Order Exposure in High Frequency Markets

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ABSTRACT

We examine hidden orders usage by algorithmic traders (ATs) and non-ATs. ATs extensively use hidden orders but of smaller size than non-ATs, who are the primary contributors to hidden volume. ATs' relative share of hidden volume decreases with volatility, adverse selection costs, and the relative tick-size. Proprietary ATs (HFTs), who differ from agency ATs (AATs) in their information sets and potential gains from trade, hide orders to reduce competition for liquidity provision, whereas AATs use hidden orders to conceal information in their more informed orders and manage picking off risk. Finally, superior technology provides limited benefit for hidden order execution.

Keywords: Hidden orders; transparency; high frequency trading; order exposure

JEL Classification: G11; G12; G14; G15, G24

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I. Introduction

Stock exchanges allow traders to hide their orders. Reserve (or 'iceberg') orders are more prevalent in Europe and the Asia-Pacific (e.g., Australia, India, France, Spain) while fully hidden orders are more common in North America (e.g., NYSE, Nasdaq, TSX). Hidden orders are not new in financial markets, but their usage is increasing. For instance, in the US, the share of hidden volume grew from 15% to 50% between 2012 and 2021.[1]

Despite the growing opacity, little is known about how it relates to the recent rise in algorithmic trading (AT). We use message level data from the National Stock Exchange of India (NSE) identifying algorithmic versus manual orders to examine hidden order usage by algorithmic traders (ATs) and non-ATs (NATs). ATs are faster and more technologically sophisticated traders, allowing ATs vs. NATs comparison to provide insights into how technology influences order exposure.

Within ATs, agency algorithms facilitate institutional clients building or liquidating positions based on longer-lived information and liquidity/hedging needs while proprietary algorithms maximize short-run trading revenues based on speed and public information (SEC, 2010).[2] Although agency ATs (AATs) and proprietary ATs (HFTs) share similar technology (O'Hara (2015)), they differ in their incentives to provide liquidity (Li, Wang, and Ye (2021)) and to hide volume in the order book. Our data allow distinguishing between AATs and HFTs and therefore comparing how differing information and holding periods affect order exposure.

The order exposure decision has been primarily studied prior to algorithmic trading's rise. Conceptually, our novel contribution is in studying the exposure decision by different trader types.

[1] https://www.sec.gov/marketstructure/datavis/ma_exchange_hiddenvolume.html#.YdInemjMKwh
[2] We discuss the differences between agency ATs and proprietary ATs in more detail in Appendix A.

Our most novel finding is that, despite their advanced technology, AATs extensively use hidden orders, mirroring what the existing literature has observed about NATs. Meanwhile, HFTs, who have similar technology differ in that they make little use of hidden orders, except when undercutting the best quote. These results are consistent with the interaction of technology and trading strategies playing an important role in traders' order exposure decision.

Order exposure involves a trade-off. Displayed orders gain priority and attract contra-side orders but risk being undercut, picked off by faster traders, and exploited by parasitic traders. *Exposure risk theory* (Harris (1997), Buti and Rindi (2013)) posits that uninformed traders hide orders to reduce the inherent option value of the orders by creating uncertainty about book depth. Supporting this theory, De Winne and D'Hondt (2007) and Bessembinder, Panayides and Venkataraman (2009) find that the use of HLOs increases with order aggressiveness and size, greater depth on the opposite side (picking off risk), and wider spreads (adverse selection costs). Pardo and Pascual (2012) find that hidden volume increases with volatility, while Chakrabarty and Shaw (2008) find greater hidden order use in times of heightened adverse selection.

Conversely, *information-revelation theory* (Moinas (2010), Boulatov and George (2013)) suggests that informed traders use hidden volume to preserve their information advantage by limiting leakage. In line with this theory, Anand and Weaver (2004), Belter (2007), and Yao (2017) find informational content in hidden depth, whereas Gozluklu (2016) and Bloomfield, O'Hara, and Saar (2015) find that informed traders in experimental settings use HLOs.

We hypothesize that traders weigh these costs differently based on their technological capabilities, information access, and trading horizons, which motivates us to investigate the extent to which, and for what purposes, HFTs, AATs, and NATs hide orders. Our main research questions are as follows: Do ATs contribute to hidden volume? Within ATs, do AATs and HFTs differ in their use of hidden orders? Which of the existing theoretical rationales better explains ATs' order exposure decisions? Finally, does superior trading technology enable more efficient use of hidden orders?

We find that NATs are the primary contributors to hidden volume, consistent with technology and speed helping ATs better manage their order exposure risk (e.g., Hoffmann, 2014). Nevertheless, ATs substantially (34%) contribute to hidden volume, driven primarily by AATs; HFTs account for only 3%. Notably, ATs leverage technology to place many smaller HLOs, with 54% of HLOs submitted by AATs and only 7% by HFTs. This is consistent with ATs trading in smaller sizes (O'Hara, Yao, and Ye (2014)) and hidden volume aligning better with the long-term oriented AATs rather than with HFTs, whose strategies prioritize speed (e.g., Baron et al., 2019).

Stock characteristics and market conditions impact the costs and benefits of order exposure. When volatility and adverse selection costs are high, the option value of limit orders increases, leading to more hidden volume. Consistent with ATs being better equipped to manage the free option risk of their limit orders (e.g., Bongaerts and Van Achter (2021)), ATs decrease hidden volume usage relative to NATs in stocks with higher volatility and adverse selection. Moreover, when the relative tick size is smaller and the risk of being undercut is higher, ATs' contribution to hidden volume increases. Specifically, AATs' (HFTs') share of hidden volume rises from 26.5% (0.66%) for stocks with larger relative tick size to 48.7% (7%) for stocks with smaller relative tick size. This aligns with ATs placing more aggressive orders where undercutting is a larger risk and hiding those orders to manage that risk (Harris (1997), Buti and Rindi (2013)). In this regard, HFTs are the most aggressive HLO users, with 55% of their HLOs undercutting the prevailing best quotes, compared to 15% for AATs.

Agency algorithms mainly cater to institutions, who often trade on private information (e.g., Boulatov, Hendershott and Livdan (2013)), whereas HFTs trade on public signals. Therefore, in line with the information revelation theory, AATs are more likely to use HLOs to prevent leakage of information than HFTs. Consistently, we find that HFTs' hidden orders have lower price impact than their displayed orders, while the reverse is true for AATs. Additionally, hidden depth in the limit order book predicts next one-minute returns, but only for AATs and NATs.

All limit orders face the risk of being picked off by traders with new information. Moreover, leveraging speed and real-time market data monitoring, HFTs capitalize on public information, increasing the exposure risk for slower traders (Biais, Foucault, and Moinas (2015)), and even other HFTs (Aquilina, Budish, and O'Neill (2022)). Therefore, according to exposure risk theory, all traders should use more HLOs when facing heightened picking-off risk and during periods of intense aggressive trading by HFTs. On the other hand, high-frequency market makers compete to gain price priority and capitalize on fleeting profit opportunities in market making, such as unusually wide spreads (Foucault, Kadan, and Kandel (2013)). In Buti and Rindi's (2013) model, market makers increase their use of HLOs when facing a higher risk of being undercut and to undercut competitors in supplying liquidity. Accordingly, we expect HFT firms acting as endogenous liquidity providers (e.g., Anand and Venkataraman (2016)) to hide more orders as undercutting risk rises.

We model the likelihood of hiding an order as a function of both the perceived risks of being picked off and undercut. We find robust positive association between picking off risk and the use of HLOs, particularly for ATs. NATs, whose monitoring capabilities are inferior, manage their picking-off risk by passively hiding large orders. Both AATs and NATs hide more orders when HFTs on the opposite side actively take liquidity. Moreover, HFTs use more HLOs when undercutting risk is higher, and they engage in low-latency undercutting using more hidden than displayed orders.

ATs' higher usage of HLOs relative to NATs' could be driven by technology enabling more efficient use of HLOs. Following Bessembinder et al. (2009), we analyze this using three interconnected dimensions of HLO execution quality: likelihood of execution, time-to-completion, and execution costs. We find little difference in the likelihood of execution between ATs and NATs after controlling for order attributes (aggressiveness and size) and very short-lived orders. The time to completion statistically favors ATs over NATs, but only by about one second. HFTs have a significantly lower implementation shortfall. When dissected into components, we show that HFTs' more aggressive HLOs lead to a higher effective cost of execution, but HFTs' less informed HLOs lead to a lower opportunity cost of non-execution. AATs' HLOs exhibit lower effective execution costs but higher opportunity costs of non-execution compared to NATs' HLOs, indicating that superior technology does not necessarily lead to better management of information leakage. Overall, we find no significant differences in the implementation shortfall between AATs' and NATs' HLOs.

Our study fits at the intersection of two important trends in financial markets – opacity and algorithmic trading. While the growth of algorithmic trading as well as increasing opacity have been accompanied by media commentaries and regulatory discussions, academic research has not systematically connected the theories of order exposure or tested how trading speed associates with this development. We show that ATs make substantial use of hidden orders. While all traders hide to lower their picking off risk, AATs also hide informed orders to prevent information leakage. Consistent with a lack of long-lived private information, HFT make relatively little use of hidden orders, except to limit undercutting when competing for liquidity supply.

II. Theories of order exposure

The existing literature examines traders' limit order exposure decisions depending on how other traders can take advantage of exposed orders. Exposure risk imposes costs on exposed orders if faster and better-informed traders adversely select those orders. If exposed orders reveal information, then other traders' reactions, e.g., repricing their orders, can reduce the value of the information. We outline the literature on both these theories before describing how we structure our empirical hypotheses.

A. The exposure (or free option) risk theory

Limit orders are free options to the counterparty (Copeland and Galai (1983)) and risk executing 'in the money' when exploited by faster (Biais et al. (2015)) or better-informed traders. The free option risk increases with order size, aggressiveness, time in the book, and volatility, which can be mitigated through active monitoring. If monitoring costs are high (Foucault, Roëll, and Sandas (2003)), a trader may place the order away from the best quotes, which raises the opportunity cost of non-execution. Alternatively, she can hide the order while still placing it close to the best quotes (e.g., De Winne and d'Hondt (2007), Bessembinder et al. (2009)).

Displaying an order exposes it to free riding. Harris (1997) suggests that uninformed traders may hide their orders to prevent such friction and shows that hidden volume decreases with the relative tick size, consistent with larger tick sizes protecting against parasitic trading. A larger tick size may also prevent predation by fast traders (Cox, Van Ness, and Van Ness (2019)). Order display may also alter the submission strategies of other traders, reducing the likelihood of execution at the posted price, and compelling the submitter to accept less favorable prices. Reserve orders can counter such adverse price impacts. By specifying a small visible part ('peak') of the order, the trader reduces this risk but prolongs the time to execution (Esser and Mönch (2007)). Empirical studies (e.g., Frey and Sandas (2009), Pardo and Pascual (2012)) show that when reserve orders are detected, traders on the opposite side aggressively respond by using matching market orders. Thus, reserve orders allow large traders to attract liquidity demand, while limiting their own price impact.

In Buti and Rindi's (2013) model, uninformed traders incur exposure costs in the form of undercutting. To mitigate this friction, traders endogenously choose the peak size that prevents undercutting. Here, the option to hide is more valuable when liquidity provision is more competitive. Aitken, Berkman and Mak (2001) confirm this prediction by showing more HLO usage when the relative tick size (undercutting cost) is lower.

B. The information revelation theory

Under the information-revelation theory, informed traders use hidden volume to mitigate information leakage. Boulatov and George (2013) examine the effect of allowing HLOs on market quality when informed traders must decide whether to make or take liquidity. When hiding is not allowed, they demand liquidity, imposing higher costs on uninformed traders, but when hiding is allowed, they supply liquidity which enhances market quality.

Moinas (2010) illustrates how HLOs expand the opportunity set of informed traders. In her model, informed liquidity providers hide orders to obscure their presence to uninformed liquidity takers, who may otherwise refuse to trade, especially when information asymmetry risk is high. Uninformed traders also hide, not to manage the option value of their limit orders, since they face no picking off risk as informed traders in Moinas' model do not trade aggressively, but to avoid being taken as informed traders. Thus, both types of traders hide for the same reason, which is decreasing the informational impact of their limit orders.

Since hidden orders may be information-motivated, revealing them should have an informational impact. Evidence on this is mixed, some studies reporting no price impact of hidden volume execution (e.g., De Winne and D'Hondt (2007), Pardo and Pascual (2012)), while others finding informational content in hidden depth (e.g., Anand and Weaver (2004), Belter (2007)). Using experimental markets, Gozluklu (2016) finds that informed traders compete for liquidity provision with uninformed traders, and both use HLOs, whereas Bloomfield et al. (2015) find that the informed traders trade less aggressively when the market is opaque.

III. Hypotheses development

Traders' motives and the technology they employ shape their reasons for using hidden volume, while their ability to hide effectively determines the extent to which they rely on hidden orders. We next map the theories of order exposure into explicit hypotheses. These hypotheses relate to the contribution to hidden volume, the underlying motivations for hiding orders, and the efficiency of hidden order usage across our trader types: NATs, AATs, and HFTs.

A. On the relative use of hidden volume

Faster technology and low-cost monitoring lower exposure risk (e.g., Bongaerts and Van Achter (2021)). Additionally, exposure risk decreases with order size. Given that HFTs use small-sized aggressive limit orders (O'Hara et al. (2014)) and AATs split their large orders into smaller ones (Foucault and Menkveld (2008)), ATs are likely to have less incentive to hide their orders than NATs. Furthermore, patient traders who prioritize execution quality over speed may benefit the most from HLOs (Bessembinder et al. (2009)). Consequently, the option to hide orders could hold greater value for AATs than for HFTs. Based on this reasoning, we hypothesize:

H1: ATs (HFTs) contribute less hidden volume than NATs (AATs) and do so through hidden orders of smaller average size.

The use of hidden volume may vary depending on market conditions. Under the exposure risk theory, hidden volume should increase with fundamental volatility (Harris (1997)). However, it is unclear whether algorithms respond more effectively to volatility. Anand and Venkataraman (2016), Kirilenko et al. (2017), and Brogaard et al. (2018) report that ATs reduce liquidity provision under unfavorable market conditions. In contrast, Brogaard, Hendershott, and Riordan (2014) and Chakrabarty and Pascual (2023) find that ATs facilitate price discovery and do not disproportionately withdraw liquidity during periods of high volatility.

Conversely, a larger tick size may decrease hidden volume by discouraging parasitic trading (Harris (1997)), undercutting (Buti and Rindi (2013)), and the submission of large orders by liquidity demanders (Moinas (2010)). Additionally, when spreads are tick-constrained, liquidity providers compete on size rather than price (O'Hara, Saar and Zhong (2019)), resulting in longer queues that may discourage hidden volume. Theory suggests that ATs' strategies are likely to be more sensitive to tick size than NATs'. Speed competition in liquidity provision could incentivize HFTs to use HLOs when the spread is not tick-constrained (Buti and Rindi (2013)). In contrast, when the tick size binds the spread, HFTs lack the incentive to use HLOs because, once they secure a top queue position leveraging their superior speed, there is no risk of being undercut (Li et al. (2021)). Finally, smaller tick sizes may enable anticipatory HFT strategies that impose adverse selection costs on AATs by undercutting their orders (Hirschey (2021)).[3] AATs could mitigate these higher costs by hiding their orders. Based on these arguments, we hypothesize that:

H2: NATs contribute more hidden volume when volatility is high, while ATs contribute more hidden volume when the relative tick size decreases.

B. On the reasons for using hidden volume

Agency algorithms primarily serve institutional traders (Hagströmer and Norden (2013)), who are known to trade based on fundamental information, often utilizing limit orders to optimize execution (Boulatov and George (2013), Hendershott, Lidvan, and Schürhoff (2015)). In contrast, NATs may be seen as less sophisticated due to their lack of advanced trading technology. Notably, Nawn and Barnerjee (2021) estimate that retail traders account for approximately 70% of NATs' trading volume on the NSE. However, recent evidence suggests that the order flow of these unsophisticated traders may carry valuable information (see, e.g., Barber, Odean, and Zhu (2009), Barardehi, Bernhart, Da, and Warachka (2022), Boehmer, Jones, Zhang, and Zhang (2021), and Farrell, Green, Jame, and Markov (2022)).

O'Hara (2015) notes that in sub-second horizons, informed trading is based on faster reactions to events, making HFTs informed traders. However, speed competition is fierce, and low-latency arbitrage strategies mainly involve liquidity-taking (Baldauf and Mollner (2020)). As for HF-MMs, their quotes incorporate public signals swiftly (Hoffmann (2014)), impacting hidden and displayed orders, with limited effect on exposure decisions. Thus, we expect the information revelation theory to be less applicable to HFTs than to AATs and propose the following:

[3] For instance, HFTs may undercut AATs' orders to interact with orders they expect less likely to be informed (Ready (1999)), to realize unusually wide spreads (Foucault et al. (2013)), or in response to public signals they process faster (O'Hara et al. (2019)). Thus, AATs' orders execute only when it is less advantageous.

