Measuring and explaining the asymmetry of liquidity

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Abstract

The paper analyses liquidity in an open, electronic, limit order book exchange, where the impact cost of a market order to buy and to sell can be directly measured. There is clear evidence of asymmetry in the liquidity offered in the spot market: large market orders to *sell* face higher costs than similar orders to buy. In the nearly identical microstructure setting, single stock futures do not face similar asymmetry. The difference in microstructure is that these futures are cash settled in India, and do not face short sale constraints, unlike the spot. The evidence suggests that short sale constraints contribute to asymmetry in securities market liquidity.

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1 Introduction

The empirical analysis of financial market returns has established several stylised empirical features, one of which is asymmetry in returns (Beedles, 1979; Conine and Tamarkin, 1981; Peiro, 1999). Much less is known about asymmetry in *liquidity*. Asymmetry in liquidity is said to exist when, for the same size of transaction, a buyer faces a different cost of liquidity when compared to a seller. The presence or absence of such asymmetry in liquidity is interesting, in that it can improve our understanding of liquidity and potentially shed new insights into the distribution of market returns.

Theoretical arguments about the difference in price impact when buying versus selling are grounded in the issues of adverse selection, the problems of holding inventory of shares as opposed to funds, and the problems of borrowing shares. While they yield predictions that asymmetry will be present, they yield inconclusive predictions about the direction of asymmetry. A body of empirical literature is currently being built to guide an understanding of the stylised empirical facts.

An important barrier affecting research in this field are difficulties in the measurement of liquidity. Measures such as the bid-offer spread only capture pre-trade liquidity for small transactions and implicitly assume symmetry of liquidity. Full information on orders from buyers and sellers is often not observed. The rise of the electronic limit order book market, worldwide, has led to great improvements in datasets. When the entire limit order book is observed, pre-trade liquidity (defined as the impact cost faced by a market order) can be directly measured for all order sizes. This permits comparison of the impact cost when buying versus the impact cost when selling.

In this paper, we develop new insights into asymmetry of liquidity, using data from equity spot trading and single stock futures trading at the National Stock Exchange in India. It is one of the most active exchanges in the world, and is an electronic limit order book market, which permits observation of impact cost for all securities at all transaction sizes, whether buy or sell. A vital feature, which we exploit in the paper, is the difference in settlement on the spot and the single stock futures market. The spot market is physically settled with delivery of shares for funds. There is no formal mechanism for borrowing shares, which exacerbates the effect of short sale constraints that are also present on the spot market. The single stock futures market, however, is cash settled, and there is no difficulty in short selling.

We test for the asymmetry of liquidity on the spot and the single stock futures market using three alternative approaches: the difference in the probability of execution of sell versus buy market order (immediacy), the difference in the impact cost of sell versus buy market orders, and the difference in the shape of the 'liquidity supply schedule' for sell versus buy orders.

We find that all three measures show some asymmetry for the spot market for larger sizes of orders, while none of the three measures indicate asymmetry of liquidity on the single stock futures market. For the spot market, all three measures suggest that sell-side liquidity (transactions costs when buying) is *higher than* buy-side liquidity for large-sized transactions.

Informed traders are likely to prefer single stock futures trading as they desire leveraged positions. Our results show that even under this adverse selection, asymmetry in liquidity is absent when there is cash settlement. After the actions of many informed traders have been skimmed off into the single stock futures market, there is clear evidence of asymmetry in liquidity on the spot market. Transactions costs are lower when *buying*. This is consistent with the idea that liquidity providers are more comfortable holding cash instead of holding an inventory of securities.

The contributions of this work are as follows. This is one of the first papers to use the full limit order book from an electronic limit order book to compare liquidity separately for buy and sell limit orders. We present a clean setting: with cash settlement on the single stock futures, and no short selling on the spot market. In this setting, we find a clear and striking result: there is little asymmetry in liquidity with cash-settled stock futures, but transactions costs are much lower when buying as compared with selling for the spot market.

The paper is organised as follows. Section 2 reviews evidence of and reasons behind liquidity asymmetry in the existing literature. Section 3 describes the uniqueness of the dataset. Section 4 proposes three measures of asymmetry in liquidity on a limit order book market. In Section 5, these measures are used to answer questions on the presence of liquidity asymmetry in the spot and single stock futures markets and whether the asymmetry can be attributed to short sale constraints. Section 6 concludes.

2 The asymmetry of liquidity

When the midpoint quote is $\bar{p}$, a market order for q shares is executed at $(1+\lambda(q))\bar{p}$. Buy orders are $q > 0$ and experience $\lambda(q) > 0$. Sell orders are $q < 0$ and experience $\lambda(q) < 0$. We use $Q > q$ to denote a large order. Liquidity is symmetric when $\lambda(q) = -\lambda(-q)$.

There are three conceptual arguments about how asymmetry might be present in market liquidity:

Inventory management costs Liquidity providers are less willing to hold a large inventory of shares compared with a large inventory of funds. Hence, they will demand a greater fee for buying large block of shares, i.e., *liquidity will be inferior for large sell orders*: $\lambda(Q) < -\lambda(-Q)$.

Adverse selection Real-world difficulties in borrowing securities and constraints on short selling make it difficult for informed traders to execute large sell trades on the spot market. The presence of such constraints makes liquidity providers more worried that the large seller is more confident about her information about an expected drop in price. In markets with such constraints, *liquidity will be inferior for large sell orders*: $\lambda(Q) < -\lambda(-Q)$.

Limited supply of shares There is an infinite amount of money in the world, but liquidity providers will run out of borrowed shares. Here, *liquidity will be superior for large sell orders* when compared with buy orders: $\lambda(Q) > -\lambda(-Q)$.

Thus, two arguments – inventory management and adverse selection from short sale constraints – predict *lower* $\lambda(Q)$ *when buying than selling*, while the third predicts the opposite.

The direction of the asymmetry of market liquidity has been explored in research based on patterns in prices after a large buy or a large sell trade (Roll, 1984; Amihud, 2002; Pastor and Stambaugh, 2003; Brennan *et al.*, 2010). This work finds that prices drop more sharply after large sell trades compared to the rise in prices after large buy trades, which shows that $\lambda(Q) < -\lambda(-Q)$. This is particularly true when information asymmetry is likely to be higher: for example, Michayluk and Neuhauser (2008) demonstrated a greater asymmetry between sell and buy prices of newly listed internet and technology stocks.

There is less established work on how problems in borrowing securities and short sale constraints affect liquidity asymmetry. There is some recent work analysing how overall market quality is affected by short sale constraints. For example, Helmes *et al.* (2010), Battalio and Schultz (2011) and Beber and Pagano (2013) analysed short sale constraints introduced in 2008 and 2009 and showed that liquidity worsened and volatility increased beyond what could be explained by the crisis alone. However, they do not analyse the effect of these constraints on liquidity asymmetry.

A significant change in the ability to measure market liquidity took place when securities markets shifted from largely being specialist or market-maker markets to becoming electronic limit order book (LOB) markets with no designated liquidity providers. However, these markets allow a higher degree of transparency about available market liquidity. Therefore, liquidity asymmetry can be observed from standing limit orders – *available market liquidity* – as compared to from traded prices.

Research about the liquidity patterns in these markets are relatively nascent. Empirical evidence based on traded prices on these markets show that liquidity asymmetry remains consistent with earlier studies with $\lambda(Q) < -\lambda(-Q)$ (Brennan *et al.*, 2010; Nguyen *et al.*, 2010). Theoretical models based on information asymmetry between traders (Glosten, 1994; deJong *et al.*, 1996; Hedvall *et al.*, 1997; Biais and Weill, 2009) or based on ability of multiple agents to place and cancel limit order (Rosu, 2009) develop predictions on the behaviour of various market liquidity characteristics such as the bid-ask spread and the price impact of transactions, but not asymmetry of liquidity. None of these studies analyses the effect of the adverse selection caused by restrictions on borrowing and short sale constraints.

