Pre-Trade Opacity, Informed Trading, and Market Quality

By

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Abstract

We empirically examine on-exchange hidden liquidity in the context of informed trading, pricing efficiency, and trading costs. Using a number of proxies for informativeness and a number of different specifications, we find that when an on-exchange option to hide orders exists, traders prefer to use hidden orders when they are informed. Further, the use of hidden orders by informed traders increases pricing efficiency, with prices more closely approximating their information-efficient values. Quoted spreads also reduce, and in particular, uninformed liquidity demanders face lower effective spreads. Overall, our results provide reasonably strong support to the core implications of Boulatov and George (RFS, 2013).

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1. Introduction

A significant fraction of the liquidity offered and taken in today's equity markets is explicitly hidden, both on-exchange and off-exchange.[1] This paper examines on-exchange hidden liquidity: hidden or "iceberg" orders that allow traders to hide (at least) a fraction of their liquidity-supplying standing limit orders (hereafter "SLOs") and their liquidity-demanding market orders or marketable limit orders (hereafter "MLOs"). These hidden orders execute automatically with the same price priority as fully displayed orders, except for the hidden part of the order losing time priority to displayed orders at the same price.[2] Hidden orders empower traders to create pre-trade opacity in an otherwise transparent environment.

Informed traders should arguably be the principal users and beneficiaries of hidden orders, since they can thereby reduce parasitic "front-running" of their orders, avoid leaving signaling-related "footprints" when they trade, and mitigate adverse-selection transaction costs (Harris, 1997). This has generated significant regulatory interest across multiple jurisdictions in view of the consequential pricing and fairness implications across hidden/displayed market segments, particularly relative to uninformed public or retail investors. Whether and how informed traders condition their trading if an option to hide is available, and how this affects market quality for others, is an empirical question that is important and interesting for regulators, market participants, and academic theorists. Our aim in this paper is to empirically investigate whether and how different categories of traders choose to hide different types of on-exchange orders depending on their level of informativeness, and how this affects pricing efficiency and trading costs for others, particularly relatively uninformed traders.

The theoretical model of informed traders and on-exchange hidden liquidity that is most directly relevant to this paper is Boulatov and George (2013) (hereafter "BG"). BG allow informed traders to hide their orders or display them, and coexist as both liquidity demanders and liquidity providers. Their key reasoning is that informed traders want to capture the extra rents from providing liquidity, but if they have to display their liquidity-providing orders, they lose some of their informational advantage to uninformed traders, and this causes informed traders to provide liquidity relatively more actively in markets with hidden orders, increasing competition among liquidity providers. BG offer three main conclusions for a market with hidden orders. First, informed traders will choose to be liquidity providers trading aggressively on

[1] Off-exchange hidden liquidity is in dark pools that typically match buyers and sellers without displaying bids or offers, without general public access, and sometimes without disclosing the basis of trade-matching algorithms used.
[2] On-exchange hidden or iceberg orders constitute about 45% of Euronext depth and volume (De Winne and D'Hondt (2007), Bessembinder, Panayides and Venkataraman (2009)), 26% of executions on the Spanish Stock Exchange (Pardo and Pascual (2012)), 16% on Xetra (Frey and Sandås (2009)), and 25% of NASDAQ dollar depth (Tuttle (2006)). Dark reserve orders on the NYSE enable orders to be completely hidden.

their information, and any uninformed liquidity providers will have to compete with these informed liquidity providers, thereby earning lower rents, or exiting liquidity provision. Second, the greater dominance of informed traders in liquidity provision will result in information becoming more accurately and quickly incorporated into the best SLO prices on both the buy and the sell side, because of which *mid-quotes* will more closely approximate the security's true value. Finally, the greater competition in liquidity provision will result in uninformed liquidity demanders facing lower effective spreads. Moinas (2010), in another relevant theoretical model, considers a more restricted setting in which informed traders can only supply liquidity (but not demand it), and concludes, consistent with BG, that informed traders should be the dominant liquidity suppliers in a market with hidden orders.[3] The literature related to sunshine trading (e.g. Admati and Pfleiderer, 1991; Forster and George, 1992) also notes that informed traders have greater incentive to hide their identity than uninformed ones.[4] We empirically test the BG predictions in this paper.

Bloomfield, O'Hara, and Saar (2015) and Gozluklu (2016) address, in an experimental laboratory setting, how hidden orders affect trader behavior. The key findings from these papers are that, while both informed and liquidity (uninformed) traders use hidden orders, the behavior of informed traders is more sensitive to changes in opacity; and consistent with BG, informed traders use hidden orders to execute more of their trades to keep their informational advantage longer: in particular, in information intensive periods like around earnings announcements. Kovaleva and Iori (2015) similarly use an experimental laboratory setting to examine the impact of hidden orders on market quality, and find, consistent with BG, a reduction in transaction costs and better price discovery.

The first bottom line conclusion from existing theory and laboratory experimental evidence is that, in a market with on-exchange hidden orders, informed traders should dominate uninformed traders in the placement of hidden SLOs, but with no clear implications for the hiding of MLOs. While extant empirical research has not directly addressed this specific issue, the overwhelming inference on this issue that appears to follow tangentially from current empirical evidence is precisely the opposite – that it is the uninformed and not the informed traders who use liquidity supplying hidden orders. First, using a sample of medium-sized hidden orders on the Australian Stock Exchange, Aitken, Berkman, and Mak (2001) find that the permanent price impact of hidden orders are no different from that of a matched set of fully-displayed

[3] Some other theoretical models of on-exchange hidden liquidity assume that informed traders do not supply liquidity. These are hence not relevant for this paper. These include, for example: Baruch (2005); Madhavan, Porter, and Weaver (1999); and Buti and Rindi (2012).

[4] Models of off-exchange hidden liquidity in dark pools are not directly relevant to this paper, since dark pool price formation is segregated. Zhu (2014) shows that informed traders face greater execution risk in dark pools relative to uninformed traders, and hence prefer to trade on the more transparent exchange. He also illustrates that adding a dark pool alongside an exchange improves price discovery but reduces exchange liquidity. In contrast, Ye (2011) shows that dark pools reduce price discovery and exchange volatility since informed traders migrate to dark pools. Nimalendran and Ray (2013) use proprietary data to find concurrent informed trading in dark pools and on exchanges.

orders. Second, Bessembinder, Panayides, and Venkataraman (2009) show that the opportunity cost of unexecuted hidden orders is lower than that of unexecuted fully-displayed orders. Given the lower adverse price movement after the submission of hidden orders when compared to fully-displayed orders, they conclude that hidden orders are more likely uninformed. Third, Frey and Sandås (2009) find that the greater the fraction of a hidden order that is executed, the smaller is its price impact, which is also consistent with uninformed traders using hidden orders. And fourth, inferring hidden quantities of executed orders on the Spanish Stock Exchange, Pardo and Pascual (2012) find that the detection of hidden quantity has no significant price impact. That said, De Winne and D'Hondt (2007) observe that traders on the Euronext submit more aggressive orders when they detect hidden depth, which is consistent with BG; and Anand and Weaver (2004) document that informed traders use hidden limit orders to minimize price impact of aggressive orders, again consistent with the spirit of BG.

The second bottom-line conclusion from the theory (BG), consistent with the evidence from experimental markets, is that, in a market with hidden orders, information will be more effectively incorporated into prices, and uninformed liquidity demanders will face lower effective spreads. Once again, there is no empirical evidence on the impact of hidden liquidity on market quality. The evidence that exists relates generally to transparency of the limit order book *per se,* and here the overall evidence, while mixed, shows that higher pre-trade opacity is associated with *lower* pricing efficiency, again *opposite to* what is predicted in BG and seen in evidence from experimental markets.[5]

This paper is an empirical examination of hidden orders in the context of trader information. BG provide the theory, there is a body of laboratory experimental evidence, and our aim is to provide the third leg of the stool – the empirical evidence. We empirically investigate the use of hidden SLOs and MLOs, and relate it to their information level using a variety of different measures and tests. Specifically, we test, *inter alia*, the central implications of BG that: (a) informed traders tend to use hidden orders when they place SLOs; (b) hidden orders reduce the magnitudes of deviations of mid-quotes from fundamental values; and (c) hidden orders reduce the effective spreads of uninformed liquidity demanders. In addition, we formulate and test other hypotheses on related issues where the theory has no specific predictions.

We use a proprietary dataset of orders and trades from the National Stock Exchange of India (hereafter, NSE). Most importantly, this dataset includes the coded identities of each and every trading account, enabling us to estimate an informativeness level for each account. The data identify SLOs and MLOs, and indicate whether an order is hidden or not. The data also include the trader category, that enables

[5] Boehmer, Saar and Yu (2005) find that price impact of orders decreases and informational efficiency of prices improves after introduction of NYSE's Open Book. Eom, Ok, and Park (2007) examine market quality around staggered increases in transparency of the order book on the Korea Exchange, and find that market quality is increasing and concave in pre-trade transparency. On the other hand, Madhavan, Porter, and Weaver (2005) find that both execution costs and volatility increase after the public dissemination of the Toronto Stock Exchange limit order book.

us to classify traders as Financial Institutions ("FI"), Financial Traders ("FT"), Non-Financial Institutions ("NFI"), and Individuals. Foreign Institutional Investors, Banks, Mutual Funds, Insurance Companies, and Other Domestic Financial Institutions are grouped together as FIs. FTs are exchange members trading on their own account, essentially as voluntary market-makers. All other institutional traders form the NFIs category. We also alternatively classify traders as fundamental traders, day traders, and others, along the lines of Kirilenko et al. (2017). Our data is from an 18-month period from January 2005 to June 2006. During that period, the number of trades on the NSE is about a third of that on the NYSE and Nasdaq but several times greater than that on Euronext or the London Stock Exchange. Virtually all the results reported in current version of the paper are based on an investigation of a random sample of 100 stocks over the full 18-month sample period. These 100 stocks account for about 18% of NSE market capitalization.[6] 11% of all incoming SLOs and 30% of the total value of incoming SLOs have a hidden component. The corresponding numbers for MLOs are 5% and 32%, respectively. Larger orders are more often hidden, consistent with traders of larger orders wanting to reduce their "footprint".

The undisplayed component of hidden orders loses time priority to displayed orders at that price, delaying its execution. Hence, when informed traders use hidden orders, the likely usable life of their information can be expected to play a key role in their trade-off between immediacy and risk of order exposure. Hence, among informed traders, those trading on long-lived information are more likely to use hidden SLOs relative to those trading on short-lived information. Within our trader categories, FIs can be expected to be trading on long-lived information, and FTs on short-lived information, given that FTs likely generate any private information from observing market conditions and the order flow. It is not obvious whether Individuals and NFIs are more or less likely to trade on long- or short-term information, and hence more or less likely to use hidden orders. MLOs reflect immediacy and should be at least partially executed immediately; but if the order is not executed completely, the unfilled order being displayed in the order book risks revealing the private information in the order, and this is what motivates informed traders to hide their large MLO orders.

First, we investigate whether traders prefer to hide their orders to a greater extent when they are informed. Following Anand, Chakravarty, and Martell (2005), we initially measure informativeness of each order based on the extent to which the quote midpoint moves in the direction of the order from one minute prior to the order to the end of different time horizons after order submission: 60 minutes, 1 trading day, and 5 trading days for short-lived, medium-horizon, and longer-lived informativeness measures respectively. Not surprisingly, we find that orders of FIs have much higher informativeness than those of

[6] However, this paper is still work in progress, and the analyses of earnings announcements reported in this version is still based on an early pilot sample of the 50 stocks in Standard & Poor's CNX Nifty index (representing about 60% of NSE market capitalization) over a sample period of only 63 trading days.

other traders regardless of the time horizon or the nature of the order or across different sub-samples within the sample period, followed by orders of NFIs and Individuals. Orders of liquidity-supplier FTs have much lower informativeness. Order informativeness is also higher for less liquid stocks.

Importantly, regardless of stock liquidity, trader type, time horizon after order submission, and the type of limit order, hidden orders are associated with significantly greater informativeness. Across trader categories, consistent with FIs being more informed, the largest difference in the informativeness of hidden and non-hidden orders is for FIs. The difference in the information level of hidden and non-hidden orders is also several times higher for MLOs (relative to SLOs) a – understandable since informed traders would not want any unexecuted portion of their orders to reveal their private information. It is also highest for stocks in the least liquid quintile.

We estimate the probability of an informed trader submitting a hidden order in a framework similar to that of De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009), duly controlling for investor type, various stock characteristics, and contemporaneous market conditions. We have a host of results, but most importantly, we find that a one-standard deviation increase in FIs' informativeness increases the likelihood of hiding the order by around 2 percent. This is true for both SLOs as well as MLOs, though statistically stronger for SLOs, and for buy as well as sell orders. The link between informativeness and use of hidden orders is much weaker for Individuals, NFIs, and FTs, where a one-standard deviation increase in informativeness also results in an increase in the likelihood of submitting hidden orders, but by less than 20 basis points.

As our data provides a masked ID for each trader in our sample, we are also able to track each trader's usage of hidden and non-hidden orders across stocks and across time, and accordingly use trader profits scaled by trader volume as a proxy for trader informativeness. We sort traders based on their scaled profits, and classify traders into three profit terciles. For each trader category, scaled profits are significantly positive for the highest profit tercile, not significantly different from zero for the middle tercile, and significantly negative for the lowest profit tercile. We also find that for FIs, Individuals, and FTs, the usage of hidden orders is significantly higher for larger scaled trader profits – i.e., higher informativeness – for traders in the highest and middle scaled profit terciles. These profitability-based results are largely consistent with informed traders being more likely to use hidden orders.

We conduct robustness tests of our results also with two other measures of informativeness used in the literature, specifically: (a) the Kaniel and Liu (2006) measure – which is the non-parametric method equivalent of Anand, Chakravarty, and Martell (2005); and (b) the contribution to cumulative price change measure used in Barclay and Warner (1993) and Chakravarty (2001). As a further robustness check, we use an alternate method of trader categorization inspired by Kirilenko et al. (2017). We split the sample into two sub-periods, one from January 2005 through June 2005 and another from July 2005 through June 2006.

We categorize traders as Fundamental Traders, Day Traders, and Others based on their net inventory position in each stock at the end of each day over the first sub-period and examine the relationship between informativeness and hidden order usage over the second sub-period. The results from our robustness checks are largely consistent with our earlier finding that a greater usage of hidden orders is associated with orders of higher informativeness, supporting the BG prediction that informed traders use hidden orders.

That said, even though our results above are consistent across a variety of informativeness measures and testing specifications, the results reflect associations and not formal causal inferences. Given that our use of ex-post measures as proxies for the information level of traders could potentially lead to endogeneity problems, we also investigate the proportion of hidden orders around an exogenous information-intensive event, specifically around earnings announcements. We compare hidden order usage around earnings announcements to that during "normal" trading periods. We find that FIs and traders in the highest informativeness decile hide a significantly larger proportion of their orders around earnings announcements than during "normal" trading periods; while there are no significant differences for NFIs, FTs, Individuals, and traders in the lowest and middle informativeness terciles. This provides causal support for our inference – and the BG prediction – that traders hide more of their orders when they are informed, contrary to what the existing literature appears to indicate, albeit through tangential inferences.

