.95 (31.23)	1.21 (47.91)
	Lag	0.021 (2.83)	0.032 (0.99)	-0.018 (-1.34)	0.032 (0.80)	-0.137 (-9.12)
	Lead	0.146 (5.65)	-0.001 (-0.04)	-0.012 (-0.74)	-0.037 (-1.35)	0.139 (-9.94)
	System Weighted R-Sq	0.2564				
Amihud	Concurrent	0.005 (3.40)	0.026 (8.30)	0.103 (20.21)	0.217 (15.50)	4.242 (17.47)
	Lag	-0.00 (-0.05)	-0.00 (-0.00)	-0.001 (-0.39)	-0.003 (-0.27)	-0.018 (-0.07)
	Lead	-0.00	-0.00	-0.00	-0.002	-0.028

	(-0.08)	(-0.05)	(-0.13)	(-0.18)	(-0.12)
System Weighted R-Sq	0.1164				

Table 6: Panel B

Table 6 panel B presents portfolio CiL by size effects for all options (both call and put) for 143 firms *(EQ2)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Option portfolios are formed based on the firm size proxied by market capitalization. Portfolio CiL is estimated by regressing percentage change in portfolio liquidity measure on the equally-weighted average of the options market liquidity measure, stock market liquidity measure, and the residual from the regression of option market liquidity measure on the stock market liquidity. We run a set of SUR to account for the correlations in the error terms. The market average measures exclude the portfolio liquidity measure. The corresponding t-statistics are reported in the parentheses.

		Small (N=47)	**Medium (N=48)**	**Large (N=48)**
Spread	Concurrent	0.94 (83.68)	0.89 (56.30)	0.922 (72.07)
	Lag	0.074 (4.31)	0.067 (6.12)	0.09 (3.12)
	System-Weighted R-squared	0.7212		
Pspread	Concurrent	0.85 (61.31)	0.80 (47.04)	0.829 (56.28)
	Lag	0.011 (2.98)	0.09 (3.56)	0.03 (5.12)
	System-Weighted R-squared	0.8438		
Depth	Concurrent	0.003 (5.25)	0.001 (3.67)	0.009 (7.12)
	Lag	-0.12 (-3.45)	-0.23 (-2.98)	-0.001 (-3.76)
	System-Weighted R-squared	0.1912		
Volume	Concurrent	1.012 (35.12)	1.19 (28.24)	1.018 (25.65)
	Lag	0.001 (1.29)	0.002 (2.34)	0.006 (1.53)
	System-Weighted R-squared	0.7112		

Table 7: Panel A

Table 7 panel A presents results for asymmetric information as a determinant of CiL for the NSE, India equity market for 960 stocks *(EQ5)* used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Percentage change in daily trading frequency of each of the stock is regressed in time series on the percentage change in equally-weighted average of trading frequency for all the stocks in the market (as well as market and industry). The equally-weighted average of market excludes the industry and industry excludes the firm in question. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, lag and lead coefficients.

	Ntrades (Market)	**Ntrades (Market and Industry)**	
	Mean Coefficient	**Market Mean Coefficient**	**Industry Mean Coefficient**
Concurrent	1.058 (20.39)	0.773 (7.22)	0.281 (3.37)
% Positive	84.96	59.85	61.44
%Positive Significant	55.93	42.37	37.71
% Negative	15.04	40.15	38.56
% Negative Significant	3.07	23.41	19.70
Lag	-0.014 (-2.06)	-0.027 (-0.95)	0.013 (0.47)
% Positive	27.01	45.87	47.46
%Positive Significant	1.38	3.07	4.13
% Negative	72.99	54.13	52.54
% Negative Significant	18.01	5.08	2.75
Lead	0.008 (2.94)	-0.040 (-1.72)	0.065 (2.49)
% Positive	48.20	44.60	54.03
%Positive Significant	5.72	3.07	3.92
% Negative	51.80	55.40	45.97
% Negative Significant	9.85	4.03	2.86
Sum	1.052 (19.85)	0.704 (5.86)	0.361 (3.60)
Adj. R-Squared Mean	0.4417	0.4531	

Table 7: Panel B

Table 7 panel B presents results for asymmetric information as a determinant of CiL for all options (besides put and call separately) for 143 firms *(EQ5)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Percentage change in daily trading frequency of each option is regressed in time series on the percentage change in equally-weighted average of trading frequency for all the options in the market (besides put and call separately). The equally-weighted market average excludes the firm in question from the market average. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, lag and lead coefficients.

