SYNOPSIS

Liquidity of a financial asset has been identified as an important factor in the smooth functioning of financial markets as it helps market participants to overcome unexpected financial needs without undergoing major losses. The liquidity of a security and how it varies over time is of major concern to every market participant. It is generally defined in the market microstructure literature as the ease with which investors can buy and sell securities without having much impact on the prices. In the extant literature, liquidity has three dimensions associated with it; tightness, depth, and resiliency. Bid-ask spread used as proxy for tightness quantifies how far the trade prices deviate from the average market prices. Depth quantifies the change in price due to a shock in the size of the order flow and resiliency quantifies the speed with which prices recover from a random shock (Kyle, 1985). The prominence of liquidity is observed in every aspect of the functioning of stock markets. The amount of profit earned by any market participant is dependent on the liquidity of the asset.

Securities markets, the world over are classified into two major types; Quote-driven markets and the Order-driven markets. Most of the developed markets operate as quote-driven systems or as a combination of quote and order-driven systems. The order-driven systems have become predominant in many of the relatively newly developing markets because of the technology advancements and financial market reforms (Brockman and Chung, 2002). Due to the different types of market systems, the liquidity dynamics differ in these markets. As there is a designated market maker in quote-driven market, it is highly liquid as the market maker supplies liquidity to the market. Whereas, order-driven markets are less liquid as there is no liquidity supplier of last resort. The determinants of liquidity in a quote-driven versus the order-driven markets are not the same. In a quote-driven market such as the NASDAQ or the NYSE, there are three main determinants of liquidity; information asymmetry, order-processing costs, and inventory maintenance risk (Stoll, 1978). But, in an order-driven market such as NSE (India), the main determinant of liquidity is asymmetric information. As the order-driven markets are a recent phenomenon, they provide good opportunity for research into liquidity provision and consumption.

The traditional research on liquidity has been mainly concentrated on individual assets till the seminal work of Chordia, Roll and Subrahmanyam (2000) (CRS hereafter) which directed the attention of research on liquidity to a new territory. They show that individual market structure phenomenon such as liquidity has common underlying determinants and hence should not be treated in isolation. This phenomenon is termed commonality in liquidity and is formally defined as the proposition 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 the seminal work of CRS (2000), there has been an increasing volume of research documenting the presence of liquidity commonality and the role of common liquidity factors in several markets (Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Brockman and Chung, 2002; Pastor and Stambaugh, 2003; Coughenour and Saad, 2004; Domowitz, Hansch, and Wang, 2005; Kempf and Mayston, 2008; Kamara, Lou, and Sadka, 2008; Brockman, Chung, and Perignon, 2009; Hameed, Kang, and Vishwanathan, 2010; Corwin and Lipson, 2011; Karolyi, Lee, and van Dijk, 2012).

The research on liquidity commonality provides a completely new platform to understand the dynamics of liquidity, since it focuses on the market-wide common factors compared to the single asset focus. The current literature mainly focuses on liquidity commonality of the mature markets and very few studies exist for understanding the phenomenon of liquidity commonality in the context of emerging order-driven markets. Even though liquidity commonality has been widely documented in the literature, the fundamental sources of liquidity commonality are still not understood comprehensively. The variation in liquidity commonality over time is driven by microstructure factors such as inventory risk, asymmetric information risk. The supply-side factors which arise due to the funding constraints faced by market participants, demand-side factors caused due to correlated trading activity, and also macroeconomic factors have not been examined in detail. It has been proven theoretically and illustrated more recently that market liquidity risk impacts asset prices both for the equity and derivatives markets and is a priced risk factor.

The main objectives of our study are:

1. To examine liquidity commonality for stocks listed on the equity and options markets of NSE.
2. To analyze the time-series and cross-sectional determinants of liquidity commonality for stocks listed on NSE.
3. To examine the relation between commonality in liquidity and market returns for stocks listed on NSE.

We use high frequency intraday transactions and order-book snapshot data for equity and options markets separately from NSE for a period of two years from April, 2010 to March, 2012. For sources of liquidity commonality we use data from January 2001 to December 2012. For our analysis of the equity market, we estimate six liquidity proxies; Spread, Pspread, Depth, and Roll (1984) measures (constructed using intraday data). High low spread (Spread_HL) estimator of

Corwin and Schultz (2012) and Amihud (2002) illiquidity (constructed using daily data). For the options market, we construct four liquidity measures; Spread, Pspread, Depth, and Volume.

