Intraday Liquidity Patterns in Indian Stock Market

R. Krishnan* and Vinod Mishra†

Abstract
This paper attempts to study the liquidity patterns and to detect any commonality across liquidity measures, using one year intraday data from India’s National Stock Exchange (NSE). Using the data on 20 stocks from NSE’s NIFTY Index, we found that most of the volume and spread related liquidity measures exhibit an intra-day U-shaped pattern, similar to those found for a market consisting of market makers. However, we also note that the presence of U-shaped pattern in both the volume related and spread related measures, implying a concurrent high trading volume and wide spreads. While such a phenomena has been reported previously for a market with a specialist liquidity provider and can be explained using the Brock and Kleidon (1992) model [Journal of Economic Dynamics and Control, 16, 451-489 ], it is for the first time we observe such a behaviour in Indian stock market; an order driven market where there is no market maker. Besides, we find only a weak evidence of co-movement or commonality in liquidity measures. This suggests that market wide factors may not play a significant role in affecting the liquidity of individual stocks, hinting that such factors need not be a part of the asset pricing process.

JEL Classification: G15
Keywords: Liquidity, Intraday data, Commonality, NSE, India

* R. Krishnan Indira Gandhi Institute of Development Research Mumbai - 400065, India. Email: kittu@igidr.ac.in
† Vinod Mishra Department of Economics, Monash University VIC - 3800, Australia. Email: vinod.mishra@monash.edu

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1 Introduction

This study analyses the liquidity patterns in the Indian equity market, using intraday data from the National Stock Exchange (NSE). We use 20 most traded stocks from National Stock Exchange’s Fifty (NIFTY) index. NIFTY is the main stock market index of NSE and it tracks the price movements of 50 stocks that represent 21 sectors of the Indian economy and accounts for about 65.57% of the total free float market capitalization of the stocks traded on NSE as on March 2012 ¹. NSE is a pure order driven market, a market characterized by the absence of any market maker and where the market transactions are carried out anonymously through a centralized computer. With improvements in technology, many stock exchanges around the world are opting for such pure order driven markets with the fundamental objective of providing a liquid market, which is crucial for price discovery.

Liquidity of a stock is generally defined as the ability to trade large volumes with minimal price impact, cost and delay. This definition may also be applied to a market as a whole. While this definition itself is simple, a universally acceptable measure of such a liquidity continues to be elusive, resulting in the presence of diverse measures. Moreover, liquidity is measured differently for different segments of a financial market. There are different measures of liquidity for monetary, foreign exchange, bond and equity markets. The frequency of data is also important for measuring liquidity. For example the studies looking at the determinants of stock market development, rely on data data to draw inferences about the stock market liquidity. For instance in the study by Cherif and Gazdar, (2010) liquidity is measured as traded value ratio (ratio of turnover to GDP) whereas in Levine and Zevros (1998)it is measured as the turnover ratio (ratio of turnover to market capitalization). However, these measures are of little use for studies that look at the evolution of liquidity for shorter spans of trading activity, say for example, within a day. The traded value, market capitalisation, GDP and turnover will all register only a negligible change within a day and hence will not be able to capture the true movement of liquidity. So for measuring the liquidity at intraday level we need measures that can be applied on data that is collected at a high frequency and has sufficient variations to capture the changes in liquidity within a day indicating that liquidity is a multi-dimensional concept.

¹Source: http://www.nseindia.com/content/indices/ind_cnx_nifty.pdf
According to Kyle (1985), a liquid market should have depth, tightness, resilience. And later day researchers added trading time also to this list. Depth simply measures the ability of the market to accommodate large trade volumes, with little impact on prices. Resilience is the degree to which prices recover from small trades. A market that bounces back from a price shock or can absorb a shock and restore the balance amongst orders quickly is a resilient market. Tightness denotes the cost incurred in a transaction, irrespective of market price. Bid price-ask price spread, often termed the bid-ask spread, is an indicator of tightness and a narrow spread indicates a liquid market. Clearly these three concepts are closely related, which makes their measurement difficult. This also implies the necessity to consider all three measures either individually or jointly to decide on the liquidity of individual stocks or a market.

Liquidity patterns of many markets with different designs have been analysed in the literature, with a preponderance of studies involving quote driven markets. The two markets differ in a number of ways. Typically, in a pure order driven market, there are limit order traders and market order traders. Generally, it is believed that market order traders are demanders of liquidity and limit order traders are the suppliers, but there is no unanimity in this. But, regardless of the market design, liquidity has been measured using some common proxies like the bid-ask spread, trading volume or turnover. The question is why should we study the liquidity patterns?

An understanding of the behaviour pattern of various liquidity proxies gives us an idea about the variations in the liquidity of corporate stocks and the costs involved in trading in such stocks. (See Amihud, Mendelsen, Pedersen (2005) for a survey on the role of liquidity in asset pricing.) Apart from enabling the various agents in discriminating between stock exchanges in terms of liquidity, such studies also help the regulators to design an appropriate measure of liquidity for an efficient and transparent trading system. This is particularly true of emerging markets that are generally believed to be less transparent with limited portfolio choices. But with dramatic growths in emerging markets and steady capital market liberalisation, Bekaert, Campbell and Lundblad (2007) find that liquidity may have even greater impacts in such markets. They opine that asset pricing models that incorporate local liquidity risks perform much better than those that employ market risk factors in
predicting future returns.

Empirical or stylized facts that emanate from such studies help us build theoretical models explaining the intraday behaviour of the underlying market. For example, a U-shaped or an L-shaped bid-ask patterns in a quote driven market seem to indicate the role of activity, risk, information and competition (see McInish and Wood, 1992). Among the emerging markets, Brockman and Chung (1998) found a U-shaped bid-ask spread curve for an order driven market like the Hong Kong market and Guo and Tian (2005) reported an L-shaped bid-ask spread for the Chinese market, which is basically an order driven market, citing the call auction at the opening of the market and asymmetric information as possible determinants.

Besides bid-ask spread and other related measures, researchers have also looked for patterns in liquidity using volume and time related measures such as depth, turnover, order ratio, trading volume, and flow ratio, which are functions of quantity or volume of shares. And these attempts have reported different patterns, hinting at different market micro structure at work. For instance, Brockman and Chung (1999) highlight the importance of using depth measures to measure liquidity. They found an inverted U-shaped pattern and they point out that systematic changes in depth may magnify or mitigate changes in spread. Similarly Admati and Pfleiderer (1988) use trading volume to explain the U-shaped pattern of the average volume of shares traded. Why do we need so many proxies? Use of such varied proxies is necessitated by the realisation that a measure that works well for one specific market need not perform well in other markets. This seems to be true especially for the emerging markets. Bekaert et al. (2007) show how zero returns, a popular proxy for liquidity, picks up a component of liquidity and transactions costs, that turnover does not. Similarly, Desmond (2005) concludes that turnover, another oft-used proxy, does not seem to be a viable measure of liquidity at all for emerging markets.

