An Analysis of Limit Order Activities: The Benefits of Technology

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Abstract

The use of algorithms to manage the trading process has become a common feature in today's marketplace with the proliferation of electronic limit order books. However, it is predominantly institutions who have access to algorithmic trading technology while retail investors are typically non-algorithmic market users. This dichotomy has been a cause of concern to regulators and cited as one of the reasons to curb the use of algorithmic trading. This study provides insight into these concerns by examining performance and behaviour of retail vs non-retail investors. Fundamental differences are found between the two groups. In contrast to retail investors, non-retail investors use more order revisions, react more quickly to liquidity opportunities and exploit fleeting orders to search for latent liquidity. Survival models indicate that technology provides non-retail investors with an advantage in managing the dual risks of limit order exposure, picking off risk and non-execution risk.
Keywords: limit orders, order revisions, order cancellations

1 Introduction

Technology has revolutionized the market structure and forever changed the way securities are traded on financial markets. Investors have embraced algorithmic trading, the use of computers to manage the trading process (Hendershott et al., 2011) which has emerged as the dominant form of trading. Markets, which traditionally comprised only of human traders are now increasingly interacting with computerized traders. Anecdotal evidence suggests that algorithmic trading accounts for between 50-70% of trading on US stock exchanges (Brogaard, 2010; Sussman et al., 2009) and 30-40% of trading volume on ASX (ASX, 2010).

There has been much debate among academics, practitioners, and regulators of the implications of increasing computerization of the trading process. One of the main concerns is the externality cost that investors with access to trading technology impose on other investors who do not have the same speed advantages, monitoring and information processing capabilities. The literature has focussed specifically on the role of high frequency traders, a subcategory of algorithmic trading known for its low latency, sophistication of its algorithms

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and high levels of order message activity. Negative perceptions over high frequency trading (HFT) are commonly held among investors. The IOSCO (2011) consultation report commented that for other investors, the presence of high frequency trading, 'discourages them from participating as they feel they are at an inherent disadvantage to these traders' superior technology'. Regulators in many countries are considering proposals to regulate HFT citing anecdotal evidence or the perception that HFT is not only harming market quality but also increasing costs for less sophisticated investors. However, the empirical evidence does not always support this view (Malinova et al., 2013).

High frequency traders represents only a small fraction of a broader class of investors utilizing algorithms to manage their trading. ASX (2010) estimates that 10% of algorithmic trading is generated by high frequency traders. For this broader class of investors, investment in superior technology and the level of sophistication of its computerized trading algorithms is viewed as vital for economic success[1]. This study contributes to the debate by providing insights on how access to trading technology benefits algorithmic trading users through their limit order activities.

The limit order activities of computers versus human traders are generally not identifiable in high frequency tick datasets making it difficult for a direct comparison to be made between the activities of algorithmic vs non-algorithmic market users. Hendershott and Riordan (2011) are able to exploit a pricing scheme by Deutsche Bank to identify algorithmic trading activity while Brogaard (2010) obtained a unique Nasdaq dataset identifying high frequency traders (HFT's) and non-HFT's. The Australian Stock Exchange (ASX) does not require their market participants to flag whether orders are submitted through algorithmic trading engines and market participants may not always be aware how their clients are conducting their trading[2]. However, there is a distinct class of investors who predominantly have access to algorithmic trading systems. It is widely used by a diverse group of institutional investors which include proprietary trading desks, market makers, investment managers, brokers and hedge funds for a variety of trading tasks while retail investors are typically non-algorithmic market users. This dichotomy between institutional and individual investors provides an avenue for evaluating the advantages bestowed to investors with access to superior trading technology.

The benefits of trading technology are assessed directly by examining the limit order performance of different investors. We also examine how access to trading technology affects order management strategies by comparing the aggregate limit order behaviour of investors with differential access to trading technology. Do non-retail inestors (algorithmic users) engage in dynamic strategies which are fundamentally different to retail investors (non-algorithmic users)? What are the order strategies of retail investors in the face of their speed disadvantages?

Biais et al. (2012) assumes that the speed advantages of trading technology provides two benefits. Firstly, search capacity for liquidity is higher as faster access to trading platforms enables traders to react to fleeting trading opportunities. Secondly, it enables the trader to react faster to new information. Garvey and Wu (2010) find that traders located closer to the exchange gain a speed advantage over other traders and incur lower execution costs.

[1]To gain a better understanding on the importance of algorithms to investors, TRADE magazine surveyed institutional buy side investors on the main reason for using algorithms. Trader productivity (15%), reduced market impact (14.6%) and cost (14.2%) were found to be the most important reasons in the 2010 survey.

[2]Nevertheless, estimates of algorithmic trading activity in ASX (2010) are sourced from estimates provided by the market participants. ASX (2010) also reported that it is currently reviewing a requirement for market participants to provide a client ID to every order.

While there is an extensive literature on order choice (Bloomfield et al., 2005; Griffiths et al., 2000), fewer studies have examined order limit behaviour after order submission. The literature has tended to focus on order cancellations (Hasbrouck and Saar, 2009; Chakrabarty et al., 2006; Lo et al., 2002) as opposed to limit order revisions (Fong and Liu, 2010) despite evidence from Liu (2009) suggesting that more orders are revised than cancelled. A closely related paper by Duong et al. (2009) examines the order aggressiveness of institutional and retail limit orders but focus is on the order placement decisions of different investors as opposed to decisions made subsequent to order submission. To the best of our knowledge, we are unaware of studies that make a distinction between the limit order revision and cancellation behaviour between retail and non-retail investors. This distinction is important given their differential access to computerized algorithms to manage their trading activities.

Liu (2009) and Fong and Liu (2010) identify two sources of risk motivating limit order revisions and cancellations. The first source, 'free-option' risk arises because limit orders provide an option for others to transact at a pre-specified limit price. Exposed limit orders are at risk of being picked-off by faster and more informed traders reacting to the arrival of new information on the value of the asset (Copeland and Galai, 1983). Bloomfield et al. (2005) argue that informed traders have a competitive advantage in limit order trading because they can manage adverse selection risk better than other traders. Recent developments in theoretical models of limit order books examining the effects of HFT typically incorporate trader heterogeneity in which traders can compete on speed and impose negative externalities on these slower traders. It is commonly thought that retail investors suffer significant losses from adverse selection.

The limit order trader also bears 'non-execution' risk, which represents the opportunity cost suffered when the order does not achieve execution. Hasbrouck and Saar (2009) finds evidence supporting the 'chasing' hypothesis, trader behaviour which is consistent with the management of non-execution risk. As the market moves away from the price of a standing limit order, the chance of execution is reduced. Under the 'chasing' hypothesis, traders with a desire to transact reposition their limit orders more aggressively ('chasing' the market).

This study analyses a unique dataset of over five million non-marketable limit orders submitted by more than a hundred market participants which includes details tracking the revisions made to each submitted limit order. Prior literature (Lo et al., 2002; Chakrabarty et al., 2006; Hasbrouck and Saar, 2009) adopted a single risk approach where the event of interest is either order cancellation or execution and the alternative risk event is treated as censored. As order cancellations could occur due to traders responding to either non-execution or picking-off risk, the availability of information on how limit orders are revised allows us to disentangle how investors respond to these two types of risks.

The competing risks framework is applied to limit order data, in which an individual limit order is exposed to order cancellation, execution or different types of order revisions. The hazard rate for the risks of interest can be modelled separately using the Cox proportional hazards duration model (Cox, 1972). Our specification incorporates time varying covariates in the manner of Hasbrouck and Saar (2009) to model the monitoring intensity and behaviour of different investors to changes in their limit order risks subsequent to order submission.

Responding to shifts in the non-execution and picking-off risk of exposed limit orders, traders can price protect themselves by order shading (submitting less aggressive limit orders), or actively monitoring the market (Liu, 2009). Foucault et al. (2003) show that Nasdaq dealers reduce their picking off risk by increasing monitoring intensity when facing professional day traders. Monitoring comes at a cost and Liu (2009) examine the trade-off between the costs of monitoring and limit order submission risks. However, most brokerage firms provide their buy-side clients with an array of algorithms to manage their execution costs avoiding the need for institutional investors to invest heavily in costly information monitoring. These agency algorithms significantly reduce the costs of monitoring their limit orders. Hence, retail and non-retail investors do not face the same trade-offs between the costs of monitoring and limit order submission risks.

There is a large strand of academic literature identifying specific sources of advantage that institutional investors may have over retail investors, related to their level of sophistication, available resources and information gathering and processing skills. For example, Irvine et al. (2007) find that institutions anticipate recommendations by receiving tips from sell-side analysts, Jegadeesh and Tang (2011) finds evidence of private information gathering while Campbell et al. (2009) shows institutions anticipate earnings surprises. On the other hand, retail investors are seen to be noise traders who are most susceptible to behavioural biases. Barber et al. (2009) document a significant wealth transfer from retail investors to institutional investors from trading and Linnainmaa (2010) attribute losses of retail investors limit orders to adverse selection. Complementing this literature, we examine specifically the extent to which retail investors experience poor limit order performance relative to non-retail investors attributed to differential access to trading technology.