To examine market-wide commonality in liquidity for equity market, we follow CRS (2000) and run market model time series regressions given by

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

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

$DLIQ_{j,t} = (LIQ_{j,t} - LIQ_{j,t-1})/LIQ_{j,t-1}$ denotes 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. We also include a lag and lead market liquidity variables in *EQ1* to capture any nonsynchronous change in liquidity due to thin trading. Cross-sectional means of time series slope coefficients are reported with the t-statistics to test the null hypothesis that there is no market-wide commonality in liquidity for stocks listed on NSE in line with Fama-Macbeth (1973). The concurrent, lag and lead market return along with idiosyncratic firm volatility act as control variables for the model. However, unlike CRS (2000), we exclude the individual stock's return in the computation of market returns. For our study, we have a total of 960 stocks.

The form of the time-series market model regression in the case of options market is given below.

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

(EQ2)

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

$DOPLIQ_{j,t} = (OPLIQ_{j,t} - OPLIQ_{j,t-1})/OPLIQ_{j,t-1}$, denotes each of the four option market liquidity measures used in the study on a given day t for a firm j. Here, $DOPLIQ_{j,t}$ 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. $DOPLIQ_{M,t}$ is the option market's liquidity measure And, $DLIQ^{res}{}_{M,t}$ is the residual from the following regression equation.

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

This is included in *EQ2* to make sure that the coefficients estimated are purely for the options market. The liquidity measure $DLIQ_{j,t}$ which belongs to stock j is included to capture the positive association between liquidities of both the markets due to hedging demand. The underlying firm's return and volatility are included in *EQ2* as additional control variables. For the analysis of options market liquidity commonality, we consider 143 options.

To examine industry-wide liquidity on firm liquidity we use the following regression model:

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

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

In total, we have seventeen industries in our study using the NIC classification. Unlike CRS (2000), we exclude the industry of the stock in the computation of market.

For testing the supply and demand-side sources of liquidity commonality we use daily data for a period of 12 years from 2001-2010 to construct quarterly measures of liquidity commonality. As the time period is very long and we don't have the intra-day data for this long period we depend on Amihud's liquidity measure (*LIQ*) to capture liquidity commonality. We use the R^2 of regressions of the individual stock liquidity on market liquidity to compute the liquidity commonality measure. First we perform the following filtering regression for each stock *J* based on observations on each day *d* within each month *t*:

$$LIQ_{J,t,d} = \propto_{J,t} LIQ_{J,t,d-1} + \sum_{k=1}^{5} \beta_{J,t,k} Dum_k + \varepsilon_{J,t,d} \qquad (EQ5)$$

Here Dum_k is the weekly dummy for controlling seasonality. We have lagged liquidity measure as an explanatory variable and take the estimated residuals $\varepsilon_{J,t,d}$ of daily liquidity as our interest lies in examining if the changes in individual liquidity of firms co-move. We use the innovations from *EQ6* to obtain monthly measures of liquidity commonality for each firm by making use of R^2 from the following regressions, using daily observations within a month:

$$\varepsilon_{J,t,d} = \alpha_{J,t} + \gamma_{J,t,1}\varepsilon_{M,t,d} + \gamma_{J,t,2}\varepsilon_{M,t,d-1} + \gamma_{J,t,3}\varepsilon_{M,t,d+1} + \vartheta_{J,t,d} \qquad (EQ6)$$

Where $\varepsilon_{M,t,d}$ is the sum total of estimated market residuals $\varepsilon_{J,t,d}$ from *EQ5* computed as market value weighted mean of the residuals for all the firms in the sample. We also include one lead and one lag market residuals. This R^2 measure capturing commonality is not appropriate to use as a dependent variable in the regressions to follow because its value ranges between 0 and 1. So, we apply the logistic transformation of the commonality measure (Morck, Yeung, and Yu, 2000) as $Ln[R_t^2/(1-R_t^2)]$. Where, $Ln[R_t^2/(1-R_t^2)]$ is denoted by $LiqCom_t$ which is the monthly liquidity commonality for all the stocks in the sample. The measure is constructed in a similar fashion for different size-based portfolios.

To test for the impact of asymmetric information on liquidity commonality, we make use of the following regression model:

$$DNTrades_{j,t} = \propto_J + \beta_{1,j} DNTrades_{M,t} + \beta_{2,j} DNTrades_{M,t+1} + \beta_{3,J} DNTrades_{M,t-1} + \beta_{4,j} DNTrades_{I,t} + \beta_{5,j} DNTrades_{I,t+1} + \beta_{6,j} DNTrades_{I,t-1} + \delta_{1,j} Return_{M,t} + Return_{M,t-1} + Return_{M,t+1} + \varepsilon_{J,t} \quad (EQ7)$$

Where $DNTrades_{J,t}$ measures the percentage change in the transaction frequency for the firm on a given day. $DNTrades_{M,t}$ ($DNTrades_{I,t}$) measures the equally-weighted transaction frequency of all the firms in the sample for the market (industry) except firm *j*. The industry transaction frequency is excluded from the market transaction frequency.