Based on such findings about the liquidity measures, some theoretical models have been proposed to explain intraday trading in both quote and order driven markets. Based on adverse selection, a particular strand of theoretical work points to asymmetric information as the reason for bid-ask spread (Glosten, 1994) in order driven markets. He finds positive correlation between bid-ask spread
and the level of informed trading. A second theory points to the existence of monopolistic traders who exploit the liquidity inelasticity at the beginning of the day. (Brock and Kleidon, 1992). This model predicts a U-shaped pattern in bid-ask spread because of such monopolistic power wielded by the liquidity providers. A third theory attributes inventory management as the reason for the presence of such empirical facts, especially the spread behaviour towards the end of a trading day. A fourth theory asserts that it is not asymmetric information but waiting costs and competition among liquidity providers that track the dynamics of a limit order model (Rosu, 2009).

While such an analysis of evaluating the liquidity of individual stocks is very much in line with market microstructure view, it is not sufficient. A strand of empirical research on asset pricing states that expected return of an asset is correlated with a market wide component of liquidity. (See Pastor and Stambaugh, 2003). Empirical financial literature analysing such a relation calls it the systematic, time varying component of liquidity or simply systematic liquidity. (See Huberman and Halka (2001) and Kempf and Mayston (2005)). An evidence of such a component normally manifests in liquidity comovement. Since investors often trade in a portfolio of securities rather than individual stocks, the question if the liquidity measures comove is important. This is often called the liquidity commonality. An important result by Chordia, Roll and Subrahmanyam (2000) tells us that individual liquidity comoves with market liquidity, which may imply that market-wide liquidity or factors may play some role in determining liquidity of individual stocks. Kempf and Mayston (2005) explain how the presence of commonality has implications for individual investors and the market as a whole. In this paper, we use principal component analysis (PCA) to identify any commonality amongst the liquidity measures.

All these are pointers to the fact that the first step in understanding the working of the microstructure of any financial market, is to understand the behaviour pattern of liquidity using a variety of liquidity proxies. Thus, our primary idea in this paper is to trace out the liquidity pattern of the Indian stock market using both spread and volume related measures and to check for any comovement amongst such measures. Hence, trying to test and predict which of the above theories work for the Indian market is not our focus. We use stocks contained in the NIFTY index. To the best of our knowledge, the present exercise is first of its kind for the Indian market and is important for several reasons.
1. In spite of clear evidence in favour of using multiple liquidity measures, BSE uses mostly turnover to measure liquidity and changes in the liquidity pattern. And NSE uses mostly the impact cost measure for the same purpose. This paper on the other hand uses many measures to check the liquidity pattern and aims to check for the presence of a composite measure of liquidity.

2. This study uses the high-frequency intraday data on stocks contained in one of the most active indexes of India and estimates several intraday liquidity proxies suggested in the literature. Such an analysis of the liquidity pattern in a pure order driven market provides a basis for comparing such patterns on an electronic system without a market maker.

3. A separate analysis of commonality amongst liquidity dimension may reveal the necessity of a common measure of liquidity. Since liquidity defies a unique definition, a finding of commonality among selected measures of liquidity could possibly confirm the fact that one may need a mix of proxies to explain liquidity in the market and if sensitivity to such commonality should be priced.

The paper is organized as follows: Next section presents an overview of the NSE and explains its main aspects. It also outlines the stocks used for analysis. Section 3 lists out the various proxies for measuring liquidity used in the existing literature. Even though this is not an exhaustive list; the proxies have been selected keeping in mind the relevance to the market. Section 4 explains in detail the liquidity patterns in the market, correlations amongst the various liquidity measures and presents the plots of the selected proxies revealing the stylized facts. The commonality amongst the liquidity measures is also explained, and the time varying pattern of commonalities across the selected measures, is explained with the help of graphs. Finally section 5 concludes and presents the directions for future research.

2 NSE: Constituents and Main Aspects

NSE of India was commissioned as a fully anonymous and an automated screen based trading system, operating on the 'National Exchange for Automated Trading' (NEAT) system based on the principle
of an order driven market. And NIFTY index consisting of fifty stocks was set up as an alternative to the SENSEX, which is another index comprising thirty stocks and on India’s other stock exchange maintained by the Bombay Stock Exchange (BSE). The early nineties was the most volatile period for the Indian stock markets, which were plagued by various scams and the BoP crisis. It was also suspected that for the most part of the eighties and the early nineties, SENSEX, the only index which was widely used for analysis was dominated by big speculators and insiders, with little or no role for individual investors. It is in this environment that NSE was commissioned. However, with the introduction of the electronic trading system in 1995, trading in BSE also became more transparent. And with corporatisation, the internal management systems of BSE improved and investor base spread. Nevertheless, the gap between the BSE index and the NSE index is still wide in terms of market share, with NSE occupying 85.65% for market share in terms of market capitalisation.

NSE consists of two major segments _viz_. Wholesale Debt Market (WDM) segment and the Capital Market (CM) segment. Trading in equities takes place in the CM segment of NSE on all weekdays except holidays declared by the exchange in advance. The market timing for the equities segment is from 9:15AM to 3:30PM. Trading takes place in three different types of market: _viz._ (1) normal market; (2) odd lot market and (3) auction market. All orders which are of regular lot size (Rs. 5 Crore) or multiples thereof are traded in the Normal Market. All orders whose order size is less than the regular lot size are traded in the odd-lot market. In the Auction Market, auctions are initiated by the Exchange on behalf of trading members for settlement related reasons.

Buy and sell orders are directly submitted by traders to the online system, which numbers and time stamps them on receipt and then immediately processes them for a potential match. Every order is given a distinctive order number and a unique time stamp. If a match is not found immediately, then orders are stored in the book on a price-time priority basis in the sequence of best price – within best price, by time. The computerised system follows the rule of matching the best buy order with the best sell order. For order matching, the best buy order is that with the highest price, while the best

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3 These timings came into effect in beginning of 2010. The current study however is based on data for 2009, when the hours of operation for equities segment was 9:55AM to 3:30PM.

4 See [http://www.nseindia.com/content/equities/eq_mkttypes.htm](http://www.nseindia.com/content/equities/eq_mkttypes.htm) for more information
sell order is that with the lowest price. This is because the computer views all buy orders available from the point of view of sellers and all sell orders from the point of view of buyers in the market. Thus, of all buy orders available in the market at any point of time, a seller would obviously like to sell at the highest possible buy price that is offered. Hence, the best buy order is the order with highest price and vice versa.