Based on a direct examination of limit order performance across different investors, institutional limit orders are found to perform better than individual limit orders when measured using the implementation shortfall (Perold, 1988) approach. However, there is little economic significance in their expost costs under the Harris and Hasbrouck (1996) measure. The gains from trading technology to non-retail investors does not appear to be simply an adverse selection effect, but reflects the ability of algorithmic trading technology to better manage overall execution costs for non-retail investors.

Access to trading technology has brought about two benefits. Speed allows investors to be able to access the market quickly and take advantage of fleeting order opportunities. While we observe a lower incidence of fleeting orders (c8% for institutional investors) than documented in Hasbrouck and Saar (2009), fleeting orders are more aggressively priced consistent with the search hypothesis and originate primarily from institutional investors. Due to the speed required, fleeting opportunities are largely inaccessible to retail investors. Algorithms also provide autonomy, little human intervention is required once the parameters of the trading strategy is defined. This high level of automation significantly increases the ability to monitor exposed limit orders, respond instantaneously to changes in market conditions and optimally managing non-execution and picking-off risks. As expected, institutional investors utilizing algorithms will employ more order cancellations and revisions as they adjust their orders to changes in market conditions (Liu, 2009). The results from proportional hazard models confirms that non-retail investors are more responsive to changes in limit order risks, particularly non-execution risk. We find significant differences in the rate of cancellations and upward order revisions across investors as the best prices in the limit order book moves away from the limit price.

2 Data and Investor Classification

2.1 Sample Selection

We investigate the limit order performance and behaviour across investors based on a sample of 75 randomly selected Australian firms sourced from the Australian Equities Tick

History (AETHS) database[3]. The selected firms cover a broad cross-section of Australian firms in the S&P/ASX 200 as at October 31, 2009 and are ranked into market capitalization tertiles. The study utilizes two distinct datasets from AETHS. The Order Book data contains a complete audit trail of all order events, including details of the order type (ie order submission, revision, cancellation and execution), price, volume, order direction (buy or sell) and the date and time of the order measured to the nearest millisecond. Two unique features distinguishes the Order Book data from other high frequency databases. Firstly, all limit order revisions are observed as each order can be tracked from submission to either cancellation or execution. This level of detail is important in differentiating between the mitigation of non-execution risk from the avoidance of picking-off risk. Secondly, the provision of broker identification codes facilitates investor type identification for each limit order. The Market Depth dataset contains limit order book data on the five best bid and ask limit prices which can alternatively be reconstructed from the set of order records. The Order Book data is then matched to the Market Depth data for analysis.

This study analyzes only standard limit orders, excluding limit orders associated with priority crossings (typically block or dark trades) and off-market trades, fill and kill and all or nothing orders. This is further restricted to limit order revision and cancellation activities during coninuous trading hours as they are constantly exposed to non-execution and picking-off risk. The dynamics that drive limit order submissions, cancellations and revisions are believed to be driven by a different set of factors outside trading hours. Orders that are not cancelled by the close of trading are treated as right censored observations.

2.2 Investor Classification

Each market participant is classified into one of five investor categories based on the primary clientele of the brokerage firm. The institutional category (INST) refers to brokerage firms which services primarily institutional clients. Similarly, the retail category refers to brokerage firms that service primarily retail investors including both full service brokers (which provide financial advice) as well as discount brokers (which provide essentially a basic online execution service). The mixed investor category (MIXINSTRET) consists of order submitted by brokers with a mixture of both institutional and retail clientele. Brokerage firms engaged in proprietary trading and market making strategies are classified separately (MM) and hereafter referred to simply as market makers. Limit orders that are unassigned (OTHER) and those arising from the mixed investor category (MIXINSTRET) are excluded from our analysis. The number of limit orders excluded represents less than 1% of the total number of non-marketable limit orders and less than 7% of all trading volume in the sample.

The classification was conducted by examining three sources of information: (1) official websites of market participants on the activities, products and services and clientele of the firm, (2) past newspaper and magazine articles and (3) notifications and online publications from the ASX[4]. While there is inevitably some degree of misclassification[5], broker identities have been found to be strong predictors of investor identities (Duong et al., 2009) and is closely related to the classification approach of Jackson (2003) and Fong et al. (2013).

[3]Data supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of ASX. See http://www.sirca.org.au/.

[4]The ASX provides a list of full service and discount brokers. http://www.asx.com.au/resources/find-broker.htm

[5]Institutional brokerages typically services a wide range of clients from traditional buy side investors to high frequency trading firms. While the data does not permit the identification of individual trading accounts, what distinguishes institutional brokerages from retail brokerages is their access to algorithmic trading technology.

Figure 1: Investor Categories

3 Limit Order Activities Across Investors

3.1 Statistics of Limit Order Submissions

For the full sample across all investors, we find that 50% of all non-marketable limit orders are cancelled, 27% of orders have been revised one or more times and 43% achieve partial or full execution. Cancellation rates are found to be relatively low compared to recent empirical evidence from other trading venues. As a comparison, Hasbrouck and Saar (2009) find that 93% of orders are cancelled on INET and Ellul et al (2007) document that traders on the NYSE cancelled almost half of all limit orders. Table 1 presents summary statistics of new limit order submissions disaggregated by investor category. Significant differences emerge indicating strong heterogeneity in how these investors manage the trading process. The use of limit orders is more prevalent among non-retail investors across all size categories, accounting for 79% of all orders relative to 57% for retail investors. This contrasts with previous documented findings (Linnainmaa, 2010) but is consistent with the predictions of Hoffmann (2012) that in equilibrium, if retail traders are indeed 'slower', they are more likely to utilize market orders to avoid the adverse selection associated with limit order submission.

Cancellation and revision rates of limit orders submitted by non-retail investors are higher, as access to computerized algorithms reduce the cost of monitoring limit orders. Market makers have a greatest propensity to revise and cancel their limit orders consistent with their liquidity provision role. Limit orders that remain in the limit order book at the close of trading originate primarily from retail investors, confirming that retail investors are indeed the source of stale limit orders. The proportional of stale limit orders increases for smaller stocks. A small decrease in execution rates is also observed on limit orders in smaller stocks which are generally less liquid and have lower order arrival rates.

3.2 Statistics of Limit Order Revisions

Once a limit order is submitted, it can be revised numerous times prior to its eventual cancellation or execution. Limit order revisions can reveal important information about the underlying dynamic trading strategy. Figure 2 displays the percentage breakdown of the total number of order revisions made to each non-marketable limit order for different investor categories. Across all investors, a large proportion of limit orders are not revised. Retail investors are the least active users of limit order revisions, more than 70% of limit orders are not revised. Market makers are most active in their limit order behaviour with over 10% of their limit orders experiencing more than seven subsequent revisions.

Table 2 presents information on the type of order revisions employed by different investors.

Table 1: Frequency of Limit Order Events

This table presents summary statistics of new limit order submissions on the full sample of 75 stocks. The sample period is November 2009 consisting of 21 trading days. Only standard orders submitted between 10:10am and 4:00pm are included in the analysis. The % of nonmarketable limit orders (LOs) is defined as the number of non-marketable limit orders divided by the sum of all limit orders (marketable and non-marketable) for each investor category. % Buy and % Sell represents the proportion of bid and ask limit orders. The table also reports the percentage breakdown of all non-marketable limit orders experiencing certain order book events. % cancelled represents the proportion of orders subsequently cancelled, % revised represents the proportion with at least one observed revision, % executed represents those non-marketable limit orders which are subsequently fully or partially executed and % censored represents those orders remaining in the order book at 16:00:00. These events are not mutually exclusive so the percentages do not add to 100. For example, a limit order could be revised numerous times, partially executed and subsequently cancelled.