We examine the time-series behavior of supply-side sources of liquidity commonality by using the following model:

$$LiqCom_t = \alpha_t + \beta_1 SInt_t + \beta_2 CPSpread_t + \beta_3 BrokerReturns_t + \beta_4 BankReturns_t + \beta_5 Return_{M,t} + \beta_6 Liq_{M,t} + \beta_7 Volatility_{M,t} + \delta_1 Turnover_{M,t} + \varepsilon_t \quad (EQ8)$$

SInt is the short-term interest rate (%) which is the 91-day treasury-bill rate. *CPSpread* is the commercial paper spread, $BrokerReturns$ is the equally-weighted average returns of the brokerage industry. *BankReturns* is the equally-weighted average returns of the banking stocks listed on NSE. The above four variables serve as proxies of supply-side sources of liquidity commonality. Along with the supply-side sources, we include four other market conditions factors; Market return ($Return_M$), market liquidity (Liq_M), market volatility ($Volatility_M$), and market turnover ($Turnover_M$) as additional regressors.

We examine the time-series behavior of demand-side determinants of liquidity commonality by using the following model:

$$LiqCom_t = \alpha_t + \beta_1 NetFII_t + \beta_2 NetMF_t + \beta_3 ExchangeRate_t + \beta_4 LnExports_t + \beta_5 Return_{M,t} + \beta_6 Liq_{M,t} + \beta_7 Volatility_{M,t} + \delta_1 Turnover_{M,t} + \varepsilon_t \quad (EQ9)$$

NetFII is the net FII flow in a month in percentage terms which is calculated as (Net buy/ (buy+sell/2)). *NetMF* is net mutual fund flow in a month calculated to *NetFII*. *ExchangeRate* is the monthly percentage change in exchange rate of Indian rupee vis-à-vis dollar. *LnExports* denotes the natural logarithm of exports of each month. The above four variables serve as proxies of demand-side sources of liquidity commonality. Along with the demand-side sources, we include four other market conditions factors; Market return ($Return_M$), market liquidity (Liq_M), market volatility ($Volatility_M$), and market turnover ($Turnover_M$) as additional regressors.

Following are the main findings of our study:

The results for market-wide commonality in liquidity provide enough evidence for the existence of liquidity commonality in the context of NSE equity market using intraday liquidity measures. The concurrent mean coefficient (β_1) is 0.707 for the spread measure with a t-statistic of 27. This coefficient is positive and significant for 32.23% of the 960 time series regressions. For Pspread, the mean estimated coefficient of interest β_1 is 0.728. This coefficient is positive and significant for 35.44% of the firm regressions. The depth measure has a mean coefficient of 0.225 with a t-statistic of 5.07. However, this coefficient is positive and significant for 12.40% of firms which is quite low compared to the quote-driven as well as the other order-driven market studies. The Roll’s measure has a higher coefficient than the three snapshot based measures. It has a mean estimated slope coefficient of 0.882 with a t-statistic of 19.76. This coefficient is positive and significant for 45.18% of the 960 time-series regressions. Similar to the intraday measures, liquidity measures constructed using daily data also show high degree of liquidity commonality. For example, the concurrent (β_1) coefficient for the Spread_HL and Amihud measure is 0.920 and 0.462 respectively with high t-statistic. This coefficient is positive and significant for 88.91% and 45.99% of the firms respectively. The sum of (β_1, β_2, β_3) of intraday as well as daily measures is also highly significant which shows that liquidity commonality is highly pervasive in the context of NSE equity market.

For the options market, the concurrent mean coefficient (β_2) is 0.654 for the spread measure with a t-value of 19.11 which is significant at 1% level. We obtain the same level of significance for all the measures in our study. The coefficient is positive and significant for 79.02% of the firms for Spread, 87.41% of the firms for Pspread, and 78.3% of the firms for volume measure. However, this percentage is relatively lesser for depth measure at 21.68%. The results show a similar type of behavior by both calls and puts with respect to liquidity commonality. However, the mean estimated option liquidity coefficient is higher for call options compared to put options. Overall, our results are similar to those of quote-driven market study of Cao and Wei (2010).

In case of industry-wide commonality, except for Amihud liquidity measure which has a negative mean industry liquidity coefficient of -1.132, industry liquidity significantly explains the individual stock liquidity even after controlling for the market liquidity. For all the liquidity proxies, industry liquidity dominates market liquidity in explaining individual stock liquidity, except for depth measure. The mean industry coefficient is 0.967 for the spread measure, 0.993 for the Pspread, 1.458 for Roll measure and 1.641 for the Spread_HL measure. However, the impact of industry-wide liquidity commonality is weaker than the market-wide liquidity commonality for the sum of all coefficients. We also find significant evidence for size and portfolio effects on liquidity commonality.