H3: NATs' and AATs' HLOs convey more information than their displayed orders. In contrast, the HLOs of HFTs convey less information than their displayed orders and the HLOs of other traders.

According to the exposure risk theory, hidden volume tends to increase with the risk of being picked off, particularly for long-term uninformed traders (Bessembinder et al. (2009)). While technology can mitigate exposure risk, HF-MMs still face adverse selection (Menkveld (2013)), and their quotes are often picked off by opportunistic HFTs (Aquilina et al. (2022)). Thus, whether HFTs use HLOs to mitigate picking-off risk is an open question. We hypothesize:

H4: For all trader types, the likelihood of hiding an order increases with the ex-ante risk of being picked off.

Competition among HF-MMs manifests in the form of aggressive quoting and undercutting to attain price priority (Li et al. (2021)). According to Buti and Rindi (2013), the option to conceal volume should hold greater value for market makers when price competition in liquidity supply is intense. Since market making is the most prevalent common strategy among HFT firms (Boehmer, Li, and Saar (2018)), we hypothesize that:

H5: HFTs hide limit orders in anticipation of heightened price competition. When undercutting, HFTs prefer using HLOs over displayed orders.

C. On the efficient use of HLOs

Technology reduces monitoring and execution costs (Hendershott and Riordan (2013)), accelerates responses to market signals (Shkilko and Sokolov (2020)), enhances profitability (Baron et al. (2019)), improves return predictability (Subrahmanyam and Zheng (2016)), and aids in order anticipation (Hirschey (2021)). Moreover, liquidity providers weigh the execution costs against the opportunity costs of non-execution. As hypothesized, HFTs are likely to place their hidden limit orders (HLOs) within the best quotes to undercut others and gain price priority (H5). Consequently, we expect the effective execution costs of HFTs' HLOs to exceed those of other trader types. However, we also predict that HFTs' HLOs convey less information (H3), which could result in lower opportunity costs of non-execution compared to other traders' HLOs. The relative dominance of these effects remains uncertain. Building on these insights, we hypothesize that:

> **H6:** The execution quality of ATs' HLOs is higher than that of NATs. HFTs' HLOs exhibit higher costs of execution but lower opportunity costs of non-execution than other traders' HLOs.

IV. Data

With over 80% of the total volume, the NSE is the dominant market for its 1300+ listed stocks.[4] It is a fully order driven market that allows reserve orders with a mandatory minimum exposure of 10% of the original volume. Once the first tranche is executed, the next tranche of the same size is automatically displayed. The market operates on price-exposure-time priority whereby non-displayed volume loses time priority to displayed volume at the same price. Thus, the design of the NSE is very similar to Euronext.[5]

The NSE market provides an advantageous setting to study the use of HLOs. First, India has no dark pools, meaning traders who wish to hide orders must rely on the lit market. Second, the NSE does not allow fully hidden orders; the only HLOs available are reserve orders, which

[4] The Bombay Stock Exchange (BSE) is the only competitor. For a comparison between these exchanges, see here.
[5] For more details on the institutional features of the NSE, we refer readers to Kahraman and Tookes (2017), Nawn and Banerjee (2019), and Chakrabarty, Comerton-Forde, and Pascual (2023).

represent the weakest form of order non-exposure because a portion of the order (the peak) must be disclosed. Consequently, our NSE setting is inherently biased toward finding weaker results on order exposure.

We obtain order and trade data directly from the NSE. For each trading day we access a message file and a trade file. The message file contains every message for each stock including the ticker symbol, price, quantity and timestamp in jiffies.[6] For every order we know the entry, revision, execution, and cancellation events. The trade file contains analogous information for each trade. By allowing temporal tracking of each order and matching orders to trades, we rebuild the complete LOB at any instant of time.

We use two flags provided in the dataset: *Client*, and *Order Entry Mode*. *Client* classifies each order as submitted by *Custodian*, *Proprietary* and *Others*. *Custodian* represents traders who are members of the exchange but do not conduct their own clearing or settlement. This group comprises primarily of foreign institutional investors, mutual funds, and financial institutions. *Proprietary* applies to members of the exchange who trade for their own proprietary accounts, and *Other* applies to other customers of the exchange who employ their own clearing member.

Order Entry Mode flag shows one of the two possible order entry and management systems: *Algorithmic* and *Non-Algorithmic*, the latter meaning 'manual'. We group all orders with the *Algorithmic* flag into the ATs type and those with the *Non-Algorithmic* flag as NATs. Finally, we classify HFTs at the message level: when an AT submits a proprietary order, we classify that order as HFT, but if this same trader submits a client order, we count that as AAT.[7] This procedure

[6] One jiffy is 33.3564 picoseconds or $(1/2^{\wedge}16)^{th}$ of a second.
[7] There is not a generally accepted methodology for classifying traders into HFTs and non-HFTs as their technology and tactics can overlap. Classification approaches have used information from exchanges and/or orders, volume, cancellations, maximum and end-of-day inventory positions, speed of response, and related measures. Classifying HFTs into following particular types of strategies presents even more significant challenges.

overcomes some limitations of popular HFT identifying databases that group all HFTs as pure-play (the Nasdaq HFT database) or that allow for mixed categories (the EUROFIDAI data). The original size and the displayed size of the order identifies reserve orders. Additionally, executed volume allows us to track the lit and dark proportions of the reserve order over time. The NSE data lacks trader account information, preventing us from isolating the order flow of specific AAT or HFT firms. As a result, we must collectively model their order flow per trader type category.

We begin with the 1254 listed stocks in the NSE in September 2013, filter out 286 stocks that are not in continuous trading session in October - December 2013 and exclude firms that (i) have a closing price of ≤1 rupee (₹), (ii) have ≤ 100 trades a day on average, (iii) trade < 1,000 shares a day, (iv) have a traded value per day of less < ₹100,000, (v) have market-cap values in the Bloomberg and CMIE Prowess databases that diverge by over 10%, or (vi) are involved in NSE or MSCI index changes. These filters reduce our universe of stocks to 695, which we sort by market capitalization and group into deciles. We draw the top 10 stocks from each of the top 3 deciles to form our sample of 30 stocks.[8] We select one month (21 trading days) of December 2013 for our sample period. Panel A of Table 1 shows the descriptive statistics of this sample.

[Table 1]

The average firm has over ₹1,493 billion market capitalization (23.9 billion USD), which is smaller than the large firms but much larger than the median Nasdaq-listed firm. The quoted spread is ₹0.31 while the relative spread is 8.72 bps, which is slightly lower than the relative spread (10.34 bps) for the NYSE sample reported in Bessembinder, Hao and Zheng (2020). Panel B shows message traffic and cancellation statistics for ATs vs NATs and for different types of ATs (AAT

[8] Stocks below decile three are excluded because they do not have adequate observations for all econometric tests.

vs HFT). As we expect, HFTs account for much greater message traffic (submissions, cancellations, and revisions) than either the AATs or the NATs. When we scale message traffic by the number of trades executed, HFTs show a 10 times larger statistic than AATs, and 100 times larger than NATs.

V. Empirical findings

A. On the relative use of hidden volume

Figure 1A shows the cross-sectional average contribution of ATs and NATs to hidden (dark bars) and displayed (light bars) volume, and for AATs and HFTs separately.[9]

[Figure 1]

H1 predicts that ATs should contribute relatively less to hidden volume than NATs, as technology helps reduce their exposure risk. Supporting this hypothesis, we find that ATs contribute about 34% to the overall hidden volume, while NATs account for the remaining 66%. This stands in contrast to their respective contributions to the displayed LOB depth, 63.45% and 36.55%. Given the lower option value of their orders and their reliance on speed, **H1** posits that HFTs should be less inclined than AATs to use hidden volume. In support, Figure 1A reveals that HFTs contribute only 2.98% of the hidden volume while AATs contribute a much more significant 31%.

In Figure 1B, we analyze the share of HLOs submitted by each trader type. We observe that ATs are responsible for 61% of the HLOs, slightly surpassing their share of displayed limit orders (56.3%). AATs are the primary users of HLOs, accounting for 54.1% of all orders placed

[9] We include orders up to 20 ticks since there are few HLOs beyond this level; results are similar without this filter.

in the book. Thus, our findings show that the access to superior technology does not preclude traders from extensively using HLOs. Even HFTs account for 7.1% of all the HLOs placed in the LOB. Consistent with **H1**, Figure 1B also reveals that ATs place HLOs of smaller average size than those placed by NATs.

In **H2**, we posit that ATs' relative contribution to hidden volume may vary depending on market conditions such as volatility or the relative tick size. To test **H2**, we rank stocks daily based on their relative tick size (minimum price variation divided by the time-weighted average quote midpoint over the trading session), realized volatility (standard deviation of the quote midpoint every five minutes), and adverse selection costs (volume-weighted average relative quote midpoint impact of trades, calculated 5-second after each trade). We assign the stocks to three subsamples of ten stocks each according to each metric. For the relative-tick-size-based rankings, we estimate the pooled regression in equation (1). It includes stock and day-of-the-week (*dw*) fixed effects, with standard errors clustered by stock and day (Thompson (2011)),

$$\begin{aligned} Y_{i,s,d} = {} & \alpha_0 + \beta_1 HFT_{s,d} + \beta_2 AAT_{s,d} + \\ & +\delta_1 HighTick_{i,s,d} + \delta_2 HighTick\_AAT_{i,s,d} + \delta_3 HighTick\_HFT_{i,s,d} + \\ & +\gamma_1 LowTick_{i,s,d} + \gamma_2 LowTick\_AAT_{i,s,d} + \gamma_3 LowTick\_HFT_{i,s,d} + \\ & +\rho' Controls_{s,d} + \lambda_s + \chi_{dw} + \varepsilon_{i,s,d} \end{aligned} \tag{1}$$

where $i = \{\text{NAT, AAT, HFT}\}$, *s* is stock, and *d* is day. Dependent variables are the daily percentage of hidden, displayed, and total volume provided per trader type through limit orders. Explanatory variables consist of dummy variables for trader types (*AAT*, *HFT*), dummies for high-ranked and low-ranked stocks according to the relative tick size (*HighTick*, *LowTick*), and interactions. Additionally, we include the daily time-weighted relative quoted spread, and the volume traded (in thousands of ₹) to capture daily variations in trading costs, and trading activity, respectively.

We repeat this modeling approach for rankings based on realized volatility, and adverse selection costs. In Table 2, we present the estimated shares of volume per trader type and subsample.[10]

[Table 2]

Consistent with **H2**, NATs' contribution to hidden volume goes from 48% in low-volatility to 73.3% in high-volatility stocks (Panel A). Since volatility increases the option value of limit orders, our finding indicates that NATs may be more inclined to hide orders to manage exposure risk, vis-à-vis ATs. Both AATs and HFTs contribute relatively less hidden volume in more volatile stocks: AATs' contribution halves, from 47% to 22.8%, while HFTs' overall contribution to liquidity supply also declines.

In line also with **H2**, the contribution of NATs (ATs) to hidden volume is higher (lower) when adverse selection is high. NATs contribute 74.75% of the hidden volume in stock-days with the highest price impact, compared to 42.75% in stocks-days with the lowest price impact (Panel B). As Yao and Ye (2018) for the Nasdaq, HFTs contribute less to displayed liquidity on stock-days with high (24.85%) than low (72.45%) adverse selection risk. When adverse selection costs are high, the quoted spread is less likely to be tick-constrained, allowing AATs to gain execution priority over HFTs' orders. In such a scenario, HF-MMs may use HLOs to mitigate undercutting. Consistently, HFTs double their contribution on stock-days with high adverse selection, from 2.8% to 5.8%.

Finally, Panel A of Table 2 reveals that ATs' contribution to hidden volume is higher in stocks with a relatively lower tick size, which also aligns with **H2**. AATs' contribution increases from 26.5% in stocks with a high relative tick size to 48.71% in stocks with a low relative tick

[10] Complete model estimates are in Table IA1 of the Internet Appendix.

size. However, the most striking variation is observed for the HFTs' contribution, increasing from 0.66% for stocks with a large relative tick size to 7% for stocks with a small relative tick size.[11] Hence, our results underline the increased sensitivity of HFTs to variations in the relative tick size previously evidenced by O'Hara et al. (2019).

Theory predicts that both informed and uninformed traders are more likely to hide aggressively priced orders, especially when these orders are relatively large. This is because risks of information leakage, exposure to predatory trading, and undercutting increase with both order aggressiveness and size (Moinas (2010), Harris (1997), Buti and Rindi (2013)). Consequently, we should find greater hidden volume concentrated at the top of the book. In Figure 2, we plot the cross-sectional average percentage of hidden depth in the LOB up to 10 ticks from the best quotes. These statistics are derived from one-minute snapshots of the book, averaged first per stock-day, then across days per stock, and finally across stocks. As expected, the average percentage of hidden depth increases from 25.8% at 10 ticks from the market quotes to 52% at the top of the book.

[Figure 2]

In Figure 3, we plot for each trader type the cross-sectional daily average likelihood of a HLO submission conditional on both order aggressiveness and order size. Following Biais, Hillion, and Spatt (1995), we categorize each new order submission into one of three levels of order aggressiveness: 'Better' (within the best bid and ask quotes), 'At' (at the best bid and ask), 'Rest' (beyond the best quotes). For NATs and AATs, Figures 3A and 3B, respectively, show a positive correlation between the likelihood of hiding and order size across all order aggressiveness levels. Moreover, the likelihood of hiding is higher for aggressively priced orders, holding size constant.

[11] If we rank stocks by the percent of time the spread is tick-constrained, the HFTs' contribution to hidden volume rises from 0.4% for stocks with high tick-constrained spreads to 10.43% for stocks with low tick-constrained spreads.

Figure 3 also reveals that AATs have the highest probability of hiding aggressive orders of all sizes. For a relatively large ‘Better’-placed order, AATs choose hiding over displaying with a 70% probability (36% for NATs). These findings align with both the information-revelation and the exposure risk theories.

[Figure 3]

Figure 3C shows that HFTs are different; they are more likely to hide small (≤50 shares) orders inside the best quotes way more (20.25%) than away from best quotes (6.06%). For an equally aggressive but larger (50 to 100 shares) order, the likelihood of hiding falls to 11.06%, and for over 1000 shares it is 1.09%. This result aligns with HFTs acting as endogenous market makers (e.g., Anand and Venkataraman (2016)) and using HLOs strategically to mitigate the risk of being undercut by competing HFTs. Since the risk of being undercut rises with order aggressiveness, HFTs predominantly hide volume within the prevailing best bid and offer when the spread is not tick-constrained. Indeed, we estimate that the likelihood of HFTs concealing a ‘Better’ (‘At’)-placed limit order is 16.19% (6.59%) and they seldom hide orders positioned away from the best quotes. HFTs allocate 54.9% (50%) of their hidden orders (volume) within the best quotes, in contrast to 15.43% (10.9%) for AATs and 22.38% (13.16%) for NATs.[12] This behavior is consistent with the theoretical framework proposed by Buti and Rindi (2013).

In Table 3, we provide cross-sectional average statistics on the contributions of hidden volume to total volume (Panel A), and HLOs to total orders (Panel B), double sorted by order size and aggressiveness. Table 3 confirms that most of the hidden volume is concentrated at the top of the order book. Furthermore, large aggressive orders are more likely to include hidden volume

[12] We provide these statistics in Table IA2 in the IA. In Table IA3, we also show that HFTs place more HLOs within the best quotes when spreads are tick-unconstrained.

compared to small aggressive orders. However, this pattern is primarily driven by NATs. NATs' hidden volume accounts for 2.12% of the total volume placed within the best quotes for small orders, compared to 21.2% for large orders (Panel A). Similarly, HLOs by NATs represent only 1.63% of all the small aggressive orders, compared to 22.64% for large aggressive orders (Panel B). In contrast, the contribution of hidden volume by AATs to total volume placed within the best quotes remains relatively stable across order size categories, ranging between 10.47% and 13.73%. For HFTs, hidden volume represents 3.1% of the total aggressively placed volume for small orders but drops to a negligible 0.05% for large orders.

[Table 3]

In Panels C and D of Table 3, we provide statistics on the share of hidden volume and HLOs, respectively, by trader type, conditional on order size and order aggressiveness. In line with Panels A and B of Table 3, the share of both hidden volume and HLOs for NATs increases with order size. In contrast, AATs are the primary contributors to hidden volume for orders of 500 shares or fewer, regardless of their level of aggressiveness. As previously noted, HFTs predominantly place their HLOs within the prevailing best quotes, achieving a notable 19.9% share of hidden volume when these orders are no larger than 50 shares.

Based on these results, we can reject neither **H1** nor **H2**.

B. On the motives for using hidden volume

1. Testing the information revelation theory

In **H3**, we postulate that NATs and AATs are more likely to use HLOs to conceal information than HFTs. If so, then their HLOs should be more informative than the HFTs' HLOs, and the HLOs of NATs and AATs should convey more information than their own displayed orders.