Panel A: Large Cap								
Investor Category	Total Non-marketable LOs	% of Non-Marketable LOs	% Buy	% Sell	% Cancelled	% Revised	% Executed	% Censored
INST	2846721	79.1%	49.8%	50.2%	49.1%	32.2%	51.9%	0.3%
RET	127748	55.0%	54.1%	45.9%	16.7%	24.1%	58.5%	24.9%
MM	400002	84.1%	46.4%	53.6%	67.8%	41.5%	33.6%	0.1%
Panel B: Mid Cap								
Investor Category	Total Non-marketable LOs	% of Non-Marketable LOs	% Buy	% Sell	% Cancelled	% Revised	% Executed	% Censored
INST	1174489	78.8%	51.0%	49.0%	52.4%	31.8%	48.9%	0.3%
RET	46226	60.3%	55.5%	44.5%	16.9%	26.3%	55.5%	27.7%
MM	98261	80.6%	48.2%	51.8%	54.9%	41.5%	46.4%	0.3%
Panel C: Small Cap								
Investor Category	Total Non-marketable Limit Orders	% of Non-Marketable LOs	% Buy	% Sell	% Cancelled	% Revised	% Executed	% Censored
INST	393772	76.5%	50.9%	49.1%	53.3%	32.9%	47.9%	0.4%
RET	26106	63.6%	51.2%	48.8%	17.2%	25.5%	48.4%	34.6%
MM	43601	83.5%	52.3%	47.7%	61.7%	37.2%	39.9%	0.3%
Panel D: Total								
Investor Category	Total Non-marketable Limit Orders	% of Non-Marketable LOs	% Buy	% Sell	% Cancelled	% Revised	% Executed	% Censored
INST	4414982	78.8%	50.2%	49.8%	50.3%	32.2%	50.7%	0.3%
RET	200080	57.2%	54.1%	45.9%	16.8%	24.8%	56.5%	26.8%
MM	541864	83.4%	47.2%	52.8%	65.0%	41.2%	36.4%	0.2%

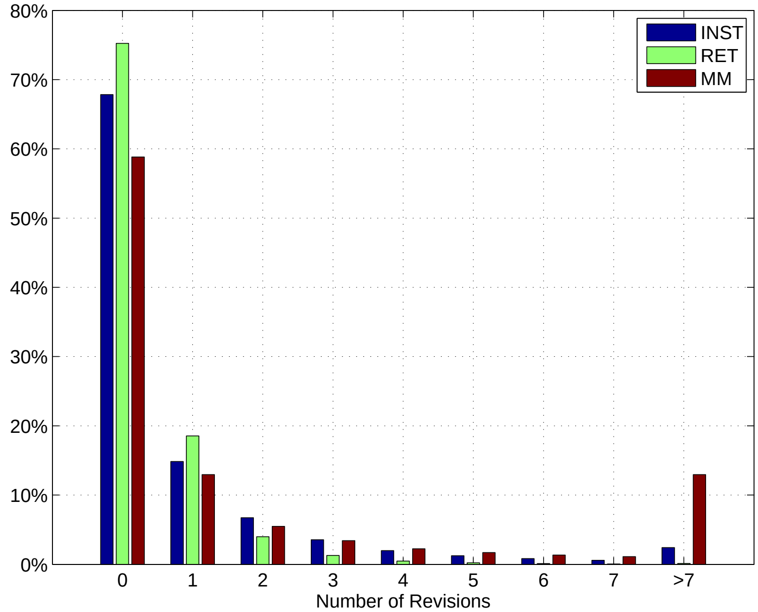


Figure 2: Number of Limit Order Revisions
This figure presents the percentage breakdown of the total number of revisions of non-marketable limit orders by investor category. It is based on all standard orders submitted between 10:10am and 4:00pm on pooled sample of 75 ASX listed stocks. The sample period is November 2009 consisting of 21 trading days.

Table 2: Transition Matrix of Revised Orders
This table presents the empirical transition frequencies of all revised orders for each investor category. Each row represents the level of order aggressiveness immediately prior to order revision and each column represents the order aggressiveness of the revised order. The most aggressive limit order (inside spread) is placed with a limit price that narrows the bid-ask spread. Lx represents a limit order placed at price level x (for example, L1 refers to an order placed at the best bid or offer). Lx-L$(x+1)$ represents an order with limit price placed between price level x and $x+1$.

Panel A: INST Investor Category

	Mkt	Inside Spread	L1	L1-L2	L2	L2-L3	L3	>L3	Total Obs
L1	9.1%	3.2%	72.4%	0.4%	5.8%	0.3%	4.5%	4.2%	1,570,744
L2	6.5%	1.6%	39.2%	0.8%	40.3%	0.5%	5.2%	6.0%	1,438,639
L3	8.8%	1.5%	36.5%	1.4%	14.2%	0.9%	24.6%	12.2%	630,829
>L3	3.8%	0.9%	18.5%	0.8%	11.5%	0.8%	11.7%	52.0%	1,082,156

Panel B: RET Investor Category

	Mkt	Inside Spread	L1	L1-L2	L2	L2-L3	L3	>L3	Total Obs
L1	64.8%	9.1%	12.5%	0.8%	5.7%	0.5%	2.7%	3.9%	20,482
L2	30.2%	7.0%	38.6%	1.2%	4.5%	1.0%	4.9%	12.5%	13,732
L3	23.3%	5.6%	25.7%	1.5%	19.9%	0.7%	3.8%	19.5%	9,265
>L3	13.5%	2.5%	8.7%	0.6%	8.1%	0.5%	7.2%	59.0%	66,625

Panel D: MM Investor Category

	Mkt	Inside Spread	L1	L1-L2	L2	L2-L3	L3	>L3	Total Obs
L1	3.7%	7.0%	28.7%	3.9%	40.5%	2.0%	7.0%	7.3%	394,522
L2	0.9%	2.5%	31.6%	2.2%	15.2%	3.0%	33.2%	11.5%	590,935
L3	0.3%	0.7%	6.1%	2.3%	37.5%	2.0%	10.0%	41.1%	534,266
>L3	0.0%	0.2%	1.4%	0.2%	3.2%	0.8%	10.6%	83.6%	2,115,573

A transition frequency matrix of order revision activity is estimated where each state in the matrix represents a level of order aggressiveness. Each element of the matrix represents the frequency of migration from one level of order agg to another level of order aggressiveness.

Some striking differences are found in the type of order revisions employed by investors. Firstly, institutional investors have the greatest propensity to utilize volume revisions and over 70% of revisions are volume amendments occurring at the best prices. This finding is unsurprising given the popularity of VWAP-style algorithms employed by institutional investors. Secondly, upward price revisions are more common than downward price revisions among institutional investors and retail investors than market makers. Non-execution risk appears to be of greater concern to these investors and while behaviour is consistent with the 'chasing hypothesis' (Hasbrouck and Saar, 2009). However, striking differences exist in subsequent order placement. Among institutional investors, orders are most commonly revised to the best prices while retail investors limit orders are most frequently converted to market orders. This is another sign of the high costs of monitoring imposed on retail investors. In contrast, market makers are significantly less aggressiveness with their order revisions and the observed frequencies of upward and downward price revisions indicate more symmetric concerns for non-execution and picking-off risk.

3.3 Order Exposure

Limit order events are modelled under a competing risks framework. Within this framework, a limit order is subject to multiple causes of failure[6] (ie execution, cancellation or revision). Limit orders that remain in the limit order book after the close of the days' trading are censored observations (right censoring). The set of competing risk events are mutually exclusive and compete in the sense that the occurrence of one event precludes the occurrence of the other events. This is not strictly true in the presence of data where we can observe limit order revisions. We accomodate for this in the competing risks framework by viewing an order revision as a cancellation which is accompanied by an immediate re-submission of a new limit order. Hence, multiple observations are spawned from limit orders which are revised. The inclusion of order revisions as a competing risk is valuable for examining differences in the limit order strategies between investors[7].

We analyze exposure times of limit orders prior to observing an order revision, execution or its cancellation. A common procedure in the survival analysis literature is the Kaplan-Meier estimator. However, under a competing risks framework, the Kaplan-Meier estimator tends to overestimate the incidence rates of a particular risk event in the presence of other competing risks (Pintilie, 2006). An alternative approach suggested by Kalbfleisch and Prentice (1980) is to use cumulative incidence functions (CIF's) which quantifies the cumulative probability of observing event J in the interval $(0, t]$, without assumptions about the dependence between these events. The cumulative incidence function (CIF) from type j failure is defined by

$$F_j(t) = Pr(T \leq t; C = j) = \int_0^t \lambda_j(u)S(u)du \qquad j = 1, ..., J \tag{1}$$

where $\lambda_j(t)$ is the cause-specific hazard rate

$$\lambda_j(t) = \lim \frac{1}{\Delta t} P\{t \leq T \leq t + \Delta t, C = j | T \geq t\} \tag{2}$$

[6]Terminology adopted from the survival analysis literature.

[7]An alternative modelling methodology would be to consider recurrent survival models with multiple failures. This is left for future research

and $S(t) = P(T > t)$ is the survival function. The cause-specific hazard measures the instantaneous risk of observing a particular limit order event J given the limit order has been placed in the market for t seconds. A consistent non-parametric estimate of the CIF is given by

$$\hat{F}_j(t) = \sum_{i:t_i \leq t} \frac{d_{ji}}{n_i} \hat{S}_{t_{j,i-1}} \tag{3}$$

where d_{ji} is the number of failures observed at time t_i from failure type j, n_i is the number of limit orders at risk at time t_i and $\hat{S}(t)$ is the Kaplan-Meier estimate of the survival function by considering all events to be of the same type.

