University of Technology, Sydney

Doctoral Thesis

# Essays in Market Microstructure and Investor Trading

*Author:*
Danny Lo

*Supervisor:*
Professor Anthony Hall

*A thesis submitted in fulfilment of the requirements*
*for the degree of Doctor of Philosophy*

*in the*

Finance Discipline Group
UTS Business School

June 2015

# Declaration of Authorship

I, Danny Lo, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text. I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signed: ________________________________________

Date: ________________________________________

# *Abstract*

This dissertation consists of three self-contained essays examining issues pertaining to market microstructure and investor trading. The first essay contributes to our understanding of the liquidity replenishment process in limit order book markets. A measure of resiliency is proposed and quantified for different liquidity shocks through the impulse response functions generated from a high frequency vector autoregression. The model reveals a rich set of liquidity dynamics. Liquidity shocks were found to have immediate detrimental effects on other dimensions of liquidity but the replenishment process generally occurs quickly, indicating limit order books are resilient. Cross-sectionally, resiliency is found to be consistently high across all large stocks, consistent with competition for liquidity provision coming from computerised algorithms. For other stocks, greater variation in resiliency is observed, indicating more selective participation by these liquidity providers.

The second essay is motivated by concerns raised from the investment community on the impact of algorithmic trading among investors. A strong dichotomy exists between retail and non-retail investors, with non-retail investors predominantly having access to algorithmic trading technology. We compare the limit order behaviour and execution costs of retail and non-retail investors to provide insights into the extent to which technology benefits investors. Fundamental differences are found in the trading behaviours of the two groups, consistent with their inequalities in access to trading technology. We also find evidence consistent with some non-retail investors imposing adverse selection costs on the limit orders of retail investors, but our results fall short of supporting the view that algorithmic trading technology is severely disadvantaging retail investors.

The third essay examines information-based trading by institutional and retail investors around earnings announcements. Prior to the announcement, limited and weak evidence is found of earnings anticipation, which is isolated to full-service retail investors. In contrast, strong trading patterns are observed for institutional and retail investors in response to earnings announcements, with the latter having the potential to drive the post-earnings announcement drift effect. We find that retail investor trades during the earnings announcement periods underperform their trades in non-announcement periods. This is driven mostly by the trading of discount retail investors, with top-tier institutional investors the likely beneficiaries, and cannot be attributed to the adverse selection of stale limit orders. Overall, our findings are consistent with investors having different information processing abilities. Contrary to the belief that earnings disclosures level the playing field, the release of earnings news exacerbates information asymmetries between the most and least skilled information processors.

# *Acknowledgements*

When I completed my bachelor's degree in 2005, I believed I would never undertake further studies at a university again. Ten years on, I am deeply grateful for the valuable support I received during my PhD candidature at the University of Technology, Sydney (UTS).

This thesis has benefited enormously from the many helpful discussions I've had with my supervisor, Professor Tony Hall. I am greatly indebted to Tony who not only dedicated a considerable amount of time to reviewing my work, but also provided invaluable insights, feedback and guidance. It has been a long and challenging journey but we got there.

My time at UTS has been most enjoyable thanks to my fellow research students and colleagues at the Finance Discipline Group. I would like to thank my alternative supervisors, Dave Michayluk and Jian Xin Wang for taking an interest in my research and providing helpful feedback. This thesis also benefited from editorial assistance provided by John Revington.

Furthermore, I would like to acknowledge the financial assistance received from both the Australian Postgraduate Awards (APA) and Professor Tony Hall during the early years of my PhD studies. I am also grateful to my current employer, VINVA Investment Management for providing me with enormous flexibility during the latter years of my studies. This enabled me to finish my dissertation.

The empirical studies presented in this thesis would not be have been possible without the ASX tick data and assistance provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). This research was also partially conducted on the UTS Business School High Performance Computing Cluster which has been a valuable computing resource.

Some of the results in Chapter 3 were presented to participants of the 2013 Auckland Finance Meeting. I thank the conference participants for their comments.

I am eternally grateful to my wife, Cathy Kwan for her endless support and encouragement.