Following Brogaard, Hendershott, and Riordan (2019), we assess the information content of the order flow using the impulse-response functions (IRFs) from an extended version of Hasbrouck (1991) Structural Vector Autoregressive (SVAR) model, defined in event time *t*, where *t* equals a trade, order submission, or cancellation.[13] We separate displayed from hidden and aggressive (at or within best quotes) from non-aggressive orders.[14] These partitions lead to an 18-equation model: one equation for the quote midpoint return and 17 (6 events x 3 trader types -1) for order-flow variables. The trade variable takes the value +1 (-1) for buyer- (seller-) initiated trades. Displayed, hidden, and cancellation variables on the bid (ask) side take the value 1 (-1). We estimate the model for each stock-day with at least 20 observations in each category and determine optimal lags using the Schwarz' Bayesian Information Criterion. Residual cross-correlations are negligible; nonetheless, we compute IRFs to account for them.

Table 4 reports the average accumulated IRFs, with double-clustered standard errors. We boldface those cases in which the AATs' and NATs' estimated impacts significantly differ from the corresponding impacts for HFTs.

[Table 4]

As in Brogaard et al. (2019), HFT-initiated trades show the largest average price impact. Displayed orders show significant information content, especially those of NATs.[15] Supporting

[13] We treat order revisions that improve (degrade) price or size as submissions (cancellations).

[14] We drop the HFTs' non-aggressive HLOs category because there are not enough observations.

[15] On average aggressive limit order placements have larger price impact than cancellations. Brogaard et al. (2019) also find this and discuss why these are not directly comparable. Their Table VI and related discussion demonstrate one reason cancelations have low, or negative, price impact is because of post-cancellation actions taken by the same trader who cancels, e.g., the same trader cancels a buy order and immediately follows it with a buy trade.

H3, a representative AATs' HLO has a larger permanent price impact than an equally aggressive AATs' displayed order, suggesting that AATs' HLOs are more likely to be information driven. In contrast, NATs' aggressive HLOs show a lower price impact than their comparable displayed orders, which contradicts **H3**.

The most striking case, however, is that of the HFTs. Their aggressive HLOs have an insignificant long-term price impact (0.18, *p*-value = 0.11), suggesting they convey little information, whereas their aggressive displayed orders have a significant and positive price impact (0.25, *p*-value<0.01). Thus, our results are consistent with **H3**, as they suggest that HFTs do not use HLOs to trade on information.

In Table 5, our focus shifts to the aggregated behavior of hidden volume users to examine whether hidden depth imbalances in the limit order book can predict posterior mid-quote returns (*r*).[16] Thus, our concern transitions from the informativeness of an average submitted HLO (Table 4) to the information embedded in the aggregated hidden order flow at a given point in time.

[Table 5]

From one-minute LOB snapshots, we compute depth imbalances (ask minus bid depth relative to total depth) at the best, five best, and up to 20 ticks from best quotes, and use the pooled regression in equation (2),

$$\begin{aligned} r_{s,d,m+1} = {} & \alpha_0 + \sum\nolimits_{j=0}^{5} \partial_{m-j} r_{s,d,m-j} + \sum\nolimits_{j=0}^{5} \gamma_{m-j} rm_{d,m-j} + \\ & + \beta_1 HFTHidDI_{s,d,m} + \beta_2 AATHidDI_{s,d,m} + \beta_3 NATHidDI_{s,d,m} + \\ & + \beta_4 HFTDispDI_{s,d,m} + \beta_5 AATDispDI_{s,d,m} + \beta_6 NATDispDI_{s,d,m} + \\ & + \delta_1 OI_{s,d,m} + \delta_2 Vol_{s,d,m} + \delta_3 Volat_{s,d,m} + \lambda_s + \varepsilon_{s,d,m} \end{aligned} \tag{2}$$

[16] Some previous studies attribute informational content to hidden depth but ignoring trader types. See Anand and Weaver (2004), Belter (2007), Flemming and Mizrach (2009), and Yao (2017).

where **HidDI* and **DispDI* are the hidden and displayed depth imbalances, respectively, for trader type *. We add lagged stock and market returns to account for autocorrelation and commonality. Order imbalance (*OI*), volume (*Vol*), and mid-quote volatility (*Volat*) control for market conditions. Subindex *m* represents minute.

In line with prior evidence (Cao, Hansch, and Wang (2009), Kwan, Philip, and Shkilko (2021)), displayed depth imbalances are negatively correlated with posterior stock returns, with the HFTs' best quotes showing the strongest connection. Consistent with Table 4, our results attribute additional information content to hidden depth imbalances, but only when provided by AATs and NATs.

Overall, our findings challenge the idea that HFTs hide orders to trade on valuable signals. Other traders, particularly AATs, often use HLOs to preserve information, in line with the information-revelation theory. Given these findings, we cannot reject **H3**.

2. Testing the exposure (or free-option) risk theory

The exposure risk theory combines diverse reasons why uninformed traders may use HLOs, like the risk of being picked off or undercut. In **H4**, we hypothesize that all traders, regardless of their technological sophistication or inherent trading motives, are more likely to choose hidden over displayed orders when the risk of being picked off increases. While this behavior is likely for both AATs and NATs, its applicability to HFTs is less certain. Although speed reduces the free-option risk for HFTs, they still face the possibility of being picked off by faster HFTs (Baron et al. (2019)). As such, we treat this as an open empirical question.

Moreover, we have shown that HFTs' contribution to hidden volume increases when the spread is not tick-constrained (**H2**), and that they place their HLOs primarily within the best quotes. These patterns conform with Buti and Rindi (2013). In **H5**, we formalize this intuition by predicting that HFTs' use of HLOs will increase when they anticipate a higher undercutting risk.

To test **H4 (H5)**, we need a proxy for the ex-ante risk of being picked off (undercut). We construct composite risk indicators using principal component analysis. Picking off risk increases with expected adverse price movements, approximated using three proxies. The first one is the displayed depth imbalance (*DepthIOpp*). An unbalanced limit order book (LOB) may signal future price movements (Goldstein et al. (2023)). A thicker book on the ask (bid) side may indicate higher picking off risk for buy (sell) orders. The second proxy is order flow aggressiveness (*OFAggrOpp*). As aggressive order flow carries more information (Cao et al., 2009), an asymmetric rise in order flow aggressiveness suggests higher risk. We rank the aggressiveness of opposite-side submissions or cancellations in the one-minute interval before the focal order (Biais et al. (1995)) and use the average rank as our second proxy. The third proxy is the continuously compounded quote midpoint return in the one-minute interval preceding the order, a sort of momentum in order exposure risk (*TrendOpp*). The first principal component (PC) of these three proxies, estimated stock by stock, is our index of picking off risk (*PickOff*). It explains 36.2% (std. dev., 2.2%) of their variability.

To proxy for undercutting risk, we rely on Buti and Rindi (2013). This model predicts that the option to hide is more valuable under heightened price competition. Akin to Barardehi, Dixon, and Liu (2024), we use the frequency of best quote improvements on the same side of the market shortly before the focal order as our first proxy (*UndcutSame*). The model also predicts that hiding a limit order becomes a dominated strategy when the spread is tick-constrained. So, we use the percentage of time the spread is tick-unconstrained one minute before the focal limit order (*TickUnc*) as our second proxy. Lastly, the longer the queue at the best quote, the longer the expected time to execution and the more likely that an incoming same-side trader will opt to undercut. Thus, we use depth at the same-side best quote (*DepthBestSame*) as our third proxy. The first PC of these proxies is our index of undercutting risk (*Undcut*), which explains 38.4% (std. dev., 2.9%) of their variability.

We acknowledge that the risk of an order being picked off or undercut increases with both its size and aggressiveness. However, to avoid overstating the importance of either risk factor, we adopt the conservative approach of treating these order characteristics as controls. This ensures a balanced analysis, but it biases our results towards undermining the importance of both risk factors.

As De Winne and d'Hondt (2007), we use logistic regressions to model the likelihood of a HLO submission. Namely, we estimate the pooled logit model in equation (3),

$$
\begin{aligned}
HLO_{s,d,j} = {} & \alpha_0 + \alpha_1 PickOff_{s,d,j} + \alpha_2 Undcut_{s,d,j} + \\
& + \beta_1 OrdSize_{s,d,j} + \beta_2 OrdAggr_{s,d,j} + \\
& + \delta_1 Volat_{s,d,j} + \delta_2 Vol_{s,d,j} + \delta_3 MVolat_{s,d,j} + \\
& + \partial_1 First30m_{s,d,j} + \partial_2 Last30m_{s,d,j} + \lambda_s + \lambda_d + \varepsilon_{s,d,j}
\end{aligned} \tag{3}
$$

where *HLO*, equals 1 if the *j*th order is an HLO, 0 otherwise. Additional controls are stock (*Volat*) and market (*MVolat*) volatility, and traded volume (*Vol*), both computed over the one-minute preceding the limit order *j*, and dummies for the first (*First30m*) and last (*Last30m*) thirty minutes of the session. We add stock and day fixed effects, and estimate the model separately for AATs, HFTs, and NATs. In Table 6, Model [1] columns, we report the coefficients of interest separately for buy and sell orders. To assess the relative importance of each variable, we provide odds ratios and *z*-scores for each coefficient.

[Table 6]

Consistent with **H4,** $\hat{\alpha}_1 > 0$ for all traders, meaning that our picking off risk index positively relates to the likelihood of HLO use. Based on its z-score, this risk better explains AATs' exposure decisions (94.4 for buy orders, Panel B) than HFTs' (12.1, Panel A). This aligns with the presumed lower option value of HFTs' orders (Brogaard et al., (2015), Baron et al. (2019)). Surprisingly, NATs show the least sensitivity to picking off risk (6, Panel C). Since NATs' monitoring capabilities unlikely match those of ATs (e.g., Hendershott and Riordan (2013)), they are less likely to respond to the LOB changes captured by *PickOff*. Instead, they mitigate their risk by choosing whether to hide based on order size, emerging as the primary determinant in NATs' exposure decision.

Opportunistic HFTs exacerbate other traders' picking-off risk (e.g., Biais et al. (2015), Shkilko and Sokolov (2020)). Accordingly, AATs and NATs may resort to HLOs when HFTs on the opposite side actively take liquidity. To test this, we estimate equation (4),

$$\begin{aligned}
HLO_{s,d,j} = {} & \alpha_0 + \alpha_1 PickOff_{s,d,j} + \alpha_2 Undcut_{s,d,j} + \\
& + \phi_1 PickOff_{s,d,j} HFTd_{s,d,j} + \\
& + \beta_1 OrdSize_{s,d,j} + \beta_2 OrdAggr_{s,d,j} + \\
& + \delta_1 Volat_{s,d,j} + \delta_2 Vol_{s,d,j} + \delta_3 MVolat_{s,d,j} + \\
& + \partial_1 First30m_{s,d,j} + \partial_2 Last30m_{s,d,j} + \lambda_s + \lambda_d + \varepsilon_{s,d,j}
\end{aligned} \tag{4}$$

where we interact *PickOff* with a proxy of HFT liquidity demand (*HFTd*), the percentage of opposite-side trades initiated by HFTs. Indeed, results in Table 6, Model [2] columns, show that both AATs and NATs are more likely to hide orders in the presence of opportunistic HFT ($\hat{\alpha}_1 + \hat{\phi}_1 > 0$, Panels B and C). HFTs also make greater use of HLO when other HFTs are active taking liquidity from the same side (Panel A). Intuitively, HFTs have higher risk of being picked off by other, faster, HFTs (Aquilina et al. (2022)). Comparing across panels, we find that AATs (odds ratio: 1.13, z-score: 16.9) are more successful in discerning the presence of quote snipers than NATs (1.07, 4.9). Upon detection, AATs revise up their perceived risk, leading to more frequent use of HLOs.

In **H5**, we posit that HFTs hide orders at the top of the book to mitigate undercutting. Indeed, we find that only the HFTs intensify their use of HLOs when undercutting risk increases ($\hat{\alpha}_2 > 0$, Panel A). For both AATs and NATs, $\hat{\alpha}_2 < 0$ (Panels B and C, respectively). This later result aligns with the theoretical reasoning proposed by Bongaerts and Van Achter (2021). According to their model, HFTs tend to withdraw from supplying liquidity when they perceive a heightened risk of informed trading. If greater undercutting risk reflects intensified HFT competition to gain price priority, it could also signal lower adverse selection costs (Barardehi et al., (2024)). We have already shown that both AATs and NATs respond to a higher picking off risk by choosing hidden over displayed orders (**H4**). Finding now that $\hat{\alpha}_2 < 0$ for non-HFTs in equation (4) strengthens this result. Overall, our findings in Table 6 indicate that the rationale outlined in Buti and Rindi (2013) better explains the order exposure decision of HFTs.

Also motivated by Buti and Rindi (2013), **H5** posits that HFTs use HLOs when undercutting themselves. To test this hypothesis, we examine all instances of low-latency undercutting, defined as limit order submissions in which the order is entered immediately after another submission on the same side, occurs within $k = \{10, 100, 250\}$ milliseconds of the previous order, and offers a better price. We treat revisions that increase order aggressiveness as new submissions. We model the likelihood of observing an undercutting event using the pooled logistic model in equation (5),

$$\begin{aligned}
Und_{s,d,j} &= \alpha_0 + \alpha_1 HFT_{s,d,j} + \alpha_2 HFT_{s,d,j} HLO_{s,d,j} + \\
&+\alpha_3 AAT_{s,d,j} + \alpha_4 AAT_{s,d,j} HLO_{s,d,j} + \alpha_5 NAT_{s,d,j} HLO_{s,d,j} + \\
&+\phi_1 DispSizeUnd_{s,d,j-1} + \phi_2 AggrUnd_{s,d,j-1} + \beta_1 HidVolSame_{s,d,j} + \\
&+\beta_2 RSpread_{s,d,j} + \beta_3 DepthSame_{s,d,j} + \beta_4 DepthOpp_{s,d,j} + \\
&+\delta_1 Volat_{s,d,j} + \delta_2 Vol_{s,d,j} + \delta_3 MVolat_{s,d,j} + \\
&+\partial_1 First30m_{s,d,j} + \partial_2 Last30m_{s,d,j} + \lambda_s + \eta_d + \varepsilon_{s,d,j}
\end{aligned} \tag{5}$$

where $Und_{s,d,j}$ is 1 if the j^{th} order for stock *s* on day *d* undercuts, 0 otherwise. We include trader type dummies *HFT* and *AAT* (the intercept captures NAT), and their interactions with the HLO dummy (*HLO*). Thus, $\alpha_0+\alpha_1$ ($\alpha_0+\alpha_3$) is the propensity of HFTs (AATs) to undercut relative to NATs (α_0); $\alpha_1+\alpha_2$ is informative about the HFTs' preference for hidden vs displayed orders (α_1) when undercutting, but also about the inclination of HFTs to use HLOs to undercut compared to AATs ($\alpha_3+\alpha_4$) and NATs ($\alpha_0+\alpha_5$). We expect AATs and NATs to show a significantly lower propensity to undercut than HFTs.[17]

Buti and Rindi (2013) predict that the risk of being undercut increases with the option value of the order. Thus, we include the displayed size (*DispSizeUnd*) and aggressiveness (*AggrUnd*) of the order eligible of being undercut (*j*-1th) as controls. We measure aggressiveness as ticks away from the best quote on the same side, multiplied by -1. Thus, we expect $\phi_1>0$ and $\phi_2>0$.

Hidden volume is revealed when the quantity traded at a quote exceeds the displayed depth.[18] Hidden volume detection may foster parasitic traders to undercut and capitalize on the hidden depth revelation. Conversely, the prospect of a depth improvement could elicit aggressive responses from traders on the opposite side, speeding up order execution and deterring undercutting. The dummy *HidVolSame* in equation (5) equals 1 if the *j*th limit order reveals the presence of hidden volume on the same side, 0 otherwise.

In Foucault, Kadan and Kandel (2005), traders offer larger price improvements when spreads are wide. Accordingly, we expect more undercutting when the relative quoted spread

[17] We focus our analysis on undercutting of limit orders placed at or within the prevailing best quotes. Similar conclusions hold when we consider orders placed within the five best quotes.
[18] Pardo and Pascual (2012) use this feature to examine the impact of publicly revealing hidden volume at the top of the book on order aggressiveness, liquidity, and volatility, as well as to test the informativeness of hidden volume.

(*RSpread*) increases. In Handa, Schwartz and Tiwari (2003), a thicker book on the bid side indicates more high-valuation traders, which should intensify buy competition and bid-side undercutting. Conversely, a high concentration of low-value traders should diminish the non-execution risk of high-value traders and bid-side undercutting. We include the quoted depth on the same (*DepthSame*) and opposite (*DepthOpp*) sides as controls, expecting $\beta_3 > 0$ and $\beta_4 < 0$. Additional controls are as defined in Appendix B.

In Table 7, we present the estimated coefficients. Our findings consistently support **H5**. Specifically, HFTs engage in low-latency undercutting ($\hat{\alpha}_1 > 0$), and when they do, they opt for hidden over displayed orders ($\hat{\alpha}_2 > 0$). Neither AATs nor NATs use HLOs for low-latency undercutting ($\hat{\alpha}_4 < 0$ and $\hat{\alpha}_5 < 0$). These findings further support that HFTs' use of hidden volume for liquidity competition.

