Hiding Behind the Veil: Pre-Trade Transparency, Informed Traders and Market Quality

By

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Abstract

This paper investigates, from a market design perspective and in the context of informed trading and liquidity supply, the trade-offs or positive associations between pre-trade transparency and the different dimensions of market quality in the rapidly proliferating electronic order-book markets. We find that financial institutional investors are more informed than other investors and prefer to restrict pre-trade transparency, through the use of hidden orders, when they supply liquidity. Specifically, they choose to restrict pre-trade transparency when their orders and trades impound information. Restricting pre-trade transparency leads to more efficient price discovery and better market quality. These results also hold when pre-trade transparency and market quality are determined endogenously.

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Keywords: Electronic order-book markets; Market quality; Pre-trade transparency; Hidden orders; Trading clienteles.

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Hiding Behind the Veil:

Pre-Trade Transparency, Informed Traders and Market Quality

1. Background and Motivation

There has been an extensive interest in the association between market transparency and market quality. Transparency is the ability of market participants to observe information in the trading process (O'Hara (1999)). Market quality has several dimensions, all of which signal the ability of a market center to efficiently provide exchange services. For example, it represents the ability to trade at low cost, it refers to the ability to be able to trade in large quantities, and, importantly, it stands for the ability to trade at "fair" information-efficient equilibrium prices that are attractive to both buyers and sellers, and that deviate from their information-efficient values by relatively small amounts, and for short periods.

Market transparency is clearly fundamental to the existence of fairness and a level playing field across different market participants. It can also be argued that greater transparency should generate greater confidence to trade more freely and hence lead to price formation that better reflects extant information and quicker reversal of temporary disequilibrium pricing errors. Hence, transparency has been conjectured to be important also for more information-efficient prices (SEC (2000)), an important dimension of market quality.[1] However, the benefits of greater transparency are conditioned by two important factors. First, the active participation of informed traders in the trading process is critical for the existence of information-efficient equilibrium prices in order for their private information to be quickly reflected in these prices. Informed traders are clearly hesitant to expose their positions in an overly-transparent market center, and would like to trade instead in a less-transparent market center making that less-transparent center

[1] There has been no empirical validation of this conjecture.

have better price discovery. Second, the active commitment and participation of (voluntary or obligated) liquidity suppliers is essential for virtually all dimensions of market quality, and once again, liquidity suppliers will arguably be more unwilling or hesitant to provide free options through their quotes or limit prices in a high-transparency environment, eroding the depth and the quality of prices at that market center. Both these influences are reflected, for example, in the debate surrounding the battle for order flow between the London dealer market (low transparency, high information content and high depth) and the Paris order-book market (high transparency, low information context and low depth) (Pagano and Roell (1996)).

In the context of informed traders and liquidity suppliers, the general perception is that of a tradeoff rather than a positive association between transparency and market quality. This perception comes from the dealer markets literature where most of the debate has so far taken place. Such markets disseminate (to different degrees) information on the quotes of different dealers (pre-trade transparency), and also information on trades that are finally executed (post-trade transparency). There has been an extensive debate about the need to restrict post-trade disclosure in order to allow market dealers and other dealers time to offset their inventory without being "squeezed", and hence provide incentives to them to quote in reasonable size[2]. Naik et al. (1999) examine the disclosure issue theoretically in relation to information and inter-dealer trading[3]. The experimental economics work of Bloomfield and O'Hara (1999) and Flood et al. (1999) investigates the effect of quote information, and hence pre-trade transparency on trading strategies and market performance and Bloomfield and O'Hara (2000) examine if

[2] For example, in the United Kingdom, the Financial Services Authority allows the reporting of large trades to be delayed for a period of time because it believes that immediate disclosure would expose market makers to undue risk as they unwind their positions and so discourage them from providing liquidity. Gemmill (1996) uses associated U.K. data to empirically examine trade reporting and disclosure.

[3] The differential availability of information has been used for theoretical models characterizing markets (Madhavan (1992), Biais (1993)).

transparent markets can really survive. The clear bottom line from the dealer markets literature is that full and complete transparency is not a policy-desirable from the perspective of market quality, and, in particular, there is a trade-off between transparency and market quality.

Order-matching markets, particularly electronic order-matching systems, are inherently much more transparent than dealer markets in at least two ways. First, these markets display not just the best quotes, or the quotes for a particular size, but the entire schedule of "quotes" for different quantities.[4] The information is two dimensional – price and quantity – not just price, and provides a much more complete picture of trading interests of different market participants. Second, in contrast to dealer markets, not just dealers but any public investors can display their trading interests and compete directly in these markets[5]. In this context, Boehmer et al. (2005) examine the effects on market quality of "lifting the veil", i.e., the change in pre-trade transparency resulting from the introduction of the NYSE OpenBook, and hence the change from a system where we observed just quotes (and hence just prices) to a system where we now observe the limit order book, i.e. both prices and quantities.

New exchanges and trading platforms developing across the world are typically electronic order-matching systems since these are often deemed fairer and enable the possibility of counter-party orders directly crossing in price, instead of being necessarily intermediated by a dealer. According to the Annual Report and Statistics 2007 of the World Federation of Exchanges, the proportion of liquidity being traded in non-US equity markets through electronic order-matching systems is 76% and growing. And within the US as well, electronic order matching systems have been increasingly taking hold over the years, culminating in NYSE's

[4] Typically, order-matching markets display the five best prices and corresponding quantities on both sides of the market.

[5] In dealer markets like NASDAQ, there may be public investor displays of trading interests with a specific dealer but not centralized across the market.

formal introduction of electronic order matching in April 2007. Even the oldest dealer market - London - now trades largely through its new electronic order-matching SETS system.

Given the evidence of the effect of transparency in dealer markets, the higher transparency of order-matching markets relative to dealer markets, and the proliferation of order-matching markets, it becomes important to investigate the trade-offs or positive associations between pre-trade transparency and the different dimensions of market quality of electronic order-book markets, and consider the associated market design issues. This is the aim of this paper.

We know relatively little about the nuances of the empirical association between pre-trade transparency and different aspects of market quality, particularly in the context of the rapidly growing sector of electronic order matching markets, which are inherently much more transparent than dealer markets[6]. We also know little about how informed different trader clienteles – individuals, financial institutions, and non-financial corporate entities - really are, and virtually nothing about how these different trader clienteles, with different levels of information, supply liquidity and demand liquidity in their trading, how they interface with limited pre-trade transparency, and how all this impacts market quality.

This paper contributes to the evolving literature on pre-trade transparency in the increasingly compelling context of electronic order-matching markets. Our focus is on a market design perspective rather than a trading strategy perspective,[7] and specifically in relation to the effects of limitations in pre-trade transparency on the different clienteles of participants that trade

[6] Even for dealer markets, evidence on pre-trade transparency comes only from experimental markets. There is little direct empirical evidence on the trade-off between transparency and market quality, and the limited empirical evidence that exists, is confined to trade reporting and disclosure, i.e. post-trade transparency.
[7] See Belter (2007) for evidence on trading strategies based on information content of displayed and hidden orders.

in markets, and on the endogenous equilibrium of pre-trade transparency with the ability of the financial market to trade quickly at low cost in large size at an information-efficient price.

In this context, many electronic order-matching markets have found it expedient to restrict pre-trade transparency by providing liquidity suppliers and demanders the opportunity to hide behind a veil of “hidden orders”. The rationale is to increase liquidity not only by restricting parasitic trading through “front-running”, but also by enabling informed traders to trade without leaving as much of a “footprint”. This encourages greater liquidity supply by lowering the value of the free options provided by liquidity suppliers through their limit orders. In a completely transparent electronic order matching system, liquidity suppliers are “sitting ducks”, but become less so with the lower transparency afforded by hidden orders.

The literature on hidden orders and pre-trade transparency in relation to electronic order-matching markets is just starting to develop. Baruch (2005) constructs a theoretical model that examines how revealing more or less information about the order book affects the market. Harris (1996, 1997) theoretically examines the risks associated with full transparency in the limit order book: an informed trader may reveal private information about the value of the security without wanting to leave a “footprint”; and a “parasitic” trader may engage in active front-running. Madhavan et al. (2005) examine an interesting experiment relating to the real-time public dissemination of the limit order book on the Toronto Stock Exchange and empirically find significantly greater liquidity when pre-trade transparency was restricted. We also know from De Winne and D’Hondt (2005, 2007) that when order matching systems provide the ability to restrict pre-trade transparency through hidden orders, a very large proportion of trading does actually take place through such hidden orders, showing that at least some clienteles value the ability to restrict pre-trade transparency. And finally, we know from Bessembinder et al. (2008)

how investors change their order-exposure strategies in response to market forces in a system that allows them to restrict such exposure. However, the current literature on hidden orders has been developed almost entirely from a trading strategy perspective. In contradistinction, this paper has a market design perspective.