3 The research setting

In this paper, we exploit access to a very liquid equity market to analyse the effect of short sale constraints on liquidity asymmetry in an electronic, limit order book market. The National Stock Exchange (NSE), in India, is one of the most active exchanges in the world in trading equity. Table 1 shows NSE as the largest exchange in 2012 by number of shares traded on the spot market and the 4th largest in terms of the contracts traded of single stock futures.

We analyse limit orders from the LOB to measure the buy-side liquidity ($\lambda(q), \lambda(Q)$) and sell-side liquidity ($-\lambda(-q), -\lambda(-Q)$) for both the spot equity and single stock futures for the same securities. Both these markets trade using an anonymous, electronic, *limit order book* (LOB) mechanism. By default, all traders can see the best five prices to both the buy and sell side of the LOB. At each price, the available quantity is aggregated over all the limit orders placed at that price automatically without the intervention of designated specialists or market makers. Hidden orders placed at the price are not included in the reported quantity.

Trades on both spot and single stock futures markets are cleared through a clearing corporation. Spot market trades are settled on a $T + 2$ basis, while the mark-to-market changes in single stock futures exposure are cleared on a $T + 1$ basis. However, the spot equity market has short sale constraints and no established market mechanism from which to borrow securities. The single stock futures markets at the NSE, on the other hand, are cash settled. Thus, traders in these markets are free from both costs of inventory management of shares, restrictions on borrowing shares and short sale constraints.

Thus, the microstructure features of these two markets are the same other than the settlement process and the constraints on short sales and on borrowing shares on the spot market. Any significant difference in the liquidity and liquidity asymmetry between these two markets are likely because of short sale constraints and restrictions on borrowing securities.

We analyse liquidity using the LOB of the 100 largest securities by market capitalisation trading on the NSE and their related single stock futures contracts. Liquidity or transactions costs are measured based on *snapshots* of the entire LOB. The snapshots are taken at five times during the trading day (10 A.M., 11 A.M., 12 P.M., 1 P.M. and 2 P.M.) for every trading day in the year. Unlike the five-deep LOB that is visible to traders, the snapshots we analyse contain price and quantity information for every order present in the limit order book, including all hidden orders. In total, the dataset comprises more than half a million LOBs, each for a security at one of the listed snapshots for all days in a year. With such a dataset, it is possible to map the entire schedule of available quantity (to buy or sell) at any given price (to buy or sell), unlike with the dataset used in the previous literature where only traded prices and quantities are observed.

We analyse these data for the following three years, where each year captures varying levels and depths of overall market liquidity:

2006: Indian securities markets had a positive growth trend between 2003 and 2008, which led to a steady improvement in liquidity over this period.

2009: After the 2008 global financial crisis, there was a sharp drop in both price and liquidity levels compared to 2006.

2012: Four years after the global financial crisis, the market had recovered to pre-crisis levels, with much higher levels of market liquidity, even compared to before the crisis period.

Table 2 presents descriptive statistics of the spot market liquidity in the sample, including traditional measures of liquidity such as the *bid-ask spread* and *depth*. The depth measures are presented for the buy-side and sell-side separately. The values reported are the median for the overall sample and for size-based quintiles, with the standard deviation in parentheses showing the variation of the median within each group.

We see that the bid-ask spread increases across firm size systematically, showing that larger firms have relatively better liquidity. Depth does not show a similarly consistent pattern. Smaller firms may show a higher depth in terms of shares, but could still be less liquid in terms of transactions costs.

4 Measuring liquidity asymmetry in the LOB market

In much of the existing literature, $\lambda(q), -\lambda(-q)$ was measured by how far the last traded price TP is from the observed mid-point quote, $\bar{P} = (bid + ask)/2$. The percentage degradation of TP compared with $\bar{P}$ is called the *price impact* of the trade. This can be measured differently for buy and sell trades, but only for the size that was observed in the market. A comparison of buy and sell costs for the same trade size could not be ensured.

With access to the full LOB, it is possible to estimate $\lambda(q), -\lambda(-q)$ directly, for a market order of any size q. This gives us the expected liquidity cost based on available limit orders, rather than based on a post-facto traded price. A snapshot of the LOB at any given time allows us to calculate the expected price per unit, P_Q, for a market limit order of size Q. This allows us to calculate the *impact cost of a market order of size* q, (IC_q) as:

$$\text{IC}_Q = 100(P_Q - \bar{P})/\bar{P}$$

IC_Q can be calculated for all trade sizes from $Q = q \ldots Q$. When this is drawn for all possible q from $q_{\min}$ to $Q_{\max}$, the relationship of liquidity cost to transaction size can be graphed as *liquidity supply schedule* (LSS).[1]

In the dataset, the LSS is observed for all securities at all order book snapshots. An example of the LSS_{sell} and LSS_{buy} for a given security is presented in Figure 1. This shows that the impact cost of a market order is weakly monotonic and increasing in q. This leads us to hypothesise that there is a single function form ($f(Q)$) to fit the LSS, but with different parameter values for the buy and sell limit orders.

The information from the LSS becomes the source of multiple measures to capture the behaviour of asymmetry at small order sizes, $\lambda(q), -\lambda(-q)$, as well as large sizes, $\lambda(Q), -\lambda(-Q)$. We calculate three measures of liquidity asymmetry from these data:

1. Probability that a market order of size Q can be fully traded.
2. Difference in the estimated IC to buy, IC_Q, and to sell, IC_{-Q} ($= \text{IC}_{(\text{sell},Q)}$ - $\text{IC}_{(\text{buy},Q)}$)
3. Difference in the estimated parameters of fitted functional form model of the LSS for sell and buy transactions.

[1] The LSS can be related to what Chacko *et al.* (2008) term the 'quantity structure of immediacy prices'.

4.1 Probability of full market order execution

If the available depth in the LOB is larger than the order size Q, the probability that order can be fully executed is 1, while if the depth is lower than Q, the probability of full execution will be less than 1. These probabilities can be calculated separately for sell and buy orders. If liquidity is symmetric, then we expect to see *equal probability of full execution* for market order to sell or to buy at all order sizes.

As an example, Table 3 shows the percentage of all the LOB snapshot observations in the sample dataset where a market order of Q can be fully executed, calculated separately for sell and buy market orders.

4.2 Difference in the estimated IC to buy versus to sell

The LSS information can be used to calculate the sell-side IC for market orders to buy and sell of size Q for any security. We analyse IC for six order sizes: Rs.25,000 (the average size of trade on the spot market), Rs.250,000 (the smallest size of trade on the single stock futures market), Rs.1 million, Rs.10 million, Rs.25 million and Rs.50 million.

IC_Q will only be considered for the analysis if the order can be fully and instantly executed using the orders in the LOB. A LOB observation where the order cannot be fully executed is not included in the analysis. As an example, Table 3 shows that only a market order of $Q = 25000$ can be fully executed for all securities for all available LOB snapshots, with no missing data. For larger transaction sizes, the true IC is sometimes unobserved because the order cannot be fully executed.

This means that different securities have different numbers of observations in the sample. It also implies that the sample mean of IC_Q is a biased estimator if there are a lot of missing data for a security. We use the following two approaches to overcome the problem of missing data to address this:

Median rather than mean impact cost We know that the true IC for an order that is partially executed will be larger than the partial estimate. In this case, the sample median is a good location estimator of IC_Q because it is insensitive to the specific value adopted for missing data.

For example, suppose that there are five order book snapshots and that the IC_Q values observed for a buy market order of Q =1000 shares are $0.5, 0.6, 0.7, NA, NA$. The last two observations are missing because the order book was not able to support a market buy order. The sample mean is 0.6 and is biased downwards since liquidity is worse when the true IC_Q is unobserved. A better estimator is the sample median value of 0.7.