Lastly, I would like to dedicate this thesis to my father, whose memory is a constant source of inspiration. To my daughter, Alicia Lo who brightens me every day, I hope this study can be a future source of inspiration.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

Over the last two decades, technological innovations have led to phenomenal changes in the trading landscape and has drawn the attention of researchers to the field of market microstructure. This transformation of securities markets by technology has fundamentally changed the way liquidity is provided and leads us to re-evaluate how it should be measured. Concerns have also been raised over the optimality of market structures where liquidity arises endogenously through the submission of limit orders. Yet investigating this issue requires first a deeper understanding of the nature of liquidity provision for these market mechanisms.

According to Kyle's (1985) taxonomy, liquidity has three main dimensions: tightness, depth and resiliency. Tightness and depth can be measured by information from visible limit orders. While it is important to capture the cost of immediacy, the current trading landscape has increased the importance of resiliency, the temporal dimension of liquidity.

Trading now predominantly occurs through algorithms which are capable of monitoring and responding to changes in market conditions at lightning speeds. The flash crash of May 6, 2010 in which the prices of some US securities took a precipitous decline, illustrates the speed at which liquidity conditions can change. Then there is the emergence of fleeting liquidity (Hasbrouck and Saar, 2009) and certain practices such as quote stuffing (Egginton et al., 2014), which raise the issue of whether these represent genuine liquidity. There are also the recent trends towards lower average trading sizes and the widespread use of order splitting strategies, where algorithms break up large orders to optimally trade price and execution risk. The optimal execution strategy is dependent on the resiliency of the stock and an understanding of the evolution of liquidity becomes important for market participants wanting to minimise the transaction costs on their portfolios.

It is thus surprising that resiliency has received so little attention in the literature, prompting Dong et al. (2007) to refer to resiliency as the 'neglected dimension of market liquidity'. Motivated by the need for a greater understanding of this market attribute, Chapter 2 proposes an econometric model to measure the resiliency in the limit order book and capture its short-term liquidity dynamics. The technological changes that have occurred in the Australian equity market are no less dramatic than in many other markets around the world, yet we are not aware of another empirical study that quantifies order book resilience to liquidity shocks arising from trading and order cancellations for Australian stocks.

The impact of computerised trading has raised a number of other important issues, many of which remain the subject of intense debate among academics, practitioners and regulators. A particularly important concern is the unequal playing field created by access to trading technology. The focus of much of the literature has been on high frequency traders, which are generally known for their speed and level of sophistication in trading technology. However, doing so excludes a significant group of buy-side institutional investors utilizing agency algorithms to manage their trading process. Brokerage firms typically offer an array of execution algorithms to their buy-side clients[1] and the demand for these products suggest that institutional investors derive significant value from them. Hence, there is a growing divide between retail and non-retail investors resulting from the widespread adoption of algorithmic trading systems.

[1]For a description of the type of algorithms on offer, see http://www.itg.com/marketing/ITG_Algo_ExecutionStrategies_Guide_20130701.pdf.

There is a large body of literature documenting the trading advantages of institutional investors from their superior ability in acquiring or processing information regarding an asset's fundamental value. In contrast, the potential advantages arising from trading technology take on a very different form. Speed in itself has become an information advantage. Haldane (2011) states that 'being informed means seeing and acting on market prices sooner than competitors'. The benefits, however are more wide-ranging. Trading technology allows investors to process real-time information on order flow or market conditions and they also provide autonomy, with little human intervention required once the parameters of the trading strategy are specified.

Despite concerns raised by the investment community on the effects of unequal access to trading technology, only recently have studies emerged addressing concerns of this nature although the focus has been specifically on the impact of high frequency trading. Little is known of the extent to which trading technology translates to better order execution outcomes for investors. In Chapter 3, we compare the limit order behaviour and execution costs of retail and non-retail investors. An evaluation of their execution costs is an important step towards assessing concerns raised over the unequal playing field arising from trading technology. Examining differences in their trading behaviours provides insight into the sources of these differences and also increases our understanding of the price formation process.

Many models of market microstructure involve the interaction of informed and uninformed traders. While the literature does not always specify who is informed, conventional wisdom dictates that this role is played by institutional investors, while retail investors are uninformed. This makes the findings of recent studies (Kaniel et al., 2012, Kelley and Tetlock, 2013) documenting the presence of informed trading by retail traders appear both counterintuitive and contradictory. Of particular interest is whether these findings hold in other markets. We provide such an investigation in Chapter 4, with the advantage that our dataset eliminates sample selection bias concerns and allows us to partition between full-service and discount retail investors.