3 Intraday Market Liquidity: Issues and Measures

3.1 Issues in measuring liquidity

The measurement of the market liquidity involves tricky issues that may be attributed to the following factors. Firstly, there is no single all-encompassing measure of market liquidity. The measures by construction are multidimensional because any liquid market allows trading of any volume size and demands an immediate execution of such trading with no price impacts. Secondly, while a liquid market implies absence of market impacts, market efficiency instead requires continuous and significant price adjustments to market news.

The main point against coming to any conclusion about liquidity of a market using intra day data is that, such studies are conducted over a limited period of time. This is true for many markets, simply because one does not get such high frequency data for an extended period of time. And for many markets we don’t get continuous data. Since liquidity varies over time and the factors that affect liquidity also may vary over different time periods – an idea captured by analyzing the commonality among the liquidity proxies – any such conclusion on the role of liquidity may be altered, depending on the frequency of the data and the size of the sample used. Hence, most of the studies use daily data to come to any conclusion about the liquidity of any market or a stock. Even if one can somehow obtain and analyze intra day data over an extended period of time, then any conclusion about liquidity could be termed robust. One such study is by Chordia, Roll and Subrahmanyam (2001), which ends-up analyzing 3.5 billion intra day observations for more than over 10 years over a comprehensive sample NYSE stocks on each trading day.
Another issue relating to liquidity measurement is that the market system and trading mechanism also play a role in deciding a valid proxy for liquidity. What is true for a market with market maker may not be true for a pure limit order market. Moreover institutional changes, ways by which a stock market operates, changes in the government policy over time, structural changes in the domestic or external economy may all affect the liquidity measures, thereby making at least some of them inconsistent over time. Due to these reasons there is no single agreed upon proxy for measuring liquidity. As per Aitken and Forde, (2003) there are 68 extant measures of liquidity in the market used for various purposes. These measures or proxies differ depending on the frequency of data that we want to use – that is these proxies differ for intra day, daily, monthly or annual data. Not all the extant measures can be used for measuring the liquidity of any given market type or for any given frequency of data. There are only some, like Rolls measure, that can be used for any given set up. But in practice these measures are used interchangeably irrespective of the type of market or frequency of data. Liquidity proxies also differ depending on whether we want to comment on the liquidity of an entire market or individual stocks or compare across stock exchanges within a country and across countries.

Next we come to the second part of the study of this study – a study of commonality of the liquidity pattern, an idea proposed by Chordia,Roll and Subrahmanyam (2000). Studies on commonality among liquidity proxies in pure order driven markets are limited. Why study commonality? Because commonality has implications for asset pricing. Presence of commonality in liquidity proxies implies that assessing liquidity using any single measure is weak. It also implies that common factors affect returns and flows and hence supports the idea that liquidity contributes to systematic, market wide risk, which has to be priced. However evidence on the presence of commonality is mixed. Apart from Chordia,Roll and Subrahmanyam (2000), weak evidence of commonality in liquidity among NYSE stocks has been reported by Hasbrouck and Seppi (2001). But Bauer (2004) finds commonality in Switzerland’s order driven market.

While this paper definitely does not claim to address all the issues listed above, it does have the modest aim of measuring liquidity of some Indian stocks employing many common liquidity proxies used in the literature. And we also check if liquidity should be a priced factor Prior to that we describe next the data set used in this study and the adjustments done on the data set before calculating the
liquidity measures.

3.2 Dataset and Adjustments

The data for the study was collected from Thomson Reuters Tick History Database. Thomson Reuters Tick History database is a near real-time historical market data service, which offers global intra-day Time and Sales, Time and Quotes and Market Depth content from 1-Jan-1996 for an extensive range of Equities from stock markets across the world. Data request and retrieval are performed using a web interface accessible from:

https://tickhistory.thomsonreuters.com/TickHistory/login.jsp

This service captures trades and quotes data from Reuters real-time network and provides it in a near real time basis. All the data is time stamped to the nearest milliseconds. The Quotes data includes the best price quotes for Buy and Sell orders, the aggregated size of the order, the number of market makers where available, the exchange identifier and qualifiers or market condition indicators associated with the quote. The trade data includes the execution price and volume, exchange timestamps, sequence numbers where available, the exchange identifier and trade qualifiers or market condition indicators associated with the trade.

The raw data on trades and quotes for the period of 1 January 2009 to 31 December 2009 was downloaded for 20 most active stocks in NSE NIFTY index. For the purpose of this initial round of selection, the "active" stocks were decided by their market capitalization in the year 2008 - 2009. We have listed out in Table – 1 the list of 20 stocks selected for this study.

Insert Table 1 Here

Two large raw data files were used. The first one containing data set on quotes, consisting of the following variables:

- Bid Price
• Bid Size

• Ask Price

• Ask Size

We present below a small specimen snapshot of the raw quote data file

TISC.NS,01-JAN-2009,09:55:10.236,Quote,,,219,523,219.55,99,,,
TISC.NS,01-JAN-2009,09:55:22.266,Quote,,,219.85,100,219.9,1900,,
TISC.NS,01-JAN-2009,09:55:26.316,Quote,,,5,219.95,585,,,
TISC.NS,01-JAN-2009,09:55:30.515,Quote,,,219.9,200,220,254,,
TISC.NS,01-JAN-2009,09:55:34.341,Quote,,,220,895,220.8,158,,
TISC.NS,01-JAN-2009,09:55:38.302,Quote,,,220.1,517,220.55,700,,
TISC.NS,01-JAN-2009,09:55:42.289,Quote,,,220.2,226,220.5,1299,,
TISC.NS,01-JAN-2009,09:55:46.338,Quote,,,220.25,1917,220.75,221,,
TISC.NS,01-JAN-2009,09:55:50.300,Quote,,,220.5,509,220.55,112,,
TISC.NS,01-JAN-2009,09:55:54.320,Quote,,,220.6,600,220.7,985,,

This data set was used for calculating the spread-based measures of liquidity. The second data file was the Trade data, consisting of all the Transactions that actually took place. This data has the following variables:

• Price

• Volume

• Turnover

And we present below a small specimen snapshot of the raw trade data file

TISC.NS,01-JAN-2009,09:55:10.236,Trade,219.55,83,,,,,83,0,
TISC.NS,01-JAN-2009,09:55:14.295,Trade,219,429,,,,,512,0,
This data set was used for trade-based measures of liquidity. Before the data could be used for analysis, it was cleaned for errors and missing values. The large data set was sliced into 20 different data files. All the programs for calculating the liquidity measures were written to work iteratively on one data file at a time.