Here, liquidity asymmetry = (median(buy IC_Q) - median(sell IC_Q))

Mean of the difference between buy and sell IC_Q For a given security i, the asymmetry is measured as $\text{dIC}_{(Q,i)}$:

$$\mathrm{dIC}_{(Q,i)} = \mathrm{IC}_{(\text{sell-side},Q,i)} - \mathrm{IC}_{(\text{buy-side},Q,i)}$$

where dIC is available only when *both* buy and sell IC can be observed. The mean value of dIC is then uncontaminated by missing data and is used as a measure of liquidity asymmetry.

4.3 A parametric model of the LSS

A criticism of the probability of full execution and the difference in the buy-side and sell-side ICs is that they are both calculated for a limited number of order sizes, Q, where each value of Q selected is ad-hoc.

In the third measure that we propose, we utilise the full LSS to measure liquidity asymmetry. We first model the full LSS using a parametric function:

$$\mathrm{IC}_{\text{sell/buy},Q} = f(Q_{\text{sell/buy}})$$

Here, $\mathrm{IC}_{\text{sell/buy},Q}$ is the price impact of a market order to sell or buy Q shares. Once this functional form is fit to the LSS, liquidity asymmetry can be measured as the difference in the parameter values for the function on the buy and the sell LSS.

Theoretical models of the price impact have been proposed to describe the trajectory of the prices after trades, but there has been little consensus so far. Kyle (1985) assumed that impact is both linear in the traded volume and permanent in time. Bertimas and Lo (1998) assumed a linear permanent price impact while deriving dynamic optimal trading strategies that minimise the expected cost of trading Q over a fixed time horizon. Kempf and Korn (1999) modeled the price impact using a neural network model and found a non-linear relation between net order flow and price changes. Gatheral (2010) assume a no dynamic arbitrage principle that implies that the expected cost of trading should be non-negative so that price manipulation is not possible.

Empirical studies broadly conclude that the price impact of trades is an increasing, concave function of trade size ($\sqrt{Q}$) (Evans and Lyons, 2002; Gabaix *et al.*, 2003; Hasbrouck, 1991; Kempf and Korn, 1999; Plerou *et al.*, 2002; Potters and Bouchaud, 2003). A minority of recent studies find no significant deviation from linearity (Engle and Lange, 2001; Breen *et al.*, 2002; Korajczyk and Sadka, 2004). Almgren *et al.* (2005)) rejects the common square root model in favour of a *3/5 power law* function across the range of trade sizes considered. However, these studies differ from ours as they analyse the traded prices to estimate a price impact function, while we analyse the pre-trade liquidity to estimate a liquidity supply schedule. Ting and Warachka (2003) and (Huang and Ting, 2008) use intraday trade data to show that an S-curve model captures liquidity supply curves the best in terms of parameter t-statistics and adjusted R^2 performance. Rosu (2009) shows that the shape of the LSS can be a quadratic or an exponential, or a mixture of the two.

Based on the above literature, we evaluate the following functional forms for the LSS of Indian equities:

1. Linear polynomial: $\text{IC}_Q = \alpha + \beta Q$
2. Quadratic polynomial : $\text{IC}_Q = \alpha + \beta Q + \gamma Q^2$
3. Exponential : $\text{IC}_Q = exp^{\alpha+\beta Q}$
4. Stretched exponential : $\text{IC}_Q = exp^{(\alpha+\beta Q+\gamma Q^2)}$

Each of these functions are monotonically increasing in Q, and they have an *intercept* term and one or more *slope* coefficients, which capture how the price IC changes for larger order sizes. In all cases, Q is the log of the transaction size expressed in rupees.

Unlike the existing literature, which models liquidity asymmetry on data that are limited to *traded prices* that are then used to estimate price impact, we use the data observed on the orders placed in the LOB to directly calculate the IC of the market order for any trade size Q. This produces a rich dataset with which to estimate functions for the LSS for any given security at any given point in time.

Once the LSS is estimated, we can test for asymmetry by comparing the estimated parameter values. Similarly, we can estimate the impact of short sale constraints on liquidity by calculating the difference between the parameters of the buy-side and sell-side LSS functions for the *spot* market and then testing whether the parameters for the SSF market are significantly different or not.

All the four functions can be estimated using the LSS for each LOB observation for a security, separately for the buy-side and the sell-side limit orders. Table 4 reports the average adjusted R^2 for each of the four models for the buy-side and the sell-side separately. The best-fit model is taken as that with the highest adjusted R^2. These results strongly suggest that the *stretched exponential* (Model 4) is the best model for the LSS of the Indian equity markets.

As an illustration of how well Model 4 performs, Table 5 compares actual values against model predictions for one security from the *S-big* sample and one security from the *S-small* sample. We find that estimates of IC_Q from the stretched exponential function compare well against the IC_Q measured from the LOB. This implies that liquidity in the electronic LOB market is more sensitive to changes in Q than is expected if the LSS is modeled as a simple linear or exponential function in Q. We calculate that:

$$\begin{aligned}\frac{\partial \text{IC}}{\partial Q} &= (\beta + 2\gamma Q)\text{IC}_Q \\ \frac{Q}{\text{IC}_Q}\frac{\partial \text{IC}}{\partial Q} &= (\beta + 2\gamma Q)Q\end{aligned}$$

where the first equation is the change in liquidity by Q and the second equation is the elasticity of liquidity. This shows that as Q increases, IC_Q worsens not just as a function of β but also with γ in the case of the stretched exponential function. We can expect both first-order and second-order changes in IC_Q in response to changes in Q with a stretched exponential as compared with the simple linear or exponential function.

We then use the estimated parameter values of the stretched exponential function - $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ - to test for asymmetry. If $\alpha_s, \beta_s, \gamma_s$ are the parameters for the LSS on the sell-side of the LOB and $\alpha_B, \beta_B, \gamma_B$ are those for the LSS on the buy-side, then we test the following hypothesis:

$$H_0 : \hat{\alpha}_S - \hat{\alpha}_B = 0$$

$$H_A : \hat{\alpha}_S - \hat{\alpha}_B > 0$$

This hypothesis is similarly tested for $\hat{\beta}_S, \hat{\beta}_B$ and $\hat{\gamma}_S, \hat{\gamma}_B$. If any of these are individually or jointly rejected, we infer this as evidence of the presence of asymmetry in the full LSS. We use the Kolmogorov-Smirnov (KS) test on the distributions of estimated α_B, α_S, β_B, β_S, γ_B, γ_S to establish which of the stated hypotheses holds in each market.

We apply the above three measures to jointly answer the question of whether there is asymmetry in the available liquidity of the equity spot and single stock futures markets. If there is a significant difference in any of the three measures for the buy-side compared to the sell-side of a given market, this can be construed as evidence that there is liquidity asymmetry in that market. Further, if there is evidence of liquidity asymmetry in the spot market (where there are short sale constraints) but none in the single stock futures markets (where there are none), we can infer that the presence of liquidity asymmetry is linked to the short sale constraints.

5 Results

We examine the presence of liquidity asymmetry in the spot market, with inventory management costs of holding securities and constraints on short selling and of borrowing shares. We also examine similar evidence from the single stock futures markets, where these costs are missing. If there is a difference in liquidity asymmetry, it can be attributed to these microstructural differences.

5.1 Is there liquidity asymmetry in the spot market?

We answer this question using each of the following three measures in the order of the probability of fully executing market orders, the difference in the IC that would be incurred in the execution and the difference in the liquidity supply schedule for the buy and the sell side of the market.

Fully executing market orders

Table 8 presents the probability of full execution for buy and sell market orders on the spot market in 2006. The corresponding data for 2009 and 2012 are presented in Tables 9 and 10.

In each table, the results are presented for the full sample and for quintiles by market capitalisation. Columns $2-7$ present the probability of full execution for *buy* market orders $(\lambda(q), \lambda(Q))$ and Columns $8-13$ that for *sell* market orders

$(-\lambda(-q), -\lambda(-Q))$. Probabilities of execution that are significantly higher to the seller compared to buyers at a 5% level of significance are marked in boldface.