O'Hara (1999) has emphasized how, in the context of market design, the market microstructure effects of certain aspects of the trading structure are different for different categories of players. Hence, the effects of transparency are potentially very different for liquidity suppliers and liquidity demanders, very different for informed and uninformed investors, and very different for individuals, corporate bodies and institutional investors. Market microstructure theory does not provide guidance on whom the system should be structured to benefit, but understanding of the effects on different clienteles is valuable for suitably informing potential value judgments in this regard. We do not really know anything about the effects of pre-trade transparency on different clienteles. This is also one of the gaps this paper addresses.

The work of Boehmer et al. (2005) provides valuable evidence on the effects on market quality of "lifting the veil", when, with the introduction of the NYSE OpenBook, the information in the limit order book was first made available to participants in the hybrid NYSE market. At the opposite end, our paper investigates the market quality effects of "hiding behind the veil" of hidden orders in centralized order-matching systems. We can think about the consequences of restricting pre-trade transparency in electronic order-matching markets in two important ways. We can think in terms of the direct effects on the trading strategies of market participants: this has been examined, for example, by Bessembinder et al. (2008). Or we can think of it from a market design perspective in terms of how the welfare of different clienteles in financial markets are affected by restrictions on pre-trade transparency and the effect of restricting pre-trade transparency on the efficiency of the information dissemination process and the “quality” of the resultant prices. This latter market design perspective is the focus of this paper. Additionally, it is not just the extent of pre-trade transparency that determines market quality, but it is also transparency that endogenously determines the extent of market quality. We know nothing about this endogeniety. This is another gap in the literature this paper addresses.

Specifically, this research makes at least three major contributions. First, we examine which clientele of market participants are informed, and how their information level interfaces with their preference to restrict pre-trade transparency when they supply liquidity and preference to restrict pre-trade transparency when they demand liquidity. Second, we examine a wide spectrum of market quality proxies, not just spreads, volatility and volume as the extant literature has done, but also the depth of the order book, and very importantly, the efficiency of the information dissemination process prices in terms of price discovery, the variance of pricing errors and the speed with which prices revert to their information-efficient values. And finally, we examine how market quality and the equilibrium level of pre-trade transparency are endogenously determined in the context of the trading interests of different clienteles of market participants, and the extent of information flows and asymmetries.

We document several results of far-reaching interest for regulators, market participants and academics. First, we find that there are strong systematic differences in the information reflected in the orders and trades of different trading clienteles, with financial institutional investors more informed than non-financial corporations and individuals. Second, we find that informed traders in general and financial institutional investors in particular prefer restricted pre-trade transparency when they are supplying liquidity by placing limit orders in the order-book, and prefer significantly lower pre-trade transparency when their orders and trades impound information. However, there is only one trader clientele that, consistent with the restrictions on pre-trade transparency reducing time priority, prefers not to restrict pre-trade transparency when they are demanding liquidity by placing market orders or marketable limit orders. Third, we find that, consistent with informed traders preferring restricted pre-trade transparency, the presence of more hidden order submissions and associated trades leads to more efficient price-discovery. Finally, in a market where pre-trade transparency, informedness, and market quality are determined endogenously, we find that liquidity suppliers prefer to restrict pre-trade transparency through the use of hidden orders when they are informed and this improves overall market quality. However, we do not find such a relationship when liquidity demanders restrict pre-trade transparency.

The remainder of this paper is organized as follows. Section 2 develops the hypotheses tested in the paper. Section 3 describes the institutional structure of the market and the data used for the empirical analyses. Section 4 documents and discusses the methodologies used and the empirical results. Finally, Section 5 concludes.

2. Development of Hypotheses

In microstructure literature, it is usually assumed that financial institutional investors are informed, whereas individual investors are uninformed. Prior research has shown empirical support for this conjecture.[8] However, these studies are for developed markets and given the differences in the regulatory and legal environments between developed and emerging markets, it is not clear whether the same can be extended to emerging markets. This leads to our first hypothesis.

[8] See, for example, Szewczyk et al. (1992), Alangar et al. (1999), Chakravarty (2001), and Dennis and Weston (2001)

H_1: There are strong systematic differences in the information reflected in the orders and trades of different trading clienteles, with financial institutional investors being more informed than non-financial corporations and individuals.

Harris (1997) argues that informed traders may be unwilling to expose their trading intentions for a number of reasons. "Parasitic" traders may front-run the exposed orders or they may attempt to extract value from the trading options these exposed orders offer. Other ("defensive") traders may refuse to trade with informed traders or to offer them good terms to trade on. All of these impose costs on informed traders, especially when their orders are expected to sit on the book (liquidity supplier) rather than execute immediately (liquidity demander). To reduce these expected costs, informed traders would prefer to restrict pre-trade transparency by using more hidden limit orders when they are demanding liquidity. However, restricting pre-trade transparency through hidden limit orders reduces time priority of their orders. So when informed traders demand immediacy, they would prefer using market or marketable limit orders.

H_{2A}: Informed traders in general and financial institutional investors in particular prefer restricted pre-trade transparency when they are supplying liquidity by placing limit orders, and prefer significantly lower pre-trade transparency when their orders and trades impound information.

H_{2B}: Since restrictions on pre-trade transparency reduce time priority, informed traders will prefer not to restrict pre-trade transparency when they are demanding liquidity by placing market orders or marketable limit orders.

Harris (1997) contends that restricting pre-trade transparency would improve price efficiency in the long-run by reducing the expected costs of order exposure. The lower costs provide incentives to traders to invest in information and trade on that information leading to better price efficiency. Madhavan (1996) shows that market quality suffers in transparent markets. Madhavan et al. (2005) observe that liquidity deteriorates after the Toronto Stock Exchange increased transparency of its limit order book. On the other hand, Glosten (1999) and Baruch (2005) argue that increased transparency improves price efficiency and liquidity. Boehmer et al. (2005) find that the informational efficiency of prices and liquidity improve after the introduction of the NYSE's OpenBook. Eom et al. (2007) find that market quality increases with pre-trade transparency and is concave in pre-trade transparency. Chung and Chuwonganant (2008) find that market quality improves on the Nasdaq after pre-trade transparency increased through the introduction of the SuperMontage.[9] Given the prior evidence, it is unclear how pre-trade transparency affects market quality and price discovery. Our third hypothesis attempts to address this inconsistency in the literature by finding the direction of the relation between pre-trade transparency and market quality and information efficiency of prices.

H_3: Restricting pre-trade transparency affects market quality, though the direction of this effect is an empirical question.

3. Data

Our empirical analyses are based on a rich proprietary database of the *National Stock Exchange of India* (hereafter, NSE). NSE is an order-matching open electronic limit-order book market that operates on a strict price-time priority. It has an automated screen-based trading system that enables members from across India to communicate, through satellite, with the centralized computer system and trade anonymously with one another on a real-time basis. The

[9] Additionally, using Korean data, Eom et al. (2007) also find that market quality increases with pre-trade transparency.

types of orders and systems that exist internationally in order-driven markets also typically exist on NSE, including limit orders, market orders, and hidden orders (hereafter HO)[10].

The NSE, together with a securities markets regulator, the *Securities and Exchanges Board of India* (SEBI), was created as part of major economic reforms in India in the early 1990s.[11] SEBI has introduced, and NSE has implemented, a rigorous regulatory regime to ensure fairness, integrity, transparency, and good practice that is comparable to the best anywhere globally. As a result, the trading volume on NSE has grown strongly to make it among the most liquid markets in the world. Table 1 Panel A lists the total number of trades executed on leading stock exchanges in 2006 and 2007 on the basis of the annual reports of the *World Federation of Exchanges*. Even though the NSE trades relatively fewer stocks than, for example NASDAQ, London or New York, it has been first among all electronic limit order book markets on the basis of number of trades 2006 and second in 2007, and has been fourth, just behind NASDAQ, NYSE and Shanghai Stock Exchange among all markets irrespective of market structure. The number of trades on NSE has been more than seven times greater than the number of trades on, say, Euronext.[12]

Our sample consist of all 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. Our sample period is from April 1 through June 30, 2006, covering 56 trading days.