Figure 3 illustrates some striking differences in the estimated CIF's across investors for BHP. Both institutional investors and market makers are active users of limit order revisions. Market makers are most active, with over 80% of limit orders revised within 10 minutes while cancellations are more prevalent among institutional investors. In contrast, execution is the most common outcome for a retail investor's limit order. Table 3 presents the cross-sectional averages of estimated CIF's for each investor category, confirming the differences observed are robust across stocks. The CIF's of limit order cancellations and revisions from non-retail investors rise very sharply before leveling off, consistent with their utilization of computer algorithms to actively manage their limit order strategies. Retail investors experience high execution rates with few limit order cancellations or revisions observed less than 30 seconds from order submission. Consistent with retail investors experiencing higher monitoring costs, they are willing to bear greater exposure risks with their limit orders.

We also confirm the presence of fleeting orders, defined as an order that is cancelled (or amended) within two seconds (Hasbrouck and Saar, 2009). Fleeting orders are almost entirely placed by institutional investors and market makers. On institutional limit orders, the average cumulative incidence of order amendments after two seconds ranges between 3% to 4% and is slightly higher at 5% to 6% on order cancellations. The cumulative incidence of fleeting order amendments for market makers is significantly higher at 21% for large cap stocks but falls to just 4% for small stocks.

Hasbrouck and Saar (2009) asserts that the search for latent liquidity is the motive behind dynamic strategies utilizing fleeting orders. In markets which allow traders to submit hidden orders, market participants attempt to 'ping' for hidden liquidity inside the spread by posting fleeting orders. Hidden order functionality was not available on the ASX during the sample period, but fleeting orders can be submitted to attract 'reactive traders' (Harris, 1996), a counterparty who is actively monitoring the market for liquidity opportunities but is not disclosing their trading intentions.

Table 4 presents the positioning of fleeting orders relative to non-fleeting orders. Consistent with the search hypothesis, fleeting limit orders are much more likely to be positioned inside the bid-ask spread and this effect is stronger for stocks with smaller market capitalization. The results also provide insights into how retail investors adjust their order submission strategy in the presence of algorithmic trading. Significant 'order shading' is observed from retail investors limit orders with 65% of retail investors limit orders placed more than three price levels from the best prices. Retail investors indeed compensate for the lack of attention in monitoring orders by placing orders further behind the limit order book.

To examine who benefits from the liquidity provided by fleeting orders, we estimate for each competing risk j and investor i, $P(T \leq t|J = j, I = i)$, the cumulative probabilities of limit order execution conditional on execution from a market order submitted by each investor category. Table 3.3 presents the cross-sectional average of the estimated cumulative

Table 3: Cumulative Incidence Function Estimates

The table presents the cumulative incidence estimates of order revision (AMEND), cancellation (DELETE) and execution (TRADE) events at various timepoints. Cumulative incidence functions are estimated separately for each of 75 stocks in the sample by investor category. The results presented are the cross-sectional averages of the cumulative incidence estimates at the specified timepoints. Time to the occurrence of a competing risk event is measured from the last order submission or amendment. It is based on all standard orders submitted between 10:10am and 4:00pm.

Panel A: Large Caps

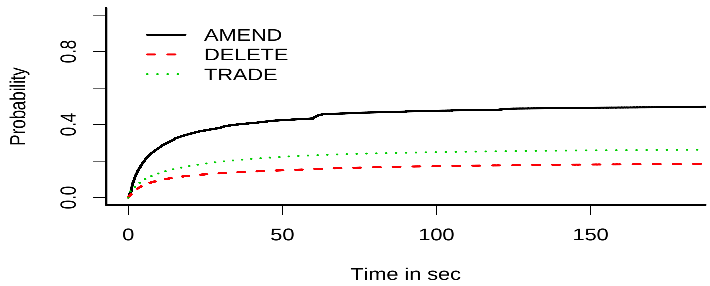
	INST			RET			MM		
Time	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE
1s	4.3%	3.6%	4.8%	0.3%	0.2%	3.4%	14.7%	2.3%	0.8%
2s	8.6%	5.3%	5.7%	0.3%	0.2%	4.2%	21.2%	3.4%	1.1%
5s	15.0%	7.6%	7.5%	0.5%	1.3%	5.8%	33.4%	6.4%	1.6%
10s	21.2%	10.1%	9.4%	1.1%	1.7%	7.7%	43.3%	8.0%	2.0%
30s	32.6%	14.1%	13.1%	4.2%	2.7%	12.5%	57.9%	9.7%	2.8%
1m	38.0%	16.3%	15.9%	10.3%	3.7%	16.5%	65.1%	10.5%	3.4%
5m	47.8%	21.4%	21.3%	19.9%	6.2%	26.9%	75.5%	11.9%	4.7%
10m	49.8%	22.7%	22.6%	23.6%	7.5%	31.7%	78.0%	12.2%	5.1%
30m	51.1%	23.9%	23.5%	29.2%	9.5%	38.9%	80.2%	12.6%	5.5%
1h	51.4%	24.2%	23.7%	32.0%	10.8%	42.6%	80.8%	12.9%	5.6%

Panel B: Mid Caps

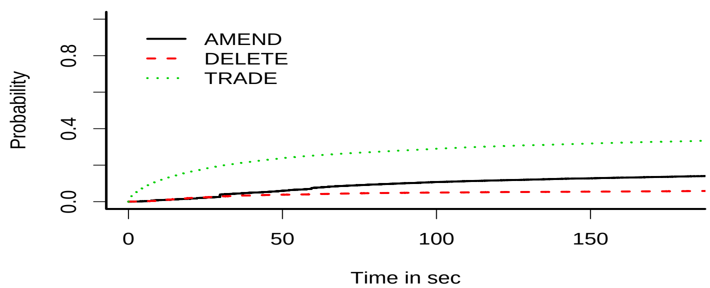
	INST			RET			MM		
Time	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE
1s	3.8%	4.7%	4.4%	0.4%	0.3%	3.8%	8.7%	0.8%	0.9%
2s	6.9%	6.4%	5.0%	0.5%	0.4%	4.3%	12.7%	1.2%	1.2%
5s	11.8%	8.3%	6.1%	0.9%	1.8%	5.3%	22.3%	4.0%	1.7%
10s	17.0%	10.4%	7.4%	1.4%	2.3%	6.6%	30.8%	5.7%	2.3%
30s	28.6%	13.9%	10.2%	4.0%	2.9%	9.9%	44.8%	7.7%	3.6%
1m	34.7%	16.1%	12.5%	9.2%	3.5%	13.0%	53.1%	8.6%	4.6%
5m	47.1%	22.0%	18.6%	17.5%	6.4%	23.2%	68.6%	9.9%	7.2%
10m	49.9%	23.7%	20.4%	21.5%	7.8%	28.3%	73.0%	10.3%	8.3
30m	51.4%	25.0%	21.9%	27.4%	10.6%	36.6%	76.8%	11.0%	9.2%
1h	51.7%	25.4%	22.2%	30.7%	12.2%	40.7%	77.7%	11.5%	9.4%

Panel C: Small Caps

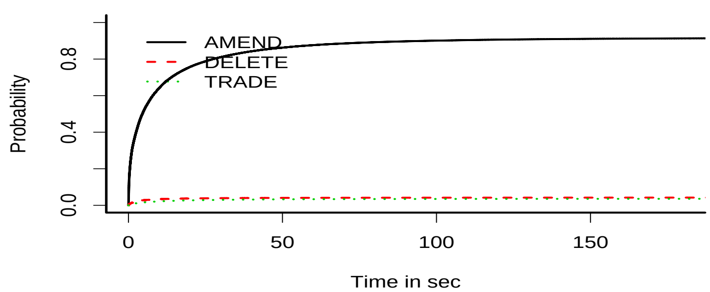
	INST			RET			MM		
Time	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE	AMEND	DELETE	TRADE
1s	3.2%	4.9%	3.3%	0.1%	1.0%	5.3%	3.6%	0.5%	0.9%
2s	4.9%	6.2%	3.7%	0.2%	1.0%	5.7%	5.4%	0.8%	1.3%
5s	7.6%	7.4%	4.3%	0.4%	2.9%	6.3%	10.9%	7.3%	1.9%
10s	10.6%	8.7%	5.0%	0.7%	3.6%	7.1%	16.3%	10.9%	2.4%
30s	19.8%	11.1%	6.7%	1.8%	4.2%	9.0%	26.6%	14.1%	3.6%
1m	25.6%	12.9%	8.2%	5.0%	4.8%	11.1%	31.6%	15.3%	4.9%
5m	42.3%	18.8%	13.3%	14.6%	7.2%	18.9%	43.5%	17.1%	9.1%
10m	46.7%	21.4%	15.6%	18.4%	8.5%	23.8%	48.3%	17.8%	11.6%
30m	50.2%	23.9%	18.8%	24.6%	11.3%	32.9%	54.1%	19.2%	16.0%
1h	51.4%	25.1%	19.9%	28.1%	13.0%	38.7%	56.1%	19.9%	17.8%



(a) Institutional Investors (INST)



(b) Retail Investors (RET)



(c) Proprietary Trading and Market Makers (MM)

Figure 3: Cumulative Incidence Plots for BHP

The figures displayed are the estimated cumulative incidence functions of order revision (AMEND), cancellation (DELETE) and execution (TRADE) for BHP. Separate cumulative incidence functions are estimated for each investor category.