The results shows that when order sizes are small (Q =Rs.25,000 or Rs.250,000), a buyer and a seller face the same probability that their market orders get fully executed in the market, or $\lambda(q) = -\lambda(-q)$. There is no liquidity asymmetry for small orders.

However, for larger order sizes (Q =Rs.10 million or Rs.50 million),[2], there is a higher probability that a market order on the *buy-side* will get fully executed compared to the *sell-side* for the spot market. This implies that $\lambda(Q) < -\lambda(-Q)$ or that there is liquidity asymmetry for larger orders.

This liquidity asymmetry is found across all the securities in the sample from the largest to smallest securities and is consistent with the existing evidence about liquidity asymmetry in markets with inventory costs and information asymmetry among traders.

Evidence of buy-side versus sell-side IC

Table 11 presents the average dIC_Q for the sample for 2006. These values are also calculated for 2009 in Table 12 and for 2012 in Table 13.

Columns $2-7$ show the average $\text{dIC}_{(Q,i)}$ for various order sizes for the spot market, and columns $8-13$ show equivalent values for the single stock futures market. The standard deviation of the sample average is presented in parentheses.

The results show that liquidity is symmetric for buyers and sellers for smaller-sized market orders, or $\lambda(q) = -\lambda(-q)$.

However, for larger values of Q, $\text{dIC}_{(Q,i)}$ becomes positive and significant. This implies that $\lambda(Q) < -\lambda(-Q)$.

For example, in the overall sample, IC_{sell} for $Q \geq$ Rs.10million is, on average, 1.35% higher than the value of IC_{buy} for the same Q.

The difference appears to be the lowest in 2006, where the difference in IC for the sellers compared to the buyers started becoming significant for all securities at Q =Rs.25 million and larger. However, in 2009, the year after the global financial markets faced a systematic drop in liquidity, the asymmetry in liquidity become more pronounced for the sellers compared to the buyers. Even for smaller Q =Rs.10 million, there is a significant and positive difference of 48 basis points in the IC of a market order for the seller compared to the buyer on average. Thus, a consequence of the global financial crisis in 2009 appears to be higher liquidity asymmetry in the equity markets.

This is consistent with the hypothesis that higher information asymmetry causes liquidity asymmetry: a higher degree of uncertainty about financial markets appears to have generated higher costs to sellers compared to buyers.

[2]Rs.50 million was the equivalent of USD 1.10 million in 2006 and 0.90 million in 2012.

Evidence from a parametric model of the LSS

The last measure compares estimated parameters of a function fit to the liquidity supply schedule, which maps the available impact cost for market orders at all possible order sizes. These functions have been estimated separately using buy limit orders and sell limit orders.

Table 14 presents the average values of the parameter estimates using the 2006 data, for the overall sample (denoted as *Sample*) as well as sub-samples based on quintiles by market capitalisation. $\alpha_S^S, \beta_S^S, \gamma_S^S$ are the parameters for the *Spot* market on the *sell-side*, and $\alpha_B^S, \beta_B^S, \gamma_B^S$ are the parameters for the *Spot* market on the *buy-side*. If the parameter estimate on one side of the LOB is significantly higher than the other side, it is indicated in **boldface**. Tables 15 and 16 show these using data for 2009 and 2012 respectively.

We see that the parameter estimates are positive. This is consistent with the idea that available liquidity becomes worse for larger Q. Further, the three parameter estimates for the LSS fit on the buy limit orders $(-\lambda(-q), -\lambda(-Q))$ are consistently higher than the parameter estimates fit on the sell limit orders $(\lambda(q), \lambda(Q))$.

The Kolmogorov-Smirnov test applied to the distributions of the estimated parameters supports the observation that the sell-side LSS is significantly higher than the buy-side LSS. This implies that available liquidity drops off more sharply for sellers for larger transaction sizes compared with available liquidity for the buyers in the market, or that $\lambda(q) < -\lambda(-q)$ and $\lambda(Q) < -\lambda(-Q)$.

Further, liquidity asymmetry persists across all the periods in the sample. $\hat{\alpha}_s$ indicates that higher costs are faced by sellers in all three periods. Further, the significantly higher $\hat{\beta}_s$ or $\hat{gamma}_s$ indicates the significantly higher elasticity of liquidity faced by sellers. The presence of asymmetry in the LSS appears to be the least in 2012.

These results lead us to the following observations about liquidity in the Indian equity *spot market*. First, liquidity is asymmetric between costs to potential buyers compared to that to potential sellers at larger values of order size, Q. Second, IC_Q is consistently higher for sellers of large market orders compared to similar-sized buy market orders: it is easier to execute a large buy market order on the spot market. Lastly, the difference in available liquidity worsens in a non-linear manner as Q increases.

5.2 Is there liquidity asymmetry in the single stock futures market?

We then apply the same measures of liquidity asymmetry to the single stock futures (SSF) markets. These markets are different from the spot market in two ways: (1) since SSF on equities in India are cash-settled, both buyers and sellers only require funds rather than shares, and (2) there are no short sale constraints imposed in positions on the futures. Thus, only information asymmetry between large sellers and the rest of the market can cause liquidity asymmetry in the case of the SSF, while both information asymmetry and short sale constraints shape the liquidity on the spot.

The results show that there is much less evidence of liquidity asymmetry in the SSF market compared to the spot market, as detailed in the following:

Fully executing market orders

Columns 14-25 list the probability of executing various order sizes in Tables 8, 9, 10 and present the probability of full execution of a buy-side and sell-side market order at various sizes for 2006, 2009 and 2012, respectively. Columns 14-19 present the probability for the sell side, while columns 20-25 present the same for the buy side.

We find that the levels of liquidity in the SSF market have a pattern similar to those in the spot market: the probability of full execution is *lower* for larger transaction sizes, and the probability of full execution is *lower* for the smaller-sized securities. However, there is little evidence of liquidity asymmetry: $\lambda(q) = -\lambda(-q)$ and $\lambda(Q) = -\lambda(-Q)$.

Evidence of buy-side versus sell-side IC We find a similar lack of evidence for liquidity asymmetry in the second measure. The difference in the IC of buy market orders and sell market orders for the SSF markets is presented in Tables 11, 12 and 13. Columns 8-13 give the average $\mathrm{dIC}_{(Q,i)}$ for various order sizes for the SSF market. The results suggest weak or no asymmetry in liquidity on the SSF market, or $\lambda(q) = -\lambda(-q)$ and $\lambda(Q) = -\lambda(-Q)$.

Only two out of 30 cases show some evidence of asymmetry for the year 2006.[3] This is in contrast with the corresponding table for the spot market, where 11 out of 30 cases show a significant difference. This pattern is repeated in the other periods analysed: one out of 30 cases in the SSF market in 2009 compared to 14 in spot, and two out of 30 cases in the SSF market in 2012 compared to 15 for the spot market.

Evidence from a parametric model of the LSS Lastly, we compare the evidence from the parameter estimates of function fit on the full LSS. The estimated parameters for the LSS of the SSF markets are listed in Columns $8-13$ in Tables 14, 15 and 16 for 2006, 2009 and 2012, respectively.

As in the case of the spot market estimates, the parameters for the SSF markets are also positive, but only a few are significantly different from zero. Only in 2006 are the estimated values of α significantly different from zero, for both the sell-side and the buy-side LSS. The estimated values of β and γ tend to be positive but insignificant. This indicates that the impact costs do not change significantly for larger-sized market orders compared to smaller-sized market orders in the SSF markets.

Moreover, we find that this changes in 2009 and 2012, where there is no evidence

[3] When the null is true, a test at the 95% level of significance falsely rejects 5% of the time. If the null is always true, and 30 tests are conducted, it is not unexpected to find two rejections of the null.

of liquidity asymmetry in the overall sample. It is only in the smallest quintile of securities that there is any evidence of liquidity asymmetry: where β and γ estimates are higher for the sell side of the LSS compared to the buy-side.