Our analysis is also related to the literature investigating information asymmetry around disclosures. The theoretical literature offers predictions on how disclosures could affect information asymmetry. Informed traders may gather private information in anticipation of the public information release (Diamond, 1985, Foster and Viswanathan, 1990, Verrecchia, 1982). This increases pre-announcement information asymmetry which is alleviated when the information is disclosed. On the other hand, disclosures could 'stimulate informed judgements' by some investors on the asset's fundamental value thereby turning public information into private information (Kim and Verrecchia, 1994). In Chapter 4, we take both these predictions to the data from a different perspective. While the empirical literature has tended to focus on examining these predictions using proxies for information asymmetry, we measure the consequences of this information asymmetry between investors by analysing the performance of their trades.

As the thesis focuses on the Australian equity market, we provide in this chapter an overview of the Australian Securities Exchange (ASX) and a description of the dataset used in our empirical studies. A discussion of how we classify market participants into investor categories is provided in Section 1.3. This is relevant for the empirical studies presented in Chapter 3 and Chapter 4.

## 1.1 Overview of the Australian Stock Exchange

The Australian Securities Exchange (ASX) is the dominant stock exchange in Australia, with over 2,000 entities listed[2] and a market capitalisation of around AUD 1.5 trillion, making it one of the top ten equity markets in the world ranked by market capitalisation. While the ASX lost its monopoly on 31 October 2011,

[2] http://www.asx.com.au/about/historical-market-statistics.htm#No of Companies

with the introduction of Chi-X Australia, market fragmentation in the Australian equity market remains low with the ASX accounting for approximately 90% of on-market traded volume.[3]

The ASX operates a continuous electronic order-driven market with auctions to open and close trading. In contrast with the New York Stock Exchange and NASDAQ, there are no designated market makers or specialists, and liquidity is supplied solely by traders who submit limit orders. Orders awaiting execution are consolidated into the limit order book which is transparent to all market participants, although anonymity in trading has been maintained since the removal of broker identifiers in November 2005. The position of a limit order in the bid or ask queue is governed by strict price-time priority rules. Decreasing the order volume of an existing limit order has no effect on priority, but increasing order volume will automatically generate an additional limit order, which is placed at the end of the queue while the original order maintains existing time priority in the limit order book. Amendments to the limit price causes the limit order to move to the lowest time priority for all orders at the new price level unless the order becomes marketable, in which case it is matched against an existing order in the limit order book. The ASX goes through several market phases through the day. Table 1.1 provides an overview of the flow of trading on ASX equities.[4]

During the pre-opening period from 7:00 am to 10:00 am (Eastern Standard Time), orders can be entered, amended or deleted in the system but no matching takes place. The ASX opens at 10:00 am with an auction matching algorithm to maximise traded volume at the chosen opening price. Stocks open sequentially in five groups, based on the alphabetical order of their ASX code, with normal trading beginning immediately after the conclusion of the opening algorithm for their group. This phase of continuous trading lasts until 4:00 pm. The closing auction takes

[3]http://www.asx.com.au/services/trading-services/australian-cash-market-report.htm

[4]The reader is referred to the Australian Securities Exchange (2008) for a more comprehensive description of the Integrated Trading System (ITS) and the trading rules of the ASX that are relevant to the dataset used in Chapters 2 and 3.

place between 4:10 pm and 4:12 pm, with the entering, amending or cancelling of orders permitted between 4:00 pm and 4:10 pm.

TABLE 1.1: Market Trading Schedule on ASX Equities

| Market Phase | Time | Description |
|---|---|---|
| Market Pre-Open | 7:00 am - 10:00 am | Orders can be entered, amended or deleted but no matching takes place. |
| Market Opening | 10:00 am - 10:09 am | Staggered call auctions open continuous trading. |
| Normal Trading | 10:00 am - 4:00 pm | Orders can be entered, amended or deleted. Orders that can be matched are executed. |
| Pre CSPA[a] | 4:00 pm - 4:10 pm | Trading ceases but brokers can enter, amend and delete orders in preparation of the closing price auction. |
| CSPA | 4:10 pm - 4:12 pm | Call auction establishes market closing price. |
| Adjust / Adjust ON | 4:12 p m - 6:50 pm | Only orders remaining in the queue can be deleted or amended. |
| Purge Orders | 6:50 pm - 6:59 pm | Orders that have expired or too far away from the market are purged. |