[Table 7]

Control variables line with expectations. Orders with higher option value have greater likelihood of being undercut ($\hat{\phi}_1 > 0$; $\hat{\phi}_2 > 0$); undercutting rises with the relative spread ($\hat{\beta}_2 > 0$), queue length ($\hat{\beta}_3 > 0$), and non-execution risk ($\hat{\beta}_4 < 0$). HLO detection increases undercutting ($\hat{\beta}_1 > 0$) on the same side, signaling opportunistic trading.

C. On the efficient use of HLOs

Does technology enable more efficient use of HLOs? We examine three facets of order execution quality: likelihood, time, and cost. Our analysis primarily builds on the empirical approach of Lo, MacKinlay, and Zhang (2002), who use survival analysis to model the time-to-execution of limit orders, and Bessembinder et al. (2009), who extend Perold's (1988) implementation shortfall method to assess the execution costs of HLOs. Additionally, we use ordered probit models to analyze the likelihood of HLO execution. We focus on non-marketable limit orders, placed no more than 20 ticks away from the best quotes, and not cancelled quickly ('fleeting').[19] In Hasbrouck and Saar (2009), a fleeting order is cancelled unexecuted within 2 seconds; to accommodate increased speed, we use a 100-millisecond threshold.[20]

1. Likelihood of execution

HLOs carry a higher non-execution risk. So, we first examine how technology alters the likelihood of HLO completion using the pooled ordered logit model in equation (6),

$$
\begin{aligned}
EXEC_{s,d,j} = {} & \alpha_0 + \alpha_1 AT_{s,d,j} + \alpha_2 HLO_{s,d,j} + \alpha_3 HLOAT_{s,d,j} + \\
& + \phi_1 Aggr_{s,d,j} + \phi_2 OrdSize_{s,d,j} + \phi_3 RSprd_{s,d,j} + \phi_4 DepthSame_{s,d,j} + \\
& + \phi_5 DepthOpp_{s,d,j} + \phi_6 LOBImbOpp_{s,d,j} + \phi_7 OIOpp_{s,d,j} + \beta_1 Vol_{s,d,j} + \\
& + \beta_2 Volat_{s,d,j} + \gamma_1 First30m_{s,d,j} + \gamma_2 Last30m_{s,d,j} + \lambda_s + \eta_d + \varepsilon_{s,d,j}
\end{aligned}
\tag{6}
$$

where *EXEC* is an ordinal variable that equals 1 if order *j* is cancelled before execution, 2 if it is partially executed then cancelled, and 3 if it is fully executed. Our choice of control variables draws from prior research on order exposure and order choice. Order aggressiveness (*Aggr*) and size (*OrdSize*) proxy for option value. We capture the book shape using the displayed depth at the best opposite- (*DepthOpp*) and same-side (*DepthSame*) quote, and depth imbalance between the five best opposite- and same-side quotes (*LOBImbOpp*). Order imbalance prior to submission (*OIOpp*), conveniently signed, measures opposite-direction trading activity. Illiquidity (*RSpr*), volatility (*Volat*), and trading activity (*Vol*) control for market conditions.

[19] For partially executed orders, we treat revisions as new submissions.
[20] Including fleeting orders in our efficiency tests lead to several issues. These orders are used by ATs (99.2% of all fleeting orders in our sample, 72.6% by HFTs). Including them reduces the estimated likelihood of execution of ATs' (HFTs') orders compared to those of NATs (AATs). Similarly, HLOs are rarely fleeting (2.26% of all fleeting orders). Consequently, fleeting orders inflate the likelihood of HLO execution.

We estimate equation (6) by OLS, with stock and day fixed effects and White-robust standard errors. Our results for buy and sell orders combined are in Table 8 – separated analyses yield similar conclusions. Panel A shows the estimated coefficients for equation (6) along with an alternative specification that distinguishes between HFTs and AATs.

[Table 8]

We find that ATs cancel more displayed orders than NATs ($\hat{\alpha}_1 < 0$). Although this is true for HLOs ($\hat{\alpha}_1 + \hat{\alpha}_2 + \hat{\alpha}_3 < 0$) as well, ATs exhibit less HLO than displayed order cancellation ($\hat{\alpha}_2 + \hat{\alpha}_3 > 0$). Control variables align with expectations. The probability of full execution rises with aggressiveness ($\hat{\phi}_1$>0), declines with size ($\hat{\phi}_2$<0), is higher when the book is deeper on the opposite side ($\hat{\phi}_5$>0, $\hat{\phi}_6$>0), but lower when it is deeper on the same side ($\hat{\phi}_4$<0). HLOs are more likely to execute fully when more trades are initiated by traders with opposite valuations ($\hat{\phi}_7$>0) or when there is greater activity ($\hat{\beta}_2$>0).

Using the coefficients in Panel A of Table 8 and evaluating the control variables at their average value, we obtain the likelihood of completion (*EXEC*=3) of HLOs for the different trader types (Panel B). For NATs, the HLO completion rate is 58%, higher than HFTs' (45%) and AATs' (52%). However, when we exclude orders cancelled within two seconds, the likelihoods of HLO completion level off at 56-57% for all trader types. Therefore, our findings suggest that superior technology does not result in enhanced execution rates of hidden liquidity, challenging **H6**.

2. Time to execution

To investigate how technology impacts HLOs' time to completion, we use survival analysis. Bessembinder et al. (2009) conduct a similar analysis using Euronext Paris data from

April 2003 but do not differentiate between trader types. Equation (7) represents an accelerated failure time specification of order execution, employing the generalized gamma distribution, as in Lo et al. (2002).

$$\begin{aligned}
TIME_j = {} & \alpha_0 + \alpha_1 AT_j + \alpha_2 HLO_j + \alpha_3 HLOAT_j + \\
& +\phi_1 Aggr_j + \phi_2 OrdSize_j + \phi_3 RSprd_j + \phi_4 DepthSame_j + \\
& +\phi_5 DepthOpp_j + \phi_6 LOBImbOpp_j + \phi_7 OIOpp_j + \\
& +\beta_1 Vol_j + \beta_2 Volat_j + \gamma_1 First30m_j + \gamma_2 Last30m_j + \eta_d + \varepsilon_j
\end{aligned} \tag{7}$$

For executed orders, $TIME_j$ is the time to full execution, for expired/cancelled orders, it is the time they survived in the book. The control variables are the same as in equation (6). We include day fixed effects. We estimate equation (7) for each stock, and compute aggregated t-statistics following Chordia, Roll, and Subrahmanyam (2005). Our results are in Table 9. Panel A reports the cross-sectional average coefficients, and Panel B shows the estimated time to completion for HLOs.

[Table 9]

We find that NATs' HLOs take longer to fully execute compared to their displayed orders ($\hat{\alpha}_2$>0), consistent with Bessembinder et al.'s (2009) findings for the pre-AT Euronext Paris. This does not hold for ATs ($\hat{\alpha}_3$<0). Notably, neither the *AT* nor the *AAT* and *HFT* dummies are significant at conventional levels, suggesting that differences in time to completion for displayed orders across trader types, once we control for order attributes, are negligible. Conversely, the interactions of the *HLO* dummy with *AAT* and *HFT* dummies are significantly negative, implying that ATs' HLOs take less time to execute than NATs' HLOs. However, while significant, differences across trader types are small, averaging about a second. Once more, our results do not conform to **H6**.

3. Execution costs

Finally, we evaluate differences in HLOs execution costs across trader types. As Bessembinder et al. (2009), we recognize the order splitting inherent in reserve orders (Esser and Mönch (2007)) using the implementation shortfall (IS) approach (Perold (1988)).[21] For each buy order *j*, displayed or hidden, we compute the IS as the sum of the effective cost of execution (*EFC*) and the opportunity cost of non-execution (*OPC*),

$$IS_j = EFC_j + OPC_j = k_j v_j \left(\overline{p}_j - q_0\right) + \left(1 - k_j\right) v_j \left(q_T - q_0\right) \tag{8}$$

EFC_j is the difference between the average execution price ($\overline{p}_j$) of the order and the mid-quote at the time of submission (q_0), multiplied by the number of shares executed ($k_j v_j$), where v_j is the order size and k_j the fill rate ($0 \leq k_j \leq 1$). OPC_j measures forgone profits; it is the difference between quote midpoint at terminal time T (q_T) and q_0, multiplied by the unexecuted part of the order $(1-k_j)v_j$. We differ from Bessembinder et al. (2009) in our choice of q_T. While they use the closing price for every order, independently of who submits the order and when, we use the opposite-side quote – i.e., the ask quote – at the end of the order's life cycle, that is, when the order is cancelled. If the order expires unexecuted and is automatically cancelled after the closing auction, q_T is the closing price. We believe this is a more appropriate approach in the context of modern high-frequency markets. Finally, we express both EFC_j and OPC_j (therefore IS_j) relative to q_0. Metrics for sell orders are analogously treated but conveniently signed.

After computing the *IS* for each order, we estimate equation (9) for, in turn, *IS*, *EFC*, and *OPC*, using OLS with stock and day fixed effects, and White-robust standard errors. We include

[21] Our dataset has submitted but not parent orders. This is a limitation when computing the IS for displayed orders, but not for HLOs, since they are less susceptible to order splitting than HLOs.

trader and order type dummies, order attributes (aggressiveness, size, direction) and market conditions (volume, volatility) in the one minute prior to order submission.

$$(9)\qquad \begin{aligned} Y_{s,d,j} &= \alpha_0 + \alpha_1 AT_{s,d,j} + \alpha_2 HLO_{s,d,j} + \alpha_3 HLOAT_{s,d,j} + \\ &+ \phi_1 Aggr_{s,d,j} + \phi_2 OrderSize_{s,d,j} + \phi_3 Buy_{s,d,j} + \beta_1 Vol_{s,d,j} + \\ &+ \beta_2 Volat_{s,d,j} + \gamma_1 First30m_{s,d,j} + \gamma_2 Last30m_{s,d,j} + \lambda_s + \eta_d + \varepsilon_{s,d,j} \end{aligned}$$

Model estimates are reported in Panel A of Table 10, and estimated differences in execution costs across trader types (relative to the average stock price) in Panel B. By definition, a fully executed order has an *OPC*=0, whereas a fully non-executed order has an *EFC*=0. So, for the *EFC* component, we provide results for all limit orders but also for partially executed orders ($k > 0$) only; for the *OPC* component, we provide results for all orders and for non-executed or partially executed orders (k<1) separately.

[Table 10]

We find no statistically significant difference in *IS* between ATs and NATs for HLOs. In Panel B, the average difference in IS between ATs and NATs per HLO is -0.013 $\overline{q}_0$, but not statistically significant. Examining the components of the IS, we observe that the ATs' HLOs have lower *EFC* than NATs' HLOs after excluding non-executed HLOs (k>0), with an average difference of -0.048 $\overline{q}_0$. However, we find no statistically significant differences in terms of *OPC* of non-executed or partially executed (k<1) HLOs. These results do not support that technologically advanced traders handle HLOs with greater efficiency (**H6**).

In Panels C and D of Table 10, we examine differences in *IS* among different ATs. **H6** posits that HFTs, whose HLOs are more aggressive but not information-driven (**H3**), should exhibit larger *EFC* but lower *OPC* compared to AATs. In line with **H6**, Panel D shows that the execution costs of the HFTs' HLOs are indeed higher than those of the AATs (0.08 $\overline{q}_0$) and NATs (0.135 $\overline{q}_0$), but more than offset by the much lower *OPC* (-0.232 $\overline{q}_0$ and -0.325 $\overline{q}_0$, respectively). As a result, HFTs' show a lower average *IS* compared to AATs (-0.087 $\overline{q}_0$) and NATs (-0.082 $\overline{q}_0$). Finally, Panels C and D of Table 10 also show that AATs have lower *EFC* of execution (-0.055 $\overline{q}_0$) compared to NATs, but higher *OPC* of non-execution (0.093 $\overline{q}_0$). This result aligns with AATs' HLOs being more likely to be informed, but also reveals that technology does not allow AATs to better manage information leakage. In net terms, AATs' HLOs show no statistically significant difference in *IS* compared to NATs' HLOs.

VI. Conclusion

Full transparency in financial markets has drawbacks, so exchanges allow traders to hide orders. Increased opacity from hidden orders coincided with the growth of AT and we find ATs are substantial users of hidden orders. While all traders hide to lower their picking off risk, AATs also hide informed orders to prevent information leakage. Consistent with short-lived private information, HFTs make relatively little use of hidden orders, primarily to limit undercutting when competing for liquidity supply. Consistent with technology acting as a substitute for hidden orders in managing order exposure, ATs' relative share of hidden volume decreases with volatility, adverse selection costs, and the relative tick-size. However, the benefits of technology appear to be limited in terms of execution quality for both AATs and HFTs over NATs.

Our results indicate that technology has a complex relationship with opacity. ATs, despite their faster technology, extensively hide orders, which shows that they benefit from this option. However, technologically sophisticated HFTs are the least users of hidden orders. In contrast, consistent with trying to prevent information leakage, non-HFT ATs (AATs) are heavy users of smaller hidden orders. Both NATs and AATs use hidden orders when HFTs are more active, suggesting that non-HFTs hide orders to avoid HFTs. Future research could provide deeper insights into the role that transparency plays in the interaction between HFTs and non-HFTs. This could help regulators balance the costs and benefits of financial market transparency across different market participants.

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Figure 1
Share of hidden volume by trader type

Figure 1A shows the cross-sectional average share of ATs and NATs on hidden (dark bars) and displayed (light bars) volume. The sample consists of the 30 NSE-listed stocks (top 3 deciles) in December 2013.

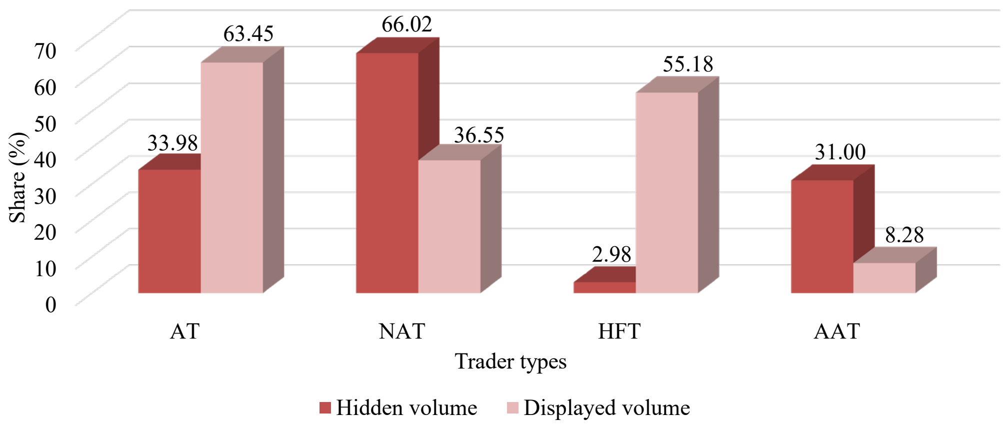

Figure 1A: Share of hidden volume

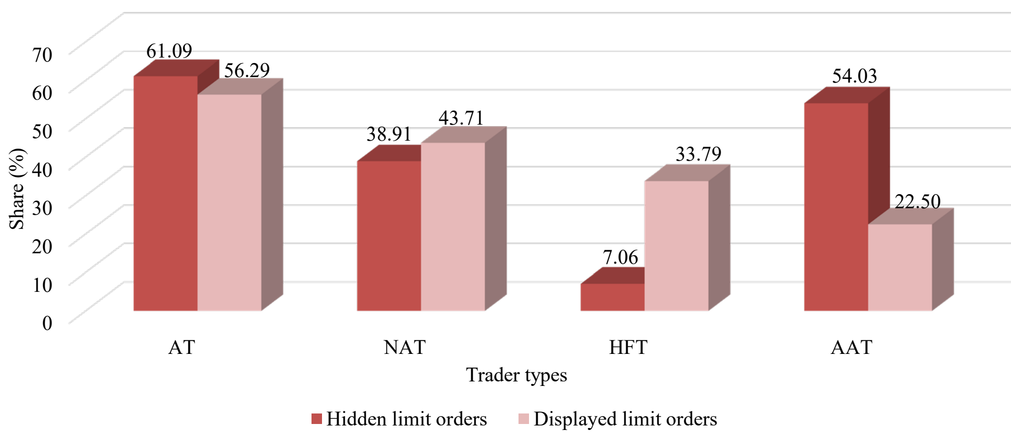

Figure 1B: Share of hidden limit orders

Figure 2
Hidden volume in the NSE limit order book

We plot the cross-sectional average percentage of hidden depth in the NSE limit order book up to 10 best ticks from the best quotes. Averages are computed from 1-minute snapshots of the book, first averaged per day for each stock, then per stock, and then across stocks. The sample consists of the 30 NSE-listed stocks (top 3 deciles) in December 2013.