The results suggests weak evidence for asymmetry of liquidity in the LSS of the SSF markets, or that $\lambda(q) = -\lambda(-q)$ and $\lambda(Q) = -\lambda(-Q)$.

5.3 What accounts for liquidity asymmetry in LOB markets?

Table 6 summarises our findings about liquidity asymmetry in equity spot and single stock futures markets. This suggests that there is no liquidity asymmetry in either spot or single stock futures markets for small orders. There is only evidence of liquidity asymmetry in the equity spot markets for large sell orders compared to large buy orders ($\lambda(Q) < -\lambda(-Q)$). Such evidence is missing for large orders in the single stock futures markets.

This is consistent with the evidence from the traditional markets with designated liquidity providers who offer to buy from large sellers at a higher cost compared to selling to large buyers. What is new in our findings is the comparison with a similar analysis on the single stock futures markets. In this market, traders face the same levels of information asymmetry as in the spot market, but there is no cost of inventory management or the restrictions on having to deliver shares. We find that there is no liquidity asymmetry in the single stock futures markets. This leads us to infer that traders in limit order book markets face similar costs of inventory management in the case of

There is some variation in the three periods examined, which are differentiated by overall market liquidity. In both 2006 and 2012, well before and after the 2008 financial crisis, the liquidity available to large sellers (with market orders of size Rs.25 million and Rs.50 million,[4]) is significantly worse than what is available to their buyer counterparts. In 2009, when there was a collapse in overall market liquidity, there is some evidence that the liquidity asymmetry worsened in the spot market: sellers even at order sizes of Rs.10 million had a significant discount compared to buyers of the same orders. On the SSF markets however, there was a consistent symmetry between costs faced by sellers and buyers, for small or large market orders, in large- or small-sized securities. If there is any difference in the liquidity available to sellers in the SSF market, it is restricted to market orders of Rs.50 million when selling the futures of the smallest-sized securities.

One possible criticism is that these comparisons are exaggerated because positions of size Q on the spot market are not directly comparable with the same-size positions on the SSF because the SSF markets have leverage. The correct comparison is to take a position on the single stock futures markets that is adjusted for the amount of leverage in the market. For example, if the leverage for the single stock futures of security i is $4\times$, then a position in the spot market of Rs.10 million should be compared with a position of Rs.40 million in the SSF.

Table 7 presents the difference in the impact cost on the sell-side and buy-side of market

[4] Rs.50 million was around USD 990,000 in 2006 and USD 900,000 in 2012.

orders on the spot market (columns marked "spot") for Q =Rs.10 million and of market orders on the single stock futures markets (columns marked "SSF") for Q =Rs.50 million as a leverage-adjusted comparison.We see that, even with the adjustment for leverage, the spot market continues to show evidence of liquidity asymmetry, but not the SSF markets. We infer that the difference in the liquidity asymmetry between spot and SSF is robust to the presence of leverage.

In summary, the evidence from the NSE clearly shows that there is liquidity asymmetry in the *spot market* LOB and none in the *single stock futures market*. This suggests that inventory management costs of holding securities and the concerns of adverse selection because of constraints on borrowing securities and short sales continues to be a factor in LOB markets as in the traditional designated liquidity provider markets. This observed difference in liquidity asymmetry is persistent across periods with different levels of market liquidity and market uncertainty.

6 Conclusion

This paper provides high-quality empirical evidence of liquidity asymmetry in one of the largest electronic, limit order book equity markets in the world. The National Stock Exchange in India has the same market microstructure setting for both the spot and single stock futures contracts on the same security, except in trade settlement. There is physical settlement and short sale constraints on the spot market, but not for the single stock futures markets. This imposes costs of managing inventory of holding securities on spot market traders which are not relevant for traders of the single stock futures markets. While the futures contracts also differ from the spot in having leverage, leverage cannot induce asymmetry since the payoff in buying or selling the SSF continues to be symmetric.

Our evidence on liquidity asymmetry is drawn from three measures, which include both non-parametric and parametric approaches. All three consistently reveal higher liquidity costs large sell orders compared to large buy orders on the spot market, which is missing in the evidence from the single stock futures market. This difference in liquidity asymmetry between the spot and single stock futures markets is found in different periods, suggesting that our findings are robust across time.

These results give us fresh insights into recent debates on short selling. Regulators such as the UK FSA banned short selling for some securities, in an attempt to avoid sharp price declines. This paper suggests that short sale constraints reduce liquidity faced by market *sell* orders and thus likely to *exacerbate* the price response to speculative selling. More generally, when liquidity is asymmetric, idiosyncratic shocks to the order flow are likely to generate asymmetric price responses. Future research will explore whether the extent of asymmetry in liquidity can help explain the asymmetry in the distribution of returns for securities that trade on open, electronic, limit order book markets.

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A Tables and Graphs

Table 1 India's NSE in global rankings

In spot and in single stock futures trading, the NSE of India is one of the largest exchanges in the world.

(a) Spot market

	Exchange	Shares (billion)
1.	NSE	1.40
2.	NYSE Euronext US	1.37
3.	NASDAQ OMX	1.26
4.	Korea Exchange	1.22
5.	Shenzhen SE	0.93

(b) Single stock futures market

	Exchange	Contracts (million)
1.	NYSE Liffe Europe	247
2.	MICEX	241
3.	EUREX	196
4.	NSE	153
5.	Korea Exchange	100

Source: World Federation of Exchanges 2012 market highlights

Table 2 Summary statistics of spot market liquidity

The table presents summary statistics of liquidity measures of the sample. The statistics are presented for both the overall sample as well as subsets of firms categorised in size quintiles, from *S-big* (largest market capitalisation) to *S-small* (smallest).
The *bid-ask spread* is the relative spread, measured as the ratio of the spread as a percentage of the mid-quote price. The *inside depth* is the sum of the quantities available at the bid and the ask limit orders, measured as the number of shares. The *buy (sell) side depth* is the total number of shares available for buying (selling).
The median value is calculated across all order book snapshots for every day for each security. For a given category, the mean of the medians is reported. The cross-sectional standard deviation (of the medians) is presented in parentheses.

	Market Capitalisation (Rs. billion)	Bid-ask spread (%)	Sell-side depth (Number of shares)	Buy-side depth
Overall sample	97.32	0.15	254700	392100
	(332.01)	(0.04)	(384290)	(711410)
S-big	516.72	0.11	217550	272190
	(473.09)	(0.02)	(130290)	(185240)
S2	164.30	0.13	204710	269840
	(53.82)	(0.02)	(161010)	(237250)
S3	97.37	0.16	285180	463270
	(13.30)	(0.04)	(492720)	(897420)
S4	60.61	0.18	330730	577400
	(12.22)	(0.03)	(591150)	(1083280)
S-small	32.43	0.20	233460	371810
	(8.72)	(0.03)	(340490)	(686130)

Table 3 Probability of complete execution of market orders of the spot market

The table presents the probability of full execution of market orders for a fixed set of order sizes, Q, where each value stands for the fraction of LOB snapshots in which a market order of size Q can be fully traded. The standard deviation reported in parentheses is calculated across the probability for each security. For instance, on average, there is 96% probability of fully trading a market order of size Rs.10 million, with a sample standard deviation of 28%.

	Probability of full execution					
Q (in Rs. million)	0.025	0.25	1	10	25	50
Overall sample	1.00	0.99	0.99	0.96	0.73	0.56
	(0.00)	(0.05)	(0.08)	(0.28)	(0.31)	(0.43)

Figure 1 The liquidity supply schedule: An example of a security at one snapshot, for a day

This figure shows one example of the liquidity supply schedule, LSS, from the snapshot of the limit order book of a single security, *Infosys Technologies*, observed at noon on 8^{th} June 2012. The y-axis is the impact cost of a market order of size Q, where Q varies continuously between the minimum and maximum possible order sizes.
The IC is positive for buy limit orders: the larger the order to buy, the higher the price paid per security compared to the price paid for a single share. As an example, a market order to buy 100,000 shares has an IC of 1.8%, which implies that the price per security for 100,000 shares is 1.8% more expensive than the price per share for a single share. The price impact is negative for sell limit orders.
The graph shows that there is liquidity asymmetry for order sizes from 70,000 to 150,000 shares: the IC to buy is smaller than IC of sell orders for the same order size.