[a] CSPA stands for closing single price auction. Source: ASX website http://www.asx.com.au/about/trading-hours.htm

## 1.2 Data Description and Preparation

The empirical investigations undertaken in this thesis are based on two datasets obtained from the Australian Equities Tick History (AETHS) database supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA).[5] The Order Book data contains the complete record of all order events, including details of the stock code, submission date and timestamp measured to the nearest millisecond, order type (one of six order events), price, volume, order direction (buy or sell) as well as two unique buyer and seller identification codes. These identification codes are unique features that distinguish the Order Book data from other high frequency databases. First, an order identification code is assigned to each newly submitted order. This allows us to track all subsequent order activity prior to its eventual cancellation or execution. A data enhancement that was added later was the provision of broker identification codes, which facilitated investor type identification for each limit order. Section 1.3 details how we infer investor identities from broker identities.

[5] The detail afforded by this dataset is unique and unavailable in many other exchanges in the world.

There are six possible order events in the Order Book data:

1. ENTER event refers to the arrival of a new order to the market.
2. AMEND event refers to the modification of an existing order.
3. TRADE event occurs when a buy or sell order is matched against an existing order in the order book.
4. DELETE event refers to the deletion of an existing limit order.
5. CANCEL event refers to a trade cancellation.[6]
6. OFFTR event refers to an off market trade.

While the Order Book data contains all the information required to completely reconstruct the limit order book, this information is also provided by the Market Depth dataset, which we obtain for the five best bid and ask limit prices.[7] Each record in the dataset is a snapshot of the limit order book over a period of time with a new entry created each time an order event is observed that changes the limit price or volume on any the five best limit prices.

Two common issues arise in preparing high frequency data for econometric analysis. The first issue arises from databases where it is not possible to identify whether each trade is buyer- or seller-initiated. When this occurs, a common approach taken in the literature is to infer trade direction from a classification algorithm. Each TRADE event in the Order Book dataset is preceded by the ENTER or AMEND order event that triggered the trade with the same timestamp and order identification code. Buyer- and seller-initiated trades can be unambiguously identified by observing the direction of the market order.

[6] The ASX prescribes certain conditions for a trade cancellation to take place.

[7] The consistency between the two datasets was checked by matching the impact of observed order events against the corresponding change in the limit order book on several random stock-days with no issues found.

A second issue arises from the treatment of trades that have the same timestamp. This commonly arises with split transactions, when an incoming market order on one side of the market 'walks the book'. Typically, trades with the same timestamp are assumed to be a split transaction but this is a dubious assumption, particularly in studies where timestamps lack precision (Dufour and Engle, 2000). While the precision of our timestamps reduces the likelihood of transactions from different traders occurring at the same timestamp, we rely on the order identifiers for exact identification of split transactions as one can identify the limit orders that match with a corresponding marketable order.

## 1.3 Investor Classification

This section describes how we classify market participants into investor categories. We begin by retrieving a list of broker names associated with each broker identification code from IRESS. The classification was then conducted by examining hand-collected information on the clientele of each brokerage firm. The use of brokerage firm identifiers to classify investors has been adopted by Griffin et al. (2011) on NASDAQ stocks while Jackson (2003) and Fong et al. (2014) apply a similar classification approach to identify retail investors in Australia.

The information was retrieved from three sources: company websites of each of the market participants (which detail the activities, products, services and in many cases, direct information on the clientele of the firm); past newspaper and magazine articles and lastly, notifications and online publications from the ASX.[8] The final classification scheme was reviewed by a senior practitioner from a major buy-side firm in the Australian equity market. Duong et al. (2009) confirm the effectiveness

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

of brokerage firm information in identifying trader types by comparing this classification approach against a confidential dataset containing ASX classifications of institutional and retail investors.

Each of the five investor categories is described below:

- Institutional (INST) - brokerage firms in this category typically service a wide range of institutional clients from traditional buy-side investors to high frequency trading firms. Firms that have a predominantly institutional clientele but offer private banking services dealing exclusively with high net worth individuals are classified as institutional brokers.
- Retail (RET) - comprises brokerage firms that service primarily retail investors including full service brokers which typically provide financial advice and discount brokers that provide a more basic online execution service.
- Mixed (MIXINSTRET) - these brokerage firms state that they provide both retail and institutional brokerage services.
- Proprietary Trading and Market Making (MM) - refers to market participants that have identified themselves as engaging in proprietary trading and market making activities. Hereafter, these firms will be collectively referred to as market makers.
- Other (OTHER) - contains all brokerage firms that have not been assigned to any of the other four categories.