Finally, we examine the impact of hidden orders on pricing efficiency and liquidity: specifically, whether hidden orders reduce the magnitudes of deviations of mid-quotes from fundamental values, and reduce the effective spreads of uninformed liquidity demanders; as posited by BG. We use pricing error measures – defined as the deviation of prices from their information-efficient "random-walk" value – as estimated in Hasbrouck (1993) and Boehmer and Kelley (2009). We also use both overall effective spreads as well as the effective spreads faced by "uninformed" liquidity demanders. First, we find that pricing errors are significantly lower when FIs, and traders in the highest tercile of informativeness, use more hidden orders, and this relationship continues to hold, in a Granger-causal way, in the VAR. This is true for both their SLOs as well as MLOs. Second, irrespective of who is trading and whether SLOs or MLOs are used, hidden orders are associated with both significantly lower overall effective spreads, as well as significantly lower effective spreads of uninformed liquidity demanders.

Finally, to have more credibly causal inferences, we also run a Panel VAR analysis involving pricing errors, effective spreads of (uninformed) liquidity demanders, and the usage of hidden and other orders by FIs and other traders on one hand, and by traders in different terciles of informativeness on the other hand. We find, in a VAR framework, that the use of more hidden orders (whether SLOs or MLOs) by FIs leads to significantly lower pricing errors in the next period, while the use of more hidden orders (whether SLOs or MLOs) by other traders significantly increases these pricing errors. This indicates that, on average, FIs hidden orders are informed and hence help to take prices towards their information-efficient values; while, on average, the orders of other traders do not. Our results in relation to similar analyses for traders in different terciles of informativeness, and for effective spreads of (uninformed) liquidity demanders, are awaiting completion and will be included in the next version of the paper.

Overall, our tests provide reasonably strong support for the core implications of Boulatov and George (2013). When the option to hide orders exists: (a) informed traders prefer to use hidden orders; (b) pricing errors are lower with mid-quotes more closely approximating the security's true value, and hence information more effectively incorporated into quoted prices; and (c) quoted spreads reduce, and in particular, uninformed liquidity demanders face lower effective spreads.

Our results have significant regulatory and policy implications. There has been a proliferation of off-exchange hidden liquidity in dark pools over the last two decades, and almost a fourth of U.S. equity market trading now takes place in these dark pools. The greatest catalyst for the growth of these dark pools in recent years has been institutional investors' growing need to trade large blocks of stock without causing markets to move against them.[7] That said, Degryse et al. (2021) show that dark pools and hidden order trading are substitutes for the traders who use them. Our results show that, in spite of pre-trade opacity, the option to have on-exchange hidden orders significantly improves both pricing efficiency and liquidity, and at the same time, gives informed institutional traders the ability to execute large trades with lower parasitic front-running and leaving of footprints, potentially providing them greater incentive to invest in the information collection and information generation that improves market quality. On the other hand, unlike with hidden orders, dark pools do not contribute directly to price formation on the main exchange since dark pool systems are totally segregated, and they clearly take liquidity away from the exchange rather than improve it, as we find hidden orders do. The level of opacity in dark pools – not just of prices but also of processes, fairness, and access restrictions – is also far greater than with on-exchange hidden orders. Not surprisingly, there have been extensive allegations and SEC investigations relating to conflicts of interest and the absence of a level playing field in some dark pools.

The remainder of the paper is organized as follows. We describe our data and present descriptive statistics of our sample in Section 2. Section 3 relates hidden order usage to the information content of orders. We examine the relationship between trader profitability and hidden order usage in Section 4. Section 5 presents a series of robustness checks using alternate measures of the information content of orders, and an alternative trader categorization. Section 6 examines hidden order usage around earnings announcements. Section 7 interrelates hidden order usage, trader informativeness, pricing efficiency, and liquidity. We conclude in Section 8.

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[7] See, for example, https://www.sec.gov/news/statement/shedding-light-on-dark-pools.html.

2. Data

A. Sample statistics

Our empirical analyses are based on a rich proprietary database from the NSE. The NSE is a fairly typical continuous 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 a centralized computer system and trade anonymously with one another on a real-time basis over the trading day.[8] The five best prices on both sides of the market, and the displayed depths at those prices, are publicly disseminated. The tick size is ₹0.05 (less than \$0.01). Unfilled orders are not carried over to the next day. The Securities and Exchange Board of India (SEBI), the securities markets regulator, created in the early 1990s, enforces a rigorous regulatory regime to ensure fairness, integrity, transparency, and good practice that is comparable to the best globally.[9] NSE is among the most liquid markets in the world. Figure 1 shows the total number of trades executed on leading stock exchanges around the world in 2006, around the time of our sample period.[10] The number of trades on the NSE is about a third of those on NYSE or NASDAQ, but more than seven times those on London Stock Exchange, Deutsche Borse, or Euronext.[11]

As indicated earlier, our proprietary data include the coded identities of each and every trading account and the trader category. The data identify SLOs and MLOs, and indicate whether an order is hidden or not.[12] We select a random sample of 100 stocks following a methodology similar to that of Bessembinder, Panayides, and Venkataraman (2009). The sample selection criteria and the list of companies in our sample are in the Appendix in Table A.I. Our sample has a total market capitalization of ₹10,583 billion or \$230 billion as of June 30, 2006, about 18% percent of the market capitalization of all listed NSE stocks.

Panel A of Table I presents summary statistics on the characteristics of the sample firms. The average firm has a market capitalization of close to \$1.4 billion. The number of order submissions per stock, traded value per stock, and the number of trades per stocks all increase with liquidity quintile and the percentage quoted spread narrows with liquidity quintile. Similar to Bessembinder, Panayides, and Venkataraman (2009), we find that there are more hidden order submissions in the least liquid quintile.

[8] In our sample period this trading session was from 9:55 AM to 3:30 PM, which changed to 9:00 AM to 3:30 PM.
[9] The other major stock exchange in India, the Bombay Stock Exchange (BSE), established in 1875 as a stockbrokers' association, is the oldest stock exchange in Asia, with 5,100 listed companies.
[10] The data is from the Annual Report and Statistics 2006 published by the World Federation of Exchanges.
[11] The US dollar equivalent average trade size on the NSE is much smaller because of the lower wealth level of the average Indian trader, but is of reasonable economic size in that context. The quality and timeliness of efficient price formation should arguably be determined by the number of trades of reasonable economic size.
[12] As our data allows us to map the orders on the two sides of a trade to the orders data, through a unique order number, we can determine the order submission and execution time for each order. This helps in identifying which order triggers the trade (MLO) and which order is on the book (SLO).

Typically, informed trading is greater in the less-liquid firms. Greater hidden order usage in these firms supports this. However, it is not clear whether informed traders in these stocks use hidden orders to protect themselves from being front-run or uninformed traders use hidden orders to protect themselves from being picked off by informed traders.

Panel B of Table I provides descriptive statistics on orders submitted. We present descriptive statistics separately for SLOs and MLOs. SLOs are limit orders that do not result in immediate execution and sit in the limit order book, waiting for execution. MLOs are limit orders that are executed at least partially upon submission.[13] Any unexecuted balance of these MLOs enters the limit order book and wait for execution. We exclude all market orders from the rest of our analyses, except where noted, as they demand immediate execution in full and never have a hidden component.

Given that MLOs are price-contingent demand for immediacy, we expect a smaller proportion of them than SLOs to contain a hidden component. Consistent with this, we find that only about 4% to 7% of MLOs have a hidden component, whereas 10% to 14% of SLOs have a hidden component. The proportion of order value with a hidden component is greater for both SLOs and MLOs than the corresponding proportion of orders with a hidden component across all liquidity quintiles. This shows that larger orders are more likely to contain a hidden component than smaller ones.

B. Trader types

The NSE categorizes each trader ID (combination of trading and client member codes) into one of 13 different types.[14] For ease of analysis, we reclassify these trader categories into four broader categories: FIs, Individuals, FTs, and NFIs, as defined in the introduction. We compare a frequency tabulation of the NSE-provided trader categories to that of our four trader categories in Panel A of Table II. Out of 2 million unique trader IDs in our data, 1.6 million are categorized as Individuals. They account for 38 percent of the traded value in our sample stocks. There are over 8,300 FIs who contribute to 24 percent of the traded value and close to 600 FTs account for 27 percent of the traded value. NFIs make up the remaining 12 percent of traded value.

We present hidden order statistics for the trader categories in Panel B of Table II. While 63% (61%) of FIs' SLOs (MLOs) are hidden, 78% (75%) of their SLOs (MLOs) in terms of order value are hidden. This again shows that FIs' larger orders are more likely to contain a hidden component. Larger

[13] In the context of Bessembinder, Panayides, and Venkataraman (2009)'s categorization of order aggressiveness, what we refer to as MLOs are equivalent to their categories 1, 2, 3, and 4 and our SLOs are equivalent to their categories 5, 6, and 7.

[14] The data does not provide trader type for some trader IDs. We present these in a separate category (14th) called Missing. For completeness, we also include traders for whom the trader category is missing. The Non-Financial Institutions category also includes traders with missing categories.

orders submitted by the other three trader categories are also more hidden across the board, though overall their usage of hidden orders is far lower than that of FIs. Individuals make the least use of hidden orders, with only 5% (3%) of their SLOs (MLOs) being hidden, corresponding to 19% (15%) by value.

Hidden order usage should be a function of an investor's trading horizon. Investors trading on short-term information are likely to be impatient and would prefer quick execution of orders. Such traders would prefer non-hidden orders as the hidden part loses time priority after the displayed portion of the order executes, delaying execution of their orders. On the other hand, investors trading on long-term information are likely to be patient. To avoid being front-run, these investors are more likely to hide their orders.

To get a sense of the trading horizon of the different trader categories, we present the distribution of end-of-day net holdings in Panel C of Table II. For each trader ID in each stock on each day, we calculate the end-of-day net holdings as the absolute difference between the number of shares bought and the number of shares sold divided by their sum. This will take a value of one on days when a trader has transactions in only one direction. On the other hand, it will be zero when the number of shares bought equals the numbers of shares sold. Longer-horizon traders will have a mean closer to one and shorter-term traders will have a mean closer to zero. The statistics in Panel C of Table II are based on trader-stock-day observations. FIs have a median (mean) of 1.00 (0.99), and are clearly long-horizon traders. FTs have a median (mean) of 0.21 (0.37), and are clearly short-horizon traders, which is not surprising since they are voluntary market-makers. NFIs and Individuals are also largely long-horizon with median (mean) of 1.00 (0.72) and 1.00 (0.66) respectively.

3. Hidden Order Usage and Order Informativeness

In this section, we present univariate and multivariate tests of the usage of hidden orders in the context of the information content of orders.

We initially proxy for the information content of an order by the change in the quote midpoint over a fixed period of time after order submission.[15] We calculate the information level of an order submitted by trader i in stock j at time t as:

$$InfoLevel_{ijt} = \ln\left(\frac{Midpoint_{j,t+m}}{Midpoint_{j,t-k}}\right) \times OrderDirection_{ijt}, \qquad (1)$$

where $Midpoint_{j,t}$ is the midpoint of the best ask and bid prices in stock j at time t, k takes a value of one minute, m takes a value of 60 minutes, one day, or five days after order submission, and $OrderDirection_{ijt}$

[15] This is similar to the measure used by Kaniel and Liu (2006) and Anand, Chakravarty, and Martell (2005).

is +1 (-1) for buy (sell) orders.[16] In this analysis, we exclude orders that are cancelled within two and a half minutes of submission with no executions.[17] If informed traders are more likely to submit hidden orders to conceal their private information, then we expect the information level of hidden orders to be greater than that of non-hidden orders. On the other hand, if uninformed traders do not want to be picked off by better-informed traders, the information level of non-hidden orders will be greater than that of hidden orders.

Table III compares information level of hidden orders to that of non-hidden orders for the different liquidity quintiles (Panel A), different trader categories (Panel B), and SLOs vs. MLOs (Panel C).[18] Regardless of stock liquidity, trader type, time horizon after order submission, and the type of limit order, hidden orders are associated with significantly greater informativeness. Information level monotonically decreases across the liquidity quintiles for both non-hidden as well as hidden orders. This is consistent with more informed trading in less-liquid stocks. This is also supported by the fact that the difference in information level between fully displayed and hidden orders is the largest in the least-liquid quintile and the least in the most-liquid quintile. Further, information level measured at all three horizons (60 minutes, one day, and five days) is consistently higher for hidden orders than for non-hidden ones across all liquidity quintiles. When broken down by trader category, this result holds for all trader categories also. Contrary to our expectations, even though FTs have short trading horizons, they still prefer to hide their orders when informed. Orders broken down by the type of limit order (SLOs and MLOs) also show that informed traders are more likely to use hidden orders than fully displayed orders.

Importantly, Table III shows strongly that orders of FIs have much higher informativeness than those of other traders regardless of the time horizon or the nature of the order or across different sub-samples within the sample period, followed by orders of NFIs and Individuals. Orders of liquidity-supplier FTs have much lower informativeness.

Next, we determine the likelihood of informed traders submitting hidden orders in a multivariate setting, controlling for stock characteristics and market conditions. We estimate the following linear probability model (LPM):

$$HiddenOrder_{ijt} = \beta_0 + \beta_1 InfoLevel_{ijt} + \beta_2 FI_i + \beta_3 Individual_i + \beta_4 FT_i + \beta_5 InfoLevel_{ijt} \times FI_i + \beta_6 InfoLevel_{ijt} \times Individual_i + \beta_7 InfoLevel_{ijt} \times FT_i + \beta_8 Buy_{ijt} + \beta_9 InfoLevel_{ijt} \times Buy_{ijt} + Controls + \varepsilon_{ijt}, \quad (2)$$

where $HiddenOrder_{ijt}$ takes a value of 1 if the order submitted by trader *i* at time *t* in stock *j* has a hidden component and 0 otherwise, $InfoLevel_{ijt}$ is as defined in (1), FI_i takes a value of 1 if trader *i* is a financial

[16] To the extent that traders use hidden orders to reduce the price impact of their orders, the measure biases us against finding significant results.
[17] Our results are qualitatively similar if we include these orders.
[18] For convenience, we refer to fully displayed orders as non-hidden orders in all our tables.

institution and 0 otherwise, $Individual_i$ takes a value of 1 if trader i is an individual trader and 0 otherwise, FT_i takes a value of 1 is trader i is a financial trader and 0 otherwise, and Buy_{ijt} takes a value of 1 if order submitted by trader i in stock j at time t is a buy order and 0 otherwise. $Controls$ include $TotalOrderSize_{ijt}$, $PriceAggressive_{ijt}$, $\%QSpread_{j,t}$, $SameDepth_{j,t}$, $OppositeDepth_{j,t}$, $OrderImbalance_{j,t}$, $LastTradeSize_{j,t}$, $RelTick_{j,t}$, $Volatility_{j,t}$, $MarketVolatility_{j,t}$, and $Ln(MarketCap_j)$, all of which are defined in Table A.II of the Appendix.[19] We include a dummy variable for buy orders as well as interact it with $InfoLevel$ because prior research has shown that buy orders are more likely to be informed than sell orders.[20] This suggests that buy orders are more likely to be hidden than sell orders.

