# Hiding Behind the Veil: Informed Traders and Pre-Trade Opacity*


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## Abstract

We investigate exchange-based hidden orders from an information perspective. We test several hypotheses and document substantial evidence on a spectrum of issues in this context. First, the contribution of hidden orders to overall price discovery is significantly greater than that of non-hidden orders. Second, traders with higher information levels are significantly more likely to hide a larger proportion of trades. Third, informed traders are significantly more likely to submit hidden orders than uninformed traders. Fourth, informed trader categories that submit hidden orders make significantly greater economic profits than those that do not; while, in contrast, uninformed trader categories make significantly lower economic profits when they submit hidden orders. Finally, relative to other periods, informed trader categories submit more hidden orders in the five days before and after earnings announcements (an exogenous information-intensive period), while the uninformed trader categories do not change their hidden order submission strategies around earnings announcements. Overall, we present overwhelming evidence linking informed traders with the propensity for pre-trade opacity.



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*Keywords*: Informed trading; Pre-trade opacity; Hidden orders; Trading clienteles.

# Hiding Behind the Veil:

# Informed Traders and Pre-Trade Opacity

Dark pools are characterized by pre-trade opacity: they match buyers and sellers without publicly displaying bids and offers, though they report the trade immediately after execution. The recent debate on "dark pools" has focused attention on this pre-trade opacity. While dark pools are typically off-exchange trading locations, traditional organized electronic limit-order-book exchanges also often allow pre-trade opacity by enabling traders to use hidden (or iceberg) orders that display only a fraction of the order, but execute automatically against demanded liquidity with the same price priority as displayed orders (albeit with the hidden part of the order losing time priority to displayed orders at the same price). Hidden orders provide traders an opportunity to increase pre-trade opacity in an otherwise transparent environment, and 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 in Pardo and Pascual (2006), 16% on Xetra in Frey and Sandås (2009), 25% of NASDAQ dollar depth in Tuttle (2006), and 12% of executions on Island ECN in Hasbrouck and Saar (2004).

Transparency is clearly fundamental to the existence of a fair level-playing-field across different market participants. Transparency should also generate greater confidence to trade more freely and hence lead to more efficient price formation that better reflects extant information and quicker reversal of temporary disequilibrium pricing errors. As an SEC representative recently emphasized, "we have a culture that highly values transparency in nearly every aspect of life".[1] It is hence no surprise that the SEC has been "taking a serious look at what regulatory actions may be warranted" to "best bring light" to dark pools,[2] and US lawmakers like Senator Charles Schumer have also been aggressively lobbying in this context. Yet, arguably for good reasons, both on-exchange hidden orders and off-exchange dark pools consciously have pre-trade opacity built into their market design, and market participants are unable to observe the total available depth at different quotes when they trade. This paper investigates exchange-based hidden orders from an information perspective. Specifically within the US, on-exchange hidden liquidity is similar in magnitude to off-exchange dark pools.[3] Outside the US, it is considerably greater, and often almost half the total exchange-based liquidity.

The primary motivation for on-exchange pre-trade opacity (through hidden orders) is to reduce the *signaling* related adverse impact of a large and/or potentially informed trade. The rationale is to enable traders restrict parasitic "front-running", and trade with a reduced information or size-related signal or "footprint". Off-exchange dark pools additionally reduce explicit execution costs when, for example, a large and potentially uninformed liquidity trade is executed in a crossing network at the mid-price rather than executed against limit orders farther and farther on the opposite side of a traditional limit order book. However, in contrast, on-exchange hidden limit orders execute jointly with displayed liquidity. Such hidden orders may be

[1] Speech of Eric Sirri, then-SEC Director of the Division of Trading and Markets, at the SIFMA 2008 Dark Pools Symposium, http://www.sec.gov/news/speech/2008/spch020108ers.htm.
[2] Speech of SEC Chairman Mary Schapiro at the New York Financial Writers Association Annual Awards dinner, http://www.sec.gov/news/speech/2009/spch061809mls-2.htm
[3] The exact numbers and the source will be indicated when we get permission to quote from the source.

able to successfully hide the information and/or the trading interest signal that exists in the displayed order size. However, order execution costs will still increase as the increased order size walks through more price points on the opposite side during execution. Hence, while on-exchange hidden orders can be either informed or uninformed, the signaling benefit of on-exchange hidden orders should arguably be greater for information rather than purely liquidity motivated trades. This raises the question as to who submits orders with a hidden component: informed or uninformed traders? When informed traders submit hidden orders, does their strategy generate greater economic profits or reduced losses? On the other hand, when uninformed traders submit hidden orders, are they able to reduce their losses to better-informed traders when compared to other uninformed traders who do not use hidden orders?

In this context, Moinas (2006) theoretically shows that hidden orders are part of an informed trader's "camouflage" strategy in equilibrium. An informed trader prefers to trade a large volume to profit from her information but displaying her entire order would likely move prices away from her order, resulting in non-execution of the order. Hence, an informed trader mimics an uninformed liquidity supplier by hiding a part of her order.

The bottom line is that it can be argued that hidden orders should be used more by informed rather than uninformed investors. However, extant empirical research (Bessembinder, Panayides and Venkataraman (2009)) appears to indicate the opposite, albeit through indirect inference rather than direct empirical evidence.[4] The issue is important because the active

[4] Frey and Sandås (2009), in work concurrent with this paper, also come to the same conclusion as Bessembinder, Panayides and Venkataraman (2009), and again through indirect inference rather than direct empirical evidence.

participation of informed traders in the trading process is critical for the existence of information-efficient equilibrium prices and in order for their private information to be quickly reflected in these prices. If informed traders are hesitant to expose their positions in an overly-transparent market center, and prefer instead to trade in a less-transparent market center, then that other less-transparent center should arguably have better price discovery. In this paper, we directly and comprehensively investigate empirically whether it is the informed or the uninformed investors who use hidden orders, and issues related thereto, using a new, proprietary and (extremely) rich and comprehensive dataset of orders and trades, duly time-stamped to the nearest "jiffy". Most importantly, this dataset includes the coded identities of each and every trader who submitted orders, whether hidden or otherwise, and categorizes incoming orders as those coming from individual traders, corporations, domestic financial institutions (hereafter, DFIs), and foreign institutional investors (hereafter, FIIs).

Harris (1997) posits that a benefit of order exposure is that it may attract traders who are willing to trade but have not revealed their trading interests as yet ("reactive" traders). On the other hand, he argues that "defensive" and "parasitic" traders impose costs to order exposure. As order exposure reveals a trader's intent, and likely her information, defensive traders are likely to cancel their orders to avoid losses from trading with better-informed traders. Parasitic traders attempt to "front-run" large exposed, and likely informed, orders as these orders offer a free option to them. For example, if there is a large buy order, a parasitic trader may trade one tick above this buy order. If prices continue to increase, he can sell his shares for a profit. If prices

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Despite the rapid increase in the number of electronic limit order markets globally (Jain (2005)), we do not have direct empirical evidence on whether informed or uninformed traders are more likely to use hidden orders.

reverse, he can sell to the large buy order at a loss of just a tick. Uninformed traders also face benefits and costs from order exposure. One benefit from order exposure is the increased likelihood of order execution as the order maintains its time priority. A cost would be the adverse selection cost of having to trade with better-informed traders. It is likely that both informed and uninformed traders have some reasons to hide at least a part of their orders. The question is who more likely to do so.

Bessembinder, Panayides, and Venkataraman (2009) find that hidden orders on the Euronext-Paris face a lower opportunity cost even after controlling for non-execution and conclude that uninformed traders are more likely to place hidden orders. Frey and Sandås (2009) find that price impact of a hidden order on the Xetra depends on the extent to which the order is filled and conclude that hidden order traders trade for liquidity reasons rather than information reasons. Aitken, Berkman, and Mak (2001) report that the price impact of hidden orders on the Australian Stock Exchange is no different from that of other limit orders. While theory predicts that informed traders are more likely to hide their orders, indirect empirical evidence shows the opposite. We address this contradiction in the literature with direct tests of who submits hidden orders and the information level of these traders. Our empirical evidence unequivocally supports the conclusion that informed rather than uninformed traders are more likely to submit hidden orders.

In this paper, we use data over a three-month period from April to June 2006 from the National Stock Exchange of India (hereafter, NSE). The number of trades on the NSE is about a third of that on the NYSE and Nasdaq and several times greater than that on the Euronext or in

London. We investigate the 50 stocks in the Standard & Poor's CNX Nifty index. The stocks account for about 60% of the market capitalization of all stocks on the NSE. We find that 9% of all incoming pure (non-marketable) limit orders and 24% of the total value of incoming pure limit orders have a hidden component. The corresponding numbers for marketable limit orders are 3% and 31%, respectively. We also observe that about 45% of the depth at the best five quotes is hidden depth.

Following Anand, Chakravarty, and Martell (2005), we measure the information level of the different categories of traders by computing the extent to which prices move over different time horizons after order submission. We measure the information of an order as follows. For buy orders, it is the difference between the quote midpoint a fixed time (5 minutes, 30 minutes, 60 minutes, or 1 day) after the order is placed and the quote midpoint at the time the order is placed, scaled by the quote midpoint at the time the order is placed, multiplied by the total orders size, and vice versa for sell orders.