Institutional brokerage firms are further partitioned based on their quality and reputation. We refer to top-tier institutional investors as those investors that direct their trades through the top 12 institutional brokerage firms as determined by their rankings in the East Coles Best Brokers Survey. This is an independent external survey of buy-side institutional investors that rates brokers based on their research, trade execution, equity capital market services and market making.

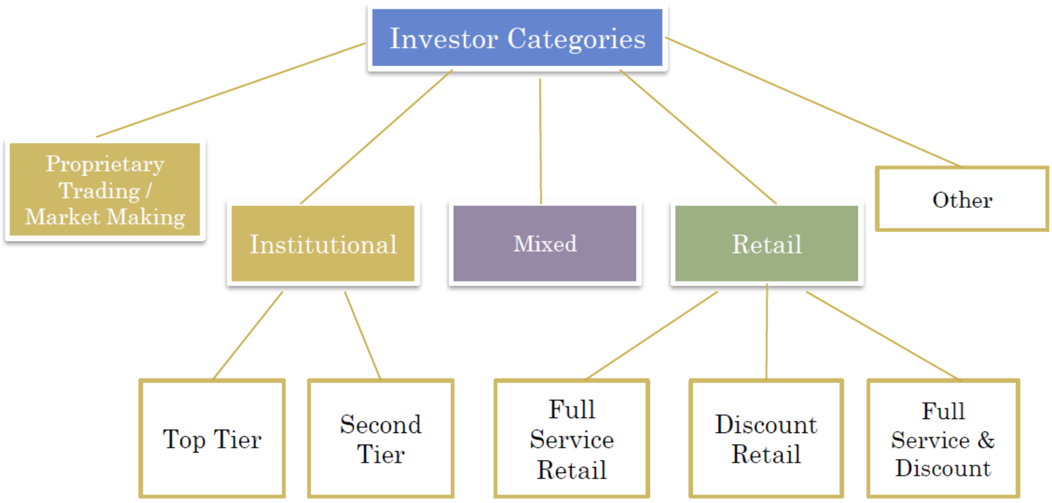



FIGURE 1.1: Investor Categories

Investors trading through the remaining set of institutional brokerage firms are referred to as second-tier institutional investors.

Retail brokerage firms can also be partitioned based on whether they provide advisory services (full-service retail) or a more basic online execution service (discount retail). These sub-categorisations are utilised in the empirical study presented in Chapter 4.

# Chapter 2

# Resiliency of the Limit Order Book

## 2.1 Introduction

While few would argue against the wisdom of the words 'no single measure can capture all aspects of liquidity', adopted measures have traditionally relied upon information from visible limit orders. An important but often missing element in completing the liquidity picture is the measurement and understanding of latent sources of liquidity. Biais et al. (1995) first documented the existence of potential liquidity outside the limit order book, which they attribute to the presence of traders who do not have exposed orders but are actively monitoring the market for favourable order placement opportunities. They find that traders quickly submit limit orders when liquidity provision is attractive and follow 'defensive strategies' (Harris, 1996) by cancelling liquidity when order flow is likely to originate from informed traders.

Latent sources of liquidity can be captured by examining the resiliency dimension of liquidity (Kyle, 1985). The literature has generally viewed resiliency from two perspectives. Taking the price recovery perspective, Kyle (1985) defines resiliency as the rate at which pricing errors caused by temporary order-flow shocks are corrected in the market. On the other hand, Garbade (1982) takes the liquidity replenishment perspective, describing resiliency as the speed of replenishment of the limit order book. Garbade (1982) determines that 'a market is resilient if new orders pour in promptly in response to a temporary order imbalance'. This perspective is also adopted by Large (2007), who measures a resilient limit order book as one that reverts promptly back to its normal shape, but his analysis restricts the cause of liquidity depletion to the presence of large trades. This study defines resiliency as the time required for liquidity to recover from a set of common liquidity shocks. These shocks are represented by *specific order events* such as a market order or an order cancellation. Our view on resiliency can capture both perspectives. We can quantify the level of resiliency in prices as well as in different dimensions of limit order book liquidity. An important difference between the two perspectives is that liquidity shocks have a permanent price impact (e.g. Hasbrouck, 1991) but a transient effect on our liquidity variables such as spread or depth.