Table 4: Limit Order Placement: Fleeting vs Non-Fleeting Orders

This table presents statistics on the price aggressiveness of newly submitted nonmarketable limit orders categorized into fleeting and non-fleeting orders. A 'fleeting order' is defined as a limit order that is cancelled within two seconds of order submission (Hasbrouck and Saar, 2009) . The table The empirical probabilities are tabulated across price aggressiveness levels separately for orders submitted by institutions (INST), proprietary trading or market makers (MM) and retail investors (RET) (non-fleeting orders only). Order amendments are considered both a cancellation and a resubmission for the purposes of classifying fleeting orders. Only standard limit orders submitted between 10:10am and 4:00pm are included. The most aggressive limit order (inside spread) is placed with a limit price that narrows the bid-ask spread. Lx represents a limit order placed at price level x (for example, L1 refers to an order placed at the best bid or offer). Lx-L$(x+1)$ represents an order with limit price placed between price level x and $x+1$.

	Fleeting Orders $\leq$ 2s		Non-Fleeting Orders > 2s		
Panel A: Large Caps	INST	MM	INST	MM	RET
Inside Spread	10.6%	5.0%	2.2%	2.4%	1.3%
L1	40.8%	30.5%	37.8%	36.9%	17.6%
L1-L2	2.0%	1.8%	0.6%	1.2%	0.7%
L2	21.8%	20.9%	17.9%	18.7%	9.0%
L2-L3	0.7%	1.4%	0.5%	1.1%	0.5%
L3	9.3%	12.6%	15.1%	11.7%	5.4%
> L3	14.7%	27.8%	25.9%	27.9%	65.5%
Panel B: Mid Caps	INST	MM	INST	MM	RET
Inside Spread	18.1%	9.4%	4.0%	3.8%	1.9%
L1	42.9%	56.8%	45.6%	58.8%	25.2%
L1-L2	3.4%	3.5%	1.2%	2.0%	0.8%
L2	16.9%	19.1%	15.9%	14.4%	10.7%
L2-L3	1.3%	1.4%	1.2%	0.8%	0.7%
L3	7.0%	2.6%	12.2%	4.3%	7.5%
> L3	10.3%	7.2%	19.9%	15.9%	53.2%
Panel C: Small Caps	INST	MM	INST	MM	RET
Inside Spread	17.2%	8.4%	2.8%	2.8%	1.4%
L1	49.0%	64.7%	49.4%	63.0%	33.1%
L1-L2	2.8%	2.6%	1.3%	2.4%	0.9%
L2	15.6%	13.9%	16.9%	10.1%	14.8%
L2-L3	0.8%	1.0%	1.1%	1.0%	0.7%
L3	7.8%	2.3%	10.4%	4.1%	10.1%
> L3	6.8%	7.0%	18.1%	16.6%	38.8%

probabilities of conditional limit order execution across different investor categories. Marked differences exist in the estimated cumulative probabilities between limit orders placed inside the spread than at lower aggressiveness levels. Between 35 to 50% of non-retail market orders are submitted within two seconds of observing a limit order placed inside the spread in contrast to only 3 to 8% of market orders by retail investors. The results are consistent with non-retail investors closely monitoring the market for trading opportunities and the speed advantages offered by trading technology allows them to react to fleeting opportunities while fleeting order liquidity is largely inaccessible for retail investors[8].

4 Limit Order Risks

4.1 Methodology

Traders are confronted with two sources of risk after limit order submission and changes in exposure to these risks are found to be strong motives behind limit order revision and cancellation activities (Fong and Liu, 2010). Picking-off risk can be mitigated by repositioning limit orders further behind the limit order book while non-execution risk can be reduced with a more aggressive limit order placement. If non-retail investors are indeed better at monitoring markets, order revision and cancellation activity would respond more quickly to changes in these limit order risks. We apply an econometric model of limit order survival times in a competing risk framework, incorporating time dependent covariates to examine the ability of different investors to actively monitor markets and make dynamic assessments of the limit order risks they face. The list of competing risk events in Table 4.1 is expanded to incorporate different types of limit order revisions.

Following Hasbrouck and Saar (2009), we model the cause specific hazard function $\lambda_k(t; X(t))$, conditional on a set of covariates $X(t)$

$$\lambda_k(t; X(t)) = \lim \frac{1}{\Delta t} P\{t \leq T \leq t + \Delta t, J = j | T \geq t, X(t)\}. \tag{4}$$

$\lambda_k(t; X(t))$ now represents the instantaneous risk of observing event j at time t, given the set of time dependent covariates $X(t)$ and in the presence of other risk events.

The cause-specific hazard rate $\lambda_j(t; x)$ takes the following semi-parametric form

$$\lambda_j(t; x) = \lambda_{0j}(t) exp(\beta_j' X(t)), \tag{5}$$

where $\lambda_{0j}(t)$ is an arbitrary, unspecified baseline hazard rate and β is a vector of regression coefficients related to event j. This is known as the Cox (1972) proportional hazards duration model[9]. Let $t_{j1} < t_{j2} < .... < t_{jk_j}$ denote the k_j times at which limit order event j is observed, $j = 1, ..., J$, and let X_{ji} be the covariates for the limit order i that experiences event j at t_{ji}. The partial likelihood function (Kalbfleisch and Prentice, 1980) is

$$L(\beta_1, ..., \beta_J) = \prod_{j=1}^{J} \prod_{i=1}^{k_j} \frac{exp(\beta_j' X_{ji}(t_{ji}))}{\sum_{k \epsilon R(t_{ji})} exp(\beta_j' X_k(t_{ji}))}, \tag{6}$$

[8]There is a chance event that a market order may be matched against a limit order submitted immediately prior

[9]A feature of the Cox hazards model is that one can estimate the effect of the covariates on the hazard rate without any assumptions about the shape of the baseline hazard function. This is more robust where we have no strong a priori knowledge of the specific functional form for the hazard function.

Table 5: Time to Execution Against Limit Orders By Investor Category

This table presents the estimated cumulative probabilities of limit order execution within different time intervals conditional on execution from market orders submitted by different investors. The results presented are the cross-sectional averages of the estimated conditional probabilities at the specified timepoints. For revised orders, limit order execution times are measured relative to the last order revision. It is based on all standard orders submitted between 10:10am and 4:00pm.

Panel A: Large Caps

	INST			RET			MM		
	Inside Spread	BBO	All	Inside Spread	BBO	All	Inside Spread	BBO	All
1s	45.9%	7.5%	11.3%	8.5%	2.2%	2.5%	55.7%	12.9%	17.7%
2s	54.7%	11.2%	15.1%	14.4%	4.2%	4.6%	68.0%	18.1%	23.3%
5s	67.1%	18.7%	22.1%	25.9%	9.6%	9.8%	79.3%	25.9%	30.6%
10s	76.4%	26.9%	29.4%	38.9%	16.7%	16.4%	86.6%	33.7%	37.4%
30s	88.0%	44.1%	44.3%	63.1%	35.1%	33.2%	93.0%	50.7%	51.5%
1m	93.3%	57.2%	55.9%	78.0%	50.4%	47.3%	96.2%	63.6%	62.5%
5m	99.2%	84.2%	81.9%	97.0%	81.6%	78.6%	99.4%	88.1%	85.9%
10m	99.7%	91.4%	89.4%	98.8%	90.2%	87.8%	99.7%	94.0%	92.3%
30m	99.9%	97.3%	96.0%	99.5%	97.6%	96.3%	100.0%	98.1%	97.0%

Panel B: Mid Caps

	INST			RET			MM		
	Inside Spread	BBO	All	Inside Spread	BBO	All	Inside Spread	BBO	All
1s	40.1%	6.0%	10.6%	6.6%	1.1%	1.4%	51.9%	13.7%	18.5%
2s	47.5%	8.4%	13.5%	10.1%	2.1%	2.5%	65.5%	17.2%	23.5%
5s	56.7%	13.1%	18.4%	18.4%	5.0%	5.6%	74.6%	21.7%	28.5%
10s	65.1%	18.7%	23.9%	27.6%	9.5%	9.9%	80.8%	26.7%	33.2%
30s	78.4%	32.1%	36.3%	45.6%	22.0%	21.8%	87.2%	37.4%	42.5%
1m	85.5%	43.7%	46.6%	63.2%	35.0%	34.3%	93.3%	50.3%	52.8%
5m	97.0%	76.3%	75.9%	91.9%	72.1%	70.1%	99.1%	81.2%	78.3%
10m	98.8%	87.1%	85.9%	96.6%	84.8%	82.6%	99.6%	89.9%	86.9%
30m	99.7%	96.9%	95.4%	99.3%	96.1%	94.5%	100.0%	98.4%	96.4%