As preliminary analysis, we estimate the information level in orders of financial institutions (DFIs and FIIs) relative to those of individual investors and corporations. Our results in this regard are extremely strong. We find that, irrespective of horizon, the information level of financial institutions is large in magnitude and significantly greater than zero on average. On the other hand, the information level of individuals is not significantly different from zero on average, and, across information horizons, sometimes small and positive and sometimes small and negative. The information level of corporations lies in between. This is true for both pure as well as marketable limit orders.[5] Our intention is not to extrapolate to general conclusions here, but it is certainly fair to conclude that, for this particular market and this particular sample, financial institutions are "informed" and individuals are "uninformed". In this context, we also note from our unconditional univariate descriptive statistics, that 62% of all pure limit orders placed by financial institutions (both DFIs and FIIs combined) have a hidden component, whereas only around 8% of all pure limit orders placed by other investors include a hidden component. In terms of value of orders placed, over two-thirds of orders placed by institutions include a hidden component, whereas less than 20% of orders placed by other investors include a hidden component. These preliminary results clearly suggest a strong positive association between pre-trade opacity and the information content of the order.

We undertake further analyses in a multivariate setting where we explicitly control for the type of investor: individual, corporation, DFI, FII or others. First, we use the *Hasbrouck Information Share* approach to examine the extent to which price discovery occurs because of hidden orders, forming two mid-quote series based on one-minute order book snapshots: one series from the pool of hidden orders and the other from the pool of non-hidden orders. We find that the mean information share of hidden orders is greater than 70%, significantly greater than that of non-hidden orders, and they hence contribute significantly more to price discovery. Second, we find that, after controlling for the type of investor, traders with higher information levels are significantly more likely to hide a larger proportion of trades. Third, we determine the

[5] Across order types, we find that marketable limit orders have higher information than pure limit orders across all types of investors. This is consistent with better-informed traders trading aggressively to profit from their information advantage.

probability of an informed trader submitting a hidden order, in a framework similar to that of De Winne and D'Hondt (2007). We again find that informed traders are significantly more likely to submit hidden orders than uninformed traders. Fourth, we compare the economic profit of different categories of traders over our sample period and determine how hidden order submission affects these profits. We find that informed trader categories that submit hidden orders make significantly greater economic profits than those that do not. On the other hand, uninformed trader categories make lower economic profits when they submit hidden orders. Finally, earnings announcements provide us with an exogenous information-intensive period. We examine the rate of hidden order submissions around these announcements and compare them to "normal" trading periods. We find that informed trader categories submit more hidden orders in the five days before and after the announcement when compared to the rest of the sample period. Other investors do not change their hidden order submission strategies around earnings announcements. This again supports the hypothesis that informed traders are more likely to submit hidden orders than uninformed traders. Overall, we present overwhelming evidence of a link between informed traders and the propensity for pre-trade opacity. We additionally document substantial other evidence on related nuances in this context.

Our findings give markets and investors a richer understanding of who submits hidden orders. Even where research identifies ways in which investors can detect hidden orders (e.g. Frey and Sandås (2009)), the important question for traders is whether to trade against these hidden orders, and that depends on whether they are informed or uninformed.

The remainder of the paper is organized as follows. Section I reviews prior literature on hidden orders and develops our hypotheses. We describe our data and present descriptive statistics of our sample in Section II. Section III presents and discusses our results and conclusions are in Section IV.

## I. Literature Review and Hypotheses

### *A. Prior Literature on Hidden Orders*

The literature on hidden orders is just starting to develop. Harris (1997) discusses the costs and benefits of order exposure for informed and uninformed traders. Harris (1996) examines the empirical relation between order exposure and tick size. Using data from the Paris Bourse and Toronto Stock Exchange, he finds that larger tick sizes are associated with greater order exposure as it makes quote-matching strategies more expensive. He also reports that order exposure is lower in volatile stocks. Moinas (2006) theoretically shows that in equilibrium informed traders hide their orders to mimic the behavior of uninformed traders. We also know from De Winne and D'Hondt (2005) that hidden depth results in large reductions in implicit transaction costs. De Winne and D'Hondt (2007) find that traders use hidden orders to reduce exposure risk as well as the risk of front-running. Further, they observe that traders attempt to take advantage of the opportunity for depth improvement when they detect hidden depth at the best quote on the opposite side by strategically changing their orders. Aitken, Berkman, and Mak (2001) do not find evidence of informed traders on the Australian Stock Exchange (ASX) submitting hidden orders more frequently than uninformed traders. However, the market knows of the existence of hidden orders on the ASX as they are displayed to the public as having size "U". Only the size of the hidden order on the ASX is unknown.

Hasbrouck and Saar (2002) report a substantial use of hidden orders on the Island ECN. They also find that over a quarter of all limit orders submitted are canceled within two seconds. Anand and Weaver (2004) study the abolishment of hidden orders in 1996 and their subsequent reintroduction in 2002 on the Toronto Stock Exchange. They find that the publicly displayed depth did not change after either event, suggesting that total depth decreases when orders cannot be hidden. Tuttle (2006) reports the use of non-displayed depth by Nasdaq market-makers on the SuperSOES and this use is greater in riskier and volatile stocks. Bessembinder, Panayides, and Venkataraman (2009) examine the costs and benefits of order exposure on the Euronext-Paris. Consistent with their hypothesis, they find that hidden orders have a lower likelihood of full execution and increased time to execution. They fail to find evidence in support of order exposure causing defensive traders to withdraw from the market. However, they find that order exposure increases execution costs. Frey and Sandås (2009) find that detection of hidden liquidity draws latent liquidity in the market in the form of market orders. They also provide evidence of hidden orders being associated with increased trading.

*B. Hypotheses*

We contribute to the literature on who submits hidden orders by examining the information level of different types of market participants. While prior research (e.g. Bessembinder, Panayides, and Venkataraman (2009), Frey and Sandås (2009)) finds that uninformed traders are more likely to submit hidden orders, the results are based on indirect evidence. We believe that the richness of our data enables a more direct test of whether informed or uninformed traders are more likely to use hidden orders. In a theoretical framework, Moinas (2006) shows that at intermediate levels of adverse selection, uninformed traders factor in the information revealed by the depth at the best quotes while placing their orders. This depth is primarily due to limit orders placed by liquidity suppliers. Not wanting to reveal their long-lived private information, informed traders mimic the behavior of uninformed liquidity suppliers by exposing only a part of their orders. Harris (1996, 1997) discusses the benefits and costs of order exposure by both informed and uninformed traders. The benefit of order exposure is the ability to attract latent liquidity in the market. This is true for both informed and uninformed traders. The cost of order exposure to uninformed traders is the adverse selection risk of having to trade with better-informed traders. The costs of order exposure to informed traders is the risk of being front-run by quote-matchers and the risk of driving away traders who are unwilling to trade with informed traders. Given the costs and benefits of order exposure to both informed and uninformed traders, it is an empirical question as to who uses hidden orders. This leads us to our first hypothesis:

$H_{1A}$: *Informed traders, while supplying liquidity, use hidden orders to protect themselves against front-running and defensive traders.*

$H_{1B}$: *Uninformed traders, while supplying liquidity, use hidden orders to diminish the option value their orders provide to better-informed traders.*

Informed traders use hidden orders to gain from their private information. If they expose their orders, front-runners may trade ahead of them, on account of which their private information will not be profitable. Similarly, informed traders' order exposure may drive away liquidity on the opposite side as defensive traders cancel their orders and exit the market. Again, the informed traders' private information will not be profitable. On the other hand, if uninformed traders submit hidden orders, their losses to informed traders will be smaller than if they expose their orders fully. Consequently, our second hypothesis is:

*$H_2$: Traders who submit hidden orders are likely to make more profits (if informed traders submit hidden orders) or less losses (if uninformed traders submit hidden orders) than those who do not use hidden orders.*

If informed traders reduce order exposure in order that they do not reveal their private information, the usage of hidden orders should increase during information-intensive periods (e.g. around earnings announcements) relative to normal trading periods. Alternatively, if uninformed traders use hidden orders to reduce the likelihood of informed traders picking off their standing limit orders, their use of hidden orders should also increase during information-intensive periods when compared to normal periods. As a result, our third hypothesis states that:

*$H_3$: Usage of hidden orders (by informed or uninformed traders) should increase around information-intensive periods (e.g. around earnings announcements).*

## II. Data

Our empirical analyses are based on a rich proprietary database from the NSE. The NSE is an order-matching open electronic limit-order book market that operates on a strict price-time priority. It has an automated screen-based trading system that enables members from across India to communicate, through satellite, with the centralized computer system and trade anonymously with one another on a real-time basis. The types of orders and systems that exist internationally in order-driven markets also typically exist on NSE, including limit orders, market orders, and hidden orders.[6]

The NSE, together with a securities markets regulator, the Securities and Exchange Board of India (SEBI), was created as part of major economic reforms in India in the early 1990s.[7] SEBI has introduced, and NSE has implemented, a rigorous regulatory regime to ensure fairness, integrity, transparency, and good practice that is comparable to the best anywhere globally. As a result, the trading volume on NSE has grown strongly to make it among the most liquid markets in the world. Figure 1 shows the total number of trades executed on leading stock exchanges around the world in 2008.[8] The numbers of trades on the NSE is about a third of those on the major U.S. exchanges but it is at least seven times those on the other major exchanges around the world.[9]

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[6] NSE operates a continuous trading session from 9:55 am until 3:30 pm local time. The tick size is INR 0.05 (less than USD 0.01). Importantly, unfilled orders are not carried over to the next day. Also, the NSE does not have a pre-designated pre-open call auction (like the Euronext) to determine the opening price, which is determined by order matching as well. Traders, who choose to hide their orders, are required to display at least 10 percent of the size of every order that they place. Further, in terms of the transparency of the limit order book, the five best prices and the respective depths at those prices on both sides of the market are publicly disseminated.