Both the trades and quotes data for each stock were sampled at 5-minute intervals to convert the irregular time series into equally spaced regular time series data. Cubic splines were used to interpolate any missing values generated in the process of sampling. After removing the weekends and other public holidays, there were 242 trading days on NSE in 2009. However, trading on 18th May 2009 was very volatile and it activated the circuit breakers at around 11:55AM, thereby causing a trading halt for rest of the day. As this day was an unusual occurrence and trading data generated on this day was incomplete, we discarded the data for this day. All further estimations were conducted using the 5-minute data for 241 trading days in 2009. The 5-minute sampling frequency gave us 68 data points per day and a total of 16,388 observations per stock for 241 trading days in 2009.

In the next section we list out the liquidity proxies used to quantify the liquidity patterns witnessed among the NIFTY stocks.

### 3.3 Liquidity measures.

We have used several measures to capture liquidity through depth, tightness resilience and trading time. Keeping in mind the necessity to use various proxies, we have divided the measures into *spread related measures*, *volume related measures* and *mixed measures* which contain features of both spread...
and volume measures. (See Wyss (2004) for a list of such measures.) We have used some of the measures from this list. A brief explanation of each of these measures is presented below:

### 3.3.1 Spread-related measures

Spread related measures are the most commonly used proxies to measure the depth of a market. The bid-ask spread is a common liquidity proxy (see for example Amihud and Mendelson, (1986). The difference between the ask and the bid price and its related measures give an approximate cost to be incurred when trading. But the principal determinants of bid-ask spread are fixed costs, adverse selection costs and inventory costs. While the seminal article of Kyle (1985) focus on the adverse selection component, Glosten and Milgrom (1985) capture the notion of asymmetric information. To consider a market liquid, the spread measures should have low values. We also use other measures of spread, since each measure has its own interpretation.

- **Absolute spread:**
  \[ |S_t| = p_t^A - p_t^B \]

  The absolute spread is the difference between the lowest ask price and the highest bid price. Naturally this measure is always positive and the minimum tick size is the lower limit. Chordia, Roll and Subrahmanyam (2001) use this measure in their study of the NYSE.

- **Log absolute spread:**
  \[ \ln|S_t| = \ln(p_t^A - p_t^B) \]

  This measure is used just to improve the distributional properties.

- **Relative spread or inside spread:** McInish and Wood (1992) use relative spread or percentage bid-ask spread as a preferred measure of liquidity and is calculated as the bid-ask spread divided by the simple average of the bid-price and the ask-price.

  \[ \text{Rel}(S_t) = \frac{2(p_t^A - p_t^B)}{p_t^A + p_t^B} \]

  The realized spread is an estimate of the gain a market-maker can expect to make from two
consecutive transactions. (See Frank de Jong and Rindi (2009) for more on spread related measures)

• **Effective spread**:

\[ \text{Eff}(S_t) = |p_t - p_t^M| \]

Here \( p_t \) denotes the last traded price before time \( t \). The effective spread is devised to measure actual trading costs. An evidence of a smaller effective spread than the quoted spread, means trading mainly occurs within the quoted spread (See Chordia, Roll and Subrahmanyam, 2000). The effective spread is considered by some analysts as the most meaningful measure of liquidity. SEC even obligates market centers to report summary statistics of effective spread periodically. (See Hasbrouck (2009) for more details.)

• **Rolls’ spread**:

Roll (1984) suggests a simple model on the spread in an efficient market. The Rolls spread uses the bid-ask bounce-induced negative auto-covariance in daily returns to estimate the effective spread. The Rolls Spread (RS) is defined as,

\[ RS_i = 2\sqrt{-\text{COV}_i} \]

where \( \text{COV}_i \) is the autocovariance of returns for stock \( i \). In calculating the Rolls spread, one may adopt the approach of Roll (1984) and convert all positive auto-covariances to negative.

### 3.3.2 Volume- and time-related measures

In a world of high-frequency trading, volume and related measures are still popular proxies to measure liquidity. See for example Chordia, Roll and Subrahmanyam (2001), Hasbrouck and Seppi (2001). Volume measure indicates the quantity of shares traded per time unit. High-volume trades also indicate that large volumes can be traded in a shorter time, implying a time dimension. Lee and Swaminathan (2000) show that trading volume is an important link between momentum and value strategies. If the volume-related liquidity measures are high, this is a sign of high liquidity. Similarly
time-related liquidity measures indicate how often transactions or orders take place. Therefore, high values of these measures indicate high liquidity.

- **Trading volume:** Admati and Pfleiderer (1988) (AP hereafter) use trading volume to propose a theory of intraday trading pattern that explains some of the stylized facts like concentrated trading during a particular time of the day and especially, a possible explanation for high return variability during periods of high trading volume. Trading volume for time $t-1$ until time $t$ is calculated as follows:

\[
Q_t = \sum_{i=1}^{N_t} q_i
\]

$N_t$ denotes the number of trades between $t-1$ and $t$, $q_i$ is the number of shares of trade $i$. Trading volume has been used in different forms to measure both liquidity and illiquidity which we show below. An interesting result from Engle and Lange (2001), (EL hereafter), points out that greater overall trading volume, may impart some nominal imbalance in the market and number of trades between duration may reduce the depth of the market. Their proposed VNET measure thus is negatively correlated with bid-ask spread. But Chordia, Roll and Subrahmanyam (2001) use trading volume to measure trading activity and report high positive correlation between trading volume and spread measures.

- **Turnover:** Turnover ($V_t$) for a specific time interval is calculated as follows:

\[
V_t = \sum_{i=1}^{N_t} p_i \cdot q_i
\]

One of the main reasons that led to the development of turnover rate as a liquidity proxy is the inconclusive evidence in the literature on the return spread relationship. (See Marshall (2006) for related literature on this.) And it has a strong theoretical appeal too. AM (1986) show that in equilibrium liquidity is correlated with trading frequency. However, cross-sectional studies analysing returns cast doubts over this measure acting as a proxy. Subrahmanyam (2005) explains that a possible reason could be its negative correlation with future returns of low performing stocks compared to its high positive correlation with well performing stocks.
Hence turnover may not a priori be a better liquidity measure than volume. Nevertheless its use is common in the literature.

- **Depth**: This is one of the traditional measures of liquidity and relates to the quantity that can be traded in a market and closely related to spread. And it is measured as number of shares. For example Corwin (1999) shows using this measure that market depth differs significantly among the specialist firms suggesting differing execution costs and liquidity among NYSE specialist firms. Greene and Smart (1999) examine if depth increases due to noise trading. It can be calculated the following way:

\[
D_t = q_t^A + q_t^B
\]

Chordia, Roll and Subrahmanyam (2001) divide market depth into bid and ask depth. \(q_t^A\) and \(q_t^B\) refer to the best bid and the best ask volume in the order book. To improve the distributional properties of the depth, the log depth may be used:

\[
\ln(D_t) = \ln(q_t^A) + \ln(q_t^B)
\]

- **Rupee depth**: We have used an equivalent of dollar depth for the Indian market and it is measured in Indian rupees. Rupee depth \(Re(D_t)\) is usually calculated in currency terms analogously to the average depth:

\[
Re(D_t) = \frac{q_t^A \cdot p_t^A + q_t^B \cdot p_t^B}{2}
\]

\(p_t^A\) refers to the best ask price at time \(t\) and \(p_t^B\) to the best bid price at time \(t\). Like turnover, with rupee depth also enables us to compare liquidity of different stocks directly.