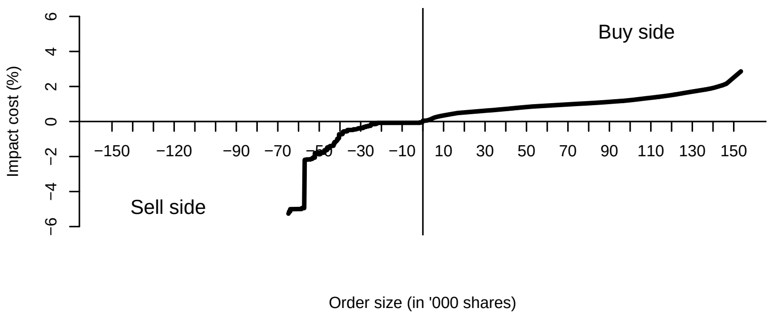

Table 4 Adjusted R^2 of alternate functions for the spot market LSS

The table reports the *adjusted* R^2 of the regression for the functional candidates, Models 1-4, for the LSS on both the buy and sell side of the limit order book. **Model 1** is the *linear* model, **Model 2** is the *quadratic* model, **Model 3** is the *exponential* model, and **Model 4** is the *stretched exponential* model. The average adjusted R^2 is reported for each quintile with the standard deviation in parentheses. *S-big* is the quintile of securities with the highest market capitalisations and *S-small* those with the lowest. The values in boldface identifies the models with the best fit in terms of adjusted R^2.

	Sell side				Buy side			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
S-big	0.53	0.81	0.85	**0.90**	0.51	0.79	0.85	**0.98**
	(0.16)	(0.13)	(0.13)	(0.06)	(0.16)	(0.10)	(0.12)	(0.05)
S2	0.54	0.80	0.88	**0.97**	0.59	0.80	0.90	**0.91**
	(0.13)	(0.10)	(0.09)	(0.03)	(0.14)	(0.11)	(0.08)	(0.03)
S3	0.57	0.83	0.88	**0.97**	0.59	0.83	0.90	**0.90**
	(0.13)	(0.10)	(0.10)	(0.04)	(0.13)	(0.10)	(0.09)	(0.04)
S4	0.57	0.84	0.89	**0.98**	0.56	0.82	0.89	**0.92**
	(0.13)	(0.09)	(0.10)	(0.04)	(0.13)	(0.10)	(0.09)	(0.03)
S-small	0.58	0.85	0.89	**0.97**	0.57	0.83	0.90	**0.90**
	(0.13)	(0.09)	(0.10)	(0.03)	(0.13)	(0.10)	(0.09)	(0.03)

Table 5 An illustration of Model 4 estimated IC versus the IC measured from the LOB for two securities

The values presented are the estimated IC ($\hat{\text{IC}}$) and the actual IC observed in the LOB for a market order of Q = Rs 0.025 million and Rs 1 million. This is done for a large market capitalisation stock, *S-big* and a small market capitalisation stock, *S-small*.

Trade Size	*S-big*				*S-small*			
(Rs Mn.)	$\hat{\text{IC}}_{\text{buy}}$	$\hat{\text{IC}}_{\text{sell}}$	IC_{buy}	IC_{sell}	$\hat{\text{IC}}_{\text{buy}}$	$\hat{\text{IC}}_{\text{sell}}$	IC_{buy}	IC_{sell}
Q = 0.025	0.066	0.066	0.065	0.060	0.146	0.129	0.202	0.144
Q = 1	0.087	0.094	0.121	0.102	1.432	1.868	1.771	2.012

Table 6 Summary of liquidity asymmetry on Indian spot and single stock futures markets

Liquidity measure	Spot	Single stock futures
1. Probability of full execution of market orders	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) < -\lambda(-Q)$	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) = -\lambda(-Q)$
2. Average of difference in buy and sell impact cost	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) < -\lambda(-Q)$	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) = -\lambda(-Q)$
3. Difference in estimated parameters of the LSS	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) < -\lambda(-Q)$	$\lambda(q) = -\lambda(-q)$ $\lambda(Q) = -\lambda(-Q)$

Table 7 Leverage adjusted comparison of liquidity asymmetry between spot and single stock futures markets

The table compares the difference in the IC for a buy and a sell market order of size Q_s in the spot market and a leverage -adjusted Q_{ssf} in the single stock futures (SSF) market.
We compare IC_Q =Rs.10 million on the spot with IC_Q =Rs.50 million on the SSF in order to adjust for leverage in the SSF. Values in **boldface** are significantly different from zero at the 95% level of significance.

	2006		2009		2012	
	Spot	SSF	Spot	SSF	Spot	SSF
S-big	0.40	0.24	0.80	0.28	**0.22**	0.15
S2	2.97	0.31	**0.49**	0.56	**0.34**	0.60
S3	0.62	0.31	**0.62**	0.93	**0.56**	1.00
S4	0.69	0.26	**0.90**	0.77	**0.71**	**1.06**
S-small	**2.15**	**0.97**	**1.15**	**1.45**	**0.92**	**0.83**
Overall sample	**1.35**	0.39	**0.65**	0.73	**0.48**	0.70

Table 8: Probability of full execution in 2006

The table shows the fraction of observations where a market order of size Q can be fully executed. This is shown as the average for the overall sample, as well as size quintiles based on market capitalisation, from *S-big* (the biggest) to *S-small* (the smallest). Values in boldface indicate where the probability of execution on one side of the book is statistically higher at a 5% level of significance.

Columns 2-9 present values for the spot market, while columns 10-17 present the probability of executing various order sizes on the single stock futures market.

A higher probability of being able to execute a single large order on the buy side indicates the presence of asymmetry between buying and selling because sell side liquidity is worse than buy side liquidity.

Quintile	Spot												Single stock futures											
	Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)						Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.82	0.82	0.81	0.45	0.32	0.06	0.82	0.82	0.81	0.59	**0.41**	**0.17**		0.68	0.68	0.62	0.48	0.26		0.68	0.68	0.66	0.57	0.30
S2	0.79	0.79	0.78	0.38	0.26	0.07	0.79	0.79	0.77	0.44	**0.34**	**0.12**		0.59	0.59	0.49	0.36	0.25		0.59	0.59	0.54	0.42	0.28
S3	0.80	0.79	0.78	0.37	0.24	0.10	0.80	0.79	0.76	**0.51**	**0.32**	**0.18**		0.54	0.54	0.50	0.41	0.23		0.54	0.54	0.52	0.40	0.28
S4	0.99	0.99	0.97	0.35	0.21	0.03	0.99	0.99	0.97	**0.56**	**0.33**	**0.09**		0.76	0.76	0.57	0.39	0.15		0.76	0.76	0.66	0.42	**0.28**
S-small	0.90	0.90	0.86	0.31	0.19	0.04	0.90	0.90	0.85	**0.43**	**0.26**	**0.10**		0.54	0.54	0.40	0.26	0.12		0.54	0.54	0.47	0.41	**0.27**
Sample	0.86	0.86	0.84	0.37	0.26	0.06	0.86	0.86	0.83	**0.51**	**0.34**	**0.13**		0.62	0.62	0.52	0.38	0.20		0.62	0.62	0.57	0.43	0.25

Table 9: Probability of full execution in 2009

The table shows the fraction of observations where a market order of size Q can be fully executed. This is shown as the average for the overall sample, as well as size quintiles based on market capitalisation, from *S-big* (the biggest) to *S-small* (the smallest). Values in boldface indicate where the probability of execution on one side of the book is statistically higher at a 5% level of significance.