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[10] NSE operates a continuous trading session from 9:55 am until 3:30 pm local time. The tick size is INR 0.05 (less than USD 0.01). Importantly, unfilled orders are not carried over to the next day. Also, the NSE does not have a pre-designated pre-open call auction (like Euronext) to determine the opening price, which is determined by order matching as well. Traders are required to display at least 10 percent of the size of every order that they place.

[11] There is another major stock exchange in India: the *Bombay Stock Exchange* (BSE). Established in 1875 as a stockbrokers association, the BSE is the oldest stock exchange in Asia. However, the exchange had suffered from a reputation of clubby manipulative practices and inefficient clearing and settlement systems.

[12] It is true that the average trade size on NSE is about fifty times smaller than Euronext, but we believe that the quality and timeliness of efficient price formation should be determined by the number of trades of reasonable economic size rather than by fewer larger trades, and we note that the average trade size on NSE is smaller because of the lower wealth level of the average Indian trader, and is hence of reasonable economic size in that context.

Our proprietary data includes virtually all information there exists on orders and trades, including in particular, all client identification codes that enable us to at least identify the *Trader Clientele*, specifically whether an order or a trade was placed by an individual, a non-financial corporation, a domestic (Indian) financial institution, a foreign (non-Indian) institutional investor, or others (for example, statutory bodies). The richness of our data enables us to rebuild the order book minute-by-minute in each trading day over the entire sample period for each of the fifty stocks in our sample.

Table 1 Panel B presents some summary statistics on the trading characteristics of the sample stocks over the sample period. There are, on average, 19,121 trades per day, or 57 trades per stock per minute. There are, on average, 24,907 order submissions per stock per day, or about 75 order submissions per stock per minute. 93% of these are limit orders (including marketable limit orders) and the remaining 7% are market orders.

Only 9% of the order submissions include buy or sell hidden quantities. However, as many as 42% of the trades include hidden orders, indicating that hidden orders are more prevalent at the top of the order book, i.e. around the best buy or sell quotes. Figure 1 presents a plot of the percentage of the overall depth attributable to hidden orders as it varies over the course of the trading day. It presents depth at the best limit prices on either side (*h1depth*), depth at the five best limit prices on either side (*h5depth*) and total depth at all limit prices (*htdepth*). On average across all stocks, these are about 30%, 45% and 35%, respectively, indicating that hidden orders are at most a few ticks away but not too distant from the best quotes.

Our data directly flags 14 different trader clienteles. These are presented in Table 1 Panel C. We aggregate these 14 clienteles into 5 broader trader clienteles, and code them from 1 to 5 for future presentation of results.

Clientele Category 1: Individuals

Clientele Category 2: Non-financial Corporations (hereafter, Corporates)

Clientele Category 3: Domestic (i.e. Indian) Financial Institutions (hereafter, DFI's)

Clientele Category 4: Foreign (non-Indian) Institutional Investor (hereafter, FII's)

Clientele Category 5: Others

The component groups within each of these broader clienteles are of similar nature, and as the summary statistics in Table 1 Panel C indicate, are roughly similar in their behaviour in relation to hidden orders.

We define liquidity demanders (hereafter, LD) as traders who demand liquidity in their trading through market orders (resulting in immediate full execution) or marketable limit orders (resulting in immediate full or partial execution). We define liquidity suppliers (hereafter, LS) as traders who supply liquidity in their trading by submitting limit orders that do not get instantly executed at their time of submission, either with full or partial disclosure of quantity. For both classes of traders in each of our five trader clientele categories, we determine the proportion of hidden quantity for each stock over each 30-minute interval during the trading day. We denote these proportions as *LSHP* (for liquidity suppliers) and *LDHP* (for liquidity demanders), which are our measures of pre-trade transparency. When traders choose a higher proportion of hidden orders, pre-trade transparency is restricted.

4. Empirical Results

4.1 Different Trader Clienteles: Information Levels

For both liquidity demanders and liquidity suppliers, consistent with Anand et al. (2005) and Kaniel and Liu (2006), we proxy the *Information Level* of an order by the change in price over a fixed period of time after submission of the order. We calculate the *Information Level* over three time intervals: 5 minutes, 30 minutes, and 60 minutes. For a liquidity supplying buy order, the information level in the order is measured as the quote midpoint 5, 30 or 60 minutes after order submission minus the quote midpoint at the time of order submission. For a liquidity supplying sell order, the information level in the order is measured as the quote midpoint at the time of order submission minus the quote midpoint 5, 30 or 60 minutes after order submission. However, since an order placed by a liquidity demander is executed immediately, partially or fully, the quote midpoint at order submission is identical to the quote midpoint at order execution. Hence, for liquidity demanding buy or sell orders, we measure the information level of an order using the adverse selection half spread (AHS), which is defined in the same way as *Information Level* for liquidity supplying orders.

Table 2 presents descriptive statistics on the information level of each of the five trader clientele categories for each of the three proxies corresponding to time horizons of 5, 30, and 60 minutes after order submission. Figure 2 presents the results pictorially. The results are unequivocally strong. Irrespective of the time horizon used to measure the information level, the information level of financial institutions, both DFI's (trader clientele category 3) and FII's (trader clientele category 4), is much higher than the information level of non-financial corporations (trader clientele category 2), which itself is an echelon higher than the information level of individuals (trader clientele category 1). The differences are very significant both economically and statistically. These results are consistent with hypothesis H_1: *there are strong systematic differences in the information reflected in the orders and trades of different trading clienteles, with financial institutional investors more informed than non-financial corporations and individuals.*

4.2 Different Trader Clienteles: Restricting Pre-Trade Transparency with Hidden Orders

Table 3 Panels A and B present descriptive analyses about the use of hidden orders by each of the five different clientele categories. Interestingly, trader clientele categories 3 and 4 submit only about one-sixth of the orders, and execute less than one-third of the total trading by value, and yet, from the previous section, we know that, on average, their level of information is much greater than that of other trader clienteles. Their level of cancellations (at about 10%) is several times lower than that of the others, and the percentage of their orders executed (at about 85%) is also much higher than that of the others. And most importantly, as liquidity suppliers, more than 75% of the trading (by value) of these informed trader clienteles is through consummation of orders with a hidden component, while less than 20% of the trading (by value) of uninformed trader clienteles 1 and 5 involves hidden orders.

It is clear that, on average, informed trader clienteles 3 and 4 prefer to use hidden orders, and thereby restrict pre-trade transparency, much more than uninformed trader clienteles 1 and 5, and the partially informed trader clientele 2 somewhere in the middle. We now proceed to establish the link between information level and the usage of hidden orders more rigorously. To do this, we run regressions where trading environment-related influences are controlled for by two variables: the one-minute volatility of mid-quote returns in every 30-minute trading interval, and the average quoted spread in that interval. In analysing the proportion of value traded through hidden orders by liquidity suppliers (demanders) in a particular 30-minute interval, we control for the information level of those liquidity suppliers (demanders) in that interval, and additionally also for the information level of the counterparty liquidity demanders (suppliers) in that interval. We condition on the information level of the counterparty when a trader is informed because there may be a greater tendency for an informed trader to restrict pre-trade transparency when the counterparty is likely to be informed than when the counterparty is uninformed. The informed trader may not want to lose out to other informed traders on the opposite side and hence may choose to use a larger proportion of hidden orders.