- **Number of transactions per time unit, \(N_t\)**: This measure simply counts the number of trades between \(t-1\) and \(t\). The number of transactions may also be reversed to waiting time between trades:

\[
WT_t = \frac{1}{N-1} \sum_{i=2}^{N} tr_i - tr_{i-1}
\]

where \(tr_i\) denotes the time of the trade and \(tr_{i-1}\) the time of the trade before. Therefore, waiting time for a specific time space has to be calculated as an average time between two
trades as done in Ranaldo (2004).

3.3.3 Liquidity: Multidimensional measures.

As mentioned earlier, Kyle’s definition makes multi-dimensional liquidity measures inevitable. Such measures combine properties of different one-dimensional liquidity measures to give a composite measure. Recent studies highlight the necessity to use such composite measures. For example, Chordia, Roll and Subrahmanyam (2001) used spreads and quoted depth to analyze the relationship between market liquidity and macro economic factors using NYSE stocks, while Goldstein and Kavajecz (2000) use both bid-ask spreads and depth in the limit order book to analyze changes in liquidity. We use the following measures:

- **Quote slope:**
  
  \[ QS_t = \frac{p_A^t - p_B^t}{\ln(q_A^t) + \ln(q_B^t)} \]

  The spread in the numerator divided by log depth yields the quote slope and this measure was introduced by Hasbrouck and Seppi (2001). Thus the quote slope mainly aggregates the depth and the tightness dimension into one figure. A high quote slope denotes low liquidity.

- **Log quote slope:** Instead of the quote slope, the log quote slope, also based on Hasbrouck and Seppi (2001) uses the logarithm of the relative spread in the numerator:
  
  \[ \ln QS_t = \ln \frac{p_A^t}{p_B^t} \ln(q_A^t \cdot q_B^t) \]

  Since the quote slope and the log quote slope are always positive, the closer \( p_A^t \) and \( p_B^t \) are to each other, the flatter is the slope of the quote and the market becomes more liquid. These two may be viewed as a summary measure of quoted liquidity supply curve. Larger \( q_A^t \) and \( q_B^t \) are, smaller will be the slope of the quote and the more liquid will be the market.

- **Composite Liquidity:** In a similar way as the quote slope, composite liquidity \( CL_T \), presented by Chordia, Roll and Subrahmanyam (2001), combines spread and depth in a single measure and measures the slope of the liquidity function in percent. By construction this measure will
be independent of the price of the stock, if the absolute spread and absolute stock price are independent. A high composite liquidity denotes low liquidity and is defined as

\[ CL_t = \frac{2(p_t^A - p_t^B)}{p_t^M (q_t^A \cdot p_t^A + q_t^B \cdot p_t^B)} \]

- **Amivest measure (ALR):** This has been named after a company by the same name and it measures the relationship between the traded volume and the absolute price change using nonzero returns. In case of zero returns over a certain interval, this ratio is set to zero. The higher the volume, the more price movement can be absorbed. Therefore, high liquidity ratios denote high liquidity. It is defined as follows:

\[ ALR_t = \frac{V_t}{|r_t|} \]

where \( V_t \) is as defined before and \( r_t \) is the return between periods \( t - 1 \) and \( t \). Another related measure is the Amihud (2002) **illiquidity ratio** which is nothing but the reciprocal of \( ALR_t \), with nonzero volumes:

\[ AMR_t = \frac{1}{ALR_t} \]

If a stocks price moves a lot in response to little volume, this stock has a high value of Amihud measure implying that the stock is illiquid. Amihud (2002) shows that over time, expected market illiquidity positively affects ex ante stock excess return, suggesting that expected stock return partly represents an illiquidity premium. This is a very popular measure but could be affected by extreme values; but the illiquidity ratio is a better proxy. Hasbrouck (2009) finds that in cross section studies, using daily data, these two measures are positively correlated with effective cost or spread. Such a result helps us understand the relation between liquidity and transaction cost.

- **Flow ratio (FR):** This was recommended by Ranaldo (2001) and is defined as:

\[ FR_t = \frac{V_t}{WT_t} \]
Since flow ratio is the ratio of turnover to waiting time it connects quantity and time dimensions of liquidity. A high value indicates high liquidity.

- **Order ratio (OR):** This is another measure proposed by Ranaldo (2001) and he uses it to quantify market depth. This measure recognizes the fact that trading volume differs from expected market depth and order ratio is expected to capture this. If the turnover in a certain time interval is equal to zero, the order ratio is set to zero. A high order ratio denotes low liquidity. A small order ratio denotes high liquidity. And it is defined as:

\[
OR_t = \frac{|q^B_t - q^A_t|}{V_t}
\]

The list of liquidity measures presented in this section is long and certainly not an exhaustive one. It has been reiterated well earlier that liquidity is not a one-dimensional variable and therefore can hardly be captured in a single one-dimensional liquidity measure, and certainly one of the multi-dimensional liquidity measures has to be used. However, the one-dimensional measures, like the bid-ask spread may give insight into some specific questions of market liquidity which more complicated measures may not give.

4 Empirical Results: Liquidity Patterns

Liquidity patterns in all the financial markets follow some stylized facts. One such is the U-shaped pattern of the measures. So we check first if this is true of the Indian market also, by plotting all the 17 standardized measures against the intra day time of day, measured over a 5-minute interval. Figures 1.1 through 1.6 display the graphs of the standardized measures.

The liquidity patterns show all the measures have the expected shapes, with many of them having the expected U-shape. But this has differing explanations depending on which measures we are referring to. Most of the volume and time related measures reveal a U-pattern that suggests that the market was liquid both at the beginning and the end of the trading hours; the depth measures
do not exhibit such a pronounced U-shape. The spread related measures, however, clearly reveal a different picture where the U-shape means the liquidity is low towards both the business ends. Some of the combined measures of volume with spread, also show that the market was not so liquid. This highlights that higher volume is not associated with narrower spreads.

Some explanations have been offered in the literature for such a concurrent high volume and wide spreads. Brock and Kleidon (1992) predict that, for a market with an NYSE specialist market maker with monopoly power, liquidity will be inelastic at both the open and end of a trading day because, such a behaviour indicates that traders are simply adjusting their portfolios to achieve an optimal portfolio mix or transfer overnight risk. But for an order driven market this is not tenable, because there is no designated market maker. And it is difficult to find a model that can explain the such a concurrent behaviour.