Columns 2-9 present values for the spot market, while columns 10-17 present the probability of executing various order sizes on the single stock futures market.

A higher probability of being able to execute a single large order on the buy side indicates the presence of asymmetry between buying and selling because sell side liquidity is worse than buy side liquidity.

Quintile	Spot												Single stock futures											
	Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)						Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.93	0.93	0.93	0.93	0.76	0.60	0.93	0.93	0.93	0.93	**0.86**	**0.75**		0.94	0.94	0.93	0.80	0.69		0.94	0.94	0.93	0.85	0.75
S2	0.94	0.94	0.94	0.86	0.56	0.25	0.94	0.94	0.94	0.89	**0.69**	**0.41**		0.95	0.95	0.91	0.59	0.36		0.95	0.95	0.92	0.70	0.51
S3	0.95	0.95	0.94	0.83	0.54	0.29	0.95	0.95	0.94	0.86	**0.61**	**0.39**		0.85	0.85	0.74	0.49	0.22		0.85	0.84	0.76	0.56	**0.33**
S4	0.94	0.94	0.94	0.63	0.45	0.13	0.94	0.94	0.94	0.70	**0.55**	**0.24**		0.90	0.90	0.65	0.47	0.17		0.90	0.89	0.69	0.46	**0.25**
S-small	1.00	0.99	0.93	0.32	0.19	0.01	1.00	0.99	0.92	**0.45**	**0.23**	**0.08**		0.75	0.74	0.39	0.20	0.04		0.75	0.73	0.46	0.23	**0.14**
Sample	0.95	0.95	0.94	0.71	0.49	0.26	0.95	0.95	0.93	0.77	**0.56**	**0.37**		0.88	0.87	0.72	0.51	0.30		0.88	0.87	0.75	0.48	**0.40**

Table 10: Probability of full execution in 2012

The table shows the fraction of observations where a market order of size Q can be fully executed. This is shown as the average for the overall sample, as well as size quintiles based on market capitalisation, from *S-big* (the biggest) to *S-small* (the smallest). Values in boldface indicate where the probability of execution on one side of the book is statistically higher at a 5% level of significance.

Columns 2-9 present values for the spot market, while columns 10-17 present the probability of executing various order sizes on the single stock futures market.

A higher probability of being able to execute a single large order on the buy side indicates the presence of asymmetry between buying and selling because sell side liquidity is worse than buy side liquidity.

Quintile	Spot												Single stock futures											
	Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)						Sell-side Q (Rs. Mln.)						Buy-side Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.99	0.99	0.99	0.98	0.96	0.92	0.99	0.99	0.99	0.99	0.94	0.92		0.72	0.69	0.62	0.59	0.56		0.72	0.69	0.62	0.58	0.57
S2	0.98	0.98	0.98	0.97	0.84	0.75	0.98	0.98	0.98	0.98	0.88	0.80		0.69	0.65	0.61	0.52	0.42		0.69	0.65	0.61	0.54	0.46
S3	0.99	0.99	0.99	0.98	0.79	0.53	0.99	0.99	0.99	0.98	0.82	**0.59**		0.70	0.65	0.62	0.46	0.34		0.70	0.66	0.62	0.45	0.40
S4	0.98	0.98	0.98	0.92	0.64	0.42	0.98	0.98	0.98	0.95	0.70	**0.47**		0.70	0.66	0.62	0.40	0.23		0.70	0.67	0.62	0.42	0.26
S-small	0.99	0.99	0.99	0.94	0.57	0.25	0.99	0.99	0.99	0.97	**0.64**	**0.31**		0.68	0.64	0.62	0.38	0.16		0.68	0.65	0.62	0.39	**0.26**
Sample	0.99	0.99	0.99	0.96	0.75	0.57	0.99	0.99	0.99	0.97	0.71	0.62		0.70	0.66	0.62	0.42	0.34		0.70	0.66	0.62	0.44	0.39

Table 11: Difference between sell-side and buy-side liquidity, 2006

The table shows the average of the difference between the buy-side and sell-side IC when a market order of size Q can be fully executed on both sides of the LOB. Here,

$$\mathrm{dIC}_{(Q,i)} = \mathrm{IC}_{(\text{sell-side},Q,i)} - \mathrm{IC}_{(\text{buy-side},Q,i)}$$

Each cell of the table shows the sample mean. The values in brackets are sample standard deviations. Values in boldface indicate when $\mathrm{dIC}_{(Q)}$ are statistically different from zero at a 95 % level. Here, sell side liquidity is worse than buy side liquidity.
As an example, for the smallest quintile of firms by market capitalisation, the sell-side IC for a market order of Rs.10 million was worse than the buy-side IC by 215 bps, on average.

Quintile	Spot Q (Rs. Mln.)						Single stock futures Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.00	0.00	0.14	0.40	**0.89**	**2.57**		0.00	0.00	0.02	0.06	0.24
	(0.00)	(0.08)	(0.54)	(0.36)	(1.12)	(3.70)		(0.00)	(0.01)	(0.06)	(0.08)	(0.26)
S2	0.00	-0.02	0.07	2.97	**3.05**	**3.41**		0.00	0.00	0.04	0.08	0.31
	(0.01)	(0.04)	(0.22)	(3.94)	(2.56)	(2.17)		(0.00)	(0.01)	(0.09)	(0.06)	(0.44)
S3	0.00	0.00	0.16	0.62	**1.25**	**4.54**		0.00	0.00	0.04	0.12	0.31
	(0.00)	(0.03)	(0.41)	(0.78)	(1.09)	(4.72)		(0.00)	(0.00)	(0.03)	(0.14)	(0.51)
S4	0.00	-0.01	0.07	0.69	**2.04**	**3.93**		0.00	0.00	0.03	0.15	0.26
	(0.01)	(0.03)	(0.18)	(1.51)	(2.64)	(5.32)		(0.00)	(0.01)	(0.07)	(0.18)	(0.24)
S-small	0.00	-0.02	0.16	**2.15**	**3.65**	**4.68**		0.00	0.00	0.03	**0.39**	**0.97**
	(0.01)	(0.02)	(0.42)	(3.68)	(3.31)	(3.61)		(0.00)	(0.00)	(0.03)	(0.54)	(2.36)
Sample	0.00	-0.01	0.12	**1.35**	**2.14**	**3.82**		0.00	0.00	0.03	0.16	0.39
	(0.01)	(0.04)	(0.37)	(2.66)	(3.02)	(4.05)		(0.00)	(0.01)	(0.06)	(0.84)	(1.00)

Table 12: Difference between sell-side and buy-side liquidity in 2009

The table shows the average of the difference between the buy-side and sell-side IC when a market order of size Q can be fully executed on both sides of the LOB. Here,

$$\text{dIC}_{(Q,i)} = \text{IC}_{(\text{sell-side},Q,i)} - \text{IC}_{(\text{buy-side},Q,i)}$$

Each cell of the table shows the sample mean. The values in brackets are sample standard deviations. Values in boldface indicate when $\text{dIC}_{(Q)}$ are statistically different from zero at a 95 % level. Here, sell side liquidity is worse than buy side liquidity.
As an example, for the smallest quintile of firms by market capitalisation, the sell-side IC for a market order of Rs.10 million was worse than the buy-side IC by 115 bps, on average.