We estimate an LPM rather than a logistic model for easier interpretation of the marginal effects of the interactive terms.[21] Wooldridge (2010) notes that the LPM produces consistent and unbiased coefficient estimates.[22] We standardize all continuous variables in the model. Further, we report standard errors clustered by trader ID and two-way clustered by stock and date.[23]

Estimates of (2) are in Table IV. We report results separately for SLOs and MLOs. Controlling for information and other variables, FIs are around 53 percent (55 percent) more likely than NFIs to hide their SLOs (MLOs). When trading aggressively by submitting MLOs, FIs still prefer to hide their order in case any part of it is unfilled and sits at the best price on the order book. On the other hand, Individuals are 5.5 percent (2 percent) less likely than NFIs to hide their SLOs (MLOs). Corresponding numbers for FTs are 10 and less than 1 percent, respectively, with the latter being statistically insignificant. We also find that the buy SLOs are 0.80 percent more likely to be hidden than similar sell orders. There is no statistical difference in the usage of hidden orders between buy and sell MLOs.

To examine the likelihood of the different informed traders submitting hidden orders, we test a number of linear hypotheses of the coefficient estimates. For example, testing $\beta_1 + \beta_5 = 0$ from (2) gives the marginal effect of FIs' information on their hidden order usage. A one standard deviation increase in FIs' $InfoLevel$ increases the likelihood of hiding an order by between 126 to 213 basis points. The evidence is statistically weaker when FIs submit MLOs, though all marginal effects are significant and positive. Further, we find that FTs are more likely to hide their SLOs when they are more informed, especially when buying. They are also more likely to hide their MLOs when buying on information. A one standard

[19] Our list of control variables are from De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009).
[20] See, for example, Chan and Lakonishok (1993) and Keim and Madhavan (1995, 1997).
[21] See Ai and Norton (2003) for a discussion of interpreting marginal effects of interaction terms in non-linear models like the logit and probit.
[22] For example, Tzioumis and Gee (2013) note the problem of interpreting marginal effects of interactive terms in a logit model and hence estimate an LPM with a binary dependent variable.
[23] A three-way clustering of standard errors by trader ID, stock, and date results in over 33 billion clusters, the estimation of which is constrained by computing resources.

deviation increase in FTs' $InfoLevel$ increases the likelihood of hiding an order by between 10 and 26 basis points. This is contrary to our hypothesis that FTs are less likely to hide their orders, especially when demanding liquidity. However, FTs are less likely to hide their MLOs when selling on information. The result for MLOs provides some support to our hypothesis that when FTs aggressively demand liquidity (most likely trading on short-term information), they are less likely to hide their orders. Also, Individuals are more likely to hide their buy SLOs and MLOs when they informed whereas the evidence for sell SLOs and MLOs is mixed. Finally, NFIs are more likely to hide their buy SLOs and MLOs when they more informed.

Overall, our results show that patient informed traders submitting SLOs, whether they are FIs, Individuals, FTs, and NFIs, are more likely to hide their orders when they are informed. On the other hand, there is some evidence that impatient informed traders, namely FTs submitting MLOs, are less likely to hide their orders. We also find that on average informed buyers are more likely to hide their orders than similar informed sellers.

4. Hidden Order Usage and Trader Profitability

We have shown that informed traders are more likely to submit orders with a hidden component, specifically when they trade on long-lived information. While the analyses in the previous section uses order informativeness data to relate information to hidden order usage, in this section, we use cross-sectional data at the trader-stock level to examine the relationship between hidden order usage and trader profitability. As the data allows us to track an investor's trades over the sample period, we calculate the profitability of each trader in each stock and relate it to her use of hidden orders. This trader profitability proxies for a trader's private information. We define the profitability of trader i in stock j as follows:

$$Profit_{ij} = \frac{ValSold_{ij} - ValBought_{ij} + PerEndVal_{ij}}{ValSold_{ij} + ValBought_{ij} + |PerEndVal_{ij}|}, \tag{3}$$

where $ValSold_{ij}$ is the total value of shares sold by trader i in stock j over the sample period, $ValBought_{ij}$ is the total value of shares bought by trader i in stock j over the sample period, and $PerEndVal_{ij}$ is the number of shares bought by trader i in stock j less the number of shares sold by trader i in stock j over the sample period times the last quote midpoint for stock j in the sample period. If the trader has a long (short) position in the stock at the end of the sample period, we assume that she sells (buys) it at the last available quote midpoint over the sample period i.e. her open position is marked to market at the last quote midpoint of the sample period.

We report descriptive statistics on $Profit$ and hidden order usage by profitability terciles in Table V. As FIs' profitability is much greater than that of other traders, we determine the profitability tercile breakpoints separately for each trader category. We assign each trader-stock combination to one of the profitability terciles based on her profitability in that stock. We report weighted-average profitability across all trader-stock combinations within each trader category and tercile, with the unsigned value traded by the trader in each stock over the sample period as weights. We use a similar weighting scheme to calculate the proportion of hidden orders used by each trader type in each tercile.

Irrespective of trader category, profitability in the lowest tercile is significantly negative, profitability in the middle tercile is not significantly different from zero, and profitability in the highest profitability tercile is significantly greater than zero. It is clear from Table V that, irrespective of trader category, it is only the highest profitability tercile that can be labelled as "informed" on the basis of the trader profitability measure.

Consistent with how we create the terciles, the profitability varies from -15 percent in the least profitable tercile to +14 percent in the most profitable tercile for FIs. Similar numbers for Individuals and FTs are -5 and 6 percent and -1 and 1 percent, respectively. Hidden order usage is always higher in the most profitable tercile when compared to the least profitable tercile for all trader categories except NFIs. This difference is 5 percent, 3 percent, and 3 percent for FIs, Individuals, and FTs, respectively. All the differences are statistically significant at the 1 percent level. This provides further support to our hypothesis that informed traders are more likely to use hidden orders.

Given that only the highest profitability tercile can be regarded as informed, and our aim is test for hidden order usage by informed traders, we need to use a non-linear model with the three profitability tercile regimes incorporated, in order to estimate the relationship between hidden order usage and trader informativeness. To control for all factors that affect hidden order usage, and we estimate the following cross-sectional OLS model:

$$PropHidden_{ij} = \beta_0 + \beta_1 LowProfit_{ij} + \beta_2 MediumProfit_{ij} + \beta_3 HighProfit_{ij} + \beta_4 FI_i + \beta_5 Individual_i + \beta_6 FT_i + \beta_7 LowProfit_{ij} \times FI_i + \beta_8 MediumProfit_{ij} \times FI_i + \beta_9 HighProfit_{ij} \times FI_i + \beta_{10} LowProfit_{ij} \times Individual_i + \beta_{11} MediumProfit_{ij} \times Individual_i + \beta_{12} HighProfit_{ij} \times Individual_i + \beta_{13} LowProfit_{ij} \times FT_i + \beta_{14} MediumProfit_{ij} \times FT_i + \beta_{15} HighProfit_{ij} \times FT_i + \beta_{16} Ln\left(OrderSize_{ij}\right) + \beta_{17} Ln\left(MarketCap_j\right) + \varepsilon_{ij} \tag{4}$$

where $PropHidden_{ij}$ is the order size-weighted proportion of hidden orders submitted by trader i in stock j, $Profit_{ij}$ is as defined in (3), where $LowProfit_{ij}$, $MediumProfit_{ij}$, and $HighProfit_{ij}$ is equal to $Profit_{ij}$ if $Profit_{ij}$ is in the first, second, or third tercile, respectively, and zero otherwise, $OrderSize_{ij}$ is the average order size submitted by trader i in stock j over the sample period, and FI_i, $Individual_i$, FT_i, and

$Ln(MarketCap_j)$ are as defined earlier. We standardize all continuous variables and two-way cluster standard errors by trader ID and stock.

Estimates of (4) are in Table VI. A one-standard deviation increase in profitability for FIs in the most profitable tercile increases the fraction of hidden orders used by 1.71 percent. Similar numbers for Individuals and FTs are 0.24 percent and 1.77 percent, respectively, and statistically significant, though these are statistically less significant than that for FIs. There is also a strong positive relationship between hidden order usage and profitability in the middle tercile for FTs. We find a highly significant increase of 17.80 percent in profitability for a one standard deviation increase in the fraction of hidden orders used. Interestingly, we find a negative relationship between hidden order usage and profitability for the uninformed traders, i.e., for the least profitable tercile for FIs, Individuals, and FTs, though the relation is statistically significant only for the first two trader categories.

Overall, our profitability-based results are also clearly consistent with informed traders being more likely to use hidden orders.

5. Robustness: Hidden Order Usage and Other Measures of Informativeness

In this section, we use alternate measures of informed trading used in the literature. Specifically, we use the nonparametric approach of Kaniel and Liu (2006) and the proportion of price change contributed by each trade measure of Barclay and Warner (1993) and Chakravarty (2001). We also repeat the $InfoLevel$ analysis using an alternate trading behavior-based trader categorization.

A. Relative Information level of Orders

Analogous to Kaniel and Liu (2006), we test the following hypotheses:

H_0: Fully displayed and hidden orders are equally informative.

H_{1a}: Fully displayed orders are more informative.

H'_{1b}: Hidden orders are more informative.

The null hypothesis states that the conditional probability that the quote midpoint is above (below) that before order submission is the same for fully displayed and hidden buy (sell) orders. H_{1a} states that this conditional probability is higher for fully displayed orders and H'_{1b} states the opposite.

Our definition of the different probabilities and other measures correspond to those in Kaniel and Liu (2006). We define P_{full} $(1 - P_{full})$ as the probability that a submitted order is a fully displayed (hidden) order. P_{full} is the fraction of submitted orders that are fully displayed. Let n denote the total number of times the quote midpoint after 60 minutes, 1 day or 5 days is in the direction of the order, that is, the quote midpoint after order submission is above (below) the quote midpoint one minute before order submission for buy (sell) orders.[24] Let n_{full} denote the number of times the quote midpoint is in the direction of a fully displayed order after its submission. So $n - n_{full}$ is the number of times the quote midpoint is in the direction of a hidden order after its submission. Under the null hypothesis, the probability that out of the n quote revisions n_{full} or more are preceded by a fully displayed order is approximately

$$1 - N\left[\frac{n_{full} - n \times P_{full}}{\sqrt{n \times P_{full} \times (1 - P_{full})}}\right] \tag{5}$$

where N is the standard normal cumulative distribution function. If this probability is less (greater) than 0.05 (0.95), we reject the null hypothesis of equal informativeness of fully displayed and hidden orders in favor of the alternative H_1 (H'_1) that fully displayed (hidden) orders are more informative.

We calculate these probabilities separately for the SLOs and MLOs and for the different trader types. We exclude orders that are cancelled within two and a half minutes of submission with no executions. The results of this analysis are in Panel A of Table VII. The probability values are greater than 99 percent for FIs submitting both SLOs and MLOs. On a relative basis, hidden SLOs (MLOs) submitted by FIs are 6 to 7 (4 to 15) percent more likely to be informed than fully displayed SLOs (MLOs). We find similar results for Individuals, NFIs, and SLOs submitted by FTs, though the magnitudes are smaller than those for FIs. This supports our hypothesis that traders trading on longer-term information are more likely to hide their orders. For MLOs submitted by FTs, we reject the null hypothesis in favor of the alternative that fully displayed orders are more informative. Consistent with our hypothesis, FTs are less likely to hide their orders when they are informed.

B. Contribution to cumulative price change

We follow Barclay and Warner (1993) and Chakravarty (2001) and determine the extent to which each trade contributes to the cumulative price change over the sample period for each sample stock. However, our analysis differs from Chakravarty (2001) in a couple of ways. While Chakravarty (2001) examines only stocks that have at least 5 percent increase over a three-month period, we do not place any restrictions on our sample. We use all 100 stocks in our sample. Chakravarty (2001) looks at the price-change contribution from the perspective of only one side of each trade, namely the liquidity demanding orders i.e., market and marketable limit orders. Earlier in this paper, we show that SLOs submitted by informed traders are likely

[24] To ensure this analysis is comparable to our earlier analyses, we use the same horizons after order submission rather than those used by Kaniel and Liu (2006). Further, we also use the quote midpoint one minute before order submission as the reference point. This is also consistent with our earlier analyses.

to be hidden.[25] To be able to examine the price-change contribution of SLOs and MLOs in our sample, we examine both sides of each trade.

For each stock, we determine the change in price from one trade to the next over the entire sample period. The sum of all these trade-to-trade price changes gives us the cumulative price change for the stock over the sample period. The contribution of trade at time t to this cumulative price change is

$$Contribution_{jt} = \frac{TradePrice_{jt} - TradePrice_{j,t-1}}{\sum_t TradePrice_{jt} - TradePrice_{j,t-1}} \times TradeSide_{jt} \tag{6}$$

where $TradePrice_{jt}$ is the transaction price of trade at time t in stock j, $TradePrice_{j,t\text{-}1}$ is the transaction price of the previous trade in stock j, and $TradeSide_{jt}$ takes a value of +1 for the liquidity demanding order that triggers the trade and -1 for the SLO that takes the opposite of the trade at time t in stock j. Our construction of the price change contribution ensures that its sum across all trades in a stock from the liquidity demanding (supplying) order's perspective is +1 (-1). Positive contribution implies informed trading.

Descriptive statistics by trader type and by order type are in Table VII, Panel B1 for SLOs and Panel B2 for MLOs. To arrive at the descriptive statistics, we aggregate the price change for each stock within each trader type and order opacity level. We then calculate a weighted-average across stocks for each trader type and order opacity level using the absolute value of the cumulative stock price change over the entire sample period as weight.[26]

For SLOs, we find that the contribution is largely negative for both hidden as well as fully displayed orders, except for hidden orders submitted by FIs and FTs. Even though hidden SLOs submitted by FIs account for only 6 (13) percent of trades (shares traded), they account for 145 percent of the cumulative price change. Similar numbers for FTs are 12 (4) percent and 93 percent, respectively. Proportionally, the price change contribution of hidden SLOs is much larger than the proportion of trading volume that they account for. This is consistent with our earlier result that patient informed traders, specifically FIs, are more likely to use hidden orders.

In Panel B2 of Table VII, we report price change contribution of market orders separate from that of fully displayed and hidden limit orders for two reasons. One, market orders are never hidden by design. Two, since they do not have a price constraint, their contribution to price change is disproportionately larger, which will likely skew our results. Consistent with this, we find that on average market orders contribute to 195 percent of the price change. When we compare the contribution to price change of only the limit orders, fully displayed orders contribute -134 percent whereas hidden orders contribute close to

[25] This is consistent with Kaniel and Liu (2006) who show that standing limit orders are more likely to be informed than marketable limit orders.
[26] Chakravarty (2001) reports descriptive statistics using the same weighting scheme.

39 percent. This suggests that hidden orders are more informed than fully displayed orders. When we examine the contribution of hidden and fully displayed orders submitted by FIs, hidden orders proportionally contribute more to the price discovery than fully displayed orders. This is again consistent with our earlier findings.