[7] There is another major stock exchange in India: the Bombay Stock Exchange (BSE). Established in 1875 as a stockbrokers association, the BSE is the oldest stock exchange in Asia and has the largest number of listed companies in the world with around 4,700. However, the exchange has suffered from a reputation of clubby manipulative practices and inefficient clearing and settlement systems.

[8] The data is from the Annual Report and Statistics 2008 published by the World Federation of Exchanges.

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

Our sample consist of all 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. Our sample period is from April 1 through June 30, 2006, covering 63 trading days. Our proprietary data includes virtually all information there exists on orders and trades. A trading member code and a client member code are attached to each order.[10] This helps us uniquely identify each trader across the entire data. Further, traders are classified into 14 different clientele categories and the trader category is also available for each order. Table I presents the 14 different trader categories. We aggregate these 14 clienteles into five broader trader clienteles, namely, Individuals, Corporations, DFIs, FIIs, and Others, as the component groups within each of these broader clienteles are of similar nature. Table I also lists the five broader trader clientele categories.

Panel A of Table II presents summary statistics on the trading characteristics of the sample stocks over the sample period. The average number of daily order submissions per stock is 24,907. 93% of these are limit orders (including marketable limit orders) and the remaining 7% are market orders (not reported in the table). The average daily turnover per stock is $21 million and there are, on average, 19,121 trades per day per stock.

[10] This is in addition to the usual information attached to an order: date and time of order submission, buy or sell order indicator, limit or market order indicator, limit price if order is a limit order, total order size, and initial displayed order size if order is a limit order.

Only 9% of the order submissions include buy or sell hidden quantities. However, as many as 42% of the trades include hidden orders.[11] This indicates that hidden orders are more prevalent at the top of the order book, i.e. around the best buy or sell quotes. Figure 2 presents a plot of the percentage of the depth at the best quotes on either side (*h1depth*), at the five best quotes on either side (*h5depth*), and across the entire book (*htdepth*) attributable to hidden orders as it varies over the course of the trading day.[12] On average across all stocks, these are about 30%, 45% and 35%, respectively, indicating that hidden orders are at most a few ticks away but not too distant from the best quotes.

Panel B of Table II reports the number of orders and percentage of hidden orders submitted by the five trader clienteles. We report results separately for Pure Limit Orders (hereafter, PLOs) and Marketable Limit Orders (hereafter, MLOs). PLOs are limit orders submitted at prices worse than the best opposite side price. Buy orders have prices lower than the best offered price. Similarly, sell orders have prices higher than the best bid price. These orders typically supply liquidity and enter the book as standing orders. MLOs are limit orders that equal or better the best opposite side price. Buy orders have prices that are equal to or higher than the best offered price. Sell orders have prices equal to or lower than the best bid price. MLOs demand liquidity. Depending on its price, all or a part of the order will be executed immediately. If the entire order does not get executed, the remainder becomes a standing limit order and

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[11] Bessembinder, Panayides, and Venkataraman (2009) report comparable numbers on the Euronext-Paris. They find that 18 percent of all incoming orders consist of a hidden component, while 44 percent of trades involve hidden orders.

[12] The plot is based on snapshots of the limit order book at one-minute intervals during the trading day for the entire sample period and for all stocks.

supplies liquidity. However, for the purposes of the analyses in this paper, all MLOs are treated the same, regardless of what fraction is executed at submission.

Individuals and corporations place a large number of orders on the NSE. DFIs and FIIs place relatively fewer orders. This is true for both PLOs as well as MLOs. A large proportion of PLOs placed by DFIs and FIIs, 57 and 66 percent, respectively, have a hidden component, while Individuals and Corporations use a relatively smaller proportion of hidden order, 4 and 17 percent, respectively. Similarly, a large proportion of MLOs submitted by DFIs and FIIs have a hidden component, 44 and 50 percent, respectively, while Individuals and Corporations use a smaller proportion of hidden orders, 2 and 4 percent, respectively. These results show that it is the institutional investors, both domestic and foreign, who are more likely to submit hidden orders than other types of traders. Further, the difference in proportion of hidden orders between PLOs and MLOs shows that when traders demand liquidity, they are less likely to submit hidden orders. This is because any unfilled portion sits on the limit order book and the hidden portion has low time priority at a given price. This result holds for all type of trader clienteles. The proportion of hidden order is higher if we look at the value of orders placed rather than the number of orders placed. In terms of trades, over two-thirds of all trades attributed to PLOs placed by DFIs and FIIs involve hidden orders, whereas less than a quarter of all trades attributed to other investors involve hidden orders. This shows that institutional investors place more aggressively-priced PLOs and hide a larger proportion of these orders.[13]

[13] We do not report trade statistics for MLOs because all of them, by definition, are at least partly executed immediately and hence the statistics for trades are not very different from the corresponding values for orders.

## III. Results

### *A. Hidden Orders and Price Discovery*

We examine the extent to which price discovery occurs because of hidden orders. The price discovery literature is extensive and follows two main approaches: the *Hasbrouck Information Share* approach and the *Gonzalo-Granger Common Factor* approach.[14] The price discovery literature looks at cases of stocks trading in multiple markets (e.g. deB. Harris, McInish, Shoesmith, and Wood (1995), Huang (2002)) or closely related assets trading in multiple markets (e.g. Eun and Sabherwal (2003), Booth, So, and Tse (1999), Chakravarty, Gulen, and Mayhew (2004), Shastri, Thirumalai, and Zutter (2008)) to examine the relative contributions of price discovery from each market segment. The underlying premise is that though different market segments appear different, they are closely integrated through common information and hence function as one market in discovering the true price.

We address the relevance of hidden orders for price discovery using the *Hasbrouck Information Share* approach. In this context, we form two mid-quote series from our constructed one-minute order book snapshots: one series from the pool of hidden orders (HP) and the other from the pool of non-hidden orders (NHP).[15] Both these mid-quote series can be thought of as proxies for the true value of the underlying stock and one can potentially examine the contribution of each series (hidden and non-hidden) to price discovery. The literature on price discovery examines the information content of prices of the same security observed in different

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[14] See Hasbrouck (1995) and Gonzalo and Granger (1995), respectively, for more details on the two approaches. A detailed discussion and comparison of these approaches can be found in Hasbrouck (2002) and de Jong (2002).
[15] We treat all standing limit orders that are fully displayed as non-hidden orders and all other standing limit orders as hidden orders.

markets, while we similarly examine the information content of prices of the same security where the price series are from two streams of order submitters: hidden orders and non-hidden orders. Our analysis is in the spirit of Kurov and Lasser (2004), in which they examine the price discovery of E-mini futures contracts and determine the contribution of exchange locals and off-exchange traders to price discovery using the price series of the two trader types. If hidden orders are submitted largely by informed traders then one expects that HP series to be a better indicator of the true value of the stock than the NHP series. On the other hand, if hidden orders are placed by uninformed traders, for example to mitigate adverse selection costs, then the HP series will react slowly to new information, and hence its share in price discovery will be lower than that of the NHP series.

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

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

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

where $\varepsilon \sim N(0,\Omega)$, $\Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$, *HP* is the mid-quote price series from orders that are not fully displayed and *NHP* is the mid-quote series from orders that are fully displayed.

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

A VECM requires all price series to be non-stationary and cointegrated. Hence, we first test for the non-stationarity of our HO and NHO series on each stock-day using *Augmented Dickey Fuller* unit-root tests. We fail to reject the unit root null at conventional five percent levels of significance showing that our HO and NHO series are all non-stationary as needed. We then test for cointegration by employing the Johansen cointegration test. In each case, for each day and for each stock, our cointegration test results reject the null of the absence of a cointegrating vector, and accept the null of a single cointegrating vector between the HO and the NHO series[16]. We finally proceed to estimate the error correction dynamics that characterizes our price discovery process.

[16] We do not report these results for compactness and brevity.

Table III reports the HO and NHO information share results. The mean information share of hidden orders across all stocks and days is 71 percent with the lower and upper quartiles being 58 percent and 87%, respectively, all of these being significantly greater than 50%. This indicates that hidden orders carry significantly greater level of information than non-hidden orders, with their users being significantly more informed than users of non-hidden orders, and they contribute significantly more to price discovery. This provides support to Hypothesis $H_{1A}$ that informed traders rather than uninformed traders use hidden orders. Taken together with the results from Table I that institutional investors (both DFIs and FIIs) are more likely to submit hidden orders, this suggests that hidden orders are more likely to be submitted by informed institutional investors

*B. Hidden Orders and Information Levels*

For both PLOs and MLOs, similar to Anand, Chakravarty, and Martell (2005) and Kaniel and Liu (2006), we proxy for the information of an order by the change in the quote midpoint over a fixed period of time after submission of the order. We calculate the Information Level over four time intervals: 5 minutes, 30 minutes, 60 minutes, and 1 day. For a buy order, the Information Level is the total order size multiplied by the quote midpoint 5, 30, 60 minutes or 1 day after order submission divided by the quote midpoint at order submission minus one. For a sell order, the Information Level is the total order size multiplied by one minus the quote midpoint 5, 30, 60 minutes, or 1 day after order submission divided by the quote midpoint at order submission.