Quintile	Spot Q (Rs. Mln.)						Single stock futures Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.00	0.00	0.00	0.08	**0.35**	**0.74**		0.00	0.01	0.03	0.12	0.28
	(0.00)	(0.01)	(0.01)	(0.06)	(0.32)	(0.57)		(0.00)	(0.01)	(0.03)	(0.09)	(0.18)
S2	0.01	0.00	0.01	**0.49**	**0.70**	**1.27**		0.00	0.00	0.10	0.27	0.56
	(0.00)	(0.01)	(0.02)	(0.62)	(0.54)	(0.80)		(0.00)	(0.01)	(0.13)	(0.21)	(0.55)
S3	0.00	0.01	0.06	**0.62**	**0.88**	**1.20**		0.00	0.00	0.24	0.45	0.93
	(0.00)	(0.01)	(0.15)	(0.66)	(0.69)	(0.97)		(0.01)	(0.02)	(0.33)	(0.36)	(0.93)
S4	0.00	0.01	0.11	**0.90**	**1.33**	**2.15**		0.00	0.00	0.59	0.68	0.77
	(0.01)	(0.02)	(0.16)	(0.87)	(1.05)	(2.80)		(0.00)	(0.02)	(0.73)	(0.63)	(1.11)
S-small	0.00	0.03	0.32	**1.15**	**1.26**	**1.64**		0.00	0.07	0.44	0.83	**1.45**
	(0.01)	(0.08)	(0.46)	(0.96)	(0.99)	(1.97)		(0.01)	(0.18)	(0.60)	(0.71)	(0.94)
Sample	0.00	0.01	0.10	**0.65**	**0.90**	**1.32**		0.00	0.01	0.27	0.45	0.73
	(0.01)	(0.04)	(0.26)	(0.79)	(0.92)	(1.53)		(0.01)	(0.08)	(0.48)	(0.49)	(0.84)

Table 13: Difference between sell-side and buy-side liquidity in 2012

The table shows the average of the difference between the buy-side and sell-side IC when a market order of size Q can be fully executed on both sides of the LOB. Here,

$$\text{dIC}_{(Q,i)} = \text{IC}_{(\text{sell-side},Q,i)} - \text{IC}_{(\text{buy-side},Q,i)}$$

Each cell of the table shows the sample mean. The values in brackets are sample standard deviations. Values in boldface indicate when $\text{dIC}_{(Q)}$ are statistically different from zero at a 95 % level. Here, sell side liquidity is worse than buy side liquidity.
As an example, for the smallest quintile of firms by market capitalisation, the sell-side IC for a market order of Rs.10 million was worse than the buy-side IC by 71 bps, on average.

Quintile	Q (Rs. Mln.)						Q (Rs. Mln.)					
	0.025	0.25	1	10	25	50	0.025	0.25	1	10	25	50
S-big	0.00	0.00	0.01	**0.22**	**0.56**	**1.04**		0.00	0.00	0.06	0.10	0.15
	(0.00)	(0.01)	(0.01)	(0.51)	(0.32)	(0.63)		(0.00)	(0.00)	(0.23)	(0.16)	(0.28)
S2	0.00	0.00	0.01	**0.34**	**0.62**	**1.46**		0.00	0.00	0.05	0.21	0.60
	(0.00)	(0.01)	(0.02)	(0.39)	(0.46)	(0.64)		(0.00)	(0.00)	(0.11)	(0.23)	(0.77)
S3	0.00	0.01	0.03	**0.56**	**0.80**	**1.59**		0.00	0.00	0.03	0.45	1.00
	(0.00)	(0.01)	(0.05)	(0.64)	(0.49)	(0.83)		(0.00)	(0.00)	(0.09)	(0.32)	(0.92)
S4	0.00	0.01	0.05	**0.56**	**0.72**	**1.27**		0.00	0.00	0.02	0.48	**1.06**
	(0.01)	(0.02)	(0.08)	(0.61)	(0.79)	(1.16)		(0.00)	(0.00)	(0.56)	(0.31)	(1.47)
S-small	0.00	0.00	0.01	**0.71**	**0.92**	**1.42**		0.00	0.00	0.26	0.56	**0.83**
	(0.00)	(0.02)	(0.03)	(0.62)	(0.64)	(2.15)		(0.00)	(0.01)	(0.32)	(0.44)	(0.91)
Sample	0.00	0.01	0.02	**0.48**	**0.79**	**1.35**		0.00	0.00	0.06	0.47	0.70
	(0.00)	(0.01)	(0.05)	(0.58)	(0.65)	(1.19)		(0.00)	(0.00)	(0.14)	(0.62)	(0.95)

Table 14: LSS function estimates for spot and futures markets, 2006

The values presented are summary statistics of the parameter estimates of the stretched exponential model - α, β, γ - for the sample. The table shows average values of the median parameter estimate for the securities in the overall sample, as well as for market capitalisation-based quintiles, $S1 - S5$. *S-big* securities have the highest market capitalisation, and *S-small* have the lowest. These parameters are calculated separately for the sell-side and the buy-side.

Quintile	Spot						Single stock futures					
	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S
S-big	**2.60**	**0.71**	0.09	2.17	0.39	0.06	**1.92**	**0.47**	0.12	1.66	0.24	0.04
S2	**2.92**	**0.81**	0.10	2.28	0.37	0.06	**1.94**	**0.69**	0.14	0.88	0.31	0.05
S3	**2.30**	**0.77**	0.09	1.89	0.37	0.06	**3.68**	0.44	0.12	2.63	0.26	0.04
S4	**2.22**	**1.15**	0.11	0.26	0.54	0.07	**3.11**	0.60	0.14	1.87	0.37	0.05
S-small	**2.87**	**0.74**	0.10	2.22	0.32	0.06	**3.66**	**0.81**	0.13	2.49	0.23	0.04
Sample	**2.65**	**0.84**	0.10	1.01	0.40	0.06	**3.43**	**0.63**	0.13	1.86	0.29	0.05

Table 15: LSS function estimates in 2009

The values presented are summary statistics of the parameter estimates of the stretched exponential model - α, β, γ - for the sample. The table shows average values of the median parameter estimate for the securities in the overall sample, as well as for market capitalisation-based quintiles, $S1 - S5$. *S-big* securities have the highest market capitalisation, and *S-small* have the lowest. These parameters are calculated separately for the sell-side and the buy-side.

Quintile	Spot						Single stock futures					
	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S
S-big	**2.93**	**0.14**	**0.44**	2.11	0.12	0.22	0.76	0.12	1.05	0.87	0.08	0.73
S2	**3.58**	**0.13**	**0.14**	2.14	0.10	0.11	0.87	0.14	**1.58**	1.06	0.08	0.84
S3	**4.63**	0.12	**0.92**	2.67	0.10	0.36	0.64	0.19	0.81	**1.02**	0.11	0.79
S4	**4.22**	**0.38**	**0.29**	2.90	0.33	0.25	0.74	1.35	0.21	0.12	2.00	**1.63**
S-small	**6.50**	**0.60**	**0.38**	3.84	0.52	0.38	0.43	0.26	2.84	**0.73**	0.15	2.64
Overall	**3.63**	**0.42**	**0.46**	2.76	0.26	0.31	0.72	0.18	1.82	1.12	0.12	0.84

Table 16: Estimates of the LSS function in 2012

The values presented are summary statistics of the parameter estimates of the stretched exponential model - α, β, γ - for the sample.
The table shows average values of the median parameter estimate for the securities in the overall sample, as well as for market capitalisation-based quintiles, $S1 - S5$. *S-big* securities have the highest market capitalisation, and *S-small* have the lowest. These parameters are calculated separately for the sell-side and the buy-side.

Quintile	Spot						Single stock futures					
	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S	α_S^S	β_S^S	γ_S^S	α_B^S	β_B^S	γ_B^S
S-big	**0.85**	0.84	0.09	0.06	0.86	0.08	0.04	**1.73**	0.13	0.95	1.13	0.10
S2	**2.15**	0.71	0.08	0.60	0.70	0.08	0.26	**1.96**	0.15	**3.75**	1.31	0.11
S3	**3.26**	0.63	0.08	1.66	0.58	0.07	1.91	1.04	0.15	1.55	1.16	0.10
S4	**8.36**	**0.48**	0.07	2.53	0.41	0.06	1.58	1.17	0.14	1.13	1.04	0.09
S-small	**9.49**	**0.82**	0.08	9.43	0.68	0.07	**1.86**	**1.95**	0.14	0.80	0.77	0.08
Sample	7.88	0.70	0.08	7.83	0.66	0.07	1.96	1.90	0.14	2.50	1.11	0.10