C. Trader Categorization

In this subsection, we categorize traders based on their trading behavior. Specifically, we split our sample period into two: one from January 2005 through June 2005 and another from July 2005 through June 2006. We categorize traders based on their trading behavior over the first sub-period and examine the relationship between $InfoLevel$ and hidden order usage for these trader categories over the second sub-period.[27]

As we have a trader ID (a combination of trading member and client member codes) for each trader in our sample, we can aggregate the trader's trades across days and across stocks. This allows us to determine the net inventory of a trader in a stock at the end of each day. We follow Kirilenko, Kyle, Samadi, and Tuzun (2017) in using the inventory position at the end of each day to separate traders into three categories. For each trader-stock combination, the net end-of-day position is the difference between the total number of shares bought by the trader in the stock and the total number of shares sold by the trader in the stock on that day. We use this measure to identify the following trader types:

1. Fundamental Traders: If on at least 90 percent of stock-days on which the end-of-day position is at least 15 percent of the unsigned total volume for the corresponding stock-day, the trader is classified as a Fundamental trader.
2. Day Traders: If on at least 90 percent of stock-days on which the end-of-day position is no more than 5 percent of the unsigned total volume for the corresponding stock-day, the trader is classified as a Day trader.
3. Others: All traders not in the above two categories.

Given the larger end-of-day positions, Fundamental Traders are likely to be trading on long-term information. We hypothesize that Fundamental Traders are more likely to hide their orders when they are informed. As Day Traders have smaller end-of-day positions, they are likely to be trading on short-term information. We predict that Day Traders are less likely to hide their orders when they are informed, especially when demanding liquidity.[28]

[27] We do not use this categorization in the main analyses because this method excludes traders who trade for the first time after June 30, 2005 and consequently would exclude their orders from our analyses.

[28] In unreported results, our earlier classification of Financial Institutions constitutes a large part of Fundamental Traders and Financial Traders constitute a large fraction of Day Traders. These results are available on request.

The comparison of the information level (as defined in (1)) of hidden orders to those of fully displayed orders for Fundamental and Day Traders are in Table VIII. Panel A shows that the information level of hidden orders is greater than that of fully displayed for all trader types. Since Day Traders are less likely to hide when they use marketable limit orders, we report information levels separately for SLOs and MLOs by trader type in Panel B. Similar to our earlier analyses with information level, we exclude orders that are cancelled within two and a half minutes of submission with no executions. Fundamental Traders' hidden orders have a higher information level than fully displayed orders. This is true for both SLOs and MLOs. The information level of SLOs with a hidden component submitted by Day Traders is greater than that of fully displayed SLOs. However, there is no significant difference in the information level of fully displayed MLOs and those with a hidden component submitted by Day Traders. We find that both SLOs and MLOs with a hidden component submitted by Others have a higher information level than fully displayed ones.

We find that, regardless of trading horizons, traders with more information are more likely to hide their orders. This is true when they both demand as well as supply liquidity.

Overall, our robustness results using other measures of informativeness are perfectly consistent with our earlier results: informed traders prefer to hide their orders.

6. Hidden Order Usage and Earnings Announcements

Even though our results above are consistent across a variety of informativeness measures and testing specifications, the results reflect associations and not formal causal inferences. Given that our use of ex-post measures as proxies for the information level of traders could potentially lead to endogeneity problems, we also investigate the proportion of hidden orders around an exogenous information-intensive event, specifically around earnings announcements. This analysis is work-in-progress for the full sample that we use in this paper. However, we have run the analyses on a pilot sample covering a shorter three-month consisting of the 50 stocks in the Standard & Poor's CNX Nifty index, accounting for about 60% of the market capitalization of all stocks on the NSE. We report the results on this smaller pilot sample in this version, and will add the results for the full sample in the next version of the paper.

We compare hidden order usage around earnings announcements to that during "normal" trading periods. We estimate the panel regression below with data aggregated over 30-minute intervals each day:

$$
\begin{aligned}
&HPPL_{ijt} \text{ or } HPML_{ijt} = \\
&\beta_1 Category1_i\, Normal_{jt} + \beta_2 Category1_i\, Before_{jt} + \beta_3 Category1_i\, After_{jt} + \\
&\beta_4 Category2_i\, Normal_{jt} + \beta_5 Category2_i\, Before_{jt} + \beta_6 Category2_i\, After_{jt} + \\
&\beta_7 DepthSame_{ijt} + \beta_8 DepthOpp_{ijt} + \beta_9 Volatility_{jt} + \beta_{10} PSpread_{jt} + \\
&\beta_{11} StkSpread_j + \beta_{12} Tick_j + \beta_{13} MktCap_j + \beta_{14} StkVolatility_j + \varepsilon,
\end{aligned}
\tag{7}
$$

where t refers to each 30-minute trading interval on each trading day over entire sample period, $HPPL_{ijt}$ is the proportion of the value of PLOs that are hidden by trader category i for stock j over time interval t, $HPML_{ijt}$ is the proportion of the value of MLOs that are hidden by trader category i for stock j over time interval t, $Category1_i$ is a dummy variable that takes value 1 for trader category $i = 1$ (FTs, Individuals, and NFIs) and 0, otherwise, $Category2_i$ is a dummy variable that takes value 1 for trader category $i = 2$ (FIs) and 0, otherwise, $Normal_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is not in the five days before or after the earnings announcement and 0, otherwise, $Before_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is in the five days before the earnings announcement and 0, otherwise, and $After_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is in the five days after the earnings announcement and 0, otherwise, $DepthSame_{ijt}$ is the order size placed by trader category i relative to the total depth at the five best prices on the same side as the order in stock j in time interval t, $DepthOpp_{ijt}$ is the order size placed by trader category i relative to the total depth at the five best prices on the side opposite the order in stock j in time interval t, $Volatility_{jt}$ is the one-minute quote midpoint changes for stock j over time interval t, $PSpread_{jt}$ is the average percentage quoted spread for stock j over time interval t, $StkSpread_j$ is the average quote spread, taken at one-minute intervals, over the entire sample period for stock j, $Tick_j$ is the inverse is the average traded price over the sample period for stock j, $MktCap_j$ is the market capitalization of stock j at the end of the sample period (June 30, 2006), and $StkVolatility_j$ is the standard deviation of the natural log of daily gross returns for stock j taken over the entire sample period.

We are able to identify earnings announcement dates for 40 out of the 50 sample stocks. Each of these 40 stocks has one earnings announcement date during the pilot sample period. We report coefficient estimates of equation (7), separately for SLOs and MLOs, in Table IX. For both PLOs and MLOs, estimates of β_1, β_2, β_3, β_4, β_5, and β_6 are all positive and significant, which shows that all trader clienteles hide non-zero proportions of their orders. Our test for the equality of β_1, β_2, and β_3 fails to reject the null that they are all equal to each other. Though our uninformed (or at least less informed) Category 1 traders hide non-zero proportions of their orders, the proportion of orders hidden does not change around earnings announcement. On the other hand, for both SLOs and MLOs, we reject the null that β_5 and β_6 are equal to β_4. This indicates that FIs – our informed traders – hide a larger proportion of their orders around earnings announcements than during "normal" trading periods, potentially to avoid revealing their private information. We fail to reject the null that β_5 and β_6 are equal, which implies that FIs have similar order exposure strategies just before and just after earnings announcements.

The above results provide causal support for our inference – and the BG prediction – that traders hide more of their orders when they are informed, contrary to what the existing literature appears to indicate, albeit through tangential inferences.

7. Hidden Orders, Pricing Efficiency, and Liquidity

In this section, we relate hidden order usage by different trader categories to informational efficiency of prices and to liquidity. Specifically, we examine whether hidden orders reduce the magnitudes of deviations of mid-quotes from fundamental values, and reduce the effective spreads of uninformed liquidity demanders; as posited by BG. We use pricing error measures defined as the deviation of prices from their information-efficient "random-walk" value. We also use quoted spreads, overall effective spreads, as well as the effective spreads faced by "uninformed" liquidity demanders, as measures of liquidity.

We follow Hasbrouck (1993) and Boehmer and Kelley (2009) and use a vector autoregression model to separate the variation in a pricing error from that of a stock's efficient price. The standard deviation of this pricing error is inversely related to the informational efficiency of prices. For each stock, we calculate the standard deviation of pricing error over each half hour over the sample period using trade prices.[29] Similar to Boehmer and Kelley (2009), we scale the standard deviation of pricing error over each half hour by the standard deviation of log trade price over the same half hour. We calculate the percentage quoted spread as the difference between the best ask and bid prices divided by their midpoint. For each half our in each stock, we determine the time-weighted average percentage quoted spread. We compute the cross-sectional mean and standard deviation of the percentage quoted spread during each half hour and report the descriptive statistics of the time-series of these estimates in Table X. On average, the scaled measure of pricing error (percentage quoted spread) is 27 (0.9) percent, with the pricing error (percentage quoted spread) being the largest in the least liquid quintile and the smallest in the most liquid quintile. This is consistent with Boehmer and Kelley's (2009) finding.

We relate the market quality measures, i.e., scaled pricing error and percentage quoted spread to hidden order usage in a multivariate setting. Over each half hour in our sample period, we estimate a trade value-weighted proportion of orders with a hidden component that are executed. We calculate this proportion separately for each of the four trader types in each half hour. We also calculate this proportion for each combination of trader type and limit order type in each half hour. We use controls similar to those

[29] For brevity, we do not discuss the estimation of the pricing error in detail here. See Hasbrouck (1993) and Boehmer and Kelley (2009) for detailed discussions on how to estimate the pricing error.

used in Boehmer and Kelley (2009). Specifically, we use three control variables: $StdLogPrice_j$, defined as the standard deviation of the log trade price in stock j during the half-hour, $Price_j$, defined as the trade-size weighted average trade price in stock j during the half-hour, and $\%QSpread_j$, defined as the time-weighted percentage quoted spread in stock j during the half-hour. We estimate a cross-sectional regression of the scaled standard deviation of pricing error and percentage quoted spread on measures of hidden order usage and three controls over each half hour in our sample period and report the time-series mean of these estimates, along with Newey-West corrected standard errors with five lags.

The mean estimates are in Table XI. Columns (1) and (3) use hidden order usage by each of the four trader types as explanatory variables, while Columns (2) and (4) uses hidden order usage by trader and limit order type as explanatory variables. We find that when FIs' executed orders contain a larger proportion of hidden orders, the standard deviation of pricing error is lower, irrespective of whether the FI is supplying liquidity through SLOs or demanding it through MLOs. This shows that informational efficiency of prices is higher when more of FIs' orders – i.e., more of the informed traders' orders – contain a hidden component. We find similar results for MLOs submitted by FTs and NFIs. On the other hand, the percentage quoted spread is lower when hidden orders are executed almost across all trader types.

Next, we explore the possible causal link between pricing efficiency and hidden order usage by trader type and order type in a Panel VAR framework. Specifically we include following endogenous variables in Panel VAR: the standard deviation of pricing error over half-hour intervals ($\sigma_{PE,}$), the time-weighted percentage quoted spreads over half-hour intervals ($\%QSpread$), the order value-weighted proportion of liquidity-supplying and liquidity-demanding orders with a hidden component submitted by financial institutions (denoted by $FILSHidden$ and $FILDHidden$, respectively), and the order value-weighted proportion of liquidity-supplying and liquidity-demanding orders with a hidden component submitted by all other traders (denoted by $OthersLSHidden$ and $OthersLDHidden$, respectively). The panel VAR is estimated using one lag. The results are reported in Table XII.

Specifically, we look at the equation with standard deviation of pricing error as dependent variable. The liquidity supplying and liquidity demanding orders with hidden component submitted by Financial Institutions reduces the standard deviation of pricing error in next period and that of the "Other" traders increases the standard deviation of pricing error. This means that the informational accuracy of prices increases (decreases) with hidden orders submitted by informed (uninformed) traders. Next, we look at the relevance of the standard deviation of pricing error as independent variable in other equations. This reveals that liquidity supplying informed investors use more hidden orders (positive value in FILSHidden equation) when the prices are not informationally accurate, i.e., when they are trading as informed traders to profit from the higher deviation from fundamental value. Liquidity demanding informed investors use less hidden orders (negative and significant coefficient in FILDHidden equation) when the prices are not informationally efficient. Further the positive and significant coefficients of standard deviation of pricing error in OthersLSHidden and OtherLDHidden implies that whenever the prices are informationally inefficient, the uninformed investors (Others) use more hidden orders as they hesitate to give free options. All these results are consistent with what one should expect.

Finally, we examine the BG prediction that the use of hidden orders reduces the effective spreads faced by uninformed traders. We identify uninformed traders as follows. We calculate the profitability (as defined in Table V) of each trader in each stock between January 2005 and June 2005. Then, in each stock, traders whose profitability is more than two standard deviations below the average trader profitability are identified as uninformed traders in that stock. Table XIII presents the results of regressing the effective spreads of uninformed traders on the usage of hidden SLOs and hidden MLOs by each of our four trader categories – $FILSHidden_j$, $FILDHidden_j$, $IndLSHidden_j$, $IndLDHidden_j$, $FTLSHidden_j$, $FTLDHidden_j$, $NFILSHidden_j$, and $NFILDHidden_j$ as defined in Table XI. Our $Controls$ include $LogVol_j$ and $RetVolatility_j$, both of which are also defined in Table XI. Standard errors are Newey-West adjusted with five lags. Our results in Table XIII show strong support for the BG prediction. Irrespective of trader category, and irrespective of whether SLOs or MLOs are hidden, the use of hidden orders significantly reduces the effective spreads of uninformed traders.

8. Conclusions

This paper examines on-exchange hidden liquidity in the context of trader informativeness, pricing efficiency, and trading costs. Hidden or "iceberg" orders allow traders to hide (at least) a fraction of their liquidity-supplying or liquidity-demanding limit orders, and thereby empower traders to create pre-trade opacity in an otherwise transparent environment. Informed traders are expected to be the main users and beneficiaries of hidden orders, since they can use them to reduce parasitic "front-running" of their orders and avoid leaving signaling-related footprints. There is strong regulatory interest in pre-trade opacity created by these hidden orders in view of the pricing and fairness implications for uninformed public or retail investors.

Boulatov and George (2013) theoretically model informed traders and on-exchange hidden liquidity. Their key reasoning is that informed traders want to capture the extra rents from providing liquidity, but if they have to display their liquidity-providing orders, they lose some of their informational advantage to uninformed traders, and this causes informed traders to provide liquidity relatively more actively in markets with hidden orders, increasing competition among liquidity providers, thereby improving pricing efficiency and reducing trading costs. There is also a body of evidence from an experimental laboratory setting that shows that the behavior of traders is more sensitive to the option to hide when they are informed and in information intensive periods, and that hidden orders reduce transaction costs and improve informational efficiency.