Table IV Panel A presents average information levels for each of the five trader clientele categories for each of the four proxies corresponding to time horizons of 5, 30, 60 minutes, and 1 day after order submission and separately for PLOs and MLOs. The results are unequivocally strong. Irrespective of the time horizon used to measure it, the Information Level of financial institutions, both DFI's and FII's, is much higher than the information level of Corporations, which itself is higher than the information level of Individuals. The results are the same for PLOs and MLOs. Broadly, the results are consistent with prior literature that finds that financial institutions are better informed than other types of investors.[17] Comparing Information Levels of PLOs and MLOs for each trader type, we find that the MLOs consistently have a higher Information Level than PLOs for all trader clienteles as well as for all time horizons over which Information Level is measured. This indicates that MLOs are placed by better-informed traders than those that use PLOs. Given the greater information of traders using MLOs, they may have an urgency to trade and profit from their private information and hence use more aggressively-priced MLOs rather than PLOs. As hidden order submission and Information Levels are similar for DFIs and FIIs, for the remainder of the paper, we treat them as one group (Category 2) and the other three trader clienteles as one group (Category 1). Our results are qualitatively similar if we treat the five trader clienteles separately.

In a univariate setting, we have shown that DFIs and FIIs are more likely to submit hidden orders and that they are better-informed than other traders. Next, we relate the

[17] See, for example, Szewczyk, Tsetsekos, and Varma (1992), Alangar, Bathala, and Rao (1999), Chakravarty (2001), Dennis and Weston (2001).

information levels of traders to the extent to which they hide their orders in a multivariate setting. To this end, we estimate the following panel regression, aggregating orders over 30-minute intervals over each trading day for each stock:

$$\begin{aligned} & HPPL_{ijt} \text{ or } HPML_{ijt} \text{ or } HP_{ijt} = \\ & \beta_1 Category1_i + \beta_2 Category2_i + \beta_3 Category1_i \, InfoLevel1day_{ijt} + \\ & \beta_4 Category2_i \, InfoLevel1day_{ijt} + \beta_5 DepthSame_{ijt} + \beta_6 DepthOpp_{ijt} + \beta_7 Volatility_{jt} \\ & + \beta_8 PSpread_{jt} + \beta_9 StkSpread_j + \beta_{10} Tick_j + \beta_{11} MktCap_j + \beta_{12} StkVolatility_j + \varepsilon, \end{aligned} \quad (3)$$

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 $t$, $HP_{ijt}$ is the proportion of the value of all limit orders 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 and 0, otherwise, $Category2_i$ is a dummy variable that takes value 1 for trader clientele category $i$ = 2 and 0, otherwise, $InfoLevel1day_{ijt}$ is the Information Level (defined earlier) over the 1 day following order submission for trader category $i$ for stock $j$ over time interval $t$, $DepthSame_{ijt}$ 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. Our coefficients of interest are those of the interactive terms, namely, $\beta_3$ and $\beta_4$. If we find that both $\beta_3$ and $\beta_4$ are significantly greater than zero, this will support Hypothesis $H_{1A}$ that informed traders are more likely than uninformed traders to hide a part of their orders. On the other hand, both coefficients being significantly less than zero will support Hypothesis $H_{1B}$ that uninformed traders are more likely to hide their orders. We include dummies for Category 1 and Category 2 traders as the tendencies of the two categories to submit hidden orders may be different when they are uninformed. The controls for market conditions and stock characteristics are based on evidence from Harris (1996), De Winne and D'Hondt (2007), and Bessembinder, Panayides, and Venkataraman (2009).

Results from regressing equation (3) are in Panel B of Table III. The coefficients of *Category1* and *Category2* are significant in all three regressions, which suggest that both categories of traders hide a significant proportion of their orders, even when they are uninformed. The usage of hidden orders by uninformed traders is similar to the findings of other research (e.g. Bessembinder, Panayides, and Venkataraman (2009), Frey and Sandås (2009)). Consistent with the univariate results in Table II, we find that financial institutions (Category 2 traders) hide a larger proportion of their orders than other investors (Category 1 traders). This is true for both PLOs and MLOs. The coefficient of $Tick_j$ is significantly negative in all three regressions. This implies that investors hide a smaller proportion of their orders when the relative tick size is larger (low-priced stocks). A larger relative tick size makes front-running more expensive and hence the costs of order exposure are lower resulting in investors being more willing to expose a larger proportion of their orders. This result is consistent with Harris (1996). However, contrary to Harris (1996), we find that traders hide a smaller proportion of their orders when markets are volatile and in volatile stocks.

Focusing on our coefficients of interest, the evidence supports Hypothesis $H_{1A}$ and not Hypothesis $H_{1B}$. We find that $\beta_3$ is not significantly different from zero in all three regressions. This shows that Category 1 traders' decision to hide a part of their order is not different between when they are informed and when they are uninformed. On the other hand, we find that $\beta_4$ is significantly positive in all three regressions. This implies that when Category 2 traders (financial institutions) are informed, they hide a larger proportion of their orders than when they are uninformed. The results are stronger when Category 2 traders use MLOs rather than PLOs. When informed financial institutions are aggressively searching liquidity, they prefer to hide a larger proportion of their orders as the entire order may not be filled immediately. Any unfilled part converts into a regular limit order and sits on the book. To prevent other investors from inferring their private information while the unfilled fraction of their order sits in the book, informed financial institutional investors prefer to hide larger fraction of their orders.

Equation (3) relates the extent to which investors hide their orders when they informed. Next, we examine how an investor's information affects the probability that she hides the order. We use a logistic regression framework similar to those of De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009). However, our logistic regression is different from the two studies as we include the Information Level of an order as an explanatory variable. We estimate the following order-by-order logistic regression:

$$\begin{aligned}\Pr(Hidden) &= \beta_1 Category1 + \beta_2 Category2 + \beta_3 Category1 \times InfoLevel1day \\ &+ \beta_4 Category2 \times InfoLevel1day + \beta_5 PriceAgg + \beta_6 LnSize + \beta_7 PSpread \\ &+ \beta_8 LnVolume + \beta_9 LnNOT + \beta_{10} DepthSame + \beta_{11} DepthOpp + \beta_{12} TransVol \\ &+ \beta_{13} StkSpread + \beta_{14} MktCap + \beta_{15} Tick + \beta_{16} StkVolatility + \varepsilon,\end{aligned} \qquad (4)$$

where *Category1* takes value 1 if the order is placed by a Category 1 trader and 0, otherwise, *Category2* takes value 1 if the order is placed by a Category 2 trader and 0, otherwise, *InfoLevel1day* is the Information Level for the order over a 1-day period after order submission, *PriceAgg* is a measure of price aggressiveness of the order, measured as one minus two times the difference between the offered price at order submission and limit price of the order divided by the quoted spread at order submission for buy orders and two times the difference between the offered price at order submission and limit price of the order divided by the quoted spread at order submission minus one for sell orders, *LnSize* is the natural logarithm of the total order size submitted, *PSpread* is the prevailing percentage quoted spread at order submission, *LnVolume* is the natural logarithm of the number of shares traded over the 5-minute interval prior to order submission, *LnNOT* is the natural logarithm of the number of trades over the 5-minute interval prior to order submission, *DepthSame* is the displayed depth at the five best prices on the same side as the order at the time of order submission, *DepthOff* is the displayed depth at the five best prices on the side opposite the order at the time of order submission, *TransVol* is a measure of transitory volatility and measured as the standard deviation of the last 300 trade price changes, and *StkSpread*, *MktCap*, *Tick*, and *StkVolatility* are the same as defined earlier. Our variables of interest are the interaction terms between trader category and Information Level. Other right-hand side variables are market condition and stock-level controls.

We report the results of the logistic regression, estimated separately for PLOs and MLOs, in Table V. Our large sample of orders drives the statistical significance of the coefficient estimates. To gauge the economic significance of the estimates, we report the marginal probabilities associated with each variable. We find that there is an 83 percent lower chance of a Category 1 trader placing a hidden pure limit order. Similarly, we find that there is a 10 percent higher change of a Category 2 trader submitting a hidden pure limit order. The corresponding probabilities for MLOs are -20 percent and -2 percent, respectively. This suggests the traders who submit MLOs are less likely to hide their orders. Given their urgency to trade, they are less likely to hide their orders as this will give them higher time priority and quicker execution. While using PLOs, a one unit increase in the Information Level of a Category 1 trader increases the probability of placing a hidden order by less than one basis point. On the other hand, a similar increase in the Information Level of a Category 2 increases the probability of placing a hidden order 26 basis points. These results are consistent with our earlier results that show Category 1 traders' hidden order submission strategies do not change if they informed, whereas Category 2 traders are more likely to hide their orders when they are informed. This is further evidence in support of Hypothesis $H_{1A}$ and against Hypothesis $H_{1B}$. When traders use MLOs, the marginal probabilities of Category 1 and 2 traders using hidden orders when their Information Level increases by one unit are 2 and 9 basis points, respectively. Though economically these numbers are small, we still find that financial institutions are more likely to use hidden orders when their private information increases, while hidden order usage by other investors does not change with their Information Level.