Accordingly, we estimate the following regressions separately for liquidity suppliers and liquidity demanders:

For Liquidity Suppliers:

$$LSHP_{i,t} = \alpha_1 LS\_\inf + \alpha_2 LSLD\_\inf + \sum_{i=1}^{5} \beta_i Cat_i + \gamma_1 Volatility + \gamma_2 Qspr + \varepsilon \tag{1}$$

For Liquidity Demanders:

$$LDHP_{i,t} = \alpha_1 LD\_\inf + \alpha_2 LDLS\_\inf + \sum_{i=1}^{5} \beta_i Cat_i + \gamma_1 Volatility + \gamma_2 Qspr + \varepsilon \tag{2}$$

where

t	30-minute trading interval
$LSHP_{i,t}$	Hidden proportion of liquidity supplied by i^{th} trader clientele category of LS during interval t,
$LDHP_{i,t}$	Hidden proportion of liquidity demanded by i^{th} trader clientele category of LD during interval t,
LS_inf	Information level (at 5-minute time horizon) of liquidity supplier in interval t,
LD_inf	Information level (at 5-minute time horizon) of liquidity demander in interval t,
Ld	Equals 1 if information level of liquidity demanders is above one standard deviation, else zero,

Ls	Equals 1 if information level of liquidity suppliers is above one standard deviation, else zero,
LSLD_inf	*LS_inf* times *Ld*, a variable that conditions the information level of liquidity suppliers by whether liquidity demanders are informed in that interval,
LDLS_inf	*LD_inf* times *Ls*, a variable that conditions the information level of liquidity demanders by whether liquidity suppliers are informed in that interval
Cat_i	Trader clientele category dummy variables (*i*=1, 2, 3, 4, 5).
Volatility	Intra-day volatility of one minute returns in interval *t*,
QSpr	Average quoted spread in interval *t*,

All independent variables, except the trader clientele category dummy variables, are standardized. The results are in Table 4 Panel A. For liquidity suppliers, irrespective of trader clientele category, the proportion of value traded through hidden orders is significantly greater when they, as liquidity suppliers, are informed, and significantly less when their counterparty liquidity demanders in that interval are informed. While the former is consistent with our hypothesis, the latter is contrary to expectations. For liquidity demanders, irrespective of trader clientele category, the proportion of value traded through hidden orders is significantly less when the liquidity demander is informed, and significantly more when the liquidity suppliers in that interval are informed. The latter result arguably indicates that when traders have information, they demand liquidity with disclosed orders without wanting to lose time priority through their use of hidden orders.

Next, we estimate regressions separately for each trader clientele category, introduce additional controls for size, and also control for the potential influence of the time of the day on the order submission strategy by including five dummy variables for five segments of the trading day[13]:

D_1 9:55 – 11:30 (the first 95 minutes of trading)

D_2 11:30 – 12:30

D_3 12:30 – 13:30

D_4 13:30 – 14:30

D_5 14:30 – close of trading (15:30)

Accordingly, we estimate the following panel regression models for each trader clientele category:

$$LSHP_{it} = \alpha_1 LS\_\inf_t + \alpha_2 LSLD\_\inf_t + \sum_{l=1}^{5} \beta_l D_l + \gamma_1 Volatility_t + \gamma_2 QSpr_t + \gamma_3 Size + \varepsilon_{i,t} \qquad (3)$$

$$LDHP_{it} = \alpha_1 LD\_\inf_t + \alpha_2 LDLS\_\inf_t + \sum_{l=1}^{5} \beta_l D_l + \gamma_1 Volatility_t + \gamma_2 QSpr_t + \gamma_3 Size + \varepsilon_{i,t} \qquad (4)$$

The time interval, *t*, in the regression models is 30 minutes. All variables are as defined previously. *Size* is the market capitalization of the stock on June 30, 2006. All independent variables, except the time interval dummy variables, are standardized. We estimate the regressions separately for each of the five trader clientele categories to capture the information level of orders.

The results in Table 4 Panel B for liquidity suppliers are consistent with those in Table 4 Panel B. For each and every trader clientele category, including the two categories that were, on average, deemed uninformed, the proportion of value traded through hidden orders is significantly greater when they, as liquidity suppliers, are informed, and significantly less when

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[13] We know from, for example, Stoll and Whaley (1990) that information content is much greater in the first hour or two of trading because of the uncertainty about the full meaning of the information arriving in the overnight non-trading interval.

their counterparty liquidity demanders in that interval are informed. For liquidity demanders, the results remain statistically significant only for trader clientele category 4, i.e. FII's.

Overall, hypothesis H_{2A} is strongly supported by our results: *Informed traders in general and financial institutional investors in particular prefer restricted pre-trade transparency when they are supplying liquidity by placing limit orders in the order-book, and prefer significantly lower pre-trade transparency when their orders and trades impound information.* However, hypothesis H_{2B} is supported only for foreign (non-Indian) institutional investors: *Since restrictions on pre-trade transparency reduce time priority, informed traders will prefer not to restrict pre-trade transparency when they are demanding liquidity by placing market orders or marketable limit orders.*

4.3 Pre-Trade Transparency and Price Discovery

Efficient price discovery is an important dimension of market quality. The price discovery literature is extensive and follows two main approaches: the *Hasbrouck Information Share* approach and the *Gonzalo-Granger Common Factor* approach.[14] A detailed discussion and comparison of these approaches can be found in Hasbrouck (2002) and de Jong (2002). The price discovery literature looks at the cases of stocks trading in multiple markets (e.g. Harris et al. (1995), Huang (2002)), or closely related assets trading in multiple markets (e.g. Eun and Sabherwal (2003), Booth et al. (1999), Chakravarty et al. (2004), Shastri et al. (2008)), to examine the relative contributions of price discovery from each market segment. The underlying premise is that though different market segments appear different, they are closely integrated through common information and hence function as one market in discovering the true price.

[14] See Hasbrouck (1995) and Gonzalo and Granger (1995), respectively, for more details on the two approaches.

We address the relevance of hidden orders for price discovery using the *Hasbrouck Information Share* approach. In this context, we form two mid-quote series from our constructed one-minute order book snapshots: one series from the pool of hidden orders (HP) and the other from the pool of non-hidden orders (NHP). Both these mid-quote series can be thought of as proxies for the true value of the underlying stock and one can potentially examine the contribution of each series (hidden and non-hidden) to price discovery. The literature on price discovery examines the information content of prices of the same security observed in different markets, while we similarly examine the information content of prices of the same security where the price series are from two streams of order submitters: hidden orders and non-hidden orders. Our analysis is in the spirit of Kurov and Lasser (2004), in which they examine the price discovery of E-mini futures contracts.

If hidden orders are submitted largely by informed traders then one expects that HP series to be a better indicator of the true value of the stock than the NHP series. On the other hand, if hidden orders are placed by uninformed traders, for example to mitigate adverse selection costs, then the HP series will react slowly to new information, and hence its share in price discovery will be lower than that of the NHP series.

The Hasbrouck (1995) approach measures the total variance of the efficient price change and measures how much of that variance is explained by the price changes of each of the different price series using a vector error correction model (VECM) of the form:

$$\Delta HP_t = \alpha_{1,0} - \alpha_1 (HP_{t-1} - \beta NHP_{t-1}) + \sum_{l=1}^{p} (\gamma_{1,l} \Delta HP_{t-1} + \delta_{1,l} \Delta NHP_{t-l}) + \varepsilon_{1,t}$$

$$\Delta NHP_t = \alpha_{2,0} - \alpha_2 (HP_{t-1} - \beta NHP_{t-1}) + \sum_{l=1}^{p} (\gamma_{2,l} \Delta HP_{t-1} + \delta_{2,l} \Delta NHP_{t-l}) + \varepsilon_{2,t}$$

$$\varepsilon \sim N(0,\Omega); \Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

In the above framework, the information share of hidden orders will be estimated as $IS\_HP = \dfrac{\alpha_1^2 \sigma_1^2}{\alpha_1^2 \sigma_1^2 + \alpha_2^2 \sigma_2^2}$; and similarly for non-hidden orders. In practice, the price innovations are correlated across VECM equations and one cannot attribute the variance of the underlying efficient price to either of the price series. Hasbrouck suggests a Cholesky factorization and orthogonalisation of the correlated error terms to obtain information shares. Different orderings in the Cholesky factorization give lower and upper bounds of information shares attributable to each price series. Baillie et al. (2002) provide evidence that the midpoint between the upper and lower bounds of information shares is a reasonable measure of a market's contribution to price discovery. In view of this, we use the mid-point of the lower and upper bounds of our information share estimates to make inferences.

A VECM requires all price series to be non-stationary and cointegrated. Hence, we first test for the non-stationarity of our HP and NHP series on each stock-day using *Augmented Dickey Fuller* unit-root tests. We are not able to reject the unit root null at conventional five percent levels of significance in any case showing that our HP and NHP series are all non-stationary as needed. We then test for cointegration by employing the Johansen cointegration test. In each case, for each day and for each stock, our cointegration test results reject the null of the absence of a cointegrating vector, and accept the null of a single cointegrating vector between the HP and the NHP series[15]. We finally proceed to estimate the error correction dynamics that characterizes our price discovery process.