The mean concurrent coefficient for the market-wide transaction frequency is 1.058 and is statistically significant with a t-statistic of 20.39. The percentage of firms with a positive coefficient is 84.96% and 55.93% of the firms have a significant and positive concurrent coefficient. This is 25% more than that reported by Brockman and Chung (2002) for the Hong Kong market. The sum of concurrent, lag, and lead coefficients is 1.052 and highly significant with a t-statistic of 19.85. When the analysis is carried out for market and industry, market-wide concurrent coefficient is 0.773 and the industry concurrent coefficient is 0.281 which suggests that asymmetric information at the market level is stronger than that of the industry-wide asymmetric information. Similarly, for the options markets, we observe that the market-wide commonality in liquidity denoted by the concurrent mean coefficient is 1.72 which is higher than that of 1.05 reported for the equity market. Overall, these results show that asymmetric information is a significant factor contributing to liquidity commonality for the options market.

The results for supply-side determinants of commonality suggest that short-term interest rate and CP Spread are negatively related to commonality with low level of significance. This is because of the fact that an increase in interest rates decreases supply of limit orders and hence less trading activity leading to a decrease in commonality. However, an increase in broker returns or bank returns impact liquidity commonality positively. The results for portfolio level (small, medium, and large) sources show that none of the sources explain the liquidity commonality of small firms which is quite possible as small firms are less affected by liquidity commonality. The commonality of medium-size firms is explained by short-term interest rate, CP Spread, and bank returns, but the significance is weak. However, the commonality of large firms is explained significantly by broker returns and bank returns and the sign of the coefficients are positive.

For the demand-side determinants of commonality, FII flow is positive and significant with a coefficient of 0.374 and Ln_Exports is negative and significant with a coefficient of 0.147. The reason for a positive impact of FII flow on commonality may be due to the correlated trading activity of FIIs. We also find that ExchangeRate and Ln_Exports variables significantly impacting liquidity commonality; ExchangeRate positively and Ln_Exports negatively. The liquidity commonality of small-firms is not explained by any of the demand-side factors of interest. This may be due to the less degree of liquidity commonality for small stocks.

Our Fama-Macbeth monthly regressions to examine determinants of liquidity commonality for the cross-section of stocks show that stock price, stock liquidity, and firm size proxied by market capitalization impact liquidity commonality positively with high level of significance and stock return volatility impacts commonality negatively with less significance.

The results for index inclusion hypothesis show that for the *Spread* measure, 33.3%, 60%, 40%, 76%, 86% of the firms of Bank Index, IT Index, Infra Index, Midcap 50 Index, and Nifty Index respectively have a positive and significant commonality coefficient and it is 29.31% for the non-index firm portfolio. For the *Pspread* measure, 33.3%, 40%, 60%, 46%, and 80% of the five index firms' concurrent commonality coefficients respectively are positive and significant and it is 26.79% for the non-index based portfolio. For the *Depth* based measure, the commonality coefficient is positive and significant for 25%, 20%, 32%, 42%, 54% of the five index constituents respectively and it is 13% for the non-index firm portfolio. Also, the 'Sum'

values are positive and significant for all the liquidity proxies. The results prove that index inclusion hypothesis of Brockman and Chung (2006) that firms included in any equity product trading in the corresponding derivatives market holds good for the NSE equity market.

In general there is a negative relation between liquidity commonality and market returns. The coefficient is -0.323, but it is insignificant. However, there is a significant impact of large negative returns on liquidity commonality. The interaction dummy has a coefficient of -3.31 which is significant. This emphasizes that liquidity commonality and market returns are negatively related and the impact of market returns on commonality is severe during periods of large negative returns. However, there is no negative relation between liquidity commonality and market returns during periods of high market returns. For small portfolios, market returns though has a negative coefficient does not impact liquidity commonality significantly. The same is true even for periods of large negative returns. For the medium-size portfolio of stocks, there is a significant impact on liquidity commonality due to large negative returns; the interaction dummy coefficients is -0.428 and during normal market return states commonality coefficient is -0.179. Also, for small firms, there is significant increase in commonality due to increase in large market returns as shown by the interaction dummy for large market returns. For the large firm portfolio, the impact of large decline in negative market return states is very high with a coefficient of -0.4.

Keywords: Liquidity Commonality, Order-driven market, Equity Market, Options Market, Market Returns, Sources of Commonality