	All Options	**Put Options**	**Call Options**
	Mean Estimated Coefficient	**Mean Estimated Coefficient**	**Mean Estimated Coefficient**
Concurrent	1.72 (5.49)	0.665 (1.98)	1.565 (5.31)
% Positive	86.71	71.33	84.62
%Positive Significant	55.94	34.42	55.24
% Negative	13.29	28.67	15.38
% Negative Significant	0.00	4.90	0.00
Lag	-0.170 (-0.99)	0.182 (1.31)	-0.097 (-0.68)
% Positive	51.75	57.34	48.95
%Positive Significant	0.00	2.10	0.00
% Negative	48.25	42.66	51.05
% Negative Significant	4.20	6.29	6.29
Lead	-0.272 (-3.36)	-0.119 (-1.75)	-0.249 (-2.78)
% Positive	28.67	45.45	30.07
%Positive Significant	0.00	1.40	0.00
% Negative	71.33	54.55	69.93
% Negative Significant	18.18	18.88	20.28
Sum	1.286 (9.02)	0.728 (2.89)	1.218 (8.03)
Adj. R-Squared Mean	0.1370	0.9950	0.1152

Table 8

Table 8 presents cross-sectional dependence in time-series estimation errors *(EQ6)*. In this table we examine the cross-sectional dependence of the error terms among the stocks and options by using firm by firm time-series regression. For each of the liquidity measure for both stock and options markets, we perform pair-wise time-series regressions on the residuals of first stock with the second and so on. In total we have 959 pairs for stocks and 142 pairs for the options. The mean slope coefficient and t-value are reported along the median t-value and also the percentage of absolute t-values that are greater than 5% significance level.

Liquidity Measure	Mean Coefficient	Mean t-Value	Median t-value	|t| > 1.96 (%)	Number of Pairs
Panel A: Stocks					
Spread	-0.001	0.012	-0.013	5.144	959
Pspread	0.000	0.001	-0.001	3.122	959
Depth	0.004	0.000	-0.015	3.453	959
Roll	0.008	0.001	-0.019	3.156	959
Spread_HL	-0.001	-0.001	-0.009	6.121	959
Amihud	-0.001	-0.002	-0.009	4.001	959
Panel B: All Options					
Spread	0.000	0.003	-0.010	6.191	142
Pspread	0.006	-0.001	-0.161	4.134	142
Depth	-0.007	0.004	-0.111	4.111	142
Volume	-0.004	0.004	-0.013	5.122	142

Appendix A1

Appendix A1 presents the market-wide CiL for call options for 143 firms *(EQ2)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Market-wide CiL for call options is estimated using the firm time series regression of percentage change in option liquidity and its lag measure for the corresponding firm on the equally-weighted average of the option market liquidity, stock market liquidity, and the residual from the regression of stock market liquidity measure on the option market liquidity measure and its lag for 143 option listed firms. The time-series regression also includes control variables. The equally-weighted market average measure excludes the liquidity of the dependent variable stock. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, and lag coefficients. For brevity, we report the coefficients of concurrent and lag of option market liquidity, stock market liquidity, and the residual liquidity measures.