The conclusion that follows from extant theoretical models and laboratory experimental evidence is that, in a market with on-exchange hidden orders, informed traders should dominate in the usage of hidden orders. Extant empirical research has *not* directly addressed this question, but the overwhelming inference on this issue that follows tangentially from current empirical evidence is precisely the opposite – that it is the uninformed and not the informed traders who use hidden orders. Similarly, the other conclusion from the theory is that, in a market with hidden orders, pricing efficiency will increase, and transaction costs will decrease. Once again, while there is no direct empirical evidence on the impact of hidden orders on market quality, the evidence that relates generally to transparency of the limit order book shows that higher pre-trade opacity is associated with *lower* pricing efficiency, again *opposite to* what is predicted by theory. Our aim in this paper is accordingly to empirically investigate whether and how different types of traders choose to hide different types of on-exchange orders depending on their level of informativeness, and how this affects pricing efficiency and trading costs, particularly for uninformed traders. *Inter-alia*, we empirically test the predictions of Boulatov and George (2013) in this paper.

Overall, our tests provide reasonably strong support for the core implications of Boulatov and George (2013). We document a host of empirical results using a number of proxies for informativeness and a number of different specifications, but most importantly, we find that when an on-exchange option to hide orders exists, traders prefer to use hidden orders when they are informed. Further, the use of hidden orders by informed traders increases pricing efficiency, with prices more closely approximating their information-efficient values. Quoted spreads also reduce, and in particular, uninformed liquidity demanders face lower effective spreads.

Our results have significant regulatory and policy implications. There has been a proliferation of off-exchange hidden liquidity in dark pools over the last two decades, and almost a fourth of U.S. equity market trading now takes place in these dark pools. The greatest catalyst for the growth of these dark pools in recent years has been institutional investors' growing need to trade large blocks of stock without causing markets to move against them. However, Degryse et al. (2021) show that dark pools and hidden order trading are substitutes for the traders who use them. Our results show that, in spite of pre-trade opacity, the option to have on-exchange hidden orders significantly improves both pricing efficiency and liquidity, and at the same time, gives informed institutional traders the ability to execute large trades with lower parasitic front-running and leaving of footprints, providing them greater incentive to invest in the information collection and information generation that improves market quality. On the other hand, unlike with hidden orders, dark pools do not contribute directly to price formation on the main exchange since dark pool systems are totally segregated, and they clearly take liquidity away from the exchange rather than improve it, as we find hidden orders do. The level of opacity in dark pools – not just of prices but also of processes used and access restrictions – is also far greater than with on-exchange hidden orders. Not surprisingly, there have been extensive allegations and SEC investigations relating to conflicts of interest and the absence of a level playing field in some of the dark pools. Given the substitutability documented by Degryse et al. (2021), our results point to the need for a regulatory rethinking that encourages lit-exchange hidden orders, but strongly regulates the opaque dark pools in the U.S. equity trading landscape.

Appendix

Table A.I
List of companies in the sample

We start with 981 firms for which we have intraday data between January 2005 and June 2006 from the National Stock Exchange of India (NSE). We apply the following filters sequentially: 1. Exclude firms that made an initial public offering over this period (133 firms), 2. Exclude firms that were delisted from the NSE during this period (18 firms), 3. Exclude firms that were suspended from the NSE for any length of period over the 18 months (46 firms), and 4. Exclude firms that did not trade even once during 2004 (9 firms). We assign the resulting sample of 775 firms to liquidity quintiles based on total number of shares traded during 2004. We randomly select 20 firms from each quintile, resulting in a sample size of 100 firms.

Liquidity quintile 1 (least liquid)

B L B Ltd.
Eimco Elecon (India) Ltd.
Entegra Ltd.
Gujarat Fluorochemicals Ltd.
I M P Powers Ltd.
I T D Cementation India Ltd.
I V P Ltd.
Indian Card Clothing Co. Ltd.
Indian Hume Pipe Co. Ltd.
Kanoria Chemicals & Inds. Ltd.
Khaitan (India) Ltd.
M R F Ltd.
Nippo Batteries Co. Ltd.
O C L India Ltd.
Remsons Industries Ltd.
Sandesh Ltd.
T C I Finance Ltd.
Vatsa Music Ltd.
Yokogawa India Ltd.
Zodiac Clothing Co. Ltd.

Liquidity quintile 2

Automotive Stampings & Assemblies Ltd.
Bajaj Finance Ltd.
Chemplast Sanmar Ltd.
Deccan Chronicle Holdings Ltd.
Electrosteel Castings Ltd.
F A G Bearings India Ltd.
Finolex Cables Ltd.
Ingersoll-Rand (India) Ltd.
Kabra Extrusiontechnik Ltd.
Kalpataru Power Transmission Ltd.
Krishna Engineering Works Ltd.
Lumax Automotive Systems Ltd.
Oudh Sugar Mills Ltd.
R P G Transmission Ltd.
S R H H L Industries Ltd.
Sterlite Industries (India) Ltd.
T T K Prestige Ltd.
Torrent Pharmaceuticals Ltd.
United Phosphorus Ltd.
V L S Finance Ltd.

Liquidity quintile 3

Agro Dutch Inds. Ltd.
Archies Ltd.
Asian Paints Ltd.
Axis-I T & T Ltd.
B A S F India Ltd.
Bharat Forge Ltd.
Centum Electronics Ltd.
Creative Eye Ltd.

Liquidity quintile 4

Ajanta Pharma Ltd.
Aksh Optifibre Ltd.
Alps Industries Ltd.
Apollo Hospitals Enterprise Ltd.
Axis Bank Ltd.
Aztecsoft Ltd.
Crest Animation Studios Ltd.
Cummins India Ltd.

Dhanlaxmi Bank Ltd.
First Leasing Co. Of India Ltd.
Igate Global Solutions Ltd.
J B F Industries Ltd.
Kajaria Ceramics Ltd.
Mphasis Ltd.
Parekh Platinum Ltd.
Patspin India Ltd.
Prakash Industries Ltd.
Pritish Nandy Communications Ltd.
Regency Ceramics Ltd.
Williamson Tea Assam Ltd.
Elder Pharmaceuticals Ltd.
Garden Silk Mills Ltd.
H E G Ltd.
Hexaware Technologies Ltd.
Indo Rama Synthetics (India) Ltd.
Indraprastha Medical Corpn. Ltd.
Jain Irrigation Systems Ltd.
Kohinoor Foods Ltd.
Nahar Poly Films Ltd.
Pan India Corpn. Ltd.
Shyam Telecom Ltd.
Su-Raj Diamonds & Jewellery Ltd.

Liquidity quintile 5 (most liquid)

Alok Industries Ltd.
Canara Bank
Cipla Ltd.
G A I L (India) Ltd.
Grasim Industries Ltd.
Gujarat Sidhee Cement Ltd.
Hindustan Unilever Ltd.
I F C I Ltd.
Indraprastha Gas Ltd.
Lloyds Steel Inds. Ltd.
N T P C Ltd.
Patni Computer Systems Ltd.
Punjab National Bank
Reliance Infrastructure Ltd.
Sesa Goa Ltd.
Steel Authority Of India Ltd.
Sterlite Technologies Ltd.
Tata Consultancy Services Ltd.
Tata Motors Ltd.
Tourism Finance Corpn. Of India Ltd.

Table A.II
Definition of control variables used in the regressions in Tables V, VII, and IX

Variable	Definition
$TotalOrderSize_{ijt}$	The total size of the order, in shares, submitted by trader *i* at time *t* in stock *j* scaled by the daily average traded volume in stock *j*
$PriceAggressive_{ijt}$	The difference between the limit price (best bid price at the time of order submission) and the best ask price at the time of order submission (limit price) for buy (sell) orders scaled by the quote midpoint at the time of order submission for the order submitted by trader *i* at time *t* in stock *j*
$\%QSpread_{j,t}$	The difference between the best ask and bid prices divided by the quote midpoint at the time *t* of order submission in stock *j*
$SameDepth_{j,t}$	The displayed depth, in shares, at the five best prices on the same side as the order being submitted at time *t* in stock *j* scaled by the median displayed depth at the five best bid (ask) prices for buy (sell) orders in stock *j* over the entire sample period
$OppositeDepth_{j,t}$	The displayed depth, in shares, at the five best prices on the side opposite to that of the order being submitted at time *t* in stock *j* scaled by the median displayed depth at the five best bid (ask) prices for sell (buy) orders in stock *j* over the entire sample period
$OrderImbalance_{j,t}$	The difference between $SameDepth_{jt}$ and $OppositeDepth_{jt}$ divided by their sum
$LastTradeSize_{j,t}$	The size, in shares, of the last trade executed prior to the order submission at time *t* in stock *j* scaled by the daily average traded volume in stock *j*
$TradeSize_{ijt}$	The size, in shares, of the trade executed at time *t* in stock *j* scaled by the daily average traded volume of stock *j*
$TradedVolume_{j,t}$	The volume traded, in shares, over the one hour prior to the trade execution at time *t* in stock *j* scaled by the daily average traded volume of stock *j*
$RelTick_{j,t}$	The inverse of the quote midpoint at order submission (for information level) or trade execution (for adverse selection half-spread) time *t* in stock *j*
$Volatility_{j,t}$	The standard deviation of minute-by-minute quote midpoint returns for stock *j* from the hour prior to order submission or trade execution
$MarketVolatility_{j,t}$	The standard deviation of minute-by-minute quote midpoint returns for the Exchange Traded Fund (ETF) on the S&P CNX Nifty Index (called Nifty Bees) from the hour prior to order submission or trade execution
$Ln(MarketCap_j)$	The natural logarithm of the end-of-sample period market capitalization in millions of U.S. dollars, converted to U.S. dollars at the June 30, 2006 exchange rate of ₹ 46.01 per U.S. dollar

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Table I
Sample descriptive statistics

This table presents descriptive statistics on stock (Panel A) and order (Panel B) characteristics for a random sample of 100 firms (as explained in Table A.I), which trade on the National Stock Exchange of India, between January 2005 and June 2006. Market capitalization is measured on the last day of the sample period and converted to U.S. dollars at the end-of-sample-period exchange rate of ₹ 46.01 per U.S. dollar. Daily traded value per stock is the trade size times the trade price aggregated over each trading day for each stock. It is converted to U.S. dollars at the end-of-sample-period exchange rate of ₹ 46.01 per U.S. dollar. Percentage of traded value with hidden component is the percentage of traded value that includes an order with a hidden component on at least one side of the trade. Percentage quoted spread is the difference between the best ask and bid prices divided by their midpoint. Standing limit orders are liquidity-supplying orders with a limit price attached. Marketable limit orders are liquidity-demanding orders with a limit price attached.

Panel A. Stock characteristics

	Market capitalization (millions of dollars)		Number of order submissions per stock		Percentage of orders with a hidden component		Traded value per stock (millions of dollars)		Percentage of traded value with a hidden component	
Liquidity quintile	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1 (Least)	1,811.98	26.98	97,577	57,132	13.30%	12.37%	22.66	6.95	44.86%	44.38%
2	400.98	112.65	573,484	302,936	9.88%	8.84%	204.41	46.34	50.52%	48.53%
3	200.59	32.26	529,129	264,805	8.90%	8.05%	147.39	46.07	46.59%	40.24%
4	224.10	59.13	1,026,447	953,508	8.29%	8.10%	234.91	159.68	47.44%	51.87%
5 (Most)	4,224.38	1,940.83	4,991,006	5,084,841	8.69%	8.73%	2,610.65	2,374.85	49.18%	49.99%
All	1,372.41	61.69	1,443,529	413,537	9.81%	8.85%	650.28	82.47	47.75%	48.30%

Table I (continued)

Liquidity quintile	Number of trades per stock		Percentage of trades with a hidden component		Percentage quoted spread	
	Mean	Median	Mean	Median	Mean	Median
1 (Least)	52,152	29,625	35.53%	35.89%	2.38%	2.12%
2	363,615	174,807	37.03%	35.23%	0.95%	0.67%
3	333,150	139,228	36.08%	33.62%	0.87%	0.69%
4	667,053	619,569	37.08%	38.36%	0.57%	0.33%
5 (Most)	3,478,254	3,361,047	41.03%	41.24%	0.18%	0.09%
All	988,205	249,700	37.37%	36.91%	0.99%	0.54%

Panel B. Order characteristics

Liquidity quintile	Standing limit orders				Marketable limit orders			
	Number of orders	%Hidden	Total order value (millions of dollars)	%Hidden	Number of orders	%Hidden	Total order value (millions of dollars)	%Hidden
1 (Least)	1,308,868	14.19%	1,000.93	38.70%	560,285	6.84%	663.33	32.59%
2	7,272,493	10.22%	9,718.87	30.17%	3,535,939	5.05%	6,344.00	27.18%
3	6,901,168	11.76%	7,173.00	39.27%	3,127,917	6.24%	4,605.15	35.63%
4	13,113,864	10.40%	9,701.77	31.25%	6,282,645	5.19%	7,056.66	31.98%
5 (Most)	61,107,283	10.86%	115,647.46	29.29%	31,604,881	4.25%	78,187.14	32.29%
All	89,703,676	10.86%	143,242.03	30.05%	45,111,667	4.62%	96,856.27	32.10%

Table II
Trader categories

This table presents descriptive statistics of the different trader categories for a random sample of 100 firms (as explained in Table A.I), which trade on the National Stock Exchange of India (NSE), between January 2005 and June 2006. We use the NSE-provided trader categories to assign traders to four broader trader categories: Financial Institutions, Individual, Financial Traders, and Non-Financial Institutions. We identify a trader as a Financial Trader if the broker trades on his own account. Mutual Funds, Other Domestic Financial Institutions, Banks, Insurance, and Foreign Institutional Investors are identified as Financial Institutions. Individuals, Hindu Undivided Family, and Non-Resident Indians are categorized as Individuals. All other traders are classified as Non-Financial Institutions. Panel A provides the distribution of the number of traders and value traded for the 14 different NSE-provided trader categories across the four broader trader categories. Order characteristics by the four trader categories and type of limit orders are in Panel B. Standing limit orders are liquidity-supplying orders with a limit price attached. Marketable limit orders are liquidity-demanding orders with a limit price attached. In panels A and B, rupees are converted to U.S. dollars at the end-of-sample-period exchange rate of ₹ 46.01 per U.S. dollar. The distribution of trader end-of-day net holdings is in Panel C. The end-of-day net holdings for each trader (identified uniquely by a combination of trading member and client member codes) in each stock is the absolute difference between the number of shares bought on that day less the number of shares sold on the same day divided by their sum. The minimum, maximum, median, mean and different percentiles are presented.