Table 5 Panels A and B report the HP and NHP information share results. The median information share of hidden orders across all stocks and days is as high as 84% with the lower and upper quartiles being 56% and 91%, respectively, all of these being significantly greater than

[15] We do not report these essentially trivial results for compactness and brevity.

50% at high levels of significance. Clearly, hidden orders carry significantly greater level of information than non-hidden orders, their users are significantly more informed traders, and they contribute significantly more to price discovery and hence to market quality. Hence, we find evidence that restricting pre-trade transparency, through the usage of hidden orders, improves market quality. This is consistent with Madhavan (1996) and Madhavan et al. (2005).

In the spirit of Chakravarty et al. (2004), we examine the determinants of the information share of hidden orders. Table 5 Panel B reports the results of a fixed effects panel regression. We find that that the price discovery from hidden orders is significantly higher when the frequency of trades is higher, when the quoted spreads are narrower, and when the volatility is lower.

4.4 Pre-Trade Transparency, Informedness, and Market Quality

Our results from Tables 4 and 5 show that hidden orders are more informative and lead to greater price discovery than non-hidden orders. However, the use of hidden orders and informedness of traders are endogenously determined. Informed traders may prefer hidden orders to hide their information. Alternatively, since recent trading activity reveals information, the use of hidden orders may depend on the extent to which information is revealed through prior trading. Also, traders may choose to become informed as they can use hidden orders to reduce the risk of front-running and other costs of order exposure. In this case, the profits from informed trading outweigh the costs of order exposure. So we cannot make any inferences on causality from our earlier results. Similarly, use of hidden orders and market quality are endogenously determined in the market. We use a vector autoregression (VAR) framework to address these endogeneity issues. As we have a cross-section of firms, running a VAR for each firm and then averaging coefficient estimates makes interpretation of significance of the coefficients challenging. Hence, we estimate a panel VAR.[16]

In the panel VAR, we use two measures of informedness, namely, information content (*Inf_Content*) and information asymmetry (*Inf_Asymmetry*), two measures of pre-trade transparency, *LSHP* and *LDHP*, and three measures of market quality, average quoted spread in each 30-minute interval (*QSpr*), average slope on both sides of the order book (*Slope*), and inverse of the variance of pricing error (*InvVarPrErr*). *Inf_Content* is the unexpected (residual) volatility determined from a AR(1)-GARCH(1,1) model over each 30-minute interval. *Inf_Asymmetry* is the standard deviation of information level calculated over a 30-minute interval. *Slope* is the average of the mean slope on the sell side of the order book and absolute value of the mean slope on the buy side of the order book at the end of each 30-minute interval. *InvVarPrErr* is the inverse of the variance of pricing error determined using Hasbrouck's (1993) transaction-cost model. All variables are standardized. The panel VAR uses one lag for each of the seven variables.

Estimates of the panel VAR model are in Table 6. Since we are interested in determining the impact of restricted pre-trade transparency on informedness of traders and market quality, our variables of interest are *LSHP* and *LDHP* in the equations on which measures of informedness (*Inf_Content* and *Inf_Asymmetry*) and market quality (*QSpr*, *Slope*, and *InvVarPrErr)* are left-hand side variables. The coefficient estimate of *LSHP* is negative and significant in the *Inf_Content* equation and positive and significant in the *Inf_Asymmetry* equation. This suggests that when liquidity suppliers submit a higher proportion of hidden orders, unexpected volatility is lower and information asymmetry in the market is higher. Larger use of hidden orders reduces unexpected volatility as they add more depth to the limit order book. An incoming order seeking

[16] See Love and Zicchino (2006) for details on the panel VAR and its estimation.

immediacy would have to walk through a fewer price points to be filled and hence we observe lower unexpected volatility. Hidden orders suggest that there are more informed traders in the market and hence greater information asymmetry. The submission of hidden orders by liquidity demanders, however, has not effect on either of the informedness measures. Hence, it is the liquidity suppliers who prefer to restrict pre-trade transparency through the use of hidden orders when they are informed.

Next, we examine the coefficient estimates of *LSHP* and *LDHP* in the equations were market quality variables are the dependent variables. Here, we find that larger use of hidden orders by liquidity suppliers results in narrower quoted spreads, a flatter average slope (larger depth at each price) in the order book, and lower variance of pricing error. All three market quality measures improve when liquidity suppliers restrict pre-trade transparency. These results are consistent with the predictions of Madhavan (1996) and evidence from Madhavan et al. (2005). The impact of liquidity demanders restricting pre-trade transparency on market quality is ambiguous. Greater use of hidden orders by liquidity demanders widens quoted spread (worsens market quality), results in a flatter average slope in the order book (improves market quality), and has no effect on the variance of the pricing error.

The results from the panel VAR suggest that liquidity suppliers prefer to restrict pre-trade transparency when they are informed and this preference improves the overall market quality. On the other hand, there is no evidence of increased hidden order use by liquidity demanders when they are informed and their use of hidden orders has an ambiguous effect on overall market quality.

5. Summary and Conclusions

This paper investigates, from a market design perspective and in the context of informed trading and liquidity supply, the trade-offs or positive associations between pre-trade transparency and the different dimensions of market quality in the rapidly proliferating electronic order-book markets.

We document several results of far-reaching interest for regulators, market participants and academics. First, we find that there are strong systematic differences in the information reflected in the orders and trades of different trading clienteles, with financial institutional investors more informed than non-financial corporations and individuals. Second, we find that informed traders in general and financial institutional investors in particular prefer restricted pre-trade transparency when they are supplying liquidity by placing limit orders in the order-book, and prefer significantly lower pre-trade transparency when their orders and trades impound information. However, there is only one trader clientele that, consistent with the restrictions on pre-trade transparency reducing time priority, prefers not to restrict pre-trade transparency when they are demanding liquidity by placing market orders or marketable limit orders. Third, we find that, consistent with informed traders preferring restricted pre-trade transparency, the presence of more hidden order submissions and associated trades leads to more efficient price-discovery. In the spirit to Madhavan (1996) and Madhavan et al. (2006), these results are consistent with restricted pre-trade transparency improving market quality.

Finally, we also document the endogeneity in the relationship between restricted pre-trade transparency, informedness, and market quality in a panel VAR setting. We find that liquidity suppliers restrict pre-trade transparency when they are more informed leading to better market quality. However, we do not find any significant results for liquidity demanders.

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Figure 1

This is a plot of the intra-day variation of hidden depth as a percentage of the total depth in the order book. Additionally, *H1Depth* is the percentage of hidden depth at the best quotes, *H5Depth* is the percentage of hidden depth at the best 5 quotes, and *HTDepth* is the percentage of the total hidden depth in the entire book.