Some activity seen in the volume-related measures may be related to the fact that they are calculated from best bid and ask quotes which can have a wider range. One may explain that such activity seen in the period between 12 noon and 1400 hours even with higher quotes, to the fact that orders are not being met. But towards the end of the day, the liquidity position changes. In most of the cases we see a dip around 1400 hours and the liquidity position improves sharply after 1500 hours.

Overall we see that all the measures are relatively less volatile except the order ratio which is very volatile during the period the market normally does not see much activity. With the turnover measure turning out to be smooth, a probable reason for this increased volatility could be attributed to the wider bid-ask spread observed during this time of the day. Recall that we witnessed some volatility pattern in volume related measures. Engle et al. (2011) suggest that, since volatility of liquidity is related to volatility of price, such a relatively less volatile liquidity of most measures, could be an indication of the presence of a “deep” order book where market orders are small compared to available depth.

In summary, a finding of such stylized shapes of liquidity proxies, in a pure order driven market, which are features of markets with market makers, negates the idea generally propounded in intraday
theories that it is the actions of monopolistic market makers and noise traders that give rise to such stylized relations. But the mixed evidence about the liquidity of the market, with spread measures and volume related measures both displaying a U-shaped pattern is difficult to reconcile with an order driven market.

Next we display the tables explaining the rankings of and rank correlations between the liquidity measures. Table 2 exhibits the ranking matrix of the selected stocks according to the liquidity measures used. In the ranking matrix a value of 1 denotes that stock is the most liquid with respect to the particular indicator and a value of 20 indicate that it is the most illiquid. According to table 1, liquidity ranks expectedly differ according to the measure used. For example, HALC which is the most liquid of all stocks going by the depth and spread measures, it is the most illiquid by order ratio. While Reddy labs and Hindustan computers are the most illiquid of the stocks, the top five places are occupied by stocks of companies belonging to different sectors. Interestingly, according to the popular media, the most liquid stocks for the year 2009 were Reliance Industries, SBI, Infosys and ONGC. While market micro structure could be the primary reason for existence of such varied rankings of stocks, corporate policies and institutional trading also could contribute to different dynamics.

**Insert Table 2 Here**

Table 3 displays the Spearman rank correlation between the various liquidity measures. To determine the statistical significance of these correlations we have used the critical values Spearman rank correlations tabled in Kanji (1999). We note that the correlations amongst the measures within each group in both the one dimensional and multi-dimensional measures, if existing, are high and significant, whereas, the correlations between the various liquidity measures and Amivest liquidity ratio, $ALR_t$, and Amihud illiquidity ratio, $AMR_t$, are on expected lines – that is positive correlation between $ALR_t$ and liquidity measures is matched by negative correlation with $AMR_t$.. However the correlation between $ALR_t$ and $AMR_t$ is negative but not significant. GM (1985) show empirically that bid-ask spread rises with information asymmetry and the resultant adverse selection. But in this study, traded volume, proxied by $Q_t$ as a measure of market activity, is positively correlated with many spread measures which is in agreement with a proposition by Brock and Kleidon (1992) in
their market closure model. According to them this positive correlation between volume and spread measures shows an increased demand for liquidity at both end of the trading hours, thus making liquidity demand more inelastic.

Insert Table 3 Here

On the other hand, studies by Handa, Scwarz and Tiwari (2003) and Biais, Hillion, Spatt (1995) provide evidence that new orders are still placed even when spread is large, generating mean reversion in the bid-ask spread. So Ranaldo (2001) claims such a behaviour should result in a negative correlation between spread size and order ratio or expected market depth. In our study, we do get significant negative correlation between spread measures and order ratio.

4.1 Commonality among liquidity measures

To detect any commonality amongst the liquidity measures we use the principal components analysis (PCA) of the liquidity measures. Principal components look for linear combinations of the data that explain as much variance as possible. A working knowledge of PCA is available in Manly (1986, Chapter 5.)

As before, we have used data on trade and quotes for the year 2009 and after adjusting for holidays, we get a total of 241 trading days. We have done the PCA on a 15-minute interval data which seems to be the norm. To tackle the presence of intraday seasonality, we have employed cubic splines and standardize all the liquidity proxies we have used before.

Next comes the question of transforming the proxies to achieve stationarity if necessary. Some prefer to first difference the liquidity measures like Chordia,Roll and Subrahmanyam (2001); some use HP filter and some do not recommend any detrending or differencing Hasbrouck and Seppi (2001). However, we do not transform our liquidity measures and use them as they are. We have selected only 8 of the 17 proxies listed above, because the intra-day behaviour of many of these proxies is similar. The proxies we have selected for PCA are: turnover, log depth, waiting time, absolute spread, log spread, effective spread, quote slope and log quote slope. And we use the standardized measures of
We do two types of PCA, one to check the commonality across measures and the second to check the time variation across liquidities within a given day.

For the first analysis, we first calculate the liquidity proxies for every 15-minute intervals and then average every proxy over 15-minute intervals to get one figure. So if we have 23 15-minute observations everyday, and then we average over these 23 observations, to get one representative figure for the day. Such a representative figure is calculated for all 20 stocks for any chosen proxy so that an average will give us a representative figure for the chosen proxy for all stocks. Calculating this way for all 241 trading days for all stocks, will give us 8 such time series of length 241 on which we do a PCA.

PCA involves calculating 8 eigen values and obtaining 8 eigen vectors. These results are tabulated in Table 4. The results clearly show only very weak commonality across measures, with the very first eigen value explaining only 18% of the total variation. This implies no specific common measure had a larger impact on liquidity in the year 2009. Kempf and Mayston (2006) suggest three reasons for an evidence of weak commonality: (i) use of inadequate liquidity proxies (ii) best quotes are noisy and subject to idiosyncratic variation, because of fierce competition amongst liquidity suppliers, and (iii) weak commonality could be due time varying pattern in commonalities across measures and particularly low in falling markets.

Insert Table 4 Here

So, next we address the question, if commonality varies within the day. Following Hasbrouck and Seppi (2001) we calculate a time series of first liquidity proxy – turnover – over the first 15-minute interval for the entire sample over all the 20 selected stocks. And we repeat this for every fifteen minute interval. Likewise we calculate the time series for other proxies. We have plotted these intraday variations in various liquidity proxies in figures 1.9 through 1.11. The plots do not reveal any undue variations within the day, except waiting time. Though turnover exhibits high eigenvalues, the commonality remains generally flat throughout the day with a tendency to peak towards the end
of the day.