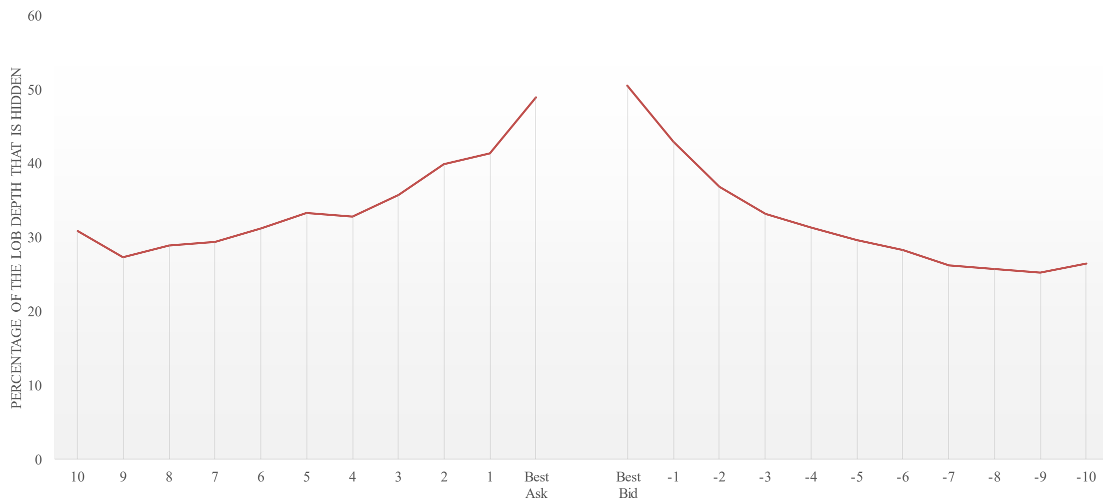

Figure 3
Likelihood of hiding and order characteristics

We plot cross-sectional daily average probabilities of hidden order submission conditional on aggressiveness and size. We construct order book snapshots at each order submission; the top level of aggressiveness is when a hidden order is placed within the prevailing bid-ask spread ('Better'), followed by orders at the best quotes ('At') and, then beyond the best quotes ('Rest'). Traders are categorized as algorithmic traders (ATs), further distinguished as high-frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). We show the percentage of hidden orders for each order size, aggressiveness category, and type of trader. Figures 3a, 3b, and 3c are for NATs, AATs, and HFTs, respectively. The sample consists of the 30 NSE-listed stocks (top 3 deciles) in December 2013.

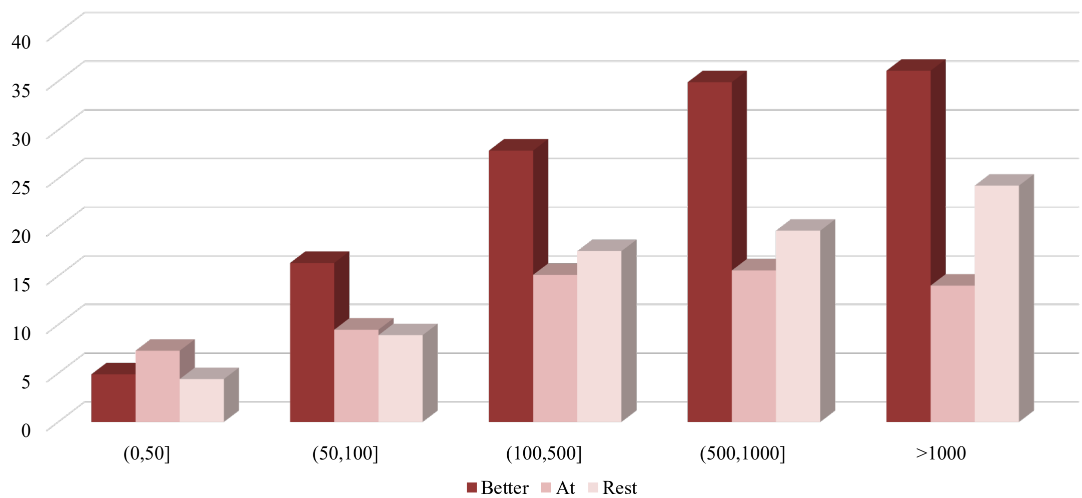

Figure 3A: NAT

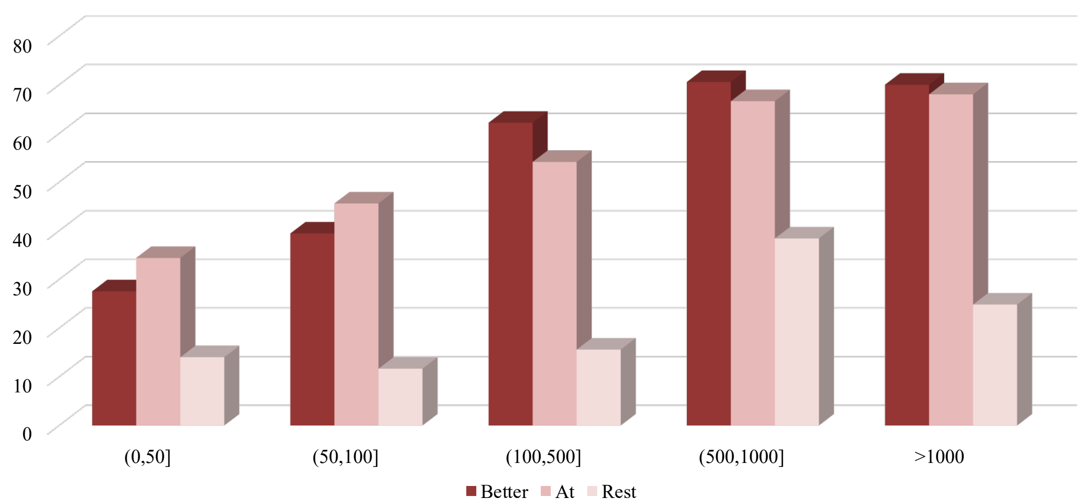

Figure 3B: AAT

Figure 3 (Cont.)
Likelihood of hiding and order characteristics

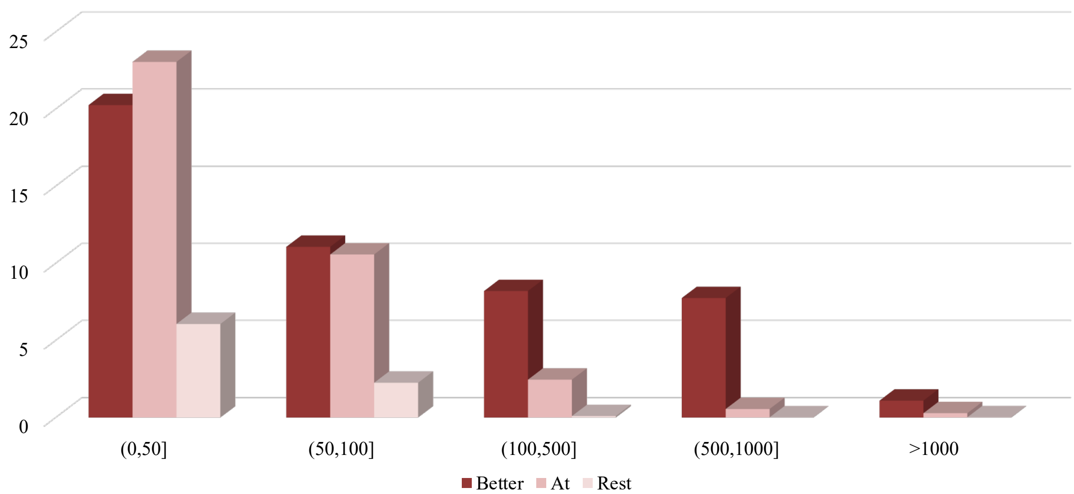

Figure 3C: HFT

Table 1
Descriptive statistics

We provide summary statistics for 30 NSE-listed stocks (top 3 deciles) in December 2013. Market capitalization is in billions of Rupees (₹), volume is in 10,000-share units, number of trades is in 100-trade units, depth (displayed and hidden) is in 1000-share units, and Price is in ₹. Daily volatility is 100((maximum price/minimum price) –1). Quoted bid-ask spread is the difference between the best offer and bid quotes, weighted by time. Relative bid-ask spread is the ratio of the quoted spread to the quote midpoint, in bps. Displayed (hidden) depth is the accumulated displayed (non-displayed) depth in the whole limit order book. NMLO is non-marketable limit orders. Message traffic (MT) is the number of messages (sum of submissions, cancellations, and revisions) in 1000-message units. MT/Trd is the ratio of MT to trades, and CAN/Trd is the ratio of cancellations to trades. Share in MT (volume) is each trader type's share in message traffic (trading volume, in shares), where trader types are algorithmic traders (ATs), which we further split into high frequency traders (HFT) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). Metrics are generated from one-minute snapshots of the order book. Significance is evaluated using Wilcoxon rank-sum test. In Panel B, significance under the AATs column tests for the difference between HFTs and AATs, and in the NATs column the differences between ATs and NATs.

Panel A: Sample statistics

	Average	25th quartile	Median	75th quartile
Market capitalization (billions of ₹)	1493.84	66.7	184.61	1536
Volume ('0000)	226.38	40.85	135.48	330.54
Number of trades ('00)	297.69	103.58	198.34	525.34
Volatility	29.41	22.75	26.15	36.82
Relative bid-ask spread (bps)	8.72	3.08	6.57	11.78
Quoted bid-ask spread (₹)	0.31	0.08	0.19	0.37
Displayed depth ('000)	217.12	56.46	117.59	242.59
Hidden depth ('000)	57.26	19.01	30.2	61.39
% NMLO	74.37	68.89	77.49	83.27
Price (₹)	619.02	130.57	374.46	841.76

Panel B: Message traffic per traders' technology and motivation

	Technology-based trader types		Types of ATs	
Variable	ATs	NATs	HFTs	AATs
MT	1226.72	37.09 ***	1098.98	127.74 ***
MT/Trd	69.67	2.31 ***	233.31	23.47 ***
CAN/Trd	3.08	0.25 ***	9.55	1.90 ***
Share in MT	82.68	17.32 ***	56.41	26.27 ***
Share in trading volume	33.35	66.65 ***	10.08	23.27 ***

Table 2
Contribution to hidden volume:
Volatility, adverse selection costs, and tick size

We show the contribution to hidden, displayed, and overall volume for three types of traders: high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs) for 30 NSE-listed stocks (top 3 deciles) in December 2013. We group the stocks into subsamples based on: high versus low realized volatility (Panel A), high versus low adverse selection costs (Panel B), and large versus small relative tick size (Panel C). Realized volatility is the standard deviation of five-minute quote midpoint returns. Adverse selection costs are measured by the volume-weighted average relative price impact of trades, computed over a five-second window after each trade. Relative tick size is the minimum price variation divided by the daily average quote midpoint. These estimates are derived from the coefficients of pooled regression models reported in Table IA1. ***, **, * indicate statistically significant differences between subsamples at the 1%, 5%, and 10% levels, respectively, per Wald test performed on the estimated regression models' coefficients.

Panel A: Volatility

Trader type	Subsample	Hidden	Displayed	All
NAT	High	73.32 ***	39.57 ***	40.88 ***
AAT		22.81 ***	13.89 ***	15.11 ***
HFT		3.88 ***	46.54 ***	44.01 ***
NAT	Low	48.03	26.28	27.28
AAT		47.61	16.69	22.07
HFT		4.36	57.03	50.65

Panel B: Adverse selection costs

Trader type	Subsample	Hidden	Displayed	All
NAT	High	74.75 ***	58.94 ***	58.18 ***
AAT		19.45 ***	16.21 ***	15.92 ***
HFT		5.80 ***	24.85 ***	25.90 ***
NAT	Low	42.75	13.15	16.12
AAT		54.45	14.39	21.17
HFT		2.81	72.45	62.71

Panel C: Relative tick size

Trader type	Subsample	Hidden	Displayed	All
NAT	Large	72.85 ***	54.52 ***	54.22 ***
AAT		26.49 ***	15.54 ***	17.75 ***
HFT		0.66 ***	29.95 ***	28.03 ***
NAT	Small	44.30	20.28	22.05
AAT		48.71	17.89	23.96
HFT		6.98	61.82	53.99

Table 3
Hidden volume conditional on order size and aggressiveness

We provide cross-sectional average daily statistics on hidden volume contribution to total volume submitted through limit orders (Panel A), and hidden limit orders (HLOs) contribution to all limit orders submitted (Panel B) by trader type, conditional on order size and aggressiveness. We provide average contributions to hidden volume (Panel C) and HLOs (Panel D) by trader type. Our sample consists of 30 NSE-listed stocks (top 3 deciles) in December 2013. We distinguish between algorithmic traders (ATs), further split into high frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). The analysis is based on order-by-order data grouped by the full (displayed plus non-displayed) order size. Order size cutoffs are selected based on the distribution of the order size of all limit orders. To gauge aggressiveness, we construct order book snapshots at the time of each order submission. The top level of aggressiveness is when a new hidden order is placed within the prevailing bid-ask spread ("Better"), followed by at the best quotes ('At'). Aggressiveness falls as the order is placed from the best quotes up to 5 ticks away ('Near'), and is lowest when placed beyond that threshold ('Far'). Significant differences in medians between AATs (HFTs) and NATs are shown beside AATs (HFTs) numbers. We use the Wilcoxon rank-sum test and ***, **, * to indicate statistically different at the 1%, 5%, and 10% levels respectively.

Panel A: % of total volume submitted						Panel B: % of total limit orders submitted			
			By trader type				By trader type		
Size	Aggr.	Hidden	HFTs	AATs	NATs	HLOs	HFTs	AATs	NATs
(0,50]	Better	15.90	3.09 ***	10.70 ***	2.12	18.73	3.59 ***	13.51 ***	1.63
	At	23.41	0.71 ***	21.38 ***	1.31	27.48	0.89 ***	24.83 ***	1.76
	Rest	6.23	0.31 ***	4.99 ***	0.93	10.56	0.46 ***	8.81 ***	1.29
(50,100]	Better	19.87	1.01 ***	12.50 ***	6.36	25.30	2.43 ***	16.36 ***	6.51
	At	28.07	0.27 ***	25.44 ***	2.36	34.46	0.61 ***	31.45 ***	2.39
	Rest	8.35	0.12 ***	6.08 ***	2.15	9.63	0.28 ***	7.28 ***	2.07
(100,500]	Better	28.43	2.24 ***	13.29	12.90	32.01	2.32 ***	17.63 ***	12.06
	At	27.61	0.42 ***	22.37 ***	4.83	34.08	0.40 ***	29.30 ***	4.38
	Rest	3.13	0.05 ***	1.83 ***	1.25	4.22	0.07 ***	2.75 ***	1.40
(500,1000]	Better	32.89	1.86 ***	13.73 *	17.30	38.12	1.72 ***	17.87	18.52
	At	17.05	0.22 ***	11.96 ***	4.87	22.10	0.21 ***	16.57 ***	5.32
	Rest	1.14	0.01 ***	0.49 ***	0.64	1.59	0.01 ***	0.79	0.79
>1000	Better	31.72	0.05 ***	10.47 ***	21.20	40.91	0.09 ***	18.18 *	22.64
	At	16.39	0.04 ***	6.90 **	9.45	21.85	0.06 ***	14.65 ***	7.14
	Rest	8.89	0.01 ***	2.97 ***	5.91	7.29	0.01 ***	3.27 *	4.00
Panel C: Share of hidden volume						Panel D: Share of HLOs			
(0,50]	Better	100	19.92 ***	66.03 ***	14.05	100	19.44 ***	71.61 ***	8.95
	At	100	3.28 ***	90.75 ***	5.97	100	3.44 ***	89.87 ***	6.69
	Rest	100	5.36 ***	79.03 ***	15.62	100	4.65 ***	82.53 ***	12.82
(50,100]	Better	100	5.50 ***	61.58 ***	32.92	100	9.92 ***	63.55 ***	26.52
	At	100	1.05 ***	90.22 ***	8.73	100	1.92 ***	90.95 ***	7.13
	Rest	100	1.56 ***	71.33 ***	27.11	100	3.14 ***	74.30 ***	22.56
(100,500]	Better	100	7.96 ***	45.23	46.81	100	7.42 ***	53.51 ***	39.07
	At	100	1.54 ***	80.10 ***	18.35	100	1.19 ***	85.37 ***	13.44
	Rest	100	1.70 ***	57.39 ***	40.90	100	1.62 ***	64.51 ***	33.87
(500,1000]	Better	100	5.50 ***	40.06 **	54.44	100	4.46 ***	45.11	50.43
	At	100	1.44 ***	68.70 ***	29.86	100	1.06 ***	73.81 ***	25.13
	Rest	100	0.92 ***	43.17 ***	55.91	100	0.75 ***	49.43	49.82
>1000	Better	100	0.14 ***	31.73 ***	68.12	100	0.24 ***	42.47 **	57.28
	At	100	0.28 ***	40.17 ***	59.56	100	0.30 ***	64.54 ***	35.16
	Rest	100	0.09 ***	31.72 ***	68.19	100	0.18 ***	42.08 ***	57.74

Table 4
Informativeness: Permanent price impacts

We show the impulse response functions from an extended structural VAR model for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. The model is defined in event time *t*, where *t* = a submission, cancellation, or trade. Aggressive ("a") orders improve or hit the best quotes; else they are non-aggressive ("na"). We differentiate between hidden- (HLOs) and displayed limit orders (DLOs) and consider three trader types: high frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs). These partitions produce a VAR with 18 equations: one for the quote midpoint return (in bps) and 17 for order-flow variables (6 event types x 3 trader types -1) – we drop the HLOna category because non-aggressive HFTs' hidden orders are infrequent. The model is estimated each stock-day with optimal number of lags determined by the Schwarz' Bayesian Information Criterion. "Trade" variables are signed +1 (-1) for buyer- (seller-) initiated trades. "DLO", "HLO" or "Cancellation" variables on the ask (bid) side of the order book are signed (-1) +1. The trading process resets each day with all lagged values at zero. We report averages across stock-day observations clustered by stock and day (Thompson, 2011). ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. We boldface those impacts for AATs and NATs that are significantly different from corresponding impact for HFTs.