	Spread	**Pspread**	**Depth**	**Volume**
Concurrent Option Market Liquidity	0.854 (16.35)	0.889 (28.93)	0.001 (5.49)	1.816 (8.56)
% Positive	98.60	100	70.63	98.60
%Positive Significant	75.52	91.61	26.57	78.32
% Negative	1.40	0.00	29.37	1.40
% Negative Significant	0.00	0.00	1.40	0.00
Option Market Liquidity Lag	0.09 (3.99)	0.07 (2.93)	0.000 (2.78)	0.071 (0.87)
% Positive	64.34	60.84	59.44	50.35
%Positive Significant	7.69	14.69	3.50	3.50
% Negative	35.66	39.16	40.56	49.65
% Negative Significant	0.00	2.80	1.40	2.10
Stock Market Liquidity	0.006 (8.15)	0.009 (9.15)	0.12 (4.19)	1.534 (14.11)
% Positive	50.35	52.45	41.96	54.55
%Positive Significant	45.45	41.96	34.27	48.95
% Negative	49.65	47.55	58.04	45.45
% Negative Significant	2.10	3.50	7.69	2.80
Residual Liquidity	0.005 (0.05)	0.198 (3.98)	0.02 (1.58)	0.223 (0.80)
% Positive	53.15	65.73	48.25	51.05
%Positive Significant	2.10	11.89	8.39	9.79
% Negative	46.85	34.27	51.75	48.95
% Negative Significant	2.10	2.10	2.80	2.80
Sum	0.94 (14.02)	0.963 (23.35)	0.001 (5.68)	1.88 (6.93)
R-Squared (%)	0.0616	0.0641	0.0171	0.0743
Adj. R-Squared (%)	0.0535	0.0561	0.0110	0.0663

Appendix A2

Appendix A2 presents the market-wide CiL for put options for 143 firms *(EQ2)* with options listed on NSE, India used in this study using daily intraday tick-data from April 01st, 2010 to March 31st, 2012. Market-wide CiL for put options is estimated using the firm time series regression of percentage change in option liquidity and its lag measure for the corresponding firm on the equally-weighted average of the option market liquidity, stock market liquidity, and the residual from the regression of stock market liquidity measure on the option market liquidity measure and its lag for 143 option listed firms. The time-series regression also includes control variables. The equally-weighted market average measure excludes the liquidity of the dependent variable stock. Cross-sectional mean of the time-series slope coefficient is reported in the Fama-MacBeth (1973) fashion with the corresponding t-statistic in the parentheses. Concurrent, lag, and lead refers to the same, previous and next trading day market liquidity measures. % Positive (Negative) is the percentage of positive (negative) slope coefficients, % Positive (Negative) Significant is the percentage of positive (negative) coefficients significant at 5% level. Sum reports the sum of concurrent, and lag coefficients. For brevity, we report the coefficients of concurrent and lag of option market liquidity, stock market liquidity, and the residual liquidity measures.

	Spread	**Pspread**	**Depth**	**Volume**
Concurrent Option Market Liquidity	0.399 (11.25)	0.449 (12.09)	0.03 (2.55)	1.19 (12.85)
% Positive	88.11	89.51	52.45	91.61
%Positive Significant	41.26	45.45	7.69	62.24
% Negative	11.89	10.49	47.55	8.39
% Negative Significant	0.00	0.00	4.20	0.00
Option Market Liquidity Lag	0.071 (2.49)	0.01 (0.35)	-0.01 (-0.87)	0.21 (1.64)
% Positive	60.84	54.55	46.15	48.25
%Positive Significant	4.90	6.29	4.20	4.20
% Negative	39.16	45.45	53.85	51.75
% Negative Significant	0.00	2.80	6.29	0.70
Stock Market Liquidity	0.011 (6.35)	0.07 (4.38)	0.05 (5.36)	0.98 (7.12)
% Positive	62.24	55.94	62.94	65.73
%Positive Significant	46.85	43.36	37.76	53.15
% Negative	37.76	44.06	37.06	34.27
% Negative Significant	2.10	3.50	1.40	1.40
Residual Liquidity	1.213 (6.14)	-0.054 (-0.53)	0.006 (0.58)	0.67 (1.14)
% Positive	82.52	41.96	53.85	56.64
%Positive Significant	20.28	2.10	4.90	9.09
% Negative	17.48	58.04	46.15	43.36
% Negative Significant	0.70	3.50	2.80	0.70
Sum	0.471 (8.71)	0.46 (8.99)	0.01 (0.48)	1.40 (8.43)
R-Squared (%)	0.032	0.029	0.0191	0.0598
Adj. R-Squared (%)	0.018	0.015	0.0120	0.0409