Insert Figure 1.9 - Figure 1.11 Here

In sum, not accounting for time varying pattern may not be the reason for weak commonality across liquidity measures. Absence of commonality has also been reported in many studies also, suggesting that it may not be a general attribute of a financial assets.

5 Conclusion

The purpose of this study is to investigate the liquidity pattern and commonality, if any, across the liquidity measures in the stocks contained in the Nifty index of NSE. NSE is a purely order driven market, and most studies analysing liquidity use NYSE Studies analysing a pure order driven market for such features are few. With the NSE establishing itself as a premier stock exchange of India, an absence of a detailed investigation of liquidity patterns of stocks traded in its Nifty index is a big gap, which this study attempts to fill. Using intraday trading information on Nifty stocks for the year 2009, we calculated several proxies existing in the literature. We found many of them to be having the U-shaped pattern, which is a stylized fact among the quote driven or hybrid markets. This raises some questions about the established market micro structure reasons provided for such patterns. For example, the U-shaped bid-ask spread measure in a pure order market, is inconsistent with the idea that it is the presence of monopolistic liquidity providers, that contributes to the increased liquidity at both the ends of a trading day. Correlations are generally high and significant within each group. Again we find evidence, like that of positive correlation between volume and spread measures, that is normally attributed to market makers’ monopolistic behaviour.

We could find only weak commonality amongst various measures. Working on the suggestion by Kempf and Mayston (2006) that weak commonality could be due to time variation in commonality measures, we used PCA to check for intraday variation in liquidity measures. Again, we found only weak commonality amongst the measures, providing only weak evidence that such commonality in liquidity has to be a priced risk.
Needless to say that for any robust decision on liquidity of the market one has to extend such a study to a larger sample and complement it in many ways. For instance, empirically testing the reasons for the observed U-shaped patterns of bid-ask spread or other patterns could be a next useful step. For example, Guo and Tian (2005) find in their study of Chinese stock market, that bid-ask spreads pattern has a positive relation with volatility and a negative relation with stock prices. Continuing with the present study, finding valid empirical reasons for a concurrent high volume-high spread could also be a constructive step to help build a theoretical model of the market.
References


Engle, R. F., and J. Lange, (2001), Predicting VNET: A model of the dynamics of market depth,


Centre for Financial Research.


Figures and Tables

Intraday behaviour of Liquidity Proxies

Figure 1.1 Volume related liquidity measures : Trading volume and Turnover

Figure 1.2 Volume related liquidity measures : Depth, log Depth and Rupee Depth
Figure 1.3 Time related liquidity measures: Average Number of transactions and average waiting time between transactions.

Figure 1.4 Spread related liquidity measures: Absolute spread, Relative spread, Log Absolute spread and Effective spread.
Figure 1.5 Multidimensional liquidity measures: Quote slope, Log Quote Slope and Composite Liquidity

Figure 1.6 Multidimensional liquidity measures: Amivest liquidity measure and Amihud’s liquidity ratio
Figure 1.7 Multidimensional liquidity measures: Flow ratio

Figure 1.8 Multidimensional liquidity measures: Order ratio
Intraday behaviour of PCA eigenvalues

Figure 1.9 Intraday behaviour of First Eigenvalue of Turnover and Waiting Time.

Figure 1.10 Intraday behaviour of First Eigenvalue of Absolute spread, Log spread and Effective spread.
Figure 1.11 Intraday behaviour of First Eigenvalue of Log Depth, Quote slope and Log Quote slope.
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Table 2: Ranking of stocks according to different liquidity measures

|       | $Q_t$ | $V_t$ | $D_t$ | $\ln(D_t)$ | Re($D_t$) | $WT_{1t}$ | $WT_{2t}$ | $|S_t|$ | $\ln|S_t|$ | Rel($S_t$) | Eff($S_t$) | $RS_t$ | $QS_{ ' t}$ | $\ln(QST_t)$ | $CL_t$ | $ALR_t$ | $AMR_t$ | $FR_t$ | $OR_t$ | Average | Rank |
|-------|-------|-------|-------|-------------|-----------|-----------|-----------|-------|-----------|------------|------------|-------|-----------|------------|-------|--------|--------|-------|-------|---------|------|
| INFY  | 14    | 6     | 14    | 15          | 2         | 10        | 9         | 18    | 18        | 3          | 8          | 16    | 6         | 3           | 10    | 10     | 12     | 11    | 10.68 | 10      |
| ZEE   | 11    | 19    | 7     | 7           | 19        | 17        | 15        | 6     | 6         | 17         | 6          | 5     | 6         | 17          | 17    | 17     | 16     | 16    | 12.63 | 13      |
| RELI  | 6     | 1     | 11    | 11          | 1         | 2         | 2         | 13    | 13        | 1          | 13         | 16    | 12        | 1           | 1     | 4      | 6      | 5     | 6.79  | 4       |
| WIPR  | 15    | 15    | 10    | 10          | 14        | 14        | 14        | 10    | 10        | 12         | 10         | 14    | 10        | 15          | 14    | 16     | 12     | 14    | 12.79 | 15      |
| ITC   | 5     | 11    | 3     | 3           | 9         | 11        | 12        | 3     | 3         | 10         | 3          | 13    | 3         | 8           | 13    | 6      | 5      | 6     | 7.68  | 7       |
| LART  | 9     | 5     | 12    | 12          | 8         | 5         | 4         | 14    | 12        | 6          | 14         | 18    | 13        | 5           | 6     | 9      | 9      | 8     | 9.16  | 9       |
| HLL   | 7     | 13    | 4     | 4           | 12        | 16        | 16        | 5     | 5         | 11         | 4          | 1     | 4         | 9           | 11    | 7      | 7      | 11    | 8.68  | 8       |
| SBI   | 8     | 3     | 13    | 14          | 3         | 4         | 5         | 15    | 15        | 2          | 15         | 4     | 14        | 3           | 2     | 8      | 8      | 7     | 7.63  | 6       |
| RANB  | 10    | 16    | 9     | 9           | 16        | 12        | 11        | 8     | 7         | 13         | 8          | 10    | 8         | 14          | 15    | 14     | 11     | 10    | 11.26 | 11      |
| TISC  | 1     | 4     | 5     | 5           | 6         | 1         | 3         | 4     | 4         | 7          | 5          | 2     | 5         | 4           | 7     | 2      | 1      | 1     | 4.15  | 1       |
| HCLI  | 20    | 20    | 15    | 13          | 20        | 20        | 20        | 11    | 11        | 20         | 11         | 20    | 11        | 20          | 20    | 20     | 20     | 20    | 16.47 | 19      |
| BHEL  | 17    | 7     | 19    | 19          | 5         | 9         | 7         | 19    | 20        | 5          | 20         | 6     | 19        | 10          | 5     | 13     | 13     | 17    | 12.42 | 12      |
| REDY  | 19    | 18    | 20    | 20          | 18        | 19        | 19        | 16    | 16        | 16         | 19         | 18    | 19        | 18          | 15    | 18     | 19     | 4     | 16.79 | 20      |
| ICBK  | 3     | 2     | 6     | 6           | 4         | 3         | 1         | 9     | 9         | 4          | 9          | 12    | 9         | 2           | 4     | 1      | 3      | 3     | 5.21  | 2       |
| HDBK  | 16    | 9     | 17    | 16          | 11        | 15        | 13        | 17    | 17        | 8          | 17         | 19    | 17        | 11          | 8     | 12     | 14     | 18    | 13.79 | 17      |
| SAIL  | 2     | 10    | 2     | 2           | 10        | 6         | 6         | 2     | 2         | 14         | 2          | 17    | 2         | 7           | 10    | 3      | 2      | 4     | 6.32  | 3       |
| TEML  | 18    | 14    | 18    | 18          | 17        | 13        | 17        | 12    | 14        | 18         | 12         | 9     | 15        | 18          | 19    | 18     | 19     | 13    | 15    | 18      |
| JNLP  | 12    | 8     | 16    | 17          | 13        | 8         | 10        | 20    | 19        | 9          | 19         | 3     | 20        | 13          | 9     | 11     | 17     | 9     | 12.68 | 14      |
| CIPL  | 13    | 17    | 8     | 8           | 15        | 18        | 18        | 7     | 8         | 15         | 7          | 15    | 7         | 16          | 16    | 15     | 15     | 15    | 13.05 | 16      |
| HALC  | 4     | 12    | 1     | 1           | 7         | 7         | 8         | 1     | 1         | 19         | 1          | 11    | 1         | 12          | 12    | 5      | 4      | 2     | 6.79  | 4       |
### Table 3: Spearman Rank correlation between different liquidity measures