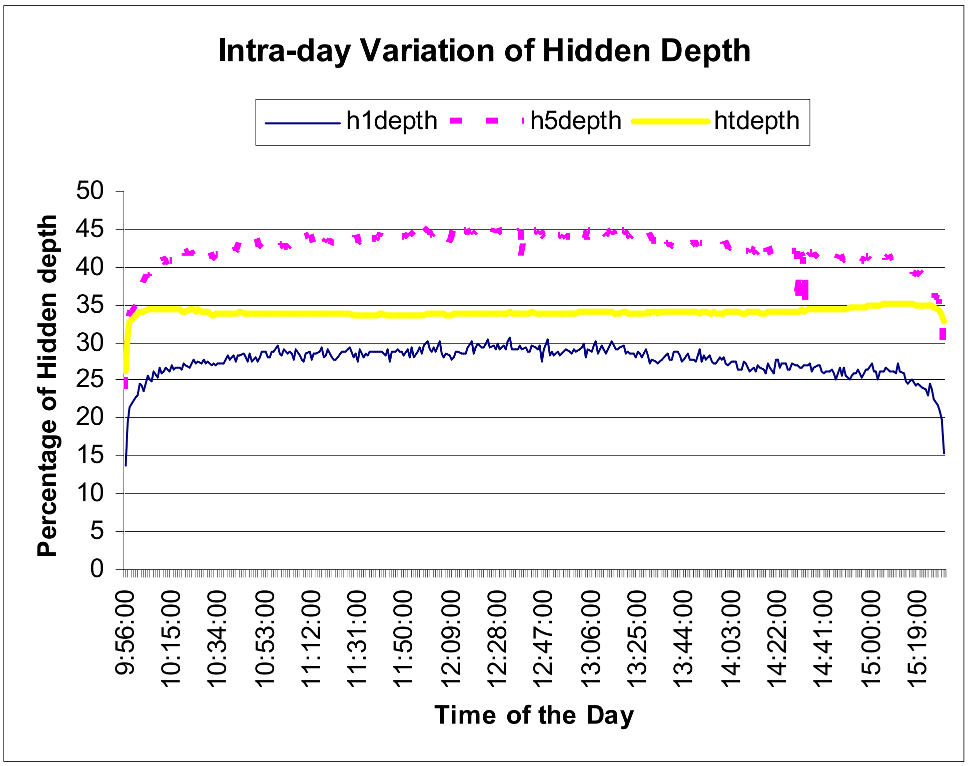

Figure 2

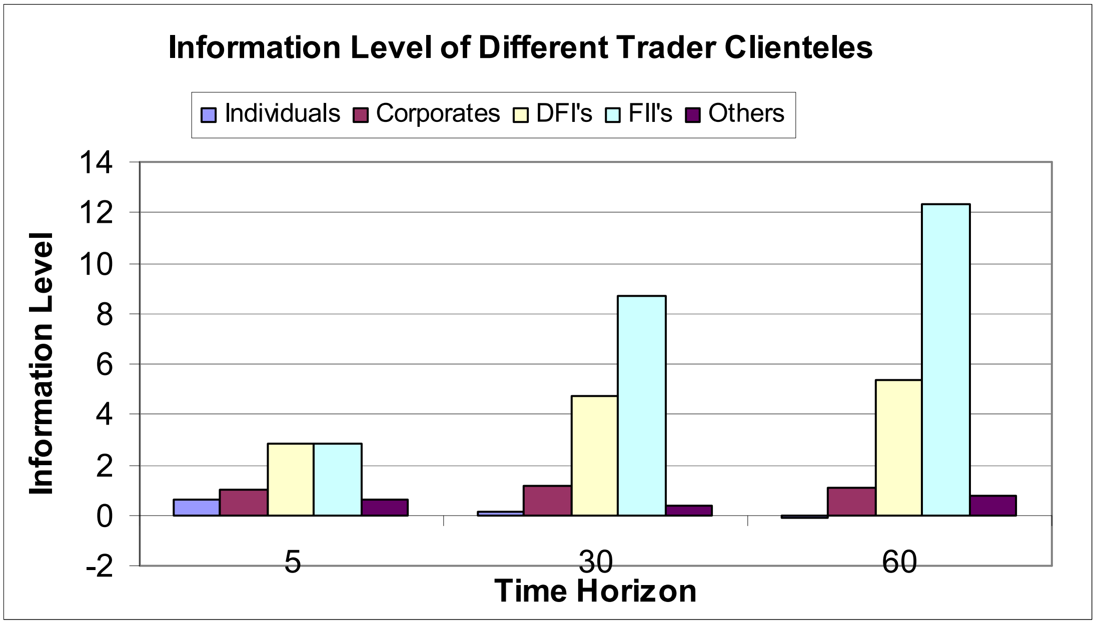

Figure 3

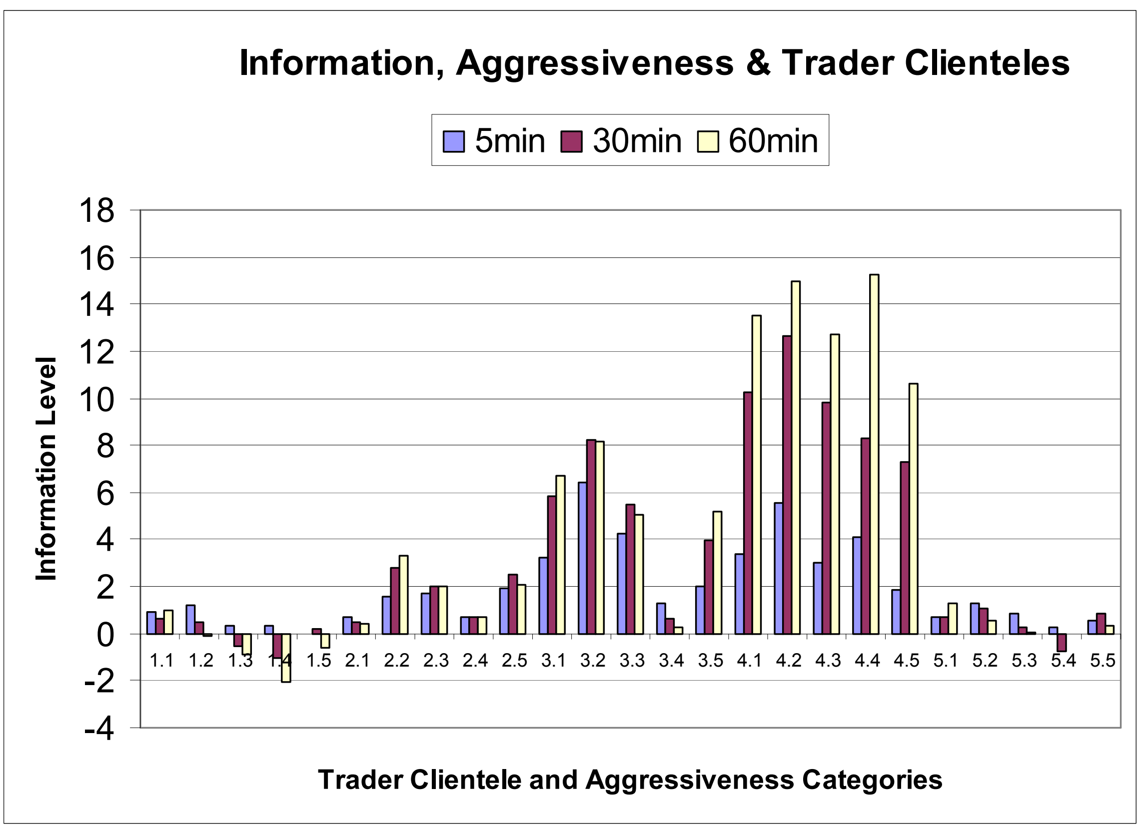

Table 1 Panel A

Number of Trades in Major World Exchanges

This table reports the total number of trades executed on leading stock exchanges around the world during 2006 and 2007. The figures below are sourced from the 2006 and 2007 Annual Report and Statistics of the *World Federation of Exchanges*.

Rank	**Exchange**	**Number of Trades (in millions)**		**Electronic Order Book Market Flag**
		2007	**2006**	
1	NYSE Group	2,321	1,264	No
2	Nasdaq	1,645	1,318	No
3	Shanghai Stock Exchange	1,617	447	Yes
4	National Stock Exchange India	1,052	747	Yes
5	Shenzhen Stock Exchange	840	274	Yes
6	Korea Exchange	606	409	Yes
7	Bombay Stock Exchange	480	328	No
8	Taiwan Stock Exchange Corp.	213	163	Yes
9	London Stock Exchange	161	95	Partially Yes
10	Euronext	155	105	Yes
11	Deutsche Börse	145	109	Yes
12	TSX Group	127	92	No
13	Hong Kong Exchanges	119	45	Yes
14	Borsa Italiana	73	58	Yes
15	Australian Stock Exchange	66	37	Yes
16	Istanbul Stock Exchange	49	46	Yes
17	OMX Nordic Exchange	49	32	Yes
18	American Stock Exchange	46	41	No
19	Bursa Malaysia	37	20	Yes
20	BME Spanish Exchanges	35	24	Yes

Table 1 Panel B
Relevant Trading Characteristics of Sample Stocks

The sample stocks comprise the 50 stocks of the Standard & Poor's CNS Nifty index of the fifty highest capitalization stocks on the National Stock Exchange of India (NSE). This table presents the descriptive summary statistics on the trading characteristics of these sample stocks over the sample period April 1 through June 30, 2006 (56 trading days). These Nifty constituent stocks cover 21 sectors of the economy including Banks, Insurance, Media, Telecommunications, Power, Pharmaceuticals, Diversified, FMCG, Refineries, and Computers. These stocks represent about 60% of market capitalization on NSE.