In this chapter, we propose a high frequency vector autoregression (VAR) model to capture short term liquidity dynamics and provide insights into the liquidity replenishment mechanism of the limit order book. The model incorporates relevant characteristics of the order arrival process including variables representing different dimensions of the limit order book. Resiliency is quantified through the impulse response functions which trace the recovery profile of different liquidity variables in a dynamic system generated by specific liquidity shocks. If the limit order book lacks resiliency, then liquidity shocks are accompanied by a slow rate of recovery to equilibrium levels.

Our approach offers a number of methodological advantages relative to the few studies examining resiliency within similar frameworks. Firstly, the impulse responses are generated from liquidity shocks representing actual order events that consume order book liquidity. Hence, the impulse response functions have a clear interpretation which contrasts with earlier studies on resiliency (e.g. Hmaied et al. 2006 and Coppejans et al. 2004). The model also lends itself to examining resiliency based on a number of alternative liquidity shocks observed in the market. Secondly, resiliency can be quantified for each liquidity variable, permitting an examination of whether resiliency differs along different dimensions. Thirdly, the inclusion of a variable to capture the duration between order events facilitates the measurement of resiliency in both event time and calendar time which is of interest to practitioners.

A number of developments have increased the relevance of resiliency as a dimension of liquidity. Improvements in exchange technology witnessed in the last two decades have resulted in substantial increases in both the speed and level of automation of the trading process. The relative ease with which market participants can actively monitor and respond to changes in market conditions challenges the value of liquidity measures based solely on displayed liquidity. Another important development has been the decision by many exchanges to facilitate market participants hiding a portion of their order flow. Hidden order strategies have become popular among traders who are cautious about exposing their full trading intentions for fear others may react by withdrawing liquidity or trading ahead of their order. Recent academic studies (De Winne and D'hondt, 2007, Pardo and Pascual, 2012) have supported the view that traders are able to detect and predict hidden liquidity by monitoring limit order activity.

Order splitting has become a common practice in which large orders are not fully exposed, but are typically split into a number of smaller child orders with their execution dynamically managed over specified trading horizons. Understanding resiliency is important for the development of these optimal execution strategies. Obizhaeva and Wang (2013) and Alfonsi et al. (2010) study this problem in a limit order market and determine that the optimal strategy is more dependent on the resiliency of the order book as opposed to their static properties such as the spread, depth or instantaneous price impact. The models of Obizhaeva and

Wang (2013) and Alfonsi et al. (2010) assume the existence of an order book resilience effect where the initial impact of trading dissipates over time as new orders arrive to replenish the book. It is thus surprising that few studies have examined the extent to which this effect has been empirically observed, and the liquidity dynamics that generate these features has been largely unexplored. To the author's knowledge, this is the first study to quantify order book resilience to liquidity shocks arising from trading and order cancellation activities for a broad cross-section of stocks on the Australian equity market.

Resiliency is also relevant for regulators and market operators. In pure limit order book markets, competition for liquidity provision drives resiliency. Price-time priority rules on limit order execution result in a 'first mover advantage' (Biais et al., 1995), creating significant incentives for liquidity suppliers to make investments in trading technology to increase the speed and efficiency with which they can identify and respond to liquidity imbalances in the limit order book. However, there are also concerns over the fragility of market structures that rely solely on endogenous liquidity provision with a growing number of academic studies (Anand and Venkataraman, 2012, Bessembinder et al., 2011, Venkataraman and Waisburd, 2007) providing support for the use of designated market makers within electronic limit order markets. The Australian equity market is part of a growing number of markets operating without designated market makers, providing a natural setting for examining these concerns.

We document a number of dynamic interactions between different dimensions of liquidity that may be useful for the enhancement of optimal execution strategies. Depth at the best prices deteriorates in response to a liquidity shock that results in a widening of the spread. Conversely, spreads tend to widen in response to a negative shock to depth at the best prices. Significant interactions are observed along two dimensions of limit order book depth. Firstly, shocks to the depth on one side of the limit order book affect depth on the other side at the best prices.