Panel A: Small Caps

	INST			RET			MM		
	Inside Spread	BBO	All	Inside Spread	BBO	All	Inside Spread	BBO	All
1s	28.9%	4.6%	8.5%	2.9%	0.6%	0.7%	31.1%	9.1%	12.4%
2s	35.5%	6.3%	10.5%	4.9%	1.1%	1.3%	37.6%	11.0%	14.9%
5s	40.5%	9.1%	13.4%	8.0%	2.6%	2.8%	42.5%	13.7%	17.8%
10s	48.0%	12.3%	17.1%	13.3%	4.8%	5.2%	54.3%	16.1%	22.9%
30s	59.3%	20.4%	25.5%	26.0%	11.3%	11.6%	61.3%	23.1%	31.3%
1m	66.9%	27.7%	32.4%	39.1%	17.7%	18.3%	71.0%	30.0%	37.8%
5m	85.8%	54.2%	57.1%	70.4%	45.6%	45.0%	77.9%	53.9%	60.2%
10m	92.4%	67.3%	68.9%	81.1%	61.6%	60.0%	81.6%	65.0%	70.2%
30m	98.5%	84.9%	84.5%	94.0%	83.0%	81.1%	83.9%	79.8%	82.1%

Table 6: List of Competing Risk Events

Risk Event	Definition
DELETE	Limit Order Cancellation
AMEND+	Upward Price Amendment of Existing Limit Order (Non-marketable)
AMEND+MKT	Existing Limit Order Amended to Market Order
AMEND-	Downward Price Amendment of Existing Limit Order
AMEND0	Volume Amendment of Existing Limit Order
TRADE	Limit Order Execution (full or partial)

where $R(t_{ji})$ is the risk set at time t_{ji}, the set of limit orders at risk immediately prior to t_{ji}. The coefficient vector β is estimated using the Efron approximation of the partial maximum likelihood function.

We focus on the quote monitoring intensity of different investors by incorporating the time dependent covariates of Hasbrouck and Saar (2009) to track subsequent price movements in bid and ask prices subsequent to order submission. For a bid limit order, these are defined as

$$\begin{aligned}\Delta q_{same} &= \frac{100(\text{best bid}_t - \text{best bid}_{t=0+})}{\text{best bid}_{t=0+}},\\ \Delta q_{opp} &= \frac{100(\text{best ask}_t - \text{best ask}_{t=0+})}{\text{best ask}_{t=0+}},\end{aligned}$$

where $t = 0^+$ represents the instant after submission. A positive value on Δq_{same} and Δq_{opp} indicates the best bid and ask prices has moved higher, decreasing the chance of limit order execution. A negative value for Δq_{same} and Δq_{opp} suggests the market is moving towards the limit price increasing the chance of execution. Δq_{opp} is a measure of the cost of immediacy. We can test directly the cost of immediacy hypothesis by examining how the intensity of limit order revisions to market orders is influenced by changes in Δq_{opp}. The Cox proportional hazards model is multiplicative. A unit change in the value of a covariate multiplies the hazard of the event of interest by a constant amount.

4.2 Results

The Cox model is estimated over a random sample of limit orders submitted to the market during continuous trading hours. Due to computational constraints, estimation was not conducted on the full sample. A stratified sampling approach was used to construct the random sample BY selecting 1,000 limit orders across each stock and investor category[10]. Time-dependent explanatory variables are estimated using the counting process formulation of Andersen and Gill (1982) and each limit order is tracked through the first three minutes. The reported results are robust to the length of time chosen to track the limit order. However, there is attenuation effect with a longer tracking period as the estimation results become unduely affected by the remaining stale limit orders that are standing in the limit order book but do not respond to market price movements.

Table 7 reports the estimation results under two model specifications for upward order revisions. The base model incorporates Δq_{same} and Δq_{opp} to capture how upward order

[10]There are a few stock and investor category partitions where less than 1,000 limit order events are observed. In these cases, all the available limit orders are utilized.

Table 7: Survival Model of Upward Limit Order Revisions ($AMEND+$)

This table reports the parameter estimates β from two specifications of a time varying proportional Cox hazards model where the risk event is an upward limit order revision ($AMEND+$). The explanatory variables are: log of the order size in millions of dollars ($m) ; trading activity defined as the log of the cumulative trading value in the prior five minute interval ($m); volatilty defined as the sum of absolute mid-quote changes in the prior five minute interval; percentage spread defined as 100(ask price - bid price)/ mid price; price aggressiveness defined for a bid limit order as 100(limit price $-$ best bid$_{t=0}$)/(best bid$_{t=0}$) (Hasbrouck and Saar, 2009). Δq_{same} and Δq_{opp} are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission. All variables are standardized to have zero mean and unit variance.

	Coef	exp(Coef)	P-value	Coef	exp(Coef)	P-value
Log Order Size($m)	- 0.107	0.898	<0.001	- 0.109	0.896	<0.001
Trading Activity	0.193	1.213	<0.001	0.189	1.207	<0.001
Volatility	0.211	1.235	<0.001	0.209	1.233	<0.001
Spread	- 0.371	0.690	<0.001	- 0.372	0.689	<0.001
Price Aggressiveness	- 0.009	0.991	<0.001	- 0.009	0.991	<0.001
Institutional Dummy	1.858	6.410	<0.001	1.830	6.234	<0.001
Market Maker Dummy	2.870	17.642	<0.001	2.835	17.037	<0.001
Δq_{same}	0.817	2.263	0.003	0.306	1.358	0.145
Δq_{opp}	0.364	1.439	0.232	0.746	2.108	0.002
Institutional x Δq_{same}	-	-	<0.001	0.683	1.979	0.007
Market Maker x Δq_{same}	-	-	<0.001	1.270	3.561	<0.001
Institutional x Δq_{opp}	-	-	<0.001	- 0.554	0.575	0.056
Market Marker x Δq_{opp}	-	-	<0.001	- 0.553	0.575	0.117

revision intensity depends on changes in bid and ask quotes after order submission. The second model specification includes interaction terms to examine whether differences exist across investors. The other explanatory variables control for order characteristics and market conditions at the time of order submission (or last amendment).

The coefficient on order size is negative and significant indicating that upward order revision intensity increases for smaller sized orders. This could be explained by order splitting, a common strategy under algorithmic trading. There is a positive effect from trading activity and volatility on the rate of upward order revisions. Greater attention is paid to non-execution risk at times of increased trading activity and high volatility. A negative relationship is observed between the price aggressiveness of the order and upward order revision intensity. Order placed further behind the limit order book experience higher non-execution risk increasing the chance that it will be repositioned more aggressively. Institutional and market maker dummies account for differences in the baseline hazard and as expected, the coefficiences indicate they experience a higher rate of upward order revision activity.

The coefficient on Δq_{same} is positive and significant, consistent with the chasing hypothesis (Hasbrouck and Saar, 2009). There are some interesting effects when the model is expanded to incorporate multiplicative dummies. Relative to retail investors, institutional investors actively reposition existing limit orders more aggressively in response to undercutting as measured by Δq_{same} x Institutional. The coefficient on Δq_{same} x Market Maker indicates the intensity for upward order revisions is even higher for market makers. The multiplicative terms on Δq_{opp} indicates that for retail investors, upward order amendments are more sensitive to changes opposing side quotes Δq_{opp} although the evidence is weaker as the coefficients are not significant at the traditional 5% level. The hazard ratio of 0.306 on Δq_{same} implies a percentage change in the hazard of 36% for a 1% increase in Δq_{same} for a retail investor. In contrast, a 1% increase in Δq_{same} results in a 169% change in the hazard for an institutional investor and 384% for a market maker. This is only partially offset by the negative relationship between upward order revision intensity and Δq_{opp}.

Table 8 presents estimates on downward order revisions. Downward order revisions is

Table 8: Survival Model of Downward Limit Order Revisions ($AMEND-$)

This table reports the parameter estimates β from two specifications of a time varying proportional Cox hazards model where the risk event is an downward limit order revision ($AMEND-$). The explanatory variables are: log of the order size in millions of dollars ($m) ; trading activity defined as the log of the cumulative trading value in the prior five minute interval ($m); volatilty defined as the sum of absolute mid-quote changes in the prior five minute interval; percentage spread defined as 100(ask price - bid price)/ mid price; price aggressiveness defined for a bid limit order as 100(limit price − best bid$_{t=0}$)/(best bid$_{t=0}$) (Hasbrouck and Saar, 2009). Δq_{same} and Δq_{opp} are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission. All variables are standardized to have zero mean and unit variance.