Characteristic	**Mean**	**Median**	**Max**	**Min**	**Q1**	**Q3**
Market Capitalization (USD Billions)	7	4	38	1	3	7
Daily Turnover per stock (USD Millions)	21	13	159	1	6	25
Percentage of Turnover with Hidden Orders	33	33	61	14	26	38
Daily Number of Trades per stock	19,121	12,710	70,129	2,870	6,597	24,390
Percentage of Trades with Hidden orders	42	41	65	20	35	48
Daily Order Submissions per stock	24,907	18,334	94,355	4,210	9,142	35,345
Percentage of Orders with Hidden component	9	9	17	4	7	11
Effective Spread in basis points	3	3	8	2	3	4

Table 1 Panel C
Hidden order Usage for Different Trader Clienteles

This table reports proportion of trades with hidden orders and the proportion of hidden order submissions for all Trader Clienteles identified in the data. The proprietary data from NSE identifies 14 different Trader Clienteles. We further aggregate these 14 categories into 5 broader categories for the remaining Tables in the paper, and code these categories from 1 to 5.

Broad Category (Code)	Category Description	Number of Registered Clients	Percentage of Trades with Hidden Orders	Percentage of Order Submissions with Hidden component
Individuals (1)	Individual	4885324	11	5
	HUF	67826	16	6
	NRI	11423	37	9
Non-Financial Corporate Investors (2)	Public and Private companies	49120	25	15
	Partnership Firms	5508	28	20
	Trusts and Societies	1364	34	21
	Other Corporate Bodies	24139	21	12
Domestic Financial Institutions (DFI) (3)	Mutual Funds	26589	74	51
	Banks	4148	77	56
	Insurance Companies	1135	77	65
	Other DFI’s	1558	66	44
Foreign Institutional Investors (FII) (4)	FII	22121	73	52
Others (5)	Statutory Bodies	214	25	7
	Others	35931	33	13

Table 2
Information Level of Different Trader Clientele Categories

We measure the information level of an order with reference to the change in the mid-quote 5 minutes or 30 minutes or 60 minutes after order submission. Panel A reports Information Level averaged over all orders submitted by the particular trader clientele category.

Category	Information Level by Time Horizon		
	5min	30min	60min
Individuals (1)	0.63	0.13	-0.07
Corporates (2)	1.03	1.15	1.13
DFIs (3)	2.86	4.74	5.40
FII's (4)	2.82	8.66	12.36
Others (5)	0.63	0.36	0.74

Table 3 Panel A
Order Submissions by Different Trader Clienteles

This table reports order submissions for different trader clienteles over the 56 trading days sample period for all stocks together with the percentage cancelled, modified and executed.

Category	Order Submissions		Percentage of Orders		
	Millions of shares	Percentage of total orders submitted	Cancelled	Modified	Executed
Individuals(1)	6702	34	31	33	64
Corporates (2)	8334	42	63	28	40
DFI’s (3)	984	5	10	49	83
FII’s (4)	2299	12	9	38	89
Others (5)	1321	7	54	26	47

Table 3 Panel B
Different Trader Clienteles: Liquidity Demand and Liquidity Supply

This table summarizes the trading activity of different trader clienteles when they trade as liquidity demanders and liquidity suppliers. Liquidity Demanders are traders who consume liquidity through market orders or marketable limit orders. Liquidity Suppliers are traders who supply liquidity through limit orders in the limit order book.

Liquidity Demanders					
Category	Number of Trades (in millions)	Value Traded (in million USD)	Proportion of value traded through		
			Hidden	Market	M-Limit
All	55	56449	19	10	72
Individuals(1)	30	21430	7	14	79
Corporates (2)	14	17458	8	3	88
DFI's (3)	2	3534	51	9	40
FII's (4)	5	11326	51	12	37
Others (5)	3	2700	8	7	85

Liquidity Suppliers						
Category	Number of Trades (in millions)	Value Traded (in million USD)	Proportion of value traded through		Mean Waiting time execution in mm:ss	
			Limit	Hidden	Hidden	Limit
All	55	56449	61	39	9:00	7:10
Individuals(1)	27	19093	83	17	9:37	7:32
Corporates (2)	18	16020	74	26	7:07	5:53
DFI's (3)	2	5312	25	75	10:26	5:57
FII's (4)	4	13235	23	77	10:37	10:10
Others (5)	4	2788	77	23	6:38	7:00

Table 4 Panel A: Hidden Order Usage and Information Level of Trader Clienteles: Overall Results

This table reports the results of running the following regression separately for Liquidity Suppliers and Liquidity Demanders over all trading participants.

For Liquidity Suppliers, $$LSHP_{i,t} = \alpha_1 LS\_\inf + \alpha_2 LSLD\_\inf + \sum_{i=1}^{5} \beta_i Cat_i + \gamma_1 Volatility + \gamma_2 Qspr + \varepsilon$$

For Liquidity Demanders, $$LDHP_{i,t} = \alpha_1 LD\_\inf + \alpha_2 LDLS\_\inf + \sum_{i=1}^{5} \beta_i Cat_i + \gamma_1 Volatility + \gamma_2 Qspr + \varepsilon$$

where

t	30-minute trading interval
$LSHP_{it}$	Hidden proportion of liquidity submitted by i^{th} category of LS during the interval t
$LDHP_{it}$	Hidden proportion of liquidity demanded by i^{th} category of LD during the interval t
LS_inf	Information level (at 5-minute time horizon) of liquidity supplier in interval t
LD_inf	Information level (at 5-minute time horizon) of liquidity demander in interval t
Ld	Equals 1 if information level of liquidity demanders is above one standard deviation, else zero
Ls	Equals 1 if information level of liquidity suppliers is above one standard deviation, else zero
LSLD_inf	*LS_inf* times *Ld*, measures the informedness of liquidity suppliers when liquidity demanders are informed
LDLS_inf	*LD_inf* times *Ls*, measures the informedness of liquidity demanders when liquidity suppliers are informed
Cat_i	Trading category-wise dummy variables (i=1, 2, 3, 4, 5)
Volatility	Intra-day volatility of one minute returns in interval t
QSpr	Average quoted spread ((Best Offer-Best Bid)/Midquote) in interval t

All independent variables, except the trader clientele category dummy variables, are standardized.

LSHP				**LDHP**		
Variable	Estimate	t-stat		Variable	Estimate	t-stat
LS_inf	1.10***	14.28		*LD_inf*	-0.23***	-3.66
LSLD_inf	-1.33***	-13.09		*LDLS_inf*	0.24***	2.75
Cat_1	11.21***	94.13		Cat_1	3.46***	32.89
Cat_2	27.19***	228.18		Cat_2	6.09***	57.79
Cat_3	65.02***	415.16		Cat_3	37.64***	271.91
Cat_4	71.77***	495.09		Cat_4	41.85***	326.61
Cat_5	12.27***	101.61		Cat_5	3.83***	35.84
Volatility	-12.86***	-36.78		*Volatility*	-2.44***	-7.89
QSpr	2.58***	47.70		*QSpr*	-0.54***	-11.30

Respectively, ***, **, and * denote significance at 1, 5, and 10 percent.

Table 4 Panel B: Hidden Order Usage vs. Information Level of Trader Clienteles: Category-wise results

This table presents client category-wise results of HO usage versus Information for April-June 2006. In Panel A, we report the results of fixed effects panel regression of percentage of hidden order usage of liquidity suppliers to their information level and when the liquidity demanders are informed apart from control variables, quoted spread, volatility, stock size and hourly trading interval dummies. In Panel B, results of similar analysis for Liquidity Demanders are reported.