Panel A. Number of traders and value traded by trader categories

	Financial Institutions		Individuals		Financial Traders		Non-Financial Institutions	
	N	Value traded (millions $)	N	Value traded (millions $)	N	Value traded (millions $)	N	Value traded (millions $)
Individuals	-	-	1,585,003	51,867.51	39	5,740.34	-	-
Partnership Firms	-	-	-	-	15	388.09	1,350	910.66
Hindu Undivided Family	-	-	17,926	1,235.23	-	-	-	-
Public & Private Companies	-	-	-	-	282	22,186.24	10,223	7,655.21
Trust / Society	-	-	-	-	-	-	323	49.23
Mutual Fund	4,481	7,369.38	-	-	-	-	-	-
Other Domestic Financial Institutions	184	250.64	-	-	-	-	-	-
Bank	1,216	1,342.62	-	-	-	-	-	-
Insurance	659	1,214.43	-	-	-	-	-	-
Statutory Bodies	-	-	-	-	5	32.10	61	199.96
Non-Resident Indians	-	-	8,066	126.82	-	-	-	-
Foreign Institutional Investors	1,784	23,586.15	-	-	-	-	-	-

Table II (continued)

	Financial Institutions		Individuals		Financial Traders		Non-Financial Institutions	
	N	Value traded (millions $)	N	Value traded (millions $)	N	Value traded (millions $)	N	Value traded (millions $)
Overseas Corporate Bodies	-	-	-	-	77	3,948.93	5,859	3,626.03
Missing	-	-	-	-	165	4,458.04	320,205	3,075.28
All	8,324	33,763	1,610,995	53,230	583	36,754	338,021	15,516

Panel B. Order characteristics by trader categories

	Standing limit orders				Marketable limit orders			
Trader category	Number of orders	%Hidden	Total order value (MM $)	%Hidden	Number of orders	%Hidden	Total order value (MM $)	%Hidden
Financial Institutions	445,679	62.78%	11,501.28	78.26%	848,981	60.72%	26,490.07	75.47%
Individuals	52,041,682	5.45%	44,828.00	19.12%	27,359,595	2.73%	30,830.86	15.44%
Financial Traders	26,899,132	20.39%	71,424.92	29.53%	11,724,110	4.78%	28,864.62	11.52%
Non- Financial Institutions	10,317,183	11.04%	15,487.82	28.25%	5,178,981	4.98%	10,670.72	28.22%

Panel C. Distribution of trader end-of-day net holdings

	Min	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	Mean
Financial Institutions	0.00	1.00	1.00	1.00	1.00	1.00	0.99
Individuals	0.00	0.00	0.00	1.00	1.00	1.00	0.66
Financial Traders	0.00	0.00	0.00	0.21	0.75	1.00	0.37
Non-Financial Institutions	0.00	0.00	0.40	1.00	1.00	1.00	0.72

Table III
Information level of orders

Descriptive statistics of information level (in basis points) of orders submitted for a random sample of 100 stocks (as explained in Table A.I) on the National Stock Exchange of India between January 2005 and June 2006 are presented in this table. The statistics are present by liquidity quintile (Panel A), trader categories (Panel B), and type of limit order (Panel C). We exclude orders that are cancelled within two-and-a-half minutes of submission. Information level is the natural logarithm of the ratio of the quote midpoint at time *t* after order submission to the quote midpoint one minute before order submission multiplied by +1 (-1) for buy (sell) orders. Time *t* takes values 60 minutes, same time one trading day, and same time five trading days after order submission. Non-hidden refers to orders that are fully displayed (no hidden component) at order submission. Hidden refers to orders that have some hidden component at the time of order submission. Trader categories are defined in the header to Table II. Standing limit orders are liquidity-supplying orders with a limit price attached. Marketable limit orders are liquidity-demanding orders with a limit price attached. t-stat tests the equality of information level of non-hidden and hidden orders.

Panel A. By liquidity quintile

	-1min to +60min			-1min to +1day			-1min to +5days		
Liquidity quintile	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat
1 (Least)	8.70	17.32	-18.99***	9.36	22.25	-13.59***	16.54	33.37	-8.92***
2	1.96	8.49	-26.53***	-2.02	9.36	-20.18***	-13.29	7.51	-17.66***
3	3.99	6.82	-15.20***	2.90	7.57	-11.01***	8.58	18.27	-11.66***
4	2.58	5.47	-20.05***	2.22	7.98	-18.94***	3.30	14.46	-18.37***
5 (Most)	-0.21	2.57	-48.11***	-2.96	3.74	-50.62***	-4.01	3.42	-29.36***

Panel B. By trader category

	-1min to +60min			-1min to +1day			-1min to +5days		
Trader category	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat
Financial Institutions	5.52	14.77	-35.29***	8.68	25.37	-29.72***	14.86	34.69	-17.36***
Individuals	0.87	5.17	-44.83***	-2.44	5.44	-37.31***	-3.80	7.70	-27.45***
Financial Traders	0.03	1.63	-21.79***	-0.12	2.53	-15.89***	0.23	2.71	-8.15***
Non-Financial Institutions	2.12	4.56	-15.77***	0.20	4.67	-13.37***	-1.14	6.50	-11.74***

Panel C. By type of limit order

	-1min to +60min			-1min to +1day			-1min to +5days		
Limit order	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat
Standing	1.20	2.66	-25.08***	-0.44	3.77	-31.42***	-0.76	5.09	-22.41***
Marketable	0.20	10.34	-88.91***	-3.24	12.79	-64.06***	-5.04	16.90	-44.25***

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table IV
Impact of information level on hidden order usage

This table presents coefficient estimates of the following OLS regression using a sample of 100 National Stock Exchange-listed stocks (as explained in Table A.I) between January 2005 and June 2006:

$$HiddenOrder_{ijt} = \beta_0 + \beta_1 InfoLevel_{ijt} + \beta_2 FI_i + \beta_3 Individual_i + \beta_4 FT_i + \beta_5 InfoLevel_{ijt} \times FI_i + \beta_6 InfoLevel_{ijt} \times Individual_i + \beta_7 InfoLevel_{ijt} \times FT_i + \beta_8 Buy_{ijt} + \beta_9 InfoLevel_{ijt} \times Buy_{ijt} + Controls + \varepsilon_{ijt},$$

where $HiddenOrder_{ijt}$ takes a value of 1 if the order submitted by trader *i* at time t in stock *j* has a hidden component and 0 otherwise, $InfoLevel_{ijt}$ is the natural logarithm of the ratio of the quote midpoint time t_l after order submission to the quote midpoint one minute before order submission at time t by trader *i* in stock *j* multiplied by +1 (-1) for buy (sell) orders, FI_i takes a value of 1 if trader *i* is financial institution and 0 otherwise, $Individual_i$ takes a value of 1 if trader *i* is an individual trader and 0 otherwise, FT_i takes a value of 1 is trader *i* is a financial trader, and Buy_{ijt} takes a value of 1 if order submitted by trader *i* in stock j at time t is a buy order and 0 otherwise. $Controls$ include $TotalOrderSize_{ijt}$, $PriceAggressive_{ijt}$, $\%QSpread_{j,t}$, $SameDepth_{j,t}$, $OppositeDepth_{j,t}$, $OrderImbalance_{j,t}$, $LastTradeSize_{j,t}$, $RelTick_{j,t}$, $Volatility_{j,t}$, $MarketVolatility_{j,t}$, and $Ln(MarketCap_j)$,, all of which are defined in Table A.II. Trader categories are defined in the header to Table II. We exclude orders that are cancelled within two-and-a-half minutes of submission. In models (1) and (4), t_l is 60 minutes after order submission. In models (2) and (5), t_l is the same time one trading day after order submission. In models (3) and (6), t_l is the same time five trading days after order submission. Standing limit orders are liquidity-supplying orders with a limit price attached. Marketable limit orders are liquidity-demanding orders with a limit price attached. All continuous variables are standardized. The t-statistic of the coefficient estimates is presented in parentheses below each estimate. The first number within parentheses uses standard errors clustered by trader and the second uses standard errors clustered by stock and date. Tests present the value of the sum of the respective coefficients and the t-statistic are within parentheses with the first number using standard errors clustered by trader ID and the second using standard errors clustered by stock and date.

	OLS: Dependent variable = Hidden order					
	Standing limit orders			Marketable limit orders		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1028	0.1029	0.1031	0.0508	0.0487	0.0487
	(7.78)***	(7.97)***	(7.97)***	(15.41)***	(14.26)***	(14.24)***
	(14.17)***	(14.34)***	(14.26)***	(24.69)***	(24.29)***	(24.00)***
$InfoLevel$	0.0010	0.0002	-0.0008	0.0023	0.0009	-0.0001
	(1.56)	(0.32)	(-0.94)	(5.51)***	(3.14)***	(-0.33)
	(1.60)	(0.32)	(-0.95)	(5.51)***	(3.62)***	(-0.33)
FI	0.5393	0.5384	0.5372	0.5608	0.5519	0.5523
	(13.59)***	(14.66)***	(14.57)***	(32.43)***	(31.68)***	(31.59)***
	(20.90)***	(21.69)***	(21.66)***	(46.44)***	(45.64)***	(45.68)***
$Individual$	-0.0556	-0.0559	-0.0559	-0.0221	-0.0215	-0.0214
	(-4.05)***	(-4.16)***	(-4.16)***	(-6.57)***	(-6.13)***	(-6.10)***
	(-6.89)***	(-6.99)***	(-6.96)***	(-14.21)***	(-13.81)***	(-13.65)***

Table IV (continued)

	OLS: Dependent variable = Hidden order					
	Standing limit orders			Marketable limit orders		
	(1)	(2)	(3)	(4)	(5)	(6)
FT	0.0971	0.0960	0.0959	0.0001	0.0010	0.0010
	(3.66)***	(3.70)***	(3.69)***	(0.02)	(0.18)	(0.18)
	(5.26)***	(5.16)***	(5.15)***	(0.04)	(0.31)	(0.30)
$InfoLevel$ ×	0.0146	0.0193	0.0204	0.0190	0.0117	0.0017
FI	(3.92)***	(3.86)***	(3.19)***	(3.76)***	(3.64)***	(0.41)
	(2.37)**	(3.55)***	(2.64)***	(1.53)	(1.45)	(0.22)
$InfoLevel$ ×	0.0001	0.0000	-0.0002	-0.0006	-0.0004	-0.0002
$Individual$	(0.24)	(0.13)	(-0.62)	(-1.53)	(-1.39)	(-0.56)
	(0.30)	(0.16)	(-0.54)	(-2.32)**	(-1.64)	(-0.54)
$InfoLevel$ × FT	0.0015	0.0006	-0.0004	-0.0022	-0.0010	-0.0005
	(1.99)**	(1.27)	(-0.87)	(-4.39)***	(-3.22)***	(-1.68)*
	(3.78)***	(1.68)*	(-0.85)	(-4.54)***	(-3.33)***	(-1.74)*
Buy	0.0083	0.0084	0.0084	-0.0022	-0.0007	-0.0007
	(4.94)***	(5.43)***	(5.45)***	(-2.99)***	(-1.06)	(-0.95)
	(10.29)***	(11.79)***	(11.76)***	(-2.42)**	(-0.91)	(-0.81)
$InfoLevel$ ×	-0.0016	0.0006	0.0030	-0.0002	0.0007	0.0018
Buy	(-2.30)**	(0.68)	(1.98)**	(-0.91)	(2.96)***	(5.98)***
	(-2.84)***	(0.82)	(2.16)**	(-1.21)	(2.06)**	(4.35)***
R^2	6.88%	6.83%	6.81%	15.00%	14.68%	14.71%
N	62,486,617	74,223,431	73,076,930	33,975,337	43,102,949	42,431,257
Tests:						
Informed FI	0.0156	0.0195	0.0196	0.0213	0.0126	0.0016
Seller:	(4.22)***	(3.89)***	(3.05)***	(4.21)***	(3.94)***	(0.39)
$\beta_1 + \beta_5 = 0$	(2.55)**	(3.62)***	(2.54)**	(1.68)*	(1.56)	(0.21)
Informed Individual	0.0012	0.0002	-0.001	0.0017	0.0005	-0.0003
Seller:	(3.23)***	(0.58)	(-1.45)	(12.23)***	(4.31)***	(-1.59)
$\beta_1 + \beta_6 = 0$	(3.87)***	(0.63)	(-1.74)*	(6.27)***	(3.30)***	(-1.30)
Informed FT Seller:	0.0026	0.0008	-0.0012	0.0001	-0.0001	-0.0006
$\beta_1 + \beta_7 = 0$	(4.25)***	(1.57)	(-1.46)	(0.33)	(-0.66)	(-2.66)***
	(4.16)***	(1.61)	(-1.48)	(0.39)	(-0.50)	(-2.18)**
Informed NFI	-0.0005	0.0007	0.0022	0.0021	0.0016	0.0017
Buyer: $\beta_1 + \beta_9 = 0$	(-0.85)	(1.34)	(2.66)***	(5.08)***	(5.34)***	(5.34)***
	(-1.10)	(1.91)*	(2.75)***	(4.84)***	(4.72)***	(4.18)***

Table IV (continued)

	OLS: Dependent variable = Hidden order					
	Standing limit orders			Marketable limit orders		
	(1)	(2)	(3)	(4)	(5)	(6)
Informed FI	0.0141	0.0201	0.0226	0.0211	0.0132	0.0034
Buyer:	(3.80)***	(4.01)***	(3.53)***	(4.20)***	(4.13)***	(0.84)
$\beta_1 + \beta_5 + \beta_9 = 0$	(2.23)**	(3.57)***	(2.83)***	(1.67)*	(1.64)	(0.44)
Informed Individual	-0.0004	0.0008	0.002	0.0015	0.0012	0.0016
Buyer:	(-1.08)	(1.76)*	(2.39)**	(10.60)***	(9.80)***	(9.63)***
$\beta_1 + \beta_6 + \beta_9 = 0$	(-1.22)	(2.12)**	(2.37)**	(5.82)***	(4.91)***	(5.35)***
Informed FT	0.001	0.0014	0.0018	-0.0001	0.0005	0.0012
Buyer:	(1.54)	(2.61)***	(2.22)**	(-0.32)	(2.39)**	(5.71)***
$\beta_1 + \beta_7 + \beta_9 = 0$	(2.28)**	(2.94)***	(2.77)***	(-0.42)	(2.24)**	(4.70)***

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table V
Profitability and hidden order usage

Hidden order usage by different trader categories across profitability terciles for a sample of 100 stocks (as explained in Table A.I), which trade on the National Stock Exchange of India, between January 2005 and June 2006 are in this table. Trader categories are defined in the header to Table II. Each trader's profitability in each stock is calculated as follows. The trader's total trading profit is calculated as total inflows from sales in the stock over the sample period less the total outflows for purchases in the stock over the sample period. The trader's end-of-period position is valued as follows. Both net long and short positions in the stock at the end of the sample period are valued at the last available quote midpoint over the sample period, which is added to (for long positions) or subtracted from (for short positions) the trader's total trading profit, giving us the trader's profit in the stock over the sample period. The trader's profitability in a stock is calculated as the ratio of the trader's profit to the sum of the unsigned value traded by the trader in the stock over the sample period and the unsigned value of end-of-period position. Tercile breakpoints are determined separately for the different trader categories. Traders are assigned to terciles based on the profitability measure. %Hidden is the order-size weighted proportion of orders with a hidden component that a trader submits in a stock during the sample period. The table presents the weighted-average of all variables across trader-stock combinations using total unsigned value traded by each trader in each stock over the sample period as the weight for each trader-stock combination. The t-statistic tests the significance of the difference of %Hidden between the Most and the Least profitable terciles.