	Coef	exp(Coef)	P-value	Coef	exp(Coef)	P-value
Log Order Size($m)	0.048	1.049	0.065	0.048	1.049	0.064
Trading Activity	0.081	1.084	0.070	0.080	1.083	0.071
Volatility	0.215	1.239	<0.001	0.214	1.239	<0.001
Spread	- 0.350	0.704	<0.001	- 0.350	0.704	<0.001
Price Aggressiveness	0.893	2.444	0.002	0.892	2.441	0.002
Institutional Dummy	1.676	5.342	<0.001	1.676	5.345	<0.001
Market Maker Dummy	3.556	35.028	<0.001	3.555	34.988	<0.001
Δq_{same}	- 0.930	0.394	<0.001	- 0.940	0.391	0.235
Δq_{opp}	- 0.367	0.693	0.050	- 0.318	0.728	0.639
Institutional x Δq_{same}	-	-	-	0.269	1.309	0.784
Market Maker x Δq_{same}	-	-	-	- 0.095	0.909	0.909
Institutional x Δq_{opp}	-	-	-	- 0.212	0.809	0.788
Market Marker x Δq_{opp}	-	-	-	- 0.074	0.929	0.917

expected to intensify as the best bid or offer moves towards the limit price as traders reposition their orders to reduce picking-off risk. The coefficients on Δq_{same} and Δq_{opp} are negative and significant indicating that investors do pay attention to picking off risk. However, no evidence is found of differences in the intensity of downward order revisions to changes in bid and ask quotes across investors.

Table 9 estimates a duration model on order cancellations. The effect of a change in the same side best bid or offer (Δq_{same}) reflects two opposing influences. On the one hand, cancellations may intensify when the best bid price moves away from the limit price of the order as traders move to reduce their non-execution risk. On the other hand, cancellations may intensify as the best bid price moves towards the limit price to mitigate picking off risk in response to a perceived increase in information asymmetry. The positive coefficient on Δq_{same} indicates that order cancellations are mainly the result of investors responding to changes in non-execution risk. Similar to earlier results, institutional investors and market makers experience a higher rate of cancellation activity in response to changes in Δq_{same}. Overall, the results suggest that investors pay more attention appears to non-execution risk than picking-off risk.

5 Limit Order Performance

The evidence presented in section 3 indicates that there are fundamental differences in the limit order behaviour across investors. In this section, we assess the economic value of non-retail investors access to technology by directly measuring the limit order performance of different investors.

A common assumption among theoretical models examining the effect of high frequency trading (Hoffmann, 2012; Biais et al., 2012) is that some traders have a speed advantage allowing them to react faster to new information and imposing an externality cost to slower (retail) traders. To examine the adverse selection costs on these investors from their orders

Table 9: Survival Model of Order Cancellations ($DELETE$)

This table reports the parameter estimates β from two specifications of a time varying proportional Cox hazards model where the risk event is an order cancellation ($DELETE$). The explanatory variables are: log of the order size in millions of dollars (\$m) ; trading activity defined as the log of the cumulative trading value in the prior five minute interval (\$m); volatilty defined as the sum of absolute mid-quote changes in the prior five minute interval; percentage spread defined as 100(ask price - bid price)/ mid price; price aggressiveness defined for a bid limit order as 100(limit price $-$ best bid$_{t=0}$)/(best bid$_{t=0}$) (Hasbrouck and Saar, 2009). Δq_{same} and Δq_{opp} are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission. All variables are standardized to have zero mean and unit variance.

	Coef	exp(Coef)	P-value	Coef	exp(Coef)	P-value
Log Order Size(\$m)	- 0.253	0.776	<0.001	- 0.254	0.776	<0.001
Trading Activity	0.200	1.221	<0.001	0.198	1.219	<0.001
Volatility	0.177	1.194	<0.001	0.178	1.195	<0.001
Spread	- 0.073	0.929	0.044	- 0.075	0.928	0.042
Price Aggressiveness	0.067	1.069	0.602	0.071	1.073	0.588
Institutional Dummy	1.641	5.160	<0.001	1.625	5.079	<0.001
Market Maker Dummy	1.273	3.573	<0.001	1.256	3.512	<0.001
Δq_{same}	0.841	2.319	<0.001	0.385	1.469	0.157
Δq_{opp}	- 0.238	0.788	0.215	0.074	1.077	0.818
Institutional x Δq_{same}	-	-	-	0.591	1.807	0.018
Market Maker x Δq_{same}	-	-	-	0.842	2.321	0.007
Institutional x Δq_{opp}	-	-	-	- 0.396	0.673	0.199
Market Marker x Δq_{opp}	-	-	-	- 0.145	0.865	0.667

being 'picked-off', we employ the Harris and Hasbrouck (1996) expost measure of performance on executed limit orders.

$$\text{Ex post cost} = \begin{cases} p^{\text{fill}} - q^{\text{ask}}_{\text{fill}+10}, & \text{for a buy order} \\ q^{\text{bid}}_{\text{fill}+10} - p^{\text{fill}}, & \text{for a sell order} \end{cases} \tag{7}$$

For limit buy orders, the expost cost is the difference between the execution price and the best ask price ten minutes after execution. This measure offers two interpretations. First, it can be viewed as the realized cost of reversing the trade at market prices a short time later. Alternatively, it can be viewed as the difference between the price the limit order was willing to buy or sell at relative to the price the market is willing to buy or sell after the same period of time. The results are robust to the time window chosen for measuring performance. However, the speed advantage offered by algorithmic trading in gathering and processing information is likely to be short-lived. Harris and Hasbrouck (1996) identifies the expost performance measure to be appropriate for a passive market maker who supplies liquidity via limit orders but may understate the costs for a trader with a precommitment to trading.

We examine the effect of monitoring intensity on the ex post performance of executed limit orders controlling for order characteristics and market conditions that may affect limit order performance. Table 10 presents the coefficients obtained from three expost regression specifications. To proxy for the level of monitoring, the first regression employs an order exposure variable defined as time elapsed between order submission or most recent order revision and execution. The logarithmic transformation reduces the effect of stale limit orders on the results. Traders who are intensively monitoring their limit orders are more likely to revise or cancel their orders frequently as market conditions change. The second regression produces results using investor category dummies to proxy for the level of monitoring. The coefficient estimates indicate that the limit orders of retail investors incur significantly higher expost costs relative to other investors consistent with their exposure to adverse selection. Regression 3 examines the same effects while also controlling for order exposure.

The coefficent estimates obtained from expost regressions on order characteristics and

Table 10: Determinants of Expost Order Performance

This table reports the regression coefficients of the Harris and Hasbrouck (1996) expost cost measure (in cents) controlling for order characteristics and market conditions. For limit buy orders, the expost cost is the difference between the execution price and the best ask price ten minutes after execution. The sample includes all nonmarketable limit orders submitted during continuous trading hours that subsequently achieve execution (partial or full). The explanatory variables in both regressions are: price aggressiveness = 100(limit price - best bid$_{t=0}$) / best bid$_{t=0}$ for a bid limit order where $t = 0$ denotes the time of order submission, which is computed as in Hasbrouck and Saar (2009); log of the order size in millions of dollars ($m), indicator variable that takes a value of 1 if it is a buy limit order, or 0 if it is a sell limit order; percentage spread defined as 100(ask price - bid price) / mid price at the time of order submission or revision; volatility defined as the sum of absolute mid-quote changes in the half hour interval prior to order submission or revision; log of the value of shares traded in millions of dollars ($m) over the previous the half hour interval prior to order submission or revision; time of day dummies for five intraday time intervals. T-statistics are calculated using clustered standard errors, where the cluster is defined by stock and day.

	(1)		(2)		(3)	
	Coeff	P-value	Coeff	P-value	Coeff	P-value
Intercept	0.1500	<0.001	0.1947	<0.001	0.1804	<0.001
Institutional Dummy			- 0.0261	0.009	- 0.0236	0.009
Market Maker Dummy			- 0.0285	0.002	- 0.0251	0.002
Order Exposure Time	0.0021	0.039			0.0019	0.056
Price Aggressiveness	0.1959	0.002	0.1918	0.001	0.2007	0.002
Order Size	- 0.0024	<0.001	- 0.0028	<0.001	- 0.0028	<0.001
Buy Dummy	0.0039	0.684	0.0039	0.686	0.0037	0.697
Spread	0.2988	<0.001	0.2989	<0.001	0.2952	<0.001
Volatility	- 0.0094	0.796	- 0.0228	0.555	- 0.0100	0.784
Trading Activity	- 0.0068	<0.001	- 0.0075	<0.001	- 0.0071	<0.001
Time 11:00 - 12:00	- 0.0082	0.028	- 0.0082	0.028	- 0.0080	0.031
Time 12:00 - 13:00	- 0.0121	<0.001	- 0.0118	<0.001	- 0.0118	<0.001
Time 13:00 - 14:00	- 0.0151	<0.001	- 0.0147	<0.001	- 0.0148	<0.001
Time 14:00 - 15:00	- 0.0164	<0.001	- 0.0160	<0.001	- 0.0159	<0.001
Time > 15:00	- 0.0170	<0.001	- 0.0169	<0.001	- 0.0165	<0.001