*C. Economic Profit from Hidden Orders*

Our evidence to this point shows that financial institutions are more likely than other types of traders to submit hidden orders and that greater their private information (measured by Information Level) the higher the probability of submitting a hidden order. In this section, we investigate if hidden order traders generate positive economic profits. While they submit hidden orders in the hope of generating profits from their private information, extant literature has not examined if informed traders succeed in this endeavor. Our data allows us to identify unique traders using the trading member and client member codes attached to each order. We track the profits of each individual trader over our sample period. For each individual trader in our sample, the economic profit in a given stock is the difference between the price at which she sells the shares in the stock and the price at which she buys the shares in the stock. If a trader only sells shares of a stock, we value her starting position using the opening quote midpoint at the beginning of the sample period. We use this as the price at which she buys the shares at the start of the sample period. Similarly, if trader only buys shares of a stock, we value her ending position using the closing quote midpoint at the end of the sample period. We use this as the price at which she sells the shares at the end of the sample period. Given the huge number of traders in our sample, we aggregate the data as follows. For each of the five trader clienteles, we sort the traders based on their economic profit from lowest to highest. The clients are divided in percentiles groups (a total of 100 groups) based on their economic profit. The average economic profit per clientele within each of the percentile groups is calculated. This is done for each of the 50 sample stocks and we estimate the following regression separately for each of the five trader clienteles as well as all trader clienteles pooled together:

$$EProfit_{ij} = \beta_0 + \beta_1 HP_{ij} + \beta_2 StkSpread_j + \beta_3 MktCap_j + \beta_4 Tick_j + \beta_5 StkVolatility_j + \varepsilon, \qquad (5)$$

where $EProfit_{ij}$ is the average economic profit of the $i^{th}$ percentile of traders for stock $j$, $HP_{ij}$ is the mean proportion of order value that is hidden by the $i^{th}$ percentile of traders for stock $j$, and $StkSpread_j$, $MktCap_j$, $Tick_j$, and $StkVolatility_j$ are as defined earlier. All variables are standardized.

Coefficient estimates of regression (5) are in Table VI. We find that a one standard deviation increase in the proportion of order value that is hidden results in reduced profits for Individuals and Corporatioons and increased profits for DFIs and FIIs. It reduces the economic profits of Individuals by 0.25 standard deviations and that of Corporations by 0.11 standard deviations. However, it increases the economic profits of DFIs by 0.07 standard deviations and that of FIIs by 0.10 standard deviations. These results partly support Hypothesis $H_2$. We have shown that informed institutional investors hide a larger proportion of their orders than when they are uninformed. Economic profit is greater for institutional investors when they hide a larger proportion of their orders. Taken together, this implies that informed institutional investors hide a large proportion of their orders as they do not want to reveal their private information to the market and this reduced-order exposure strategy does lead to higher profits. Institutional investors succeed in their attempt to profit from their private information by reducing order exposure. This is consistent with Hypothesis $H_2$. However, for other types of investors, namely Individuals and Corporations, reducing order exposure leads to lower profits, which is contrary to Hypothesis $H_2$. If the typical trader in these clienteles is uninformed, this indicates that though uninformed traders hide their orders to reduce the option value that they give to other traders, they are not successful in protecting themselves from being picked off by better-informed investors. We also find that all trader clienteles make greater economic profits in stocks with high relative ticks. This is consistent with it being expensive, and hence more difficult, to front-run orders.

*D.  Hidden-Order Usage around Earnings Annoucements*

Finally, we examine the extent of hidden order usage around an exogenous information shocks, specifically around earnings announcements. We find evidence in support of our hypothesis that informed traders hide a larger proportion of their orders than uninformed traders as they do not want to reveal their private information. However, we use an ex-post measure as a proxy for the information level of traders. This could potentially lead to endogeneity problems. To address this problem, we investigate what proportion of orders submitted are hidden around an exogenous information-intensive event, specifically around earnings announcements. We compare hidden order usage around earnings announcements to that during “normal” trading periods by estimating the following panel regression with data aggregated over 30-minute intervals in each trading day:

$$HPPL_{ijt} \text{ or } HPML_{ijt} =$$
$$\beta_1 Category1_i Normal_{jt} + \beta_2 Category1_i Before_{jt} + \beta_3 Category1_i After_{jt} +$$
$$\beta_4 Category2_i Normal_{jt} + \beta_5 Category2_i Before_{jt} + \beta_6 Category2_i After_{jt} + \quad (6)$$
$$\beta_7 DepthSame_{ijt} + \beta_8 DepthOpp_{ijt} + \beta_9 Volatility_{jt} + \beta_{10} PSpread_{jt} +$$
$$\beta_{11} StkSpread_j + \beta_{12} Tick_j + \beta_{13} MktCap_j + \beta_{14} StkVolatility_j + \varepsilon,$$

where $HPPL_{ijt}$, $HPML_{ijt}$, $Category1_i$, $Category2_i$, $DepthSame_{ijt}$, $DepthOpp_{ijt}$, $Volatility_{jt}$, $PSpread_{jt}$, $StkSpread_j$, $Tick_j$, $MktCap_j$, and $StkVolatility_j$ are as defined earlier, $Normal_{jt}$ 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. If Category 1 broadly represents uninformed traders, we expect that their hidden order usage will be higher than normal in the five days before and after an earnings announcement as they aim to reduce the option value their orders present to informed traders. This suggests that the estimates of $\beta_2$ and $\beta_3$ should be greater than the estimate for $\beta_1$. If Category 2 broadly represents informed traders, we expect their hidden order usage to be higher than normal in the five days before and after an earnings announcement as they do not want to reveal their private information by displaying their entire order. We expect the estimates of $\beta_5$ and $\beta_6$ to be greater than the estimate for $\beta_4$.

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 sample period. We report coefficient estimates of equation (6), separately for PLOs and MLOs, in Table VII. For both PLOs and MLOs, estimates of $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\beta_5$, and $\beta_6$ are all positive and significant, which shows that all trader clienteles hide non-zero proportions of their orders. Our test for the equality of $\beta_1$, $\beta_2$, and $\beta_3$ fails to reject the null that they are all equal to each other. Though Category 1 traders hide non-zero proportions of their orders, the proportion of orders hidden does not change around earnings announcement. Category 1 traders do not change their order exposure strategies around earnings announcements to attempt to avoid trading with informed traders. On the other hand, for both PLOs and MLOs, we reject the null that $\beta_5$ and $\beta_6$ are equal to $\beta_4$. This suggests that financial institutions hide a larger proportion of their orders around earnings announcements than during “normal” trading periods to avoid revealing their private information. We fail to reject the null that $\beta_5$ and $\beta_6$ are equal, which implies that Category 2 traders have similar order exposure strategies just before and just after earnings announcements. These results partly support Hypothesis $H_3$. Consistent with this hypothesis, financial institutional investors (informed traders) reduce order exposure around earnings announcements in order to avoid revealing their private information. Contrary to $H_3$, we do not find evidence of uninformed traders reducing order exposure to decrease the chances of being picked off by better-informed traders.

## IV. Conclusions

This paper contributes to the debate on dark pools by investigating exchange-based hidden orders from an information perspective. We test several hypotheses and document substantial evidence on a spectrum of issues in this context.

We use a rich dataset that has coded identities of each trader, and identifies whether they are individual investors, non-financial corporations, domestic financial institutions, foreign financial institutions or others. For our market and sample, there is extremely strong evidence that financial institutions are "informed" while individuals are "uninformed". Our empirical analysis controls for the different categories of traders.

First, we use the *Hasbrouck Information Share* approach to examine the extent to which price discovery occurs because of hidden orders, and find that the mean information share of hidden orders is greater than 70%, significantly greater than that of non-hidden orders. Second, we find that, after controlling for the type of investor, traders with higher information levels are significantly more likely to hide a larger proportion of trades. Third, we determine the probability of an informed trader submitting a hidden order, and again find that informed traders are significantly more likely to submit hidden orders than uninformed traders. Fourth, we compare the economic profit of different categories of traders over our sample period and determine how hidden order submission affects these profits. We find that informed trader categories that submit hidden orders make significantly greater economic profits than those that do not. In contrast, uninformed trader categories make lower economic profits when they submit hidden orders. Finally, we examine the rate of hidden order submissions around earnings announcements, an exogenous information-intensive period, and compare them to "normal" trading periods. We find that the informed trader categories submit more hidden orders in the five days before and after the announcement when compared to the rest of the sample period, while the uninformed trader categories do not change their hidden order submission strategies around earnings announcements, again supporting the hypothesis that informed traders are more likely to submit hidden orders than uninformed traders. Overall, we present overwhelming evidence linking informed traders with the propensity for pre-trade opacity.