	Financial Institutions		Individuals		Financial Traders		Non-Financial Institutions	
Profitability Tercile	Profitability	%Hidden	Profitability	%Hidden	Profitability	%Hidden	Profitability	%Hidden
1 (Least)	-15.33%	76.28%	-5.43%	19.33%	-0.91%	19.79%	-7.95%	45.70%
2	-0.09%	74.10%	0.03%	14.30%	0.01%	22.15%	0.07%	23.19%
3 (Most)	14.33%	80.90%	5.94%	22.42%	1.02%	23.22%	9.03%	45.72%
All	0.35%	76.84%	-0.04%	16.18%	-0.04%	21.89%	-0.01%	30.91%
Most minus Least		4.61%***		3.09%***		3.43%***		0.02%
t-stat		(14.41)		(94.22)		(8.84)		(0.17)
N	36,409		5,915,325		14,920		927,408	

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table VI
Regression of hidden order usage on profitability

This table presents the estimates the relationship between hidden order usage and profitability in a multivariate setting using a sample of 100 National Stock Exchange listed-stocks (as explained Table A.I) between January 2005 and June 2006.

The table presents the coefficient estimates of following cross-sectional OLS model:

$$\begin{aligned} PropHidden_{ij} = \beta_0 &+ \beta_1 LowProfit_{ij} + \beta_2 MediumProfit_{ij} + \beta_3 HighProfit_{ij} + \beta_4 FI_i \\ &+ \beta_5 Individual_i + \beta_6 FT_i + \beta_7 LowProfit_{ij} \times FI_i + \beta_8 MediumProfit_{ij} \times FI_i \\ &+ \beta_9 HighProfit_{ij} \times FI_i + \beta_{10} LowProfit_{ij} \times Individual_i \\ &+ \beta_{11} MediumProfit_{ij} \times Individual_i + \beta_{12} HighProfit_{ij} \times Individual_i \\ &+ \beta_{13} LowProfit_{ij} \times FT_i + \beta_{14} MediumProfit_{ij} \times FT_i + \beta_{15} HighProfit_{ij} \times FT_i \\ &+ \beta_{16} Ln\big(OrderSize_{ij}\big) + \beta_{17} Ln\big(MarketCap_j\big) + \varepsilon_{ij} \end{aligned}$$

where $PropHidden_{ij}$ is the order size-weighted proportion of hidden orders submitted by trader i in stock j, $Profit_{ij}$ is trader i's profitability in stock j (as defined in the header to Table VI), FI_i takes a value of 1 if trader *i* is a financial institution and 0 otherwise, $Individual_i$ takes a value of 1 if trader *i* is an individual trader and 0 otherwise, FT_i takes a value of 1 is trader *i* is a financial trader, $LowProfit_{ij}$, $MediumProfit_{ij}$, and $HighProfit_{ij}$ is equal to $Profit_{ij}$ if $Profit_{ij}$ is in the first, second, or third tercile, respectively, and zero otherwise, $OrderSize_{ij}$ is the average order size submitted by trader *i* in stock *j* over the sample period, and $Ln(MarketCap_j)$ is defined in Table A.II. All continuous variables are standardized. Trader categories are defined in the header to Table II. The t-statistic of the coefficient estimates is presented within parentheses below each estimate. Standard errors are two-way clustered by trader ID and stock. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: Order size-weighted proportion of hidden orders
Intercept	0.0383***
	(6.47)
$Profit$	
$LowProfit$	-0.0030*
	(-1.78)
$MediumProfit$	0.0180
	(0.81)
$HighProfit$	-0.0002
	(-0.07)
FI	0.5871***
	(50.81)
$Individual$	-0.0056**
	(-2.39)

FT	0.1297***
	(15.93)
$LowProfit \times FI$	-0.0178***
	(-3.42)
$MediumProfit \times FI$	0.0787
	(1.35)
$HighProfit \times FI$	0.0171***
	(4.33)
$LowProfit \times$	-0.0023***
$Individual$	(-3.09)
$MediumProfit \times$	0.0036
$Individual$	(0.29)
$HighProfit \times$	0.0024**
$Individual$	(2.00)
$LowProfit \times FT$	-0.0107
	(-1.19)
$MediumProfit \times FT$	0.1780***
	(2.80)
$HighProfit \times FT$	0.0177*
	(1.73)
$Ln(OrderSize)$	0.0379***
	(7.11)
$Ln(MarketCap)$	-0.0007
	(-0.14)
R^2	13.86%
Tests:	
FI LowProfit:	-0.0208***
$\beta_1 + \beta_7 = 0$	(-4.17)
FI HighProfit:	0.0169***
$\beta_3 + \beta_9 = 0$	(3.36)
Individual LowProfit:	-0.0053***
$\beta_1 + \beta_{10} = 0$	(-3.84)
Individual HighProfit:	0.0021
$\beta_3 + \beta_{12} = 0$	(0.86)
FT LowProfit:	-0.0138
$\beta_1 + \beta_{13} = 0$	(-1.53)
FT HighProfit:	0.0175
$\beta_3 + \beta_{15} = 0$	(1.57)

Table VII
Hidden orders and alternate measures of trader information

This table presents descriptive statistics on hidden and non-hidden orders for various alternate measures of trader information for a sample of 100 National Stock Exchange-listed stocks (as explained in Table A.I) between January 2005 and June 2006. Panels A and B use the relative information level of orders, and contribution to cumulative price change, respectively, as measures of information. The relative information level of orders is the ratio of the conditional probability of an increase (decrease) in the quote midpoint (relative to its level one minute before order submission) one hour, one day, or five days after the submission of a buy (sell) order with a hidden component to the corresponding conditional probability of an increase (decrease) after the submission of a fully-displayed buy (sell) order. We exclude orders that are cancelled within two-and-a-half minutes of submission. The probability of the sample event under the null against the alternative of fully-displayed orders being more informative is presented in braces. In parentheses, from left to right, are the conditional probability of the quote midpoint increasing (decreasing) given the submission of a hidden buy (sell) and the conditional probability of the quote midpoint increasing (decreasing) given the submission of a fully-displayed buy (sell). See Kaniel and Liu (2006) for more details on how the probability of the sample event under the null is calculated. Price change is the difference between the trade price and the previous trade price multiplied by +1 (-1) for liquidity demanding (supplying) orders. We aggregate the price change for each stock within each trader category and order opacity level. This is done separately for liquidity supplying (Panel B1) and demanding orders (Panel B2). We then calculate a weighted-average across stocks for each trader type and order opacity level with the absolute value of the cumulative stock price change over the sample period as weight. %Trades (%Shares) is the total number of trades (total number of shares traded) in each cell divided by the total number of trades (total number of shares traded) in the entire sample. In Panel B2, the statistics are reported separately for market orders (no price restriction).

Panel A. Relative information level of orders

	Standing limit orders			Marketable limit orders		
Trader category	-1min to +60min	-1min to +1day	-1min to +5days	-1min to +60min	-1min to +1day	-1min to +5days
Financial	1.06	1.07	1.06	1.15	1.07	1.04
Institutions	{>.99}	{>.99}	{>.99}	{>.99}	{>.99}	{>.99}
	(0.53; 0.50)	(0.53; 0.49)	(0.53; 0.50)	(0.58; 0.51)	(0.55; 0.51)	(0.53; 0.51)
Individuals	1.01	1.01	1.01	1.09	1.05	1.03
	{>.99}	{0.76}	{>.99}	{>.99}	{>.99}	{>.99}
	(0.51; 0.50)	(0.51; 0.50)	(0.51; 0.50)	(0.54; 0.49)	(0.52; 0.49)	(0.51; 0.49)
Financial	1.00	1.00	1.00	1.01	1.01	1.01
Traders	{>.99}	{>.99}	{0.88}	{0.11}	{<.01}	{<.01}
	(0.50; 0.50)	(0.50; 0.50)	(0.50; 0.50)	(0.50; 0.49)	(0.50; 0.50)	(0.50; 0.50)
Non-Financial	1.00	1.00	1.01	1.08	1.04	1.03
Institutions	{0.12}	{>.99}	{>.99}	{>.99}	{>.99}	{>.99}
	(0.50; 0.50)	(0.50; 0.50)	(0.50; 0.51)	(0.50; 0.54)	(0.50; 0.52)	(0.50; 0.51)

Table VII (continued)

Panel B. Contribution to cumulative price change

Trader category	Order	Price change	Number of trades ('000s)	%Trades	Number of shares (millions)	%Shares
		Panel B1. Liquidity-supplying orders				
Financial Institutions	Non-hidden	-8.77%	1,010	0.89%	688	3.35%
	Hidden	145.46%	7,147	6.31%	2,627	12.78%
Individuals	Non-hidden	-10.56%	45,453	40.16%	7,143	34.74%
	Hidden	-120.29%	8,623	7.62%	1,418	6.90%
Financial Traders	Non-hidden	-119.22%	24,385	21.54%	5,276	25.66%
	Hidden	93.13%	13,594	12.01%	778	3.79%
Non-Financial Institutions	Non-hidden	-55.55%	8,910	7.87%	1,962	9.54%
	Hidden	-22.79%	4,063	3.59%	668	3.25%
All	Non-hidden	-193.87%	79,759	70.47%	15,068	73.29%
	Hidden	93.87%	33,428	29.53%	5,491	26.71%
		Panel B2. Liquidity-demanding orders				
Financial Institutions	Market	-45.87%	1,107	0.98%	198	0.96%
	Non-hidden	9.19%	2,356	2.08%	1,036	5.04%
	Hidden	102.43%	6,537	5.78%	1,759	8.55%
Individuals	Market	369.39%	10,097	8.92%	1,468	7.14%
	Non-hidden	189.31%	47,417	41.89%	7,504	36.50%
	Hidden	-44.42%	3,454	3.05%	835	4.06%
Financial Traders	Market	-93.27%	3,866	3.42%	97	0.47%
	Non-hidden	-307.74%	23,862	21.08%	4,760	23.15%
	Hidden	-10.63%	1,634	1.44%	281	1.37%

Trader category	Order	Price change	Number of trades ('000s)	%Trades	Number of shares (millions)	%Shares
Non-Financial Institutions	Market	-36.87%	1,586	1.40%	150	0.73%
	Non-hidden	-24.61%	9,754	8.62%	2,069	10.06%
	Hidden	-7.49%	1,516	1.34%	402	1.95%
All	Market	195.16%	16,656	14.72%	1,913	9.31%
	Non-hidden	-133.90%	83,390	73.68%	15,369	74.75%
	Hidden	38.73%	13,140	11.61%	3,277	15.94%

Table VIII
Alternate trader categorization, information level, and hidden orders

This table compares the information level of hidden orders to that of non-hidden (fully displayed) orders for a random sample of 100 National Stock Exchange-listed (as explained in Table A.I) from July 2005 through June 2006 using an alternate categorization of traders. We use data from January 2005 through June 2005 to categorize traders. Fundamental traders are those whose end-of-day position is at least 15 percent of the unsigned total volume on the stock-day on at least 90 percent of stock-days. Day traders are those whose end-of-day position is no more than 5 percent of the unsigned total volume on the stock-day on at least 90 percent of stock-days. All traders not in the above two categories are categorized as Others. Information level is as defined in the header to Table IV. Panel A presents results by trader type and Panel B by trader and order types. LS (LD) refers to liquidity-supplying (liquidity-demanding) orders. t-stat tests the equality of information level of non-hidden and hidden orders.

Panel A. By trader type

	-1min to +60min			-1min to +1day			-1min to +5days		
Trader category	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat
Fundamental Traders	1.64	12.34	-60.88***	-2.94	18.34	-53.39***	-12.40	20.95	-41.66***
Day Traders	1.29	1.98	-3.34***	0.78	2.68	-4.09***	3.01	3.34	-0.37
Others	0.63	2.51	-21.66***	-1.86	2.83	-23.91***	-3.54	3.59	-18.44***

Panel B. By trader and limit order types

		-1min to +60min			-1min to +1day			-1min to +5days		
Trader category	Order type	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat	Non-hidden	Hidden	t-stat
Fundamental Traders	LS	1.66	6.05	-18.00***	-2.96	10.19	-22.91***	-16.14	11.90	-24.42***
	LD	1.62	19.33	-68.82***	-2.90	26.84	-53.07***	-5.34	30.32	-31.56***
Day Traders	LS	0.90	1.95	-4.66***	0.01	2.77	-5.38***	2.81	3.13	-0.32
	LD	1.93	2.16	-0.41	1.96	2.17	-0.17	3.32	4.58	-0.54
Others	LS	0.98	2.31	-14.05***	-0.97	2.77	-17.36***	-2.57	3.39	-14.05***
	LD	0.03	3.74	-16.20***	-3.30	3.18	-12.71***	-5.09	4.85	-9.84***

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table IX

Hidden Order Usage around Earnings Announcements

Results are based on 40 of the 50 stocks of the Standard & Poor's CNX Nifty index that trade on the National Stock Exchange of India (NSE) over the period April 1 through June 30, 2006 (63 trading days). This table compares the hidden order usage by different trader clienteles around earnings announcements to that during "normal" periods. Panel A presents coefficient estimates, t-statistics, and p-values of the following panel regression, with data aggregated over 30-minute intervals in each trading day for each stock:

$$HPPL_{ijt} \text{ or } HPML_{ijt} =$$
$$\beta_1 Category1_i \times Normal_{jt} + \beta_2 Category1_i \times Before_{jt} + \beta_3 Category1_i \times After_{jt} +$$
$$\beta_4 Category2_i \times Normal_{jt} + \beta_5 Category2_i \times Before_{jt} + \beta_6 Category2_i \times After_{jt} + \beta_7 DepthSame_{ijt} +$$
$$\beta_8 DepthOpp_{ijt} + \beta_9 Volatility_{jt} + \beta_{10} PSpread_{jt} + \beta_{11} StkSpread_j + \beta_{12} Tick_j + \beta_{13} MktCap_j +$$
$$\beta_{14} StkVolatility_j + \varepsilon,$$

where t refers to each 30-minute trading interval on each trading day over entire sample period, $HPPL_{ijt}$ is the proportion of the value of PLOs that are hidden by trader category i for stock j over time interval t, $HPML_{ijt}$ is the proportion of the value of MLOs that are hidden by trader category i for stock j over time interval t, $Category1_i$ is a dummy variable that takes value 1 for trader clientele category i = 1 (individuals, corporations and others) and 0, otherwise, $Category2_i$ is a dummy variable that takes value 1 for trader clientele category i = 2 (domestic financial institutions or foreign institutional investors) and 0, otherwise, $Normal_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is not in the five days before or after the earnings announcement and 0, otherwise, $Before_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is in the five days before the earnings announcement and 0, otherwise, and $After_{jt}$ is a dummy variable that takes value 1 if time interval t for stock j is in the five days after the earnings announcement and 0, otherwise, $DepthSame_{ijt}$ is the order size placed by trader category i relative to the total depth at the five best prices on the same side as the order in stock j in time interval t, $DepthOpp_{ijt}$ is the order size placed by trader category i relative to the total depth at the five best prices on the side opposite the order in stock j in time interval t, $Volatility_{jt}$ is the one-minute quote midpoint changes for stock j over time interval t, $PSpread_{jt}$ is the average percentage quoted spread for stock j over time interval t, $StkSpread_j$ is the average quote spread, taken at one-minute intervals, over the entire sample period for stock j, $Tick_j$ is the inverse is the average traded price over the sample period for stock j, $MktCap_j$ is the market capitalization of stock j at the end of the sample period (June 30, 2006), and $StkVolatility_j$ is the standard deviation of the natural logarithm of daily gross returns for stock j taken over the entire sample period.