Table 11: Expost Performance - Different Time Windows

Window	1m	5m	15m	30m	1hr
Panel A: Regression (1)					
Order Exposure Time	0.0014	0.0020	0.0025	0.0035	0.0044
(T-stat)	(1.3)	(2.01)	(2.2)	(2.81)	(2.78)
Panel A: Regression (2)					
Institutional Dummy	-0.0212	-0.0245	-0.0269	-0.0364	-0.0440
(T-stat)	(-2.48)	(-2.58)	(-2.76)	(-2.98)	(-2.63)
Market Maker Dummy	-0.0234	-0.0295	-0.0279	-0.0367	-0.0458
(T-stat)	(-2.96)	(-3.33)	(-3.15)	(-3.11)	(-2.27)
Panel A: Regression (3)					
Order Exposure Time	0.0012	0.0018	0.0023	0.0032	0.0040
(T-stat)	(1.14)	(1.85)	(2.08)	(2.67)	(2.51)
Institutional Dummy	-0.0197	-0.0222	-0.0240	-0.0322	-0.0387
(T-stat)	(-2.59)	(-2.58)	(-2.74)	(-2.88)	(-2.4)
Market Maker Dummy	-0.0213	-0.0264	-0.0238	-0.0310	-0.0386
(T-stat)	(-3.16)	(-3.37)	(-3.11)	(-2.9)	(-1.9)

market conditions show that adverse selection costs are higher when spreads are wider, for limit orders which are more aggressively placed and limit orders submitted in the first hour of trading. The coefficient estimates on log order exposure time and investor dummy variables are all statistically significant. Expost performance is found to deteriorate with order exposure and retail investors suffer higher expost costs, even after controlling for order exposure. However, the effects are not economically significant. On a hypothetical 1000 share limit order, regression 1 indicates the implied cost from a doubling in order exposure is $0.015 and regression 2 indicates that retail investors expost cost are on average $0.026 worse than institutional investors, when measured over the following ten minute window after the trade. The expost performance of retail investors deteriorates with the length of the chosen time horizon but remains relatively insignificant. The empirical evidence does not support the view that the limit orders of retail investors are routinely picked off and suffer significant adverse selection costs.

We also employ the implementation shortfall approach of Perold (1988) as an exante measure of limit order performance. The implementation shortfall consists of two component costs. Price impact is the signed difference between the volume weighted average fill price and the quote mid-point at the time of order submission. The price impact would be expected to be positive for market orders, negative on executed limit orders (without order revisions) and zero for unfilled orders. The opportunity cost is the signed difference between the reference price and the quote midpoint at the time of order submission. The reference price is the best quote on the opposing side at the time of order cancellation or the closing price at the end of trading. Harris and Hasbrouck (1996) motivate the exante cost as a measure of performance based on a trader with a precommitment to trade who will switch their cancelled limit orders to market orders when limit order execution is not achieved. Hence, this measure will tend to exaggerate the penalty on unexecuted orders.

Table 12 presents the estimation results of regressions on the price impact, opportunity cost and implementation shortfall on all new limit order submissions during continuous trading hours. Focussing on price impact, the coefficients on the institutional and market maker dummies across all orders suggest that these investors incur significantly lower price impact costs relative to retail investors. However, when conditioned on order execution, these investors actually have significantly higher price impact costs. We attribute this to variation in execution rates as a greater proportion of retail investors limit orders are executed. The coefficients on price aggressiveness, trading activity and spreads are also statistically significant, when conditioned on execution. Price impacts are higher for more aggressively priced limit orders and lower when spreads and trading activity at the time of order submission is higher.

For the opportunity cost measure, there is weaker evidence to support lower opportunity costs among non-retail investors. Opportunity costs are found to be higher for larger orders, at times of high volatility and in later trading hours. However, Institutional investors and market makers limit orders experience significantly lower opportunity costs when conditioned on non-complete execution. This is again explained by variation in execution rates across investors. Retail investors execute a large percentage of their limit orders, resulting in no opportunity costs incurred on those limit orders.

The estimation results on the implementation shortfall, which encompasses both price impact and opportunity costs shows non-retail investors incurring lower shortfall costs relative to retail investors. The coefficient estimate on the institutional investor dummy of -1.46 implies a cost differential of $14.62 on a 1000 share limit order relative to retail investors. Market makers also experience lower shortfall costs to retail investors expected to be $10.70

Table 12: Determinants of Exante Order Performance

This table reports the regression coefficients of price impact, opportunity cost and implementation shortfall (measured in cents) on order characteristics and market conditions. The sample includes all standard limit order submissions during continuous trading hours from institutions, market makers and retail investors. For a bid limit order, price impact is computed as the difference between the volume weighted average fill price and the mid-quote at the time of order submission. The co-efficient estimates of price impact regressions are reported separately conditional on full or partial execution (fill rate > 0%). Opportunity cost is computed as the difference between best ask at the time of order cancellation (or price at the close of trading) and the mid-quote at the time of order submission. Co-efficient estimates on opportunity cost regressions are reported separately for limit orders conditional on non-complete execution (fill rate < 100%). The implementation shortfall is the weighted sum of the price impact and opportunity cost with the weights determined based on the proportion of the order size at the time of submission that is executed. See Table 10 for a description of the explanatory variables. T-statistics are calculated using clustered standard errors, where the cluster is defined by stock and day.

Dependent Variable	Price Impact				Opportunity Cost				Implementation ShortFall	
	All Orders		Fill Rate > 0%		All Orders		Fill Rate < 100%		All Orders	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	0.6244	0.375	1.3260	0.323	0.5522	0.114	3.2641	0.002	1.1766	0.140
Institutional Dummy	- 0.9392	<0.001	1.9262	0.025	- 0.5224	0.075	- 3.0507	0.014	- 1.4616	<0.001
Market Maker Dummy	- 0.5426	0.157	2.2346	0.028	- 0.5276	0.078	- 3.3311	0.008	- 1.0702	0.016
Price Aggressiveness	0.5591	0.406	20.5161	<0.001	- 0.0001	0.435	0.0001	0.305	0.5590	0.406
Order Size	0.0506	0.386	0.0358	0.610	0.0215	<0.001	0.0282	<0.001	0.0721	0.215
Buy Dummy	0.1495	0.078	- 0.2561	0.096	- 0.0612	0.337	- 0.0777	0.558	0.0883	0.364
Spread	0.4477	0.352	- 7.1766	<0.001	- 0.2149	0.070	- 0.9751	<0.001	0.2328	0.625
Volatility	- 1.3256	0.132	0.6459	0.610	2.5156	0.007	4.9522	0.004	1.1900	0.244
Trading Activity	- 0.0383	0.173	- 0.1947	0.008	0.0264	0.382	0.0741	0.229	- 0.0119	0.756
Time 11:00 - 12:00	- 0.0875	0.531	- 0.3752	0.352	- 0.0538	0.071	- 0.2280	0.002	- 0.1413	0.302
Time 12:00 - 13:00	0.1044	0.029	- 0.4285	0.261	- 0.0507	0.173	- 0.3041	<0.001	0.0537	0.374
Time 13:00 - 14:00	0.1067	0.051	- 0.4931	0.210	- 0.0470	0.317	- 0.2999	0.002	0.0597	0.379
Time 14:00 - 15:00	0.1108	0.082	- 0.4681	0.209	- 0.1021	0.046	- 0.3974	<0.001	0.0087	0.903
Time ¿ 15:00	0.3890	0.011	- 0.4781	0.084	- 0.2215	0.002	- 0.6007	<0.001	0.1675	0.323

on 1000 shares. The advantages of algorithmic trading technology from non-retail investors does not appear to stem primarily from their ability to adversely select against retail investors limit orders, but from an improved ability to manage the price impact of their orders and opportunity costs of non-execution (non-execution risk).

6 Conclusion

Motivated by the intense debates within the investment community surrounding algorithmic trading, this study examines the extent to which access to trading technology benefits non-retail investors. We find evidence that the speed advantages gained from trading technology allows non-retail investors to search for latent liquidity and react to fleeting liquidity opportunities. Algorithmic trading technology also plays a central role in the dynamic management limit order risks without incurring high monitoring costs (Fong and Liu, 2010). Our empirical findings support this claim. Non-retail investors are found to respond more quickly to changes in price movements while retail investors have limited capacity to monitor their limit orders. We also find that investors have different trade-offs between the two types of limit order risks. Investors have a stronger preference for managing non-execution risks, which is the dominant effect explaining order cancellations.

It is a commonly thought that the limit orders of retail investors suffer significant losses to adverse selection from faster traders with access to trading technology. Based on a direct examination of limit order performance across different investors, we find that the expost costs experienced by retail investors are not economically significant. However, retail investors experience higher implementation shortfall costs indicating trading technology improves the ability of non-retail investors to manage their execution costs.

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