		Trader type		
Message	All traders	HFT	AAT	NAT
Trades		1.16 ***	**0.73** ***	**0.86** ***
		(0.13)	(0.10)	(0.15)
DLOa		0.25 ***	0.24 ***	**0.62** ***
		(0.05)	(0.03)	(0.07)
DLOna		0.01 *	0.00	0.00
		(0.01)	(0.01)	(0.00)
HLOa		0.18	**0.35** ***	**0.49** ***
		(0.11)	(0.04)	(0.05)
HLOna			-0.04	-0.02 **
			(0.02)	(0.01)
Cancellations		0.06 ***	0.05 ***	**0.12** ***
		(0.02)	(0.01)	(0.02)

Table 5
Informativeness: hidden volume and stock returns

We examine the informativeness of hidden liquidity on subsequent stock returns for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. Using one-minute snapshots of the book, we compute hidden depth imbalances (**HidDepthI*) for each trader type *i* as the difference between the volumes hidden on the ask side minus the bid side, relative to the total hidden volume, as provided by trader type *i.* We compute imbalances using (i) the best quotes; (ii) the top 5 levels of the book; (iii) all the levels within 20 ticks from the best quotes. We compute displayed depth imbalances (**DispDepthI*) analogously. The independent variable is the continuously-compound stock return over the next one-minute interval (in basis points). The dependent variables are the hidden and displayed depth imbalances of three trader types: high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs). As controls, we include five lags each of the one-minute stock returns and one-minute market return (unreported)s. We include the trade-initiator based order imbalance (*OrderI*), the volume traded (*Vol*) in logs, and the quote midpoint volatility (*Volat*) as reported controls. Standard errors are double-clustered by stock day. ***, **, * indicate statistically significant coefficient at the 1%, 5%, and 10% levels, respectively.

	Best quotes	Top 5 levels	No more than 20 ticks away
HFTHidDepthI	0.104	-0.139	-0.018
	(0.014)	(0.033)	(0.022)
AATHidDepthI	-0.070	-0.484 ***	-0.490 ***
	(0.003)	(0.003)	(0.004)
NATHidDepthI	-0.810 ***	-0.757 ***	-0.863 ***
	(0.011)	(0.006)	(0.006)
HFTDispDepthI	-1.317 ***	-0.610 ***	-0.705 ***
	(0.014)	(0.007)	(0.008)
AATDispDepthI	-1.059 ***	-0.564 ***	-0.466 ***
	(0.010)	(0.004)	(0.004)
NATDispDepthI	-0.752 ***	-0.701 ***	-0.679 ***
	(0.024)	(0.017)	(0.014)
OrderI	0.574 ***	0.574 ***	0.574 ***
	(0.003)	(0.003)	(0.003)
Vol	0.037 ***	0.037 ***	0.037 ***
	(0.000)	(0.000)	(0.000)
Volat	0.652 ***	0.652 ***	0.652 ***
	(0.045)	(0.045)	(0.045)
Intercept	-0.304 ***	-0.304 ***	-0.304 ***
	(0.008)	(0.008)	(0.008)
Adj.-R^2	0.0266	0.0197	0.0196
Obs.	212047	212047	212047

Table 6
Exposure risk theory

We test the whether the non-exposure decisions of traders - high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs) - conform to the exposure risk theory for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. We examine. We use a pooled logistic model to assess the decision between submitting a hidden- (HLO) or displayed limit order (DLO). In "Model [1]," our key explanatory variables are picking off risk (*PickOff*) and undercutting risk (*Undcut*), derived as composite indexes (first principal component) of three risk indicators. For picking off risk we use: (a) displayed depth imbalance (*DepthIOpp*), (b) order flow aggressiveness on the opposite side of the market (*OFAggrOpp*); and (c) quote midpoint returns (*TrendOpp*). To measure undercutting risk we use: (a) number of best quote improvements on the same side of the market (*UndcutSame*); (b) percentage of time the quoted bid-ask spread is tick-constrained; and (c) depth at the best quotes on the same side of the market (*DepthBestSame*). As controls, we include order characteristics: size (*OrdSize*) and aggressiveness (*OrdAggr*), a dummy for the first 30 (*First30m*) and last 30 minutes of a trading session (*Last30m*). Market conditions are controlled using the quote midpoint return realized volatility (*Volat*), the volume traded in shares (*Vol*), and the market-wide (NIFTY50 index) realized volatility computed *(MktVolat*). In "Model [2]," we add interaction term *PickOff x HFTd*, where *HFTd* represents the percentage of trades initiated by HFTs. Aggregation is over each one-minute window. All models include stock and day fixed effects. We provide the coefficients of the variables of interest, standard deviations in parenthesis ("Coef./(std.)"), their corresponding odds ratio, and absolute *z*-score ("or.r./(|z|)). We estimate the model for HFTs (Panel A), AATs (Panel B), and NATs (Panel C), and for buy and sell limit orders. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. More details on the variables are in Appendix B (panel B2).

Panel A: HFTs

	Buy orders				Sell orders			
	Model [1]		Model [2]		Model [1]		Model [2]	
	Coef./(std.)	o.r./(|z|)	Coef./(std.)	o.r./(|z|)	Coef./(std.)	o.r./(|z|)	Coef./(std.)	o.r./(|z|)
PickOff	0.067 ***	1.07	0.028 ***	1.03	0.054 ***	1.06	-0.016 **	0.98
	(0.006)	(12.1)	(0.008)	(3.5)	(0.005)	(9.9)	(0.008)	(2.1)
PickOff x HFTd			0.182 ***	1.20			0.352 ***	1.42
			(0.025)	(7.4)			(0.026)	(13.4)
Undcut	0.227 ***	1.26	0.224 ***	1.25	0.165 ***	1.18	0.143 ***	1.15
	(0.006)	(35.4)	(0.007)	(34.4)	(0.006)	(26.0)	(0.007)	(21.7)
OrdAggr	0.195 ***	1.22	0.196 ***	1.22	0.144 ***	1.15	0.168 ***	1.18
	(0.002)	(79.2)	(0.003)	(78.1)	(0.002)	(66.2)	(0.003)	(59.4)
OrdSize	-0.401 ***	0.67	-0.400 ***	0.67	-0.606 ***	0.55	-0.598 ***	0.55
	(0.005)	(77.1)	(0.005)	(76.2)	(0.004)	(143.8)	(0.004)	(136.3)
Controls	YES		YES		YES		YES	
Stock F.E.	YES		YES		YES		YES	
Day F.E.	YES		YES		YES		YES	
Pseudo R^2	0.4919		0.4807		0.5209		0.5164	
Obs.	3,829,068		3,812,711		4,063,940		4,063,009	

Table 6
Exposure risk theory (Cont.)

Panel B: AATs											
PickOff	0.130	***	1.14	0.048	***	1.05	0.134	***	1.14	0.099	***	1.10
	(0.001)		(94.4)	(0.002)		(26.6)	(0.001)		(92.6)	(0.002)		(52.6)
PickOff x HFTd				0.125	***	1.13				0.071	***	1.07
				(0.007)		(16.9)				(0.007)		(9.7)
Undcut	-0.149	***	0.86	-0.200	***	0.82	-0.165	***	0.85	-0.167	***	0.85
	(0.001)		(104.6)	(0.001)		(133.1)	(0.001)		(111.5)	(0.001)		(113.2)
OrdAggr	0.159	***	1.17	0.166	***	1.18	0.180	***	1.20	0.179	***	1.20
	(0.001)		(203.9)	(0.001)		(208.7)	(0.001)		(235.8)	(0.001)		(235.0)
OrdSize	0.271	***	1.31	0.272	***	1.31	0.356	***	1.43	0.355	***	1.43
	(0.001)		(233.9)	(0.001)		(235.1)	(0.001)		(300.0)	(0.001)		(299.5)
Controls	YES			YES			YES			YES		
Stock F.E.	YES			YES			YES			YES		
Day F.E.	YES			YES			YES			YES		
Pseudo R^2	0.1872			0.1875			0.1772			0.1799		
Obs.	3,439,104			3,356,876			3,487,762			3,286,861		
Panel C: NATs												
PickOff	0.016	***	1.02	-0.017	***	0.98	0.047	***	1.05	0.008	***	1.01
	(0.003)		(6.0)	(0.003)		(5.0)	(0.003)		(16.9)	(0.004)		(2.3)
PickOff x HFTd				0.072	***	1.07				0.004	***	1.00
				(0.015)		(4.9)				(0.016)		(0.2)
Undcut	-0.098	***	0.91	-0.096	***	0.91	-0.083	***	0.92	-0.082	***	0.92
	(0.003)		(35.4)	(0.003)		(34.3)	(0.003)		(30.1)	(0.003)		(29.9)
OrdAggr	0.001	***	1.00	0.001	***	1.00	0.002	***	1.00	0.002	***	1.00
	(0.000)		(10.1)	(0.000)		(9.5)	(0.000)		(18.0)	(0.000)		(18.3)
OrdSize	0.508	***	1.66	0.511	***	1.67	0.509	***	1.66	0.509	***	1.66
	(0.002)		(230.9)	(0.002)		(230.5)	(0.002)		(243.5)	(0.002)		(243.5)
Controls	YES			YES			YES			YES		
Stock F.E.	YES			YES			YES			YES		
Day F.E.	YES			YES			YES			YES		
Pseudo R^2	0.1665			0.1679			0.1667			0.1665		
Obs.	1,734,412			1,687,045			1,705,089			1,705,387		

Table 7
Undercutting

We test whether HFTs use hidden orders for undercutting in our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. Undercutting (*Und*) is a dummy variable, defined as a limit order placed immediately after another submission on the same side, within k = {10, 100, 250} milliseconds of the previous order, and improving the previous price. Trader types are high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs). We show coefficients, standard deviations in parenthesis ("Coef./(std.)"), their corresponding odds ratio, and absolute z-score ("or.r./(|z|) of logistic regressions for different values of k. The model includes a dummy variable (*HidVolSame*) indicating whether hidden volume on the same side of the book has been revealed before the focal order's submission. Control variables include the displayed size (*DispSizeUnd*) and aggressiveness (*AggrUnd*) of the order eligible for undercutting, relative quoted spread (*Rspread*), displayed depth on the same side (*DepthSame*), and opposite side (*DepthOpp*). Additional controls (not shown) comprise dummies for the first (*First30m*) and last 30 (*Last30m*) minutes of the session, quote midpoint return realized volatility (*Volat*), traded volume in shares (*Vol*), and market-wide (*NIFTY50 index*) realized volatility over the preceding one-minute window. The models include stock and day fixed effects. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	k = 10 ms		k = 100 ms		k = 250 ms	
	Coef./(std.)	o.r./(|z|)	Coef./(std.)	o.r./(|z|)	Coef./(std.)	o.r./(|z|)
HFT	0.631 ***	1.88	0.380 ***	1.46	0.220 ***	1.25
	(0.006)	(102.9)	(0.005)	(76.3)	(0.005)	(47.1)
HFT x HLO	0.063 ***	1.06	0.127 ***	1.14	0.122 ***	1.13
	(0.009)	(6.9)	(0.008)	(15.1)	(0.008)	(14.5)
AAT	0.501 ***	1.65	0.103 ***	1.11	-0.058 ***	0.94
	(0.006)	(80.2)	(0.005)	(20.0)	(0.005)	(11.9)
AAT x HLO	-1.170 ***	0.31	-0.768 ***	0.46	-0.682 ***	0.51
	(0.008)	(148.4)	(0.006)	(123.4)	(0.006)	(113.8)
NAT x HLO	-1.216 ***	0.30	-0.797 ***	0.45	-0.655 ***	0.52
	(0.025)	(49.2)	(0.016)	(49.9)	(0.014)	(47.0)
DispSizeUnd (j-1)	0.086 ***	1.09	0.036 ***	1.04	0.029 ***	1.03
	(0.001)	(112.4)	(0.001)	(50.7)	(0.001)	(41.7)
AggrUnd (j-1)	0.089 ***	1.09	0.087 ***	1.09	0.087 ***	1.09
	(0.000)	(521.1)	(0.000)	(569.8)	(0.000)	(572.3)
HidVolSame	0.232 ***	1.26	0.383 ***	1.47	0.397 ***	1.49
	(0.004)	(54.0)	(0.004)	(104.4)	(0.004)	(109.6)
Rspread	0.038 ***	1.04	0.036 ***	1.04	0.036 ***	1.04
	(0.000)	(136.9)	(0.000)	(141.5)	(0.000)	(143.8)
DepthSame	0.016 ***	1.02	0.038 ***	1.04	0.041 ***	1.04
	(0.001)	(22.2)	(0.001)	(58.9)	(0.001)	(63.1)
DepthOpp	-0.064 ***	0.94	-0.057 ***	0.94	-0.056 ***	0.95
	(0.001)	(92.4)	(0.001)	(90.4)	(0.001)	(89.7)
Intercept	-2.720 ***	0.07	-2.120 ***	0.12	-1.931 ***	0.15
	(0.011)	(257.9)	(0.009)	(225.8)	(0.009)	(210.3)
Other controls	YES		YES		YES	
Stock F.E.	YES		YES		YES	
Day F.E.	YES		YES		YES	
Pseudo R^2	0.1455		0.1466		0.1446	
Obs.	18,403,979		18,403,979		18,403,979	

Table 8
Likelihood of execution

We compare the likelihood of execution of hidden limit orders (HLOs) from high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs) for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. We use a pooled ordered logit model with stock and day fixed effects and with White-robust standard errors to model order execution likelihood. The dependent variable (*EXEC*) is ordinal, with three possible values: 1 = order is cancelled; 2 = order is partially executed then cancelled; and 3 = order is executed. In Panel A, we report coefficients from two models. In the first, we group AATs and HFTs into a single trader-type category: algorithmic traders (ATs). In the second, we treat AATs and HFTs as different. In Panel B, we report the predicted probabilities of full execution derived from the coefficients of the corresponding model, for each trader type. In estimating this model, we keep only non-marketable orders submitted within 20 ticks from the best quotes, that are not quickly cancelled after submission ("fleeting"). We consider two speed thresholds: 100 milliseconds and 2 seconds. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively. Explanatory variables are in Appendix B.

Panel A: Model estimates

Coef.*100	Fleeting orders canc. < 100 msec.		Fleeting orders canc. < 2 sec.	
AT	-124.65 ***		-95.23 ***	
HFT		-129.24 ***		-106.93 ***
AAT		-121.93 ***		-87.82 ***
HLO	-1.35 ***	-2.40 ***	-4.85 ***	-7.01 ***
HLOAT	81.45 ***		64.20 ***	
HLOHFT		69.92 ***		90.46 ***
HLOAAT		80.05 ***		58.20 ***
Aggr	211.87 ***	209.08 ***	193.93 ***	188.24 ***
OrdSize	-26.47 ***	-25.79 ***	-25.08 ***	-23.65 ***
RSprd	-0.09	-0.06	0.31	0.46 ***
DepthSame	-1.73 ***	-1.77 ***	-2.26 ***	-2.37 ***
DepthOpp	3.76 ***	3.70 ***	3.49 ***	3.30 ***
LOBImbOpp	13.08 ***	12.75 ***	12.17 ***	11.52 ***
OIOpp	9.92 ***	9.81 ***	10.42 ***	10.29 ***
Vol	9.82 ***	9.81 ***	12.04 ***	12.18 ***
Volat	-0.99 ***	-0.97 ***	-0.46 ***	-0.46 ***
First30m	3.90 ***	3.85 ***	5.13 ***	5.14 ***
Last30m	15.05 ***	14.99 ***	15.16 ***	14.57 ***
Obs./1000	14,735	14,735	11,107	11,107
Pseudo R^2	0.25	0.25	0.19	0.19

Panel B: Predicted probabilities of full execution for HLOs

NATs	0.58	0.58	0.57	0.57
ATs	0.52 ***		0.56 ***	
AATs		0.52 ***		0.56 ***
HFTs		0.45 ***		0.57

Table 9
Time to completion

We compare the time to full execution of hidden limit orders (HLOs) submitted by high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs) for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. We model time to completion using survival analysis. In Panel A, we provide coefficients for two models. In the first specification, we examine differences between algorithmic traders (ATs) and non-algorithmic traders (NATs), in the second, we further split ATs into HFTs and AATs. Models are estimated on a stock-by-stock basis, and we report aggregated coefficients and significance levels based on Chordia et al. (2005). We keep orders that are non-marketable, submitted within 20 ticks from the best quotes, and that are not quickly cancelled after submission ("fleeting"). We consider two speed thresholds for quick cancellations: 100 milliseconds and 2 seconds. In Panel B, we provide estimates of the average expected time of completion of a HLO for each trader type. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively. Explanatory variables are in Appendix B.