For liquidity suppliers in each trader clientele category, we run the following panel regression:

$$LSHP_{it} = \alpha_1 LS\_\inf_t + \alpha_2 LSLD\_\inf_t + \sum_{l=1}^{5} \beta_l D_l + \gamma_1 Volatility_t + \gamma_2 QSpr_t + \gamma_3 Size + \varepsilon_{i,t}$$

Similarly, for liquidity demanders in each trader clientele category,

$$LDHP_{it} = \alpha_1 LD\_\inf_t + \alpha_2 LDLS\_\inf_t + \sum_{l=1}^{5} \beta_l D_l + \gamma_1 Volatility_t + \gamma_2 QSpr_t + \gamma_3 Size + \varepsilon_{i,t}$$

where

t	30-minute trading interval
$LSHP_{it}$	Hidden proportion of liquidity submitted by i^{th} category of LS during the interval t
$LDHP_{it}$	Hidden proportion of liquidity demanded by i^{th} category of LD during the interval t
LS_inf_t	Information level of liquidity supplier in interval t
LD_inf_t	Information level of liquidity demander in interval t
Ld	Equals 1 if information level of liquidity demanders is above one standard deviation, else zero
Ls	Equals 1 if information level of liquidity suppliers is above one standard deviation, else zero
$LSLD\_inf_t$	LS_inf_t times Ld, measures the level of information of liquidity suppliers when liquidity demanders are informed
$LDLS\_inf_t$	LD_inf_t times Ls, measures the level of information of liquidity demanders when liquidity suppliers are informed
D_l	5 hourly trading interval dummies over the trading day (before 11:30, 11:30 to 12:30; 12:30 to 13:30; 13:30 to 14:30 and 14:30 to 15:30)
Volatility	Intra-day volatility of one minute returns in interval t
QSpr	Average quoted spread ((Best Offer-Best Bid)/Midquote) in interval t
Size	Size of firm measured by its market capitalization on June 30, 2006

All independent variables, expect the trading interval dummies, are standardized.

Table 4 Panel B: Hidden Order Usage vs. Information Level of Trader Clienteles: Category-wise results

Variable	Category 1		Category 2		Category 3		Category 4		Category 5	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Panel A : Liquidity Suppliers										
LS_inf	0.50***	5.38	0.42***	2.96	2.30***	7.19	1.55***	6.39	0.73***	6.36
LSLD_inf	-0.73***	-6.71	-1.12***	-6.60	-1.76***	-3.78	-1.59***	-4.24	-0.84***	-5.13
D_1	9.32***	75.61	26.44***	134.64	66.36***	114.35	75.16***	162.76	11.21***	54.52
D_2	10.04***	79.93	28.30***	140.56	68.03***	112.91	72.12***	149.81	11.67***	55.21
D_3	10.32***	82.09	28.97***	143.52	66.01***	108.91	72.44***	150.50	11.90***	55.90
D_4	10.60***	81.49	28.57***	137.03	65.49***	104.65	71.69***	145.85	11.94***	54.62
D_5	10.62***	77.79	28.37***	129.92	63.50***	102.99	69.09***	135.21	11.88***	52.09
Volatility	-7.02***	-19.68	-17.27***	-30.38	-15.68***	-9.74	-16.29***	-12.32	-9.61***	-15.96
QSpr	2.10***	39.39	3.64***	42.51	2.23***	8.69	2.06***	9.90	1.42***	15.69
Size	-1.79***	-35.35	-2.56***	-31.48	-2.40***	-11.07	-0.38**	-2.26	-0.57***	-6.78
Panel B : Liquidity Demanders										
LD_inf	-0.04	-1.20	-0.08	-1.30	-0.27	-0.87	-0.74***	-3.12	-0.14**	-2.17
LDLS_inf	-0.03	-0.57	0.05	0.68	0.22	0.44	0.77**	1.96	0.13	1.28
D_1	3.17***	57.25	6.13***	61.75	36.98***	61.30	43.32***	91.65	3.76***	30.56
D_2	3.27***	57.88	6.23***	61.55	38.72***	61.64	43.20***	87.52	3.83***	30.24
D_3	3.28***	57.97	6.16***	60.75	36.79***	58.18	42.12***	85.30	4.02***	31.55
D_4	3.12***	53.17	5.95***	56.69	36.76***	56.34	41.00***	81.34	3.62***	27.64
D_5	3.08***	50.29	5.83***	52.99	36.11***	56.19	41.25***	78.64	3.77***	27.65
Volatility	-0.90***	-5.61	-2.33***	-8.03	-0.07	-0.04	-5.59***	-4.15	-2.27***	-6.30
QSpr	0.11***	4.62	0.09**	2.01	-2.31***	-8.61	-2.13***	-9.99	0.12**	2.27
Size	-0.25***	-11.17	-0.30***	-7.32	0.97***	4.29	1.05***	6.08	-0.15***	-2.89

Respectively, ***, **, and * denote significance at 1, 5, and 10 percent.

Table 5 : Hidden Orders and Price Discovery

Panel A of this table reports summary statistics of the *Hasbrouck Information Share* calculated for each of the 50 stocks on each day of the sample period. HP and NHP are one minute mid-quote series obtained from two streams, the mid-quotes of hidden orders and the mid-quotes of non-hidden, orders. HP_IS and NHP_IS are measure of information shares. Panel B reports fixed effects panel regression results on relating daily HP_IS with daily trade frequency (TFQ), daily intra-day volatility (Volatility), and daily quoted spread (QSpr).

Panel A				
Summary	**HP_IS**		**NHP_IS**	
	Mean	**Median**	**Mean**	**Median**
Mean	71.32	73.18	28.68	26.82
Median	79.51	84.07	20.49	15.93
Max	92.66	98.44	75.42	85.83
Min	24.58	14.17	7.34	1.56
Q1	58.12	55.95	13.45	9.41
Q3	86.55	90.59	41.88	44.05
Stddev	19.04	22.63	19.04	22.63

Panel B Fixed Effects Panel Regression Dependent Variable : HP_IS				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFQ	0.14	0.03	4.17	0.00
Volatility	-0.10	0.02	-5.15	0.00
QSpr	-0.05	0.02	-2.69	0.01

Table 6: Hidden Orders, Informedness, and Market Quality Proxies

This table presents the GMM estimation results of a seven-variable Panel VAR model using one lag. Standard deviation of information level over 30-minute period and unexpected volatility from a GARCH(1,1) model measure informedness. We use spread, average slope of order book on both sides, and variance of pricing error as market quality proxies.

t	30-minute interval
Inf_Content	Unexpected (Residual) volatility from AR(1)-GARCH (1, 1) model
Inf_Asymmetry	Standard deviation of information level in interval t
$QSpr_t$	Average quoted spread from one minute order book snapshots in interval t
$Slope_t$	Average of mean buy and sell side order book slope at the end of interval t
InvVarPrErr	Inverse of variance pricing error from Hasbrouck's (1993) transaction-cost model
$LSHP_t$	Percentage of hidden liquidity of LS in interval t
$LDHP_t$	Percentage of hidden liquidity of LD in interval t

All variables are standardized.

DepVAR→	***Inf_Content***		***Inf_Asymmetry***		***QSpr***		***Slope***		***InvVarPrErr***		***LSHP***		***LDHP***	
IndVAR ↓	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
$\boldsymbol{Inf\_Content_{t-1}}$	0.027	0.80	0.024**	2.20	0.010**	2.48	0.004***	2.81	-0.016***	-2.65	0.010***	3.41	0.013**	2.29
$\boldsymbol{Inf\_Asymmetry_{t-1}}$	0.077	1.21	0.048	0.81	0.016***	3.65	0.0002	0.07	0.045**	2.40	-0.038**	-2.42	-0.043**	-2.32
$\boldsymbol{QSpr_{t-1}}$	0.406***	4.06	0.187*	1.79	0.330***	6.49	0.050***	3.50	0.014	0.66	-0.125***	-5.36	-0.04**	-2.09
$\boldsymbol{Slope_{t-1}}$	-0.09	-0.76	0.0009	0.06	0.003*	-1.89	0.011	0.93	0.001	-1.33	0.008*	1.80	0.004	-1.01
$\boldsymbol{VarPrErr_{t-1}}$	0.093	1.61	0.018	1.60	0.005***	2.97	0.0002	-0.17	0.558***	14.46	0.006*	1.73	0.07	1.47
$\boldsymbol{LSHP_{t-1}}$	-0.052**	-2.41	0.084***	4.27	-0.013***	-3.37	-0.018**	-2.05	0.026**	2.23	0.530***	42.77	0.096***	5.45
$\boldsymbol{LDHP_{t-1}}$	0.007	1.02	-0.011	-0.46	0.005***	-2.61	-0.007**	-2.11	0.006	0.72	0.058***	8.04	0.512***	27.42

Respectively, ***, **, and * denote significance at 1, 5, and 10 percent.