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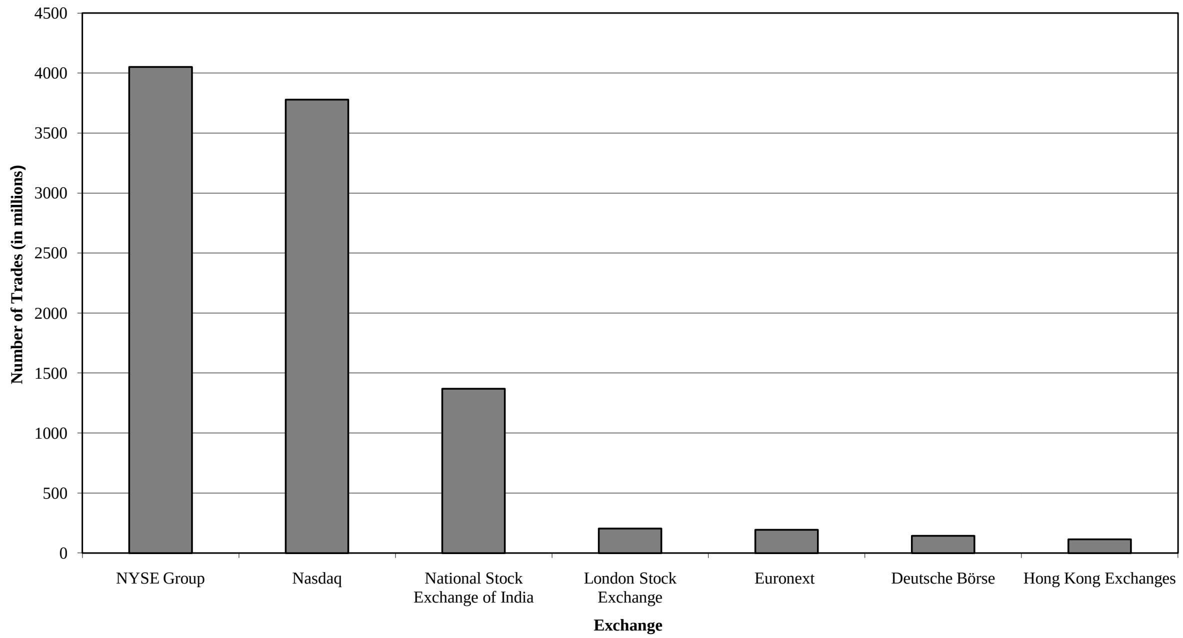


**Figure 1. Number of trades on major stock exchanges.** This figure reports the total number of trades executed on the leading stock exchanges around the world during 2008. The data are from the Annual Report and Statistics 2008 of the World Federation of Exchanges.

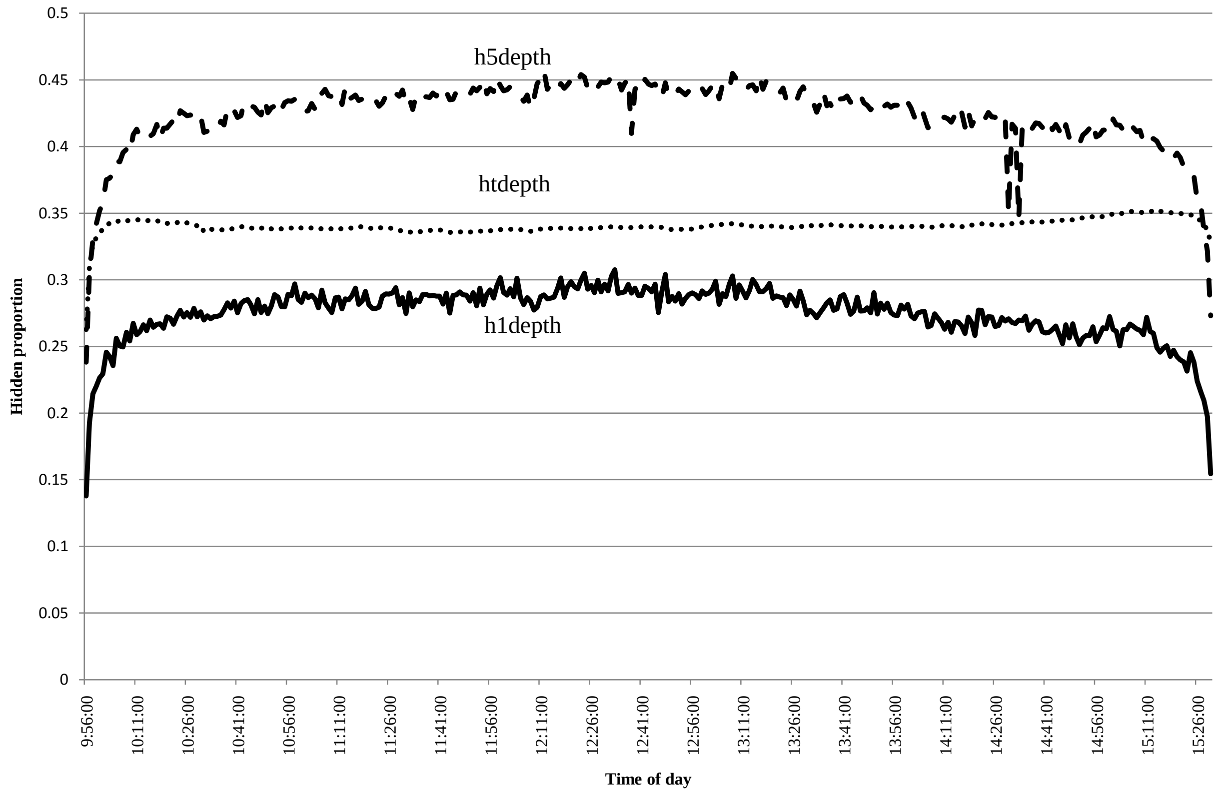


**Figure 2. Intraday variation in hidden depth.** This figures presents a plot of the intraday variation in hidden depth as a percentage of depth in the order book, using snapshots of the limit order book at the end of each minute during the trading day. *h1depth* is the percentage of hidden depth at the best quotes on either side, *h5depth* is the percentage of hidden depth at the five best quotes on either side, and *htdepth* is the percentage of hidden depth in the entire book.

## Table I
## Trader Categories

This table presents the different trader categories available with the order data from the National Stock Exchange of India. The data classifies traders into 14 different clientele categories. Based on investor characteristics, we categorize the traders into five broader trader clienteles.

| Trader category | Data coding | Broader trader category |
|---|---|---|
| Individual | 1 | Individuals |
| Hindu Undivided Family | 3 | Individuals |
| Non-Resident Indians | 11 | Individuals |
| Partnership Firm | 2 | Corporations |
| Public & Private Companies / Bodies Corporate | 4 | Corporations |
| Trust / Society | 5 | Corporations |
| Mutual Fund | 6 | Domestic Financial Institutions |
| Domestic Financial Institutions (Other than Banks & Insurance) | 7 | Domestic Financial Institutions |
| Bank | 8 | Domestic Financial Institutions |
| Insurance | 9 | Domestic Financial Institutions |
| Foreign Institutional Investors | 12 | Foreign Institutional Investors |
| Statutory Bodies | 10 | Others |
| Overseas Corporate Bodies | 13 | Others |
| Missing | 99 | Others |

**Table II**
**Sample Descriptive Statistics**

This table presents characteristics of the sample stocks comprising 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). Panel A presents the descriptive summary statistics on the order and trading characteristics of these sample stocks. Market Capitalization is the average market capitalization of the 50 stocks, measured in Indian rupees on June 30, 2006 and converted to U.S. dollars using the exchange rate on the same day. Daily Order Submissions per stock is the number of order submissions per day per stock over the entire sample period. Percentage of Orders with Hidden Component is the percentage of orders submitted daily in each stock that consists of a hidden component. Daily Turnover per stock is the average daily value traded for each of the stock, measured in Indian rupees each day and converted to U.S. dollars using the exchange rate on June 30, 2006. Percentage of Turnover with Hidden Component is the percentage of value traded daily in each stock that involves a hidden order. Daily Number of Trades per stock is the number of trades per day per stock over the entire sample period. Percentage of Trades with Hidden Component is the percentage of trades daily in each stock that involves a hidden order. Effective Spread (reported in basis points) is the unsigned difference between the traded price and prevailing mid-quote price divided by the prevailing mid-quote price, measured for each trade in our sample. Panel B reports hidden order characteristics by different trader clienteles and different order types. Pure Limit Orders are limit orders submitted at prices worse than the best opposite side price. Buy orders have prices lower than the best offered price. Similarly, sell orders have prices higher than the best bid price. Marketable Limit Orders are limit orders that equal or better the best opposite side price. Buy orders have prices that are equal to or higher than the best offered price. Sell orders have prices equal to or lower than the best bid price. Number of Orders is the total number of (Pure Limit or Marketable Limit) orders placed across all stocks over the entire sample period by each trader clientele. Value of Orders (in millions of dollars) is the size of each order multiplied by its limit price for each trader clientele and converted to U.S. dollars using the exchange rate on June 30, 2006. Number of Trades is the total number of trades across all stocks over the entire sample period for each trader clientele. Value of Trades (in millions of dollars) is the size of each trade multiplied by its trade price for each trader clientele and converted to U.S. dollars using the exchange rate on June 30, 2006. %Hidden is percentage of each characteristic (Number of Orders, Value of Orders, Number of Trades, and Value of Trades) that involves a hidden component. DFIs refer to domestic financial institutions and FIIs refer to foreign institutional investors.