Table IX (continued)

Panel A. Regression estimates

Variable	Standing Limit Orders: HPPL			Marketable Limit Orders: HPML		
	Estimate	t-stat	p-value	Estimate	t-stat	p-value
Category1 × Normal	0.2973	158.55	0.0000	0.1347	79.51	0.0000
Category1× Before	0.2947	54.79	0.0000	0.1307	26.85	0.0000
Category1 × After	0.2973	56.9982	0.0000	0.1361	28.84	0.0000
Category2 × Normal	0.6916	347.13	0.0000	0.6804	386.85	0.0000
Category2× Before	0.7093	119.74	0.0000	0.7086	136.18	0.0000
Category2 × After	0.7017	125.28	0.0000	0.7017	140.61	0.0000
DepthSame	-0.0003	-2.57	0.0103	0.0002	2.12	0.0340
DepthOpp	0.0005	2.96	0.0031	-0.0001	-0.78	0.4333
Volatility	-0.0461	-7.83	0.0000	0.0088	1.66	0.0969
PSpread	-0.0064	-3.04	0.0024	-0.0037	-1.96	0.0499
StkSpread	-0.0228	-22.87	0.0000	-0.0101	-11.28	0.0000
Tick	-0.0397	-37.86	0.0000	-0.0121	-12.93	0.0000
MktCap	-0.0329	-24.29	0.0000	-0.0029	-2.35	0.0187
StkVolatility	-0.0138	-14.09	0.0000	-0.0012	-1.41	0.1588

Panel B. Tests of equality of coefficient estimates

Test	Standing Limit Orders		Marketable Limit Orders	
	F-stat	p-value	F-stat	p-value
$\beta_1 = \beta_2$	0.230	0.631	0.660	0.415
$\beta_1 = \beta_3$	0.000	0.991	0.090	0.767
$\beta_2 = \beta_3$	0.120	0.726	0.650	0.422
$\beta_4 = \beta_5$	8.540	0.004	28.200	0.001
$\beta_4 = \beta_6$	3.090	0.079	17.400	0.001
$\beta_5 = \beta_6$	0.900	0.342	0.970	0.325

Table X
Descriptive statistics of price efficiency and liquidity measures

This table presents descriptive statistics on the standard deviation of pricing error as described in Hasbrouck (1993) and percentage quoted spreads for a sample of 100 National Stock Exchange-listed stocks (as explained in Table A.I) between January 2005 and June 2006. We estimate the standard deviation of pricing error for each sample stock during each half hour over the sample period using trade prices. This standard deviation is scaled by the standard deviation of log trade price from the same half hour. Percentage quoted spread is the difference between the best ask and bid prices divided by their midpoint. For each half hour in each stock, we determine the time-weighted average percentage quoted spread. We compute the cross-sectional mean and standard deviation of the scaled standard deviation of pricing error and percentage quoted spread during each half hour and report the statistics of the time-series of these estimates.

	Std. Dev. of Pricing Error			Percentage quoted Spread		
Liquidity quintile	Mean	Median	Mean Std. Dev.	Mean	Median	Mean Std. Dev.
1 (Least)	0.3898	0.3730	0.1656	2.13	1.83	1.82
2	0.3458	0.3368	0.1852	0.94	0.76	0.93
3	0.3343	0.3290	0.1779	0.86	0.71	0.79
4	0.3213	0.3162	0.1703	0.50	0.46	0.88
5 (Most)	0.1803	0.1790	0.1219	0.18	0.16	0.20
All	0.2688	0.2682	0.1799	0.89	0.75	1.26

Table XI
Hidden orders and price error and liquidity measures

This table reports time-series averages of the coefficient estimates of cross-sectional regressions of the standard deviation of pricing error and percentage quoted spread on hidden order used by various traders. These regressions are estimated for each half hour during our sample period from January 2005 to June 2006 for a sample of 100 National Stock Exchange-listed stocks (as explained in Table A.I). The dependent variable in models (1) and (2) is the scaled standard deviation of pricing error for stock j as defined in the header to Table X and in models (3) and (4) is the time-weighted average percentage quoted spread for stock j in each half hour. $FIHidden_j$, $IndHidden_j$, $FTHidden_j$, and $NFIHidden_j$ are the trade-value weighted proportion of hidden orders submitted by Financial Institutions, Individuals, Financial Traders, and Non-Financial Institutions, respectively, in stock j that executed during the half hour, and $FILSHidden_j$ ($FILDHidden_j$), $IndLSHidden_j$ ($IndLDHidden_j$), $FTLSHidden_j$ ($FTLDHidden_j$), and $NFILSHidden_j$ ($NFILDHidden_j$) are the trade-value weighted proportion of liquidity-supplying (liquidity-demanding) limit orders submitted by Financial Institutions, Individuals, Financial Traders, and Non-Financial Institutions, respectively, in stock j that executed during the half hour. $Controls$ for models (1) and (2) include $StdLogPrice_j$, defined as the standard deviation of the log trade price in stock j during the half-hour, $Price_j$, defined as the trade-size weighted average trade price in stock j during the half-hour, and $\%QSpread_j$, defined as the time-weighted percentage quoted spread in stock j during the half-hour. $Controls$ for models (3) and (4) include $LogVol_j$, defined as the natural logarithm of the traded volume in stock j during the half hour and $RetVolatility_j$, defined as the standard deviation over the half hour of one-minute returns of stock j. Standard errors are Newey-West adjusted with five lags. t-stats are reported in parentheses below each coefficient estimate.

	Dependent variable: Std. Dev. of pricing error		Dependent variable: Percentage quoted spread	
	(1)	(2)	(3)	(4)
Intercept	0.2275***	0.2304***	2.0122***	2.0204***
	(138.04)	(131.64)	(72.49)	(71.68)
$FIHidden$	-0.0432***		-0.1642***	
	(-34.20)		(-33.45)	
$IndHidden$	0.0986***		-0.1998***	
	(30.29)		(-14.50)	
$FTHidden$	0.0159***		-0.3881***	
	(7.62)		(-49.51)	
$NFIHidden$	0.0001		-0.2187***	
	(0.07)		(-31.67)	
$FILSHidden$		-0.0287***		-0.1682***
		(-16.85)		(-27.46)
$FILDHidden$		-0.0270***		0.0685***
		(-16.93)		(13.74)
$IndLSHidden$		0.0775***		-0.1235***
		(30.76)		(-12.17)
$IndLDHidden$		0.0079**		-0.1809***
		(2.16)		(-15.55)

Table XI (continued)

	Dependent variable: Std. Dev. of pricing error		Dependent variable: Percentage quoted spread	
	(1)	(2)	(3)	(4)
$FTLSHidden$		0.0157***		-0.3320***
		(9.60)		(-53.65)
$FTLDHidden$		-0.0307***		-0.0865***
		(-10.07)		(-11.56)
$NFILSHidden$		0.0094***		-0.1942***
		(5.83)		(-30.18)
$NFILDHidden$		-0.0211***		-0.0625***
		(-10.24)		(-9.28)
Avg. Adj. R^2	40.69%	41.55%	37.19%	36.18%
N	4,029		2,665	

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table XII
Panel VAR of pricing efficiency, liquidity, and hidden orders

This table presents estimates from a panel vector autoregressive (VAR) system of equations over half-hour trading intervals between January 2005 and June 2006 for a sample of 100 National Stock Exchange -listed stocks (as explained in Table A.I). We include the standard deviation of pricing error over half-hour intervals ($\sigma_{PE,}$), the time-weighted percentage quoted spreads over half-hour intervals ($\%QSpread$), the order value-weighted proportion of liquidity-supplying and liquidity-demanding orders with a hidden component submitted by financial institutions (denoted by $FILSHidden$ and $FILDHidden$, respectively), and the order value-weighted proportion of liquidity-supplying and liquidity-demanding orders with a hidden component submitted by all other traders (denoted by $OthersLSHidden$ and $OthersLDHidden$, respectively). The panel VAR is estimated using one lag. t-stats are in parentheses below each coefficient estimate.

	Dependent variables					
	$\sigma_{PE,t}$	$\%QSpread_t$	$FILSHidden_t$	$FILDHidden_t$	$OthersLSHidden_t$	$OthersLDHidden_t$
$\sigma_{PE,t\text{-}1}$	0.2578***	0.0003***	0.0020	-0.0525***	0.0284***	0.0147***
	(111.72)	(12.29)	(0.47)	(-12.09)	(10.95)	(6.38)
$\%QSpread_{t\text{-}1}$	4.6348***	0.7533***	-0.7309***	-0.5778***	0.7567***	-0.9425***
	(37.85)	(176.08)	(-4.67)	(-3.73)	(5.99)	(-8.36)
$FILSHidden_{t\text{-}1}$	-0.0057***	0.0000	0.4624***	0.2094***	0.0059***	0.0060***
	(-4.75)	(1.24)	(124.2)	(56.21)	(3.92)	(4.59)
$FILDHidden_{t\text{-}1}$	-0.0098***	-0.0001***	0.1414***	0.2909***	-0.0045***	-0.0003
	(-8.49)	(-11.81)	(39.97)	(76.21)	(-3.01)	(-0.25)
$OthersLSHidden_{t\text{-}1}$	0.0191***	0.0001***	0.0097**	0.0164***	0.2820***	0.0830***
	(9.16)	(5.46)	(2.40)	(3.76)	(106.94)	(35.86)
$OthersLDHidden_{t\text{-}1}$	0.0086***	-0.0004***	-0.0060	-0.0048	0.0979***	0.1398***
	(3.54)	(-18.08)	(-1.27)	(-0.96)	(31.76)	(46.67)

***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively

Table XIII
Uninformed traders' effective spreads

This table reports time-series averages of the coefficient estimates of half-hourly cross-sectional regressions of percentage effective spreads on hidden orders used by various trader types. These regressions are estimated for each half hour from July 2005 to June 2006 for a sample of 100 National Stock Exchange-listed stocks (as explained in Table A.I). Percentage effective spread is the absolute difference between the trade price and quote midpoint at the time of trade divided by the quote midpoint times 100. This is computed only for trades in which uninformed traders are demanding liquidity. Uninformed traders are identified as follows. We calculate the profitability (as defined in Table VI) of each trader in each stock between January 2005 and June 2005. In each stock, traders whose profitability is more than two standard deviations below the average trader profitability are identified as uninformed traders in that stock. $FILSHidden_j$, $FILDHidden_j$, $IndLSHidden_j$, $IndLDHidden_j$, $FTLSHidden_j$, $FTLDHidden_j$, $NFILSHidden_j$, and $NFILDHidden_j$ are as defined in Table XI. $Controls$ include $LogVol_j$ and $RetVolatility_j$, both of which are also defined in Table XI. Standard errors are Newey-West adjusted with five lags. t-stats are reported in parentheses below each coefficient estimate. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: Percentage effective spread	
	(1)	(2)
Intercept	0.5771***	0.5792***
	(73.66)	(72.27)
$FIHidden$	-0.0482***	
	(-29.08)	
$IndHidden$	-0.0102**	
	(-2.45)	
$FTHidden$	-0.0948***	
	(-48.05)	
$NFIHidden$	-0.0507***	
	(-22.19)	

$FILSHidden$		-0.0473***
		(-20.34)
$FILDHidden$		0.0031
		(1.33)
$IndLSHidden$		-0.0038
		(-0.81)
$IndLDHidden$		-0.0463***
		(-8.27)
$FTLSHidden$		-0.0908***
		(-43.46)
$FTLDHidden$		-0.0336***
		(-9.93)
$NFILSHidden$		-0.0478***
		(-17.74)
$NFILDHidden$		-0.0136***
		(-4.10)
Avg. Adj. R^2	27.96%	26.79%
N	2,665	

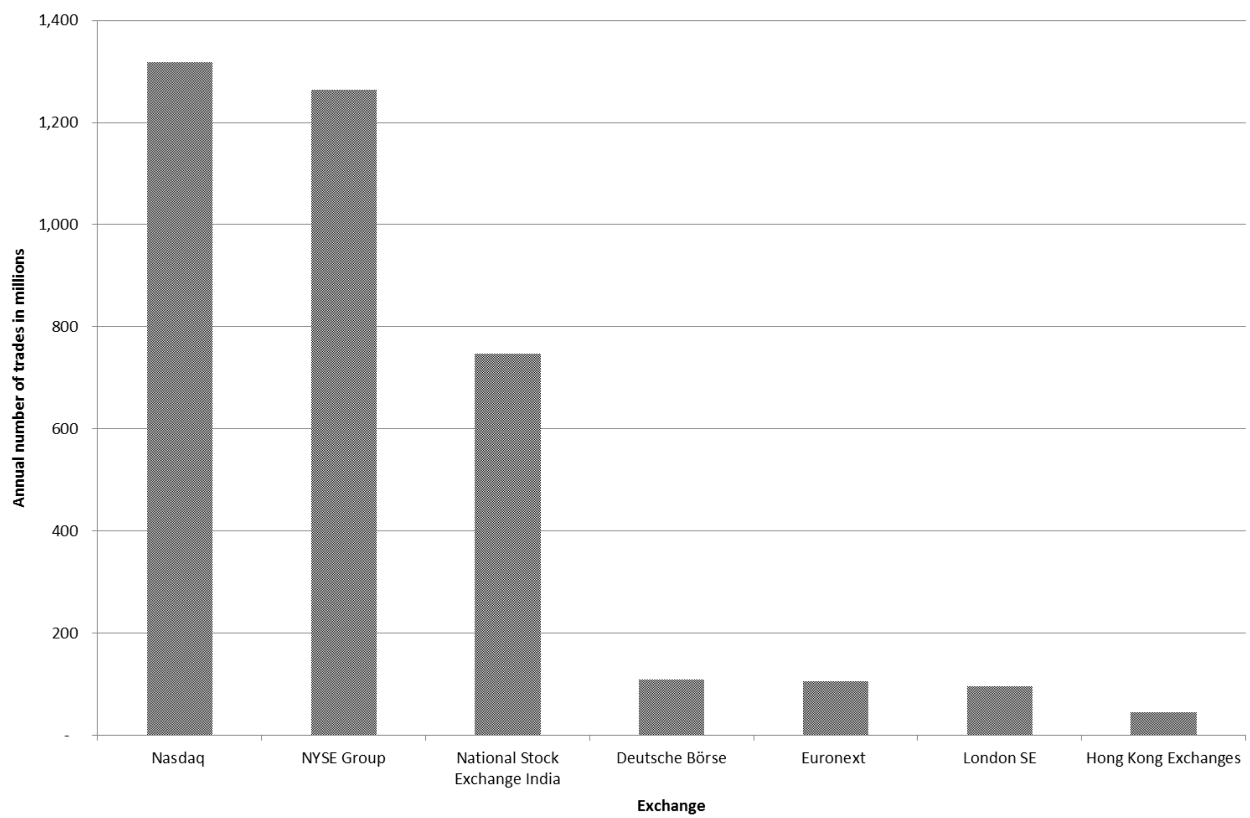

Figure 1. Number of trades on major stock exchanges. This figure reports the total number of trades (in millions) executed on the leading stock exchanges around the world during 2006. The data are from the World Federation of Exchanges' Annual Report Statistics 2006.