Panel A: Model estimates

Coef.	Fleeting orders canc. < 100 msec.		Fleeting orders canc. < 2 sec.	
AT	0.30		0.19	
HFT		0.39 *		0.35
AAT		0.19		0.06
HLO	0.77 ***	0.79 ***	0.77 ***	0.79 ***
HLOAT	-1.06 ***		-1.02 ***	
HLOHFT		-1.16 ***		-1.45 ***
HLOAAT		-1.00 ***		-0.92 ***
Aggr	-0.30 ***	-0.29 ***	-0.30 ***	-0.30 ***
OrdSize	0.41 ***	0.41 ***	0.41 ***	0.40 ***
RSprd	0.30 **	0.28 *	0.27 *	0.25
DepthSame	0.11 ***	0.11 ***	0.12 ***	0.12 ***
DepthOpp	-0.07 ***	-0.07 ***	-0.07 ***	-0.07 ***
LOBImbOpp	-0.25 ***	-0.25 ***	-0.25 ***	-0.25 ***
OIOpp	-0.15 ***	-0.15 ***	-0.15 ***	-0.15 ***
Vol	-0.49 ***	-0.48 ***	-0.50 ***	-0.50 ***
Volat	-0.13 ***	-0.12 ***	-0.14 ***	-0.14 ***
First30m	-0.21 ***	-0.21 ***	-0.22 ***	-0.22 ***
Last30m	-0.37 ***	-0.37 ***	-0.37 ***	-0.37 ***
Intercept	16.88 ***	16.91 ***	17.00 ***	17.07 ***
Obs./1000	14,735	14,735	11,220	11,220

Panel B: Expected time to completion for HLOs (sec.)

NATs	17.65	17.70	15.98	17.86
ATs	16.59 ***		14.96 ***	
AATs		16.70 ***		16.94 ***
HFTs		16.54 ***		16.41 ***

Table 10
Implementation shortfall

We investigate differences in the costs of using hidden limit orders (HLOs) across three trader types – high frequency traders (HFTs), agency algorithmic traders (AATs) and non-algorithmic traders (NATs), for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. We differentiate between the effective costs of execution (EFC) and the opportunity costs of non-execution (OPC) using the implementation shortfall (IS) methodology (Perold, 1988). For a buy order, EFC is the difference between the execution price and mid-quote at order submission time, multiplied by the number of shares traded, and OPC is the difference between opposite quote at the time the order is cancelled and the quote midpoint at the time of order submission, multiplied by the unexecuted portion of the order. Each order's IS, EFC, and OPC are normalized by the quote midpoint at the time of submission. Sell orders are analogously treated, with adjustments for signing. We estimate pooled regression models with stock and day fixed effects and White-robust standard errors for the IS, EFC, and OPC. In Panels A and B, we compare algorithmic traders (ATs) versus NATs. Panel A shows the coefficients; Panel B shows the differences in trading costs. Panels C and D provide the corresponding results for HFTs, AATs, and NATs. An executed order has zero opportunity cost, a cancelled order has zero execution cost. So, for the EFC, we provide results for partial execution ($k > 0$), and for the OPC, we provide results for non-full execution ($k < 1$), where k is the fill rate. We consider only non-marketable limit orders within 20 ticks from the best quotes. In Panels A and C, we drop 'fleeting' orders (i.e., cancelled within 100ms of submission). In Panels B and D, we provide estimates with and without fleeting orders. Revisions of non-executed orders are treated as the same order. Revisions of partially executed orders are treated as new submissions. For variables definitions, see Appendix B.

Panel A: ATs v NATs - Model estimates

	ISF	EFC (of execution)		OPC (of non-execution)	
Coef*100	All k	All k	$k > 0$	All k	$k < 1$
AT	2.22 ***	10.47 ***	3.46 ***	-7.93 ***	-38.26 ***
HLO	0.06	5.05 ***	13.70 ***	-5.96 ***	-28.52 ***
HLOAT	-3.35 ***	-8.01 ***	-8.26 ***	5.56 ***	40.40 ***
Aggr	47.74 ***	4.37 ***	160.11 ***	31.74 ***	148.36 ***
OrdSize	9.17 ***	-3.52 ***	-8.46 ***	12.79 ***	23.92 ***
Buy	2.00 ***	0.75 ***	0.36 ***	1.27 ***	1.29 ***
Volat	0.33 ***	-0.43 ***	-0.72 ***	0.77 ***	1.23 ***
Vol	0.00	-0.78 ***	-0.23 ***	0.75 ***	1.84 ***
First30m	-0.38 *	-0.03	1.13 ***	-0.41 **	0.18
Last30m	-1.49 ***	1.14 ***	2.06 ***	-2.41 ***	-5.45 ***
Intercept	-23.71 ***	12.22 ***	24.97 ***	-36.96 ***	-65.40 ***
Obs./1000	14,735	14,735	6,598	14,735	9,306

Panel B: ATs v NATs - differences in trading costs of using HLOs (relative to the stock's price)(*100)

	ISF	EFC (of execution)		OPC (of non-execution)	
Trader types	All k	All k	$k > 0$	All k	$k < 1$
ATs v NATs	-1.13	2.46 ***	-4.80 ***	-2.37 **	2.14

Table 10
Implementation shortfall (Cont.)

Panel C: HFTs, AATs, NATs - Model estimates

	ISF		EFC (of execution)				OPC (of non-execution)			
Coef*100	All *k*		All *k*		*k* > 0		All *k*		*k* < 1	
HFT	-0.07		16.57	***	9.33	***	-16.36	***	-56.53	***
AAT	3.51	***	7.00	***	0.19	*	-3.15	***	-26.03	***
HLO	-0.64		6.88	***	14.25	***	-8.51		-35.38	***
HLOHFT	-8.62	***	-8.75	***	-1.31	***	0.19	***	33.30	***
HLOAAT	-4.03	***	-5.77	***	-5.70	***	2.65	***	35.36	***
Aggr	46.97	***	6.43	***	160.53	***	28.90	***	139.30	***
OrdSize	9.56	***	-4.55	***	-8.80	***	14.22	***	28.86	***
Buy	1.98	***	0.80	***	0.27	***	1.21	***	1.05	***
Volat	0.35	***	-0.46	***	-0.78	***	0.84	***	1.35	***
Vol	-0.01		-0.76	***	-0.32	***	0.74		1.75	
First30m	-0.42	*	0.09		1.04		-0.57	*	-0.27	***
Last30m	-1.60	***	1.50	***	2.23	***	-2.87	***	-6.25	***
Intercept	-25.02	***	15.53	***	26.97	***	-41.62	***	-84.97	***
Obs./1000	14,735		14,735		6,598		14,735		9,306	

Panel D: HFTs, AATs, NATs - differences in trading costs of using HLOs (relative to the stock's price)(*100)

	ISF		EFC (of execution)				OPC (of non-execution)			
Trader types	All *k*		All *k*		*k* > 0		All *k*		*k* < 1	
AATs vs NATs	-0.52		1.23	***	-5.51	***	-0.50		9.33	***
HFTs vs NATs	-8.69	***	7.82	***	8.03	***	-16.18	***	-23.23	***
HFTs vs AATs	-8.17	***	6.59	***	13.54	***	-15.68	***	-32.56	***

Appendix A

Trader types

Algorithmic trading (AT) involves the use of computer programs (algorithms) to automatically make decisions, implement strategies, and manage orders. Our NSE dataset distinguishes the AT-generated order flow from the order flow that is handled ‘manually’. Within the NAT group, there is a diverse mix of traders, some operating on a proprietary basis, some representing clients, both local and foreign, with varying levels of market knowledge, and likely ranging from the informed to the uninformed. Similarly, not all ATs are the same, as they use algorithms for various purposes and strategies. A helpful initial step is to distinguish agency AT from proprietary AT.

According to Hasbrouck and Saar (2013), agency algorithms are primarily used by buy-side institutional traders and their brokers to minimize the cost of executing trades when making adjustments to their investment portfolios. Similarly, Hagströmer and Nordén (2013) note that these algorithms are designed to minimize execution costs relative to a benchmark, such as the Volume Weighted Average Price (VWAP). O’Hara (2015) underlines the role of agency algorithms in optimizing trading across both time (i.e., throughout the trading session) and space (i.e., across multiple trading locations) to efficiently locate liquidity.

Therefore, the consensus is that agency algorithms fundamentally reflect trading decisions made by portfolio managers, who have an investment horizon in mind, rather than short-term trading objectives. These investors could possess valuable fundamental information (van Kervel and Menkveld (2019)), their trading strategies rely less on speed of execution for success (Garriott and Riordan (2020)), and they minimize execution costs by predominantly using limit orders (Kaniel and Liu (2006), Collin-Dufresne and Fos (2015)). Agency algorithms assist these traders in efficiently executing their trading decisions, but they do not determine the investments to be made.

In contrast, technologically sophisticated HFT firms utilize proprietary algorithms to target short-term profit opportunities arising from the trading environment itself. While the HFT landscape encompasses a diverse array of trading strategies, research conducted by Boehmer et al. (2018) underscores that market making, low latency arbitrage, and directional speculation stand as the most prevalent strategies among HFT firms. High-frequency market making primarily relies on limit orders, whereas opportunistic HFT strategies primarily revolve around liquidity-taking activities (Brogaard et al. (2014), Chakrabarty et al. (2021)).

Common to all HFT strategies is the necessity to respond rapidly to market stimuli, making relative latency a pivotal determinant of success for HFT firms (Baron, et al. (2019)). To enhance their speed, HFT firms invest in state-of-the-art technology to execute their algorithms, and procure low-latency services, such as colocation (Brogaard et al. (2015)) and high-speed connectivity (Shkilko and Sokolov (2020)). The intense competition among HFT firms necessitates a continual race for technological advancement (Biais et al. (2015), Budish, Cramton and Shim (2015)).

Theoretical models on HFT suggest that HF-MMs leverage their technology and speed to manage exposure risk (Hoffmann (2014), Bogaerts and Van Achter (2021)), but also to efficiently manage their inventory positions (Ait-Sahalia and Saglam (2017)) and capitalize on abnormal profit opportunities in market making (Foucault et al. (2013)). Similarly, theory on opportunistic HFT (Biais et al. (2015), Foucault, Kohzan, and Tham (2017), Foucault, Hombert, and Roşu

(2016)) claims that these firms generate profits by trading on public signals faster than other traders and exploiting outdated quotes from slower market makers.[22]

Due to their short-term orientation, HFT firms do not operate within an investment horizon. This is evident in their short timeframes between position initiation and liquidation, their rapid mean-reverting inventory management, their inclination to avoid large open positions—particularly towards the end of the trading session—and their preference for trading in smaller quantities (Biais and Foucault (2014), Menkveld (2013, 2016)).

Thus, the consensus in the literature regarding proprietary AT is that it encompasses a diverse range of short-term-oriented trading strategies that depend on speed (low latency) and rely on a continuous stream of public (rather than private) signals. Accordingly, HFT firms contribute to the price discovery process by expediting the integration of publicly available information into prices. Similarly, HFT firms speed up price discovery when they track and back run agency algorithms working information-motivated orders (Yang and Zhu (2020), Baldauf and Mollner (2020)). However, they do not acquire long-lived private information on their own.

Given that hidden orders are limit orders, it is reasonable to anticipate that the use of hidden volume in AT is going to be predominantly associated with liquidity provision by agency algorithms working buy-side institutions' orders or proprietary algorithms of HF-MMs. Li et al. (2021) propose a model in which AATs and HFTs compete in liquidity provision. While AATs provide liquidity to minimize transaction costs, HFTs provide liquidity to earn the spread. AATs enjoy lower opportunity costs for providing liquidity than HFTs in the sense that the former are willing to lose money (the execution price is worse than a future benchmark price) as long as their

[22] Empirical studies consistently show that HFT trades have higher average price impact, and are better at anticipating short-term price changes (Brogaard et al. (2014, 2019)). However, these trades also result in an increase in the picking off risk run by liquidity providers (Chakrabarty et al. (2021), Aquilina et al. (2022)).

loss is lower than paying the bid-ask spread. HFTs, on the contrary, have no pressing need for execution. In their model, agency algorithms are fast, but slower than HFTs, allowing also for technological differences between AT types. As in the theoretical framework proposed by Li et al. (2021), our empirical analysis assigns distinct identities to AATs and HFTs.

Appendix B

Variable definitions

Panel B1: Direct variable definitions

Variable	Definition
AAT	Indicator variable that equals 1 for orders submitted by AATs and 0 otherwise
Aggr (OrdAggr)	Distance of the order's limit price from the same side best quote price, suitably signed (a higher value indicates a more aggressively priced order) divided by the quote midpoint
AggrUnd	Distance of the undercutted order's limit price from the same side best quote price, suitably signed (a higher value indicates a more aggressively priced order) divided by the quote midpoint
AT	Indicator variable that equals 1 for orders submitted by ATs and 0 otherwise
Buy	Indicator variable that equals 1 for buy orders and 0 otherwise
DepthOpp	Natural logarithm of prevailing displayed depth (in shares) at the best ask (bid) for an incoming buy (sell) order
DepthSame	Natural logarithm of prevailing displayed depth (in shares) at the best bid (ask) for an incoming buy (sell) order
DispSizeUnd	Displayed size of the undercutted order
	For a submission of non-marketable limit order to sell (buy), average realized spread over the last 5 buyer-
First30m	Indicator variable that equals 1 for orders submitted in the first half hour of the trading day and 0 otherwise
HFT	Indicator variable that equals 1 for orders submitted by HFT and 0 otherwise
HFTd	Number of trades initiated by HFT divided by total number of trades over the last 1 minute
HidVolSame	Indicator equals to 1 if presence of hidden volume on the same side is detected, 0 otherwise
HLO	Indicator variable that equals 1 for hidden orders and 0 otherwise
Last30m	Indicator variable that equals 1 for orders submitted in the last half hour of the trading day and 0 otherwise
LOBImbOpp	Prevailing displayed depth (in shares) at the best ask (bid) minus prevaling displayed depth at the best bid (ask) for an incoming buy (sell) order divided by the average quoted depth.
MktVolat	Standard deviation of the second by second NIFTY50 indexs return over the last 1 minute.
NAT	Indicator variable that equals 1 for orders submitted by NATs and 0 otherwise
OrderI	Seller-initiated volume minus buyer-initiated volume divided by total volume in last 1 minutes
OIOpp	Seller (buyer)-initiated volume minus seller (buyer)-initiated volume divided by total volume in last 1 minutes for an incoming buy (sell) order
OrdSize	Natural logarithm of total (displayed plus hidden) size of the order
Rsprd	Bid-ask spread divided by the quote midpoint
Vol	Natural logarithm of the number of shares traded in the last 1 minute.
Volat	Standard deviation of the continuously compounded quote-midpoint stock return over the last 1 minute.

Panel B2: Proxy variables for picking-off risk and undercutting risk (Table VI)

Variable	Definition
Picking off risk proxies	
DepthIOpp	Prevailing displayed depth (in shares) at the best ask (bid) minus prevaling displayed depth at the best bid (ask) for an incoming buy (sell) order divided by the average quoted depth.
OFAggrOpp	Average order flow aggressiveness on the ask (bid) side in the preceding 1-minute window for an incoming buy (sell) order. The message traffic in that 1-minute window, is ranked by aggressiveness as follows: market or marketable limit order (+5), limit order placed within the prevailing best quotes (+4), limit order at the prevailing best quote (+3), limit order placed between the 1st and the 5th prevailing best quotes ("near") (+2), limit order placed at or beyond the 5th prevailing best quote ("far") (1), cancelation of a limit order at the best quote (-3), cancelation of a limit order "near"-placed (-2), cancelation of a limit order "far"-placed (-1).
TrendOpp	Continuously compound return over the preceding 1-minute window for an incoming sell order; the same for an incoming buy order, but multiplied by -1.
Undercutting risk proxies	
UndcutSame	Number of undercutting events (orders placed within the prevailing best quotes) in the side of the market of the incoming limit order during the preceding 1-minute window.
TickUnc	Percentage of time, over the preceding 1-minute window, during which the quoted spread is not tick-constrained.
DepthBestSame	Natural log of displayed depth (in shares) prevailing at the best bid (ask) for an incoming limit buy (sell) order.