Panel A. Trading characteristics

| **Characteristic** | **Mean** | **Median** | **Max** | **Min** | **Q1** | **Q3** |
|---|---|---|---|---|---|---|
| Market Capitalization (billions of dollars) | 7 | 4 | 38 | 1 | 3 | 7 |
| Daily Order Submissions per stock | 24,907 | 18,334 | 94,355 | 4,210 | 9,142 | 35,345 |
| Percentage of Orders with | 9 | 9 | 17 | 4 | 7 | 11 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Hidden Component | | | | | | |
| Daily Turnover per stock (millions of dollars) | 21 | 13 | 159 | 1 | 6 | 25 |
| Percentage of Turnover with Hidden Component | 33 | 33 | 61 | 14 | 26 | 38 |
| Daily Number of Trades per stock | 19,121 | 12,710 | 70,129 | 2,870 | 6,597 | 24,390 |
| Percentage of Trades with Hidden Component | 42 | 41 | 65 | 20 | 35 | 48 |
| Effective Spread (basis points) | 3 | 3 | 8 | 2 | 3 | 4 |

Panel B. Hidden order characteristics

| | | Orders | | | | Trades (Executed Orders) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Number of Orders | | Value of Orders (in millions of dollars) | | Number of Trades | | Value of Trades (in millions of dollars) | |
| | **Trader Clientele** | Total | %Hidden | Total | %Hidden | Total | %Hidden | Total | %Hidden |
| **Pure Limit Orders** | Individuals | 28,822,641 | 4.45 | 39,266 | 15.74 | 17,886,264 | 4.03 | 19,870 | 15.65 |
| | Corporations | 15,040,476 | 16.81 | 62,578 | 21.63 | 8,733,184 | 15.86 | 19,316 | 24.31 |
| | DFIs | 124,811 | 56.77 | 4,027 | 68.06 | 88,999 | 62.59 | 2,909 | 69.03 |
| | FIIs | 155,560 | 66.43 | 7,707 | 67.65 | 125,237 | 70.41 | 5,844 | 67.37 |
| | Others | 4,049,701 | 6.28 | 8,694 | 16.97 | 2,496,821 | 5.80 | 3,239 | 20.93 |
| | Total | 48,193,189 | 8.79 | 122,273 | 23.84 | 29,330,505 | 8.16 | 51,178 | 28.19 |
| | | | | | | | | | |
| **Marketable Limit Orders** | Individuals | 19,402,606 | 1.68 | 23,711 | 10.83 | | | | |
| | Corporations | 7,081,944 | 4.14 | 25,891 | 12.03 | | | | |
| | DFIs | 203,158 | 44.40 | 6,481 | 69.89 | | | | |
| | FIIs | 532,320 | 49.95 | 19,170 | 70.55 | | | | |
| | Others | 2,288,956 | 1.95 | 3,693 | 12.26 | | | | |
| | Total | 29,508,984 | 3.45 | 78,946 | 30.64 | | | | |

**Table III**
**Information Share of Hidden Orders**

This table presents summary statistics of the Hasbrouck Information Share calculated for 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). We determine two price series for each day for each stock: one for hidden orders and one for non-hidden orders. For hidden orders, we use the one-minute mid-quote price series obtained from orders that are not fully displayed. For non-hidden orders, we use the one-minute mid-quote price series obtained from orders that are fully displayed. The lower and upper bounds for information share on each day for each stock are computed for each of the two price series. The midpoint of the lower and upper bounds is calculated and the summary statistics of the resulting midpoints are reported in the table. The information shares are expressed in percentages.

| | **Information Share** | |
|---|---|---|
| | **Hidden orders** | **Non-hidden orders** |
| Mean | 71.32 | 28.68 |
| Median | 79.51 | 20.49 |
| Max | 92.66 | 75.42 |
| Min | 24.58 | 7.34 |
| Q1 | 58.12 | 13.45 |
| Q3 | 86.55 | 41.88 |
| Std. Dev. | 19.04 | 19.04 |

**Table IV**
**Information Level**

Results are based on 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). Panel A reports summary statistics of Information Level for the different trader clienteles. We calculate the Information Level over time intervals: 5 minutes, 30 minutes, 60 minutes, and 1 day. For a buy order, the Information Level is the total order size multiplied by the quote midpoint 5, 30, 60 minutes or 1 day after order submission divided by the quote midpoint at order submission minus one. For a sell order, the Information Level is the total order size multiplied by one minus the quote midpoint 5, 30, 60 minutes, or 1 day after order submission divided by the quote midpoint at order submission. The results are reported separately for Pure Limit Orders and Marketable Limit Orders. Pure Limit Orders are limit orders submitted at prices worse than the best opposite side price. Buy orders have prices lower than the best offered price. Similarly, sell orders have prices higher than the best bid price. Marketable Limit Orders are limit orders that equal or better the best opposite side price. Buy orders have prices that are equal to or higher than the best offered price. Sell orders have prices equal to or lower than the best bid price. DFIs refer to domestic financial institutions and FIIs refer to foreign institutional investors. Panel B reports coefficient estimates, t-statistics, and p-value of the following panel regression:

$$HPPL_{ijt} \text{ or } HPML_{ijt} \text{ or } HP_{ijt} =$$
$$\beta_1 Category1_i + \beta_2 Category2_i + \beta_3 Category1_i \times InfoLevel1day_{ijt} + \beta_4 Category2_i \times InfoLevel1day_{ijt} + \beta_5 DepthSame_{ijt}$$
$$+ \beta_6 DepthOpp_{ijt} + \beta_7 Volatility_{jt} + \beta_8 PSpread_{jt} + \beta_9 StkSpread_j + \beta_{10} Tick_j + \beta_{11} MktCap_j + \beta_{12} StkVolatility_j + \varepsilon,$$

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 $t$, $HP_{ijt}$ is the proportion of the value of all limit orders 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, $InfoLevel1day_{ijt}$ is the Information Level (defined earlier) over the 1 day following order submission for trader category $i$ for stock $j$ over time interval $t$, $DepthSame_{ijt}$ 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.

Panel A. Information level by trader categories

| | Information Level by time horizon | | | |
|---|---|---|---|---|
| | 5-minute | 30-minute | 60-minute | 1-day |
| Trader Clientele | Pure Limit Orders | | | |
| Individuals | 0.0002 | 0.0001 | 0.0001 | 0.0005 |
| Corporations | 0.0011 | 0.0009 | 0.0009 | 0.0008 |
| DFIs | 0.0123 | 0.0251 | 0.0319 | 0.0556 |
| FIIs | 0.0101 | 0.0185 | 0.0373 | 0.0134 |
| Others | 0.0007 | 0.0007 | 0.0006 | 0.0005 |
| | Marketable Limit Orders | | | |
| Individuals | 0.0005 | 0.0005 | 0.0003 | -0.0002 |
| Corporations | 0.0015 | 0.0016 | 0.0015 | 0.0043 |
| DFIs | 0.0508 | 0.0605 | 0.0521 | 0.0881 |
| FIIs | 0.0358 | 0.0653 | 0.0908 | 0.0882 |
| Others | 0.0010 | 0.0009 | 0.0007 | 0.0003 |

Panel B. Determinants of hidden proportion of limit orders

| Dependent Variable: | Pure Limit Orders: HPPL | | | Marketable Limit Orders: HPML | | | All orders, except market orders: HP | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | t-stat | p-value | Estimate | t-stat | p-value | Estimate | t-stat | p-value |
| *Category1* | 0.3167 | 195.07 | 0.0000 | 0.1368 | 94.20 | 0.0000 | 0.2202 | 161.36 | 0.0000 |
| *Category2* | 0.7251 | 409.28 | 0.0000 | 0.6801 | 443.50 | 0.0000 | 0.7034 | 492.75 | 0.0000 |
| *Category1× InfoLevel1day* | 0.0001 | 0.10 | 0.9165 | -0.0001 | -0.40 | 0.6907 | -0.0002 | -0.29 | 0.7755 |
| *Category2× InfoLevel1day* | 0.0000 | 2.17 | 0.0296 | 0.0000 | 5.67 | 0.0000 | 0.0000 | 3.78 | 0.0002 |
| *DepthSame* | 0.0000 | 0.38 | 0.7022 | 0.0001 | 2.94 | 0.0032 | 0.0000 | 1.33 | 0.1820 |
| *DepthOpp* | 0.0000 | -1.10 | 0.2718 | 0.0002 | 4.62 | 0.0000 | 0.0001 | 2.75 | 0.0060 |
| *Volatility* | -0.0699 | -12.58 | 0.0000 | -0.0034 | -0.68 | 0.4973 | -0.0277 | -6.00 | 0.0000 |
| *PSpread* | -0.0104 | -5.51 | 0.0000 | -0.0032 | -1.91 | 0.0564 | -0.0053 | -3.33 | 0.0009 |
| *StkSpread* | -0.0195 | -19.78 | 0.0000 | -0.0086 | -9.78 | 0.0000 | -0.0118 | -14.49 | 0.0000 |
| *Tick* | -0.0365 | -36.87 | 0.0000 | -0.0147 | -16.86 | 0.0000 | -0.0243 | -29.81 | 0.0000 |
| *MktCap* | -0.0189 | -19.81 | 0.0000 | 0.0034 | 4.04 | 0.0001 | -0.0061 | -7.64 | 0.0000 |
| *StkVolatility* | -0.0172 | -17.47 | 0.0000 | -0.0012 | -1.43 | 0.1530 | -0.0083 | -10.17 | 0.0000 |