|       | $Q_t$ | $V_t$ | $D_t$ | $\ln(D_t)$ | $Re(D_t)$ | $WT_{1t}$ | $WT_{2t}$ | $|S_t|$ | $\ln|S_t|$ | $Rel(S_t)$ | $RS_t$ | $QS_{1t}$ | $\ln(QST_{t})$ | $CL_t$ | $ALR_t$ | $AMR_t$ | $FR_t$ | $OR_t$ |
|-------|-------|-------|-------|-------------|-----------|-----------|-----------|-------|-----------|------------|-------|----------|----------------|-------|-------|-------|-------|-------|
| $Q_t$ | 1     |       |       |             |           |           |           |       |           |            |       |          |                |       |       |       |       |       |
| $V_t$ | 0.39* | 1     |       |             |           |           |           |       |           |            |       |          |                |       |       |       |       |       |
| $D_t$ | 0.71** | -0.13 | 1     |             |           |           |           |       |           |            |       |          |                |       |       |       |       |       |
| $\ln(D_t)$ | 0.79** | -0.06 | 0.91** | 1       |           |           |           |       |           |            |       |          |                |       |       |       |       |       |
| $Re(D_t)$ | 0.43* | 0.86** | 0.14 | 0.15 | 1       |           |           |       |           |            |       |          |                |       |       |       |       |       |
| $WT_{1t}$ | 0.67** | 0.84** | 0.20 | 0.25 | 0.80** | 1       |           |       |           |            |       |          |                |       |       |       |       |       |
| $WT_{2t}$ | -0.42* | -0.48* | -0.19 | -0.23 | -0.63** | -0.71** | 1       |       |           |            |       |          |                |       |       |       |       |       |
| $|S_t|$ | -0.58** | 0.20 | -0.61** | -0.83** | 0.21 | -0.01 | -0.03 | 1       |           |            |       |          |                |       |       |       |       |       |
| $\ln|S_t|$ | -0.65** | 0.24 | -0.74** | -0.91** | 0.17 | -0.04 | 0.04 | 0.97** | 1       |           |       |          |                |       |       |       |       |       |
| $Rel(S_t)$ | -0.23 | -0.48* | 0.03 | -0.02 | -0.62** | -0.61** | 0.95** | -0.19 | -0.14 | 1       |       |          |                |       |       |       |       |       |
| $Eff(S_t)$ | -0.57** | 0.23 | -0.61** | 0.82** | 0.24 | 0.02 | -0.06 | 0.99** | 0.97** | -0.22 | 1       |       |          |                |       |       |       |       |       |
| $RS_t$ | -0.12 | -0.05 | -0.02 | -0.08 | -0.11 | -0.19 | 0.45* | 0.03 | 0.08 | 0.49* | 0.21 | 1       |       |       |       |       |       |
| $QS_{1t}$ | -0.59** | 0.11 | -0.59** | -0.82** | 0.12 | -0.08 | 0.00 | 0.99** | -0.95** | -0.16 | 0.98** | 0.00 | 1       |       |       |       |       |       |
| $\ln(QST_{t})$ | -0.39* | -0.46* | -0.18 | -0.25 | -0.64** | -0.65** | 0.98** | 0.01 | 0.07 | 0.97** | -0.03 | 0.48* | 0.04 | 1       |       |       |       |       |       |
| $CL_t$ | -0.28 | -0.32 | -0.15 | -0.16 | -0.50* | -0.52** | 0.96** | -0.06 | 0.01 | 0.97** | -0.09 | 0.53** | 0.05 | 0.97** | 1       |       |       |       |       |
| $ALR_t$ | 0.90** | 0.69** | 0.44* | 0.59** | 0.68** | 0.82** | -0.52** | -0.38* | -0.42* | -0.42* | -0.36 | -0.18 | -0.43* | -0.53** | -0.38* | 1       |       |       |       |       |
| $AMR_t$ | -0.27 | -0.26 | -0.15 | -0.17 | -0.43* | -0.47* | 0.94** | -0.01 | 0.05 | 0.94** | -0.04 | 0.54** | -0.01 | 0.95** | 0.99** | -0.34 | 1       |       |       |       |       |
| $FR_t$ | 0.98** | 0.46* | 0.64** | 0.70** | 0.44* | 0.73** | -0.41* | -0.49* | -0.56** | -0.22 | -0.48* | -0.13 | -0.51* | -0.37 | -0.26 | 0.90** | -0.24 | 1       |       |       |       |       |
| $OR_t$ | 0.45** | -0.26 | 0.92** | 0.85** | 0.06 | 0.00 | -0.16 | -0.60** | -0.72** | 0.03 | -0.60** | -0.10 | -0.58** | -0.17 | -0.16 | 0.27 | -0.18 | 0.41* | 1       |       |       |       |       |

Note: */ ** denotes significance at 5% and at 1% respectively.
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