Figure IA1
Size of hidden limit orders, high volatility, and relatively small tick size

Figure A1 shows the empirical distribution of the HLOs size (displayed plus hidden) for two subsamples of NSE listed stocks within our sample: the ten stocks with the highest average daily realized volatility (Figure IA1a), and the ten stocks with lower incidence of tick-constrained bid-ask spreads (Figure IA1b). The full sample consists of the 30 NSE-listed stocks (top 3 deciles) in December 2013.

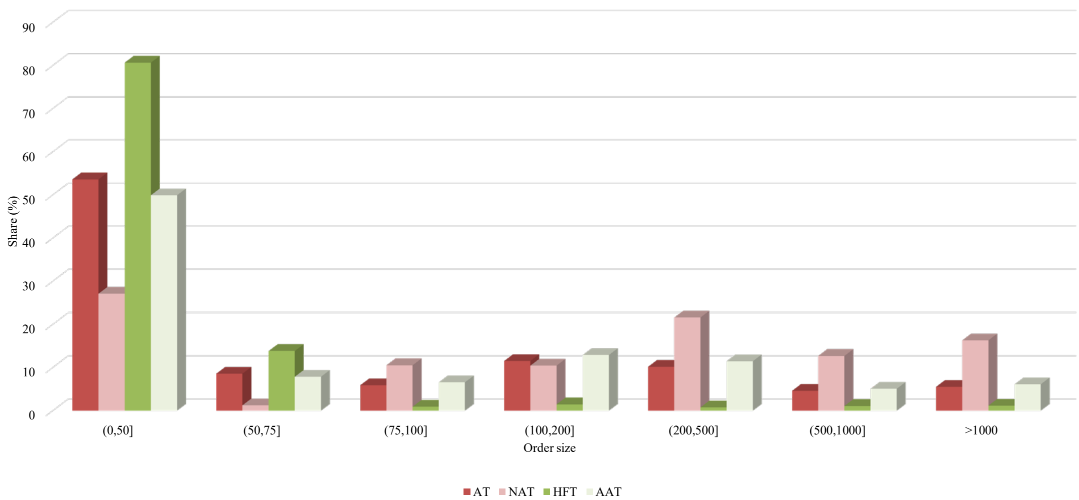

Figure IA1a: HLO size distribution in highly volatile stocks

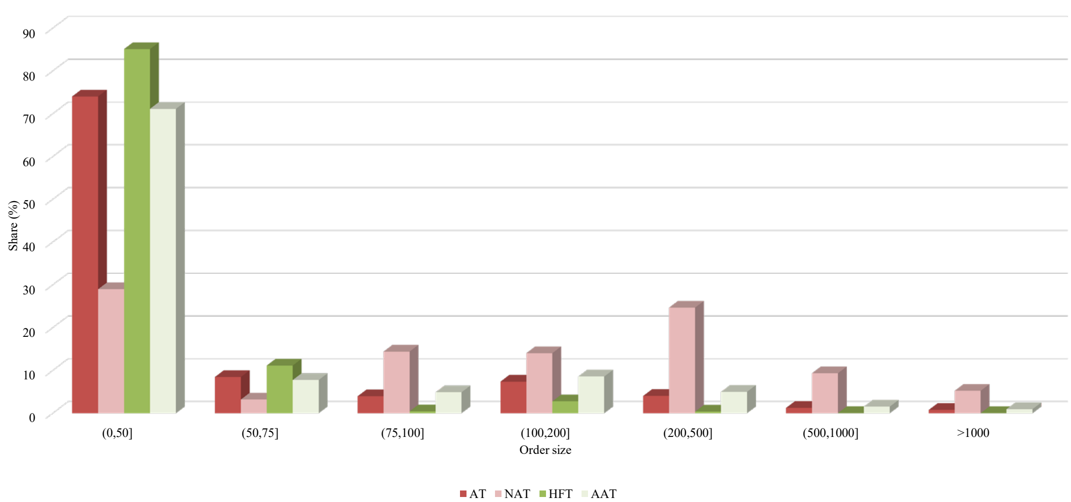

Figure IA1b: HLO size distribution in stocks with low incidence of tick-constrained bid-ask spreads

Table IA1
Contribution to hidden volume in the cross-section: volatility, tick size, and adverse selection costs

We present pooled regression estimates for the daily contribution to hidden, displayed, and overall volume in the order book for 30 NSE-listed stocks (top 3 deciles) in December 2013. We distinguish between algorithmic traders (ATs), further split into high frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). We rank the stocks based on relative tick size (Panel A), tick-constrained spread (Panel B), realized volatility (Panel C), and adverse selection costs (Panel D). Realized volatility is the standard deviation of 5-minute quote midpoint returns. Adverse selection cost is measured by the volume-weighted average relative price impact of trades, computed over a 5-second window after each trade. Relative tick size is the minimum price variation divided by daily average quote midpoint. The explanatory variables are dummies for trader type (*AAT*, *HFT*), and for 10-stock-large subsamples of high/large vs low/small realized volatility, adverse selection costs or tick size, and interactions between them. We also include the volume traded (in shares), and the time-weighed daily average bid-ask spread, as controls. ***, **, * indicate statistically significant coefficient at the 1%, 5%, and 10% levels, respectively.

	Panel A: Relative tick size			Panel B: Tick-constrained bid-ask spread		
Coef.	Hidden	Disp.	All	Hidden	Disp.	All
AAT	-0.29 *	-0.09	-0.10 *	0.09	-0.01	0.05
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
HFT	-0.56 ***	0.51 ***	0.44 ***	-0.42 ***	0.48 ***	0.38 ***
	(0.01)	(0.03)	(0.02)	(0.00)	(0.02)	(0.01)
Large/High	0.11	0.35 ***	0.32 ***	0.24 ***	0.30 ***	0.30 ***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Large/High_AAT	-0.18	-0.30 ***	-0.26 **	-0.47 ***	-0.36 ***	-0.41 ***
	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Large/High_HFT	-0.16	-0.76 ***	-0.70 ***	-0.26 ***	-0.55 ***	-0.49 ***
	(0.01)	(0.07)	(0.06)	(0.00)	(0.05)	(0.04)
Small/Low	-0.17 ***	0.01	0.00	0.21 ***	0.11	0.12 **
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Small/Low_AAT	0.33 *	0.06	0.12	-0.51 ***	-0.12 ***	-0.20 ***
	(0.03)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Small/Low_HFT	0.19 ***	-0.09	-0.12	-0.13 *	-0.22	-0.16
	(0.01)	(0.06)	(0.04)	(0.00)	(0.03)	(0.02)
Intercept	0.62 ***	0.19 ***	0.22 ***	0.44 ***	0.17 ***	0.19 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj._R2	0.53	0.40	0.36	0.55	0.30	0.26
Obs.	1890	1890	1890	1890	1890	1890

	Panel C: Realized volatility			Panel D: Adverse selection costs		
AAT	-0.20 **	-0.15 ***	-0.14 ***	-0.27 ***	-0.08 ***	-0.07 ***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
HFT	-0.53 ***	0.30 **	0.23 *	-0.57 ***	0.43 ***	0.35 ***
	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Large/High	0.16 ***	0.11	0.11	0.13 ***	0.37 ***	0.34 ***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Large/High_AAT	-0.31 ***	-0.11 *	-0.12 *	-0.28 ***	-0.34 ***	-0.35 ***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Large/High_HFT	-0.17 ***	-0.23	-0.20	-0.12	-0.77 ***	-0.67 ***
	(0.00)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Small/Low	-0.09 **	-0.02	-0.03	-0.19 ***	-0.09 ***	-0.08 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Small/Low_AAT	0.19 *	0.05	0.08	0.39 ***	0.10 ***	0.12 ***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Small/Low_HFT	0.09 **	0.00	0.01	0.17 ***	0.17 *	0.12
	(0.00)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)
Intercept	0.58 ***	0.28 ***	0.30 ***	0.61 ***	0.22 ***	0.24 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj._R2	0.53	0.24	0.19	0.69	0.55	0.52
Obs.	1890	1890	1890	1890	1890	1890

Table IA2
Order aggressiveness

We examine the order exposure of different trader types conditioned on order aggressiveness for our sample of 30 NSE-listed stocks (top 3 deciles) in December 2013. In Panel A, we show the likelihood of hidden order trades conditional on order aggressiveness; in Panel B we show the placement of hidden limit orders (HLOs) across the limit order book. We categorize traders into algorithmic traders (ATs), further split between high-frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). To gauge aggressiveness, we construct order book snapshots at the time of each new order submission. The highest level of aggressiveness occurs is when a new hidden limit order is placed within the bid-ask spread ("Better"), followed by matching at the best quotes (‘At’). Aggressiveness decreases as the order is placed from the best quotes up to 5 ticks away (‘Near’), reaching its lowest level when placed beyond that threshold (‘Far’). All statistics are expressed as percentages, computed relative to either the number of orders or the share volume. Significant differences in medians between ATs (HFTs) and NATs (AATs) are shown beside NATs (AATs) numbers. We use the non-parametric Wilcoxon rank-sum test and ***, **, * to indicate statistically different at the 1%, 5%, and 10% levels, respectively.

	Technology-based trader types				Types of ATs			
	Orders		Volume		Orders		Volume	
Aggr.	ATs	NATs	ATs	NATs	HFTs	AATs	HFTs	AATs
Panel A: Likelihood of hiding								
Better	27.89	12.65 ***	30.17	26.73 *	16.19	33.25 ***	7.25	49.31 ***
At	36.08	10.56 ***	24.32	13.82 ***	6.59	41.02 ***	0.71	52.46 ***
Near	9.57	10.49 *	4.51	19.70 ***	1.32	13.43 ***	0.10	18.22 ***
Far	1.50	7.58 ***	0.37	22.06 **	0.02	25.48 ***	0.00	20.08 ***
Panel B: HLO placement								
Better	17.74	22.38 ***	11.95	13.16 **	54.91	15.43 ***	49.98	10.90 ***
At	47.08	25.32 ***	47.48	32.94 ***	20.40	48.72 ***	23.99	48.07 ***
Near	30.42	35.51 ***	34.96	34.05	23.68	30.86 ***	23.67	35.32 ***
Far	4.76	16.79 ***	5.61	19.84 ***	1.01	5.00 ***	2.37	5.71 ***

Table IA3
Order aggressiveness and relative tick size

We examine how the order exposure decision of different trader types depends on order aggressiveness and relative tick size. In Panel A, we explore the placement of hidden limit orders (HLOs) across the order book. In Panel B, we examine the placement of hidden volume across the order book. We categorize traders into algorithmic traders (ATs), further split into high-frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). To gauge aggressiveness, we construct book snapshots at each new order submission. The highest level of aggressiveness occurs when a new hidden order is placed within the prevailing bid-ask spread ("Better"), followed by matching the prevailing best quotes ('At'). Aggressiveness decreases as the order is placed from the best quotes up to 5 ticks away ('Near'), reaching its lowest level when placed beyond that threshold ('Far'). To control for the relative tick size, we rank stocks based on relative tick size, calculated as the minimum price variation divided by the daily average quote midpoint. We report results for the subsample of 10 stocks with the highest relative tick size, and the 10 stocks with the lowest relative tick size. Our analysis is conducted on a sample of 30 stocks (drawn from the top 3 deciles) listed on the NSE. Significant differences in medians between ATs (HFTs) and NATs (AATs) are shown beside NATs (AATs) numbers. We use the non-parametric Wilcoxon rank-sum test. ***, **, * indicate statistically different at the 1%, 5%, and 10% levels respectively.

Panel A: HLO placement	Stocks with higher relative tick size			Stocks with lower relative tick size		
Aggr.	HFT	AAT	NAT	HFT	AAT	NAT
Better	32.94	11.48 ***	8.49 ***	54.87	16.30 ***	25.98 ***
At	39.21	51.06 ***	40.50	22.70	47.18 ***	20.77
Near	27.15	34.83 **	31.80 *	21.43	30.80 ***	35.26 ***
Far	0.70	2.63 ***	19.21 ***	0.99	5.72 ***	17.99 ***
Panel B: Hidden volume placement						
Better	17.36	5.85 ***	6.50 ***	52.16	15.59 ***	19.50 ***
At	61.91	40.42 ***	41.76 ***	20.20	47.64 ***	22.76
Near	18.48	47.19 ***	30.88 ***	24.89	31.36 ***	36.11 ***
Far	2.25	6.55 ***	20.86 ***	2.75	5.40 ***	21.63 ***

Table IA4
Order size

We provide cross-sectional average daily statistics on the empirical distribution of the size of hidden limit orders (HLOs) and displayed limit orders (DLOs). The sample consists of the 30 NSE-listed stocks (from the top 3 deciles) in December 2013. We distinguish between algorithmic traders (ATs), further split into high frequency traders (HFTs) and agency algorithmic traders (AATs), and non-algorithmic traders (NATs). The analysis is based on order-by-order data grouped by full (displayed plus non-displayed) order size. The order size cutoffs are based on the empirical distribution of the order size of all limit orders submissions. We provide the percentage of HLOs and DLOs in each order-size category per trader type. We use the two-sample Kolmogorov-Smirnov (Massey, 1951) test to compare the order size distributions of HLOs and DLOs submitted by the different trader types. Significant differences in medians between ATs (HFTs) and NATs (AATs) are shown beside NATs (AATs) numbers. We use the non-parametric Wilcoxon rank-sum test. ***, **, * indicate statistically different at the 1%, 5%, and 10% levels respectively.

	Technology-based trader types				Types of ATs			
	ATs		NATs		HFTs		AATs	
Order size distrib. (%)	DLOs	HLOs	DLOs	HLOs	DLOs	HLOs	DLOs	HLOs
(0,50]	21.01	57.75	64.71	28.12	4.98	68.34	62.50	57.25
(50 75]	3.76	8.49	1.54	2.79	0.95	9.93	11.03	8.42
(75,100]	2.21	5.81	11.25	11.07	1.39	0.88	4.34	6.05
(100,200]	21.64	11.27	6.66	12.23	25.97	4.54	10.44	11.59
(200,500]	33.70	10.60	9.23	22.82	43.35	12.96	8.70	10.49
(500,1000]	13.70	3.60	3.55	10.87	18.36	2.92	1.66	3.63
>1000	3.98	2.49	3.06	12.11	4.99	0.43	1.34	2.58
Tests of equal distribution:								
ATs = NATs (p-value)				0.00				
HFTs = AATs (p-value)								0.00
DLOs = HLOs (p-value)		0.00		0.00		0.00		0.00
Average size (sh.)	790.78	486.10	320.77 ***	1192.80 ***	1179.41	255.74	318.40 ***	601.19

Table IA5
Exposure risk theory: stock-level analysis

We test whether the non-exposure decisions of high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs) conform to the exposure risk theory. We estimate a logistic model to assess the decision between submitting a hidden limit order (HLO) or a fully displayed limit order (DLO). Key explanatory variables are the (ex-ante) perceived risks of being picked off (*PickOff*) and being undercut (*Undcut*) when providing liquidity. These risk indicators are derived, stock by stock, as composite indexes (first principal component) of three alternative risk indicators. For details, see Appendix B. As controls, we include incoming limit order characteristics, such as size (*OrdSize*) and aggressiveness (*OrdAggr*). We also include dummies for the first 30- (*First30m*) and last 30 minutes of each trading session (*Last30m*). Market conditions are controlled using the quote midpoint return realized volatility (*Volat*), the volume traded in shares (*Vol*), and the market-wide (NIFTY50 index) realized volatility computed over the 1-minute window. The model is estimated stock by stock and we aggregate coefficients and z-scores using the approach in Chordia et al. (2005) (CRS05). All models include day fixed effects. The sample comprises of 30 NSE-listed stocks during December 2013. We provide the cross-sectional average estimated coefficient of the variables of interest, together with their odds ratio, and the aggregated CRS05-adjusted *z*-score. We estimate the model for HFTs (Panel A), AATs (Panel B), and NATs (Panel C), separately. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A: HFTs	Coef.	Odds ratio	Adj. z
PickOff	0.15	1.16	4.90 ***
Undcut	0.08	1.09	2.02 **
OrdAggr	0.35	1.42	19.36 ***
OrdSize	-0.06	0.94	-11.44 ***
Intercept	-6.36		-12.33 ***
Panel B: AATs			
PickOff	0.13	1.13	15.15 ***
Undcut	-0.19	0.83	-17.86 ***
OrdAggr	0.13	1.14	41.80 ***
OrdSize	0.35	1.42	44.49 ***
Intercept	-1.02		-10.69 ***
Panel C: NATs			
PickOff	0.05	1.05	3.39 ***
Undcut	-0.07	0.93	-4.50 ***
OrdAggr	0.00	1.00	2.97 ***
OrdSize	0.71	2.04	66.98 ***
Intercept	-2.66		-24.24 ***