**Table V**
**Likelihood of Hidden Order Submission by Informed Trader**

Results are based on 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 presents coefficient estimates, t-statistics, p-values, and marginal probabilities of the following order-by-order logistic regression:

$$\Pr(Hidden\ order) = \beta_1 Category1 + \beta_2 Category2 + \beta_3 Category1 \times InfoLevel1day + \beta_4 Category2 \times InfoLevel1day + \beta_5 PriceAgg$$
$$+ \beta_6 LnSize + \beta_7 PSpread + \beta_8 LnVolume + \beta_9 LnNOT + \beta_{10} DepthSame + \beta_{11} DepthOpp + \beta_{12} TransVol + \beta_{13} StkSpread$$
$$+ \beta_{14} MktCap + \beta_{15} Tick + \beta_{16} StkVolatility + \varepsilon,$$

where *Category1* takes value 1 if the order is placed by an individual investor, corporation, or others and 0, otherwise, *Category2* takes value 1 if the order is placed by a domestic financial institution or foreign institutional investor and 0, otherwise, *InfoLevel1day* is the Information Level for the order over a 1-day period after order submission, *PriceAgg* is a measure of price aggressiveness of the order, measured as one minus two times the difference between the offered price at order submission and limit price of the order divided by the quoted spread at order submission for buy orders and two times the difference between the offered price at order submission and limit price of the order divided by the quoted spread at order submission minus one for sell orders, *LnSize* is the natural logarithm of the total order size submitted, *PSpread* is the prevailing percentage quoted spread at order submission, *LnVolume* is the natural logarithm of the number of shares traded over the 5-minute interval prior to order submission, *LnNOT* is the natural logarithm of the number of trades over the 5-minute interval prior to order submission, *DepthSame* is the displayed depth at the five best prices on the same side as the order at the time of order submission, *DepthOff* is the displayed depth at the five best prices on the side opposite the order at the time of order submission, *TransVol* is a measure of transitory volatility and measured as the standard deviation of the last 300 trade price changes, *StkSpread* is the average quote spread, taken at one-minute intervals, over the entire sample period for each sample stock, *Tick* is the inverse is the average traded price over the sample period for each sample stock, *MktCap* is the market capitalization of each stock at the end of the sample period (June 30, 2006), and *StkVolatility* is the standard deviation of the natural logarithm of daily gross returns for stock taken over the entire sample period. The marginal probabilities are calculated at the means of all the non-dummy explanatory variables.

| | Pure Limit Orders: Pr(Hidden order) | | | | Marketable Limit Orders: Pr(Hidden order) | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | t-stat | p-value | Marginal probability | Estimate | t-stat | p-value | Marginal probability |
| *Category1* | -0.904 | 17414.38 | 0.000 | -0.8333 | -2.907 | 61961.46 | 0.000 | -0.2054 |
| *Category2* | 1.464 | 27302.08 | 0.000 | 0.1034 | -0.360 | 837.44 | 0.000 | -0.0254 |
| *Category1*× *InfoLevel1day* | 0.000 | 0.12 | 0.727 | 0.0000 | 0.000 | 8.58 | 0.003 | -0.0002 |
| *Category2*× | 0.000 | 1566.43 | 0.000 | 0.0026 | 0.000 | 94.05 | 0.000 | 0.0009 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *InfoLevel1day* | | | | | | | | |
| *PriceAgg* | 0.001 | 6354.45 | 0.000 | 0.0053 | -0.001 | 1494.29 | 0.000 | -0.0014 |
| *LnSize* | 0.170 | 217000.20 | 0.000 | 0.0270 | 0.464 | 390429.26 | 0.000 | 0.0306 |
| *PSpread* | 0.012 | 140.46 | 0.000 | 0.0008 | 0.013 | 58.72 | 0.000 | 0.0004 |
| *LnVolume* | -0.083 | 3465.85 | 0.000 | -0.0087 | -0.304 | 16317.66 | 0.000 | -0.0134 |
| *LnNOT* | -0.203 | 13841.74 | 0.000 | -0.0157 | 0.083 | 816.64 | 0.000 | 0.0027 |
| *DepthSame* | 0.046 | 7099.93 | 0.000 | 0.1707 | 0.001 | 28.44 | 0.000 | 0.0009 |
| *DepthOpp* | 0.032 | 4303.56 | 0.000 | 0.0636 | 0.002 | 135.64 | 0.000 | 0.0019 |
| *TransVol* | 0.000 | 0.13 | 0.724 | 0.0000 | 0.015 | 151.22 | 0.000 | 0.0004 |
| *StkSpread* | -0.025 | 1515.47 | 0.000 | -0.0026 | -0.012 | 130.11 | 0.000 | -0.0005 |
| *MktCap* | -0.081 | 10865.50 | 0.000 | -0.0072 | -0.032 | 661.99 | 0.000 | -0.0012 |
| *Tick* | 0.181 | 48475.69 | 0.000 | 0.0152 | -0.064 | 1667.64 | 0.000 | -0.0023 |
| *StkVolatility* | -0.081 | 9238.06 | 0.000 | -0.0063 | -0.050 | 1386.74 | 0.000 | -0.0017 |

## Table VI
## Economic Profits Earned by Hidden Order Trader Clienteles

Results are based on 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). The profits of each individual trader over the sample period are tracked. For each trader in the sample (identified by a unique combination of trading member and client member codes), the economic profit in a given stock is the difference between the price at which she sells the shares in the stock and the price at which she buys the shares in the stock. If a trader only sells shares of a stock during the sample period, her starting position is valued using the opening quote midpoint at the beginning of the sample period. Similarly, if a trader only buys shares of a stock during the sample period, we value her ending position using the closing quote midpoint at the end of the sample period. The data is aggregated as follows. For each of the five trader clienteles, the traders are sorted based on their economic profit from lowest to highest. The clients are divided in percentiles groups (a total of 100 groups) based on their economic profit for each stock. The average economic profit per clientele within each of the percentile groups for each stock is calculated. The following cross-sectional regression is separately estimated for each of the five trader clienteles as well as all trader clienteles pooled together:

$$EProfit_{ij} = \beta_0 + \beta_1 HP_{ij} + \beta_2 StkSpread_j + \beta_3 MktCap_j + \beta_4 Tick_j + \beta_5 StkVolatility_j + \varepsilon,$$

where $EProfit_{ij}$ is the average economic profit of the $i^{th}$ percentile of traders for stock *j*, $HP_{ij}$ is the mean proportion of order value that is hidden by the $i^{th}$ percentile of traders for stock *j*, $StkSpread_j$ 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. All variables are standardized. The coefficient estimates and their associated t-statistics are reported in the table. DFIs refer to domestic financial institutions and FIIs refer to foreign institutional investors.

| Dependent Variable: EProfit | Individuals | | Corporations | | DFIs | | FIIs | | Others | | All | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat | Estimate | t-stat |
| Intercept | -0.06 | -2.28 | 0.06 | 5.52 | -0.19 | -6.78 | -0.28 | -11.71 | 0.1 | 5.78 | 0 | 0.53 |
| hp | -0.25 | -7.68 | -0.11 | -7.17 | 0.07 | 3.21 | 0.1 | 5.39 | 0 | 0.1 | -0.08 | -12.54 |
| mkap | 0.06 | 5.19 | 0.07 | 5.72 | 0.16 | 9.16 | 0.14 | 7.57 | 0.06 | 5.54 | 0.1 | 15.27 |
| tick | 0.05 | 4.05 | 0.05 | 4 | 0.15 | 8.48 | 0.12 | 6.36 | 0.05 | 4.16 | 0.08 | 12.39 |
| volatility | -0.14 | -11.84 | -0.14 | -11.37 | -0.18 | -9.94 | -0.27 | -14.49 | -0.14 | -12.01 | -0.17 | -26.25 |
| spread | 0.02 | 1.75 | 0.02 | 1.56 | 0.07 | 3.82 | 0.02 | 1.04 | 0.03 | 2.26 | 0.03 | 5.03 |
| Adj. $R^2$ | 0.05 | | 0.04 | | 0.05 | | 0.07 | | 0.04 | | 0.05 | |
| No. of Obs | 4,999 | | 5,000 | | 4,925 | | 4,332 | | 4,999 | | 24,255 | |

**Table VII**
**Hidden Order Usage by Different Trader Clienteles 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.

Panel A. Regression estimates

| | Pure Limit Orders: HPPL | | | Marketable Limit Orders: HPML | | |
|---|---|---|---|---|---|---|
| Variable | 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

| | Pure Limit Orders | | Marketable Limit Orders | |
|---|---|---|---|---|
| Test | 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 |