Secondly, shocks to the depth behind the best prices affect depth at the best prices on the same side of the limit order book.

Following model estimation, we quantify resiliency arising from different liquidity shocks and their effects on the liquidity replenishment process. Examining resiliency along each dimension of liquidity reveals that spreads and depth at the best prices have similar rates of recovery, while resiliency is significantly weaker for depth away from the best prices. A similar level of resiliency is observed from liquidity shocks having the same impact on the limit order book regardless of whether the shock is due to market orders or order cancellations. Examining resiliency over our cross-section of stocks, we find order book resilience is consistently high for all liquidity shocks across large stocks. Among smaller stocks, there is greater variation in the time to recovery although the effect of most shocks have largely dissipated after a few minutes.

## 2.2 Related Literature

Few theoretical models of limit order books consider the concept of market resiliency. Foucault et al. (2005) provide one such model containing a number of specific predictions regarding market resiliency. Limit order book dynamics are found to be determined in equilibrium by two key variables, the proportion of patient traders and the order arrival rate. Resiliency increases with the proportion of patient traders and the waiting cost, but decreases as the order arrival rate increases. However, their model only allows an examination of spread resiliency. Rosu (2009) also develops a dynamic model of the limit order book that provides a condition for a resilient limit order book, requiring that patient traders arrive faster than impatient traders.

This study adds to the literature that examines resiliency using VAR based approaches as it provides a flexible framework to capture dynamic relationships. Pioneered by Hasbrouck (1991), the VAR framework has been extensively used to examine the price impact of trading and this literature also provides insights into price resiliency. Hasbrouck (1991) finds that an unexpected trade has a positive, concave and persistent impact on prices and the full price impact is only revealed after a protracted lag due to microstructure imperfections. Dufour and Engle (2000) extend the Hasbrouck (1991) bivariate model of trades and quotes by incorporating information on the duration between trades. They find that time plays an important informational role in the dynamics between trades and quotes. High trading activity results in a greater price impact as liquidity suppliers infer a greater presence of informed traders during times of higher trading activity. Engle and Patton (2004) incorporate both bid and ask quotes in an error correction model to examine price impact. Their empirical findings support both an asymmetric impact between buys and sells, and error correcting behaviour in the spread. A large spread tends to lead to a fall in the ask price and a rise in the bid price. Hautsch and Huang (2012) propose a cointegrated VAR model of quotes and order book depths to examine the price impact of limit orders. They find that limit orders have permanent price effects and the magnitude of the effect depends on the aggressiveness and size of the order, as well as the state of the limit order book. This confirms that the market reacts to the trading intentions revealed by limit order submissions.

A small number of studies have utilised VAR models to examine limit order book resiliency. Hmaied et al. (2006) investigate the dynamics of market liquidity of Tunisian stocks through a joint model of depths, spreads and volatility. They find significant interactions between the variables and their impulse response function analysis reveals that liquidity shocks are absorbed more quickly by frequently traded stocks. Coppejans et al. (2004) analyse the dynamics of liquidity in the limit order book on the Swedish index futures market and find that increases in market liquidity measured by order book depth have the positive effect of lowering volatility. A liquidity clustering effect is also observed across bid and ask-side depth and increases in depth on one side of the market leads to increases in depth on the other side. In Danielsson and Payne (2012), a VAR model is adopted to jointly estimate the dynamic effects of the spread, depth, volume and volatility of the DEM/USD exchange rate traded on the Reuters D2000-2 FX electronic broking system. Focussing on the determination of order book depth, they find that both increased volatility and wider spreads lead to decreased depth. In times of high volatility, market participants supply less liquidity and at worse terms. The effect of volume on depth depends on the side that initiated the trading. After market buy activity, buy side depth increases while sell side depth decreases.

Empirical studies have also adopted other approaches in examining market resiliency. Degryse et al. (2005) use an event study approach, analysing the resiliency of the Paris Bourse by observing the behaviour of variables such as the spread, depth and duration at the best quotes within a window around the submission of an aggressive order. Large (2007) proposes an intensity model to quantify the resiliency of a single London Stock Exchange stock that treats order events as a multivariate point process. Dong et al. (2007) examine resiliency using a Kalman-filter estimation methodology. Using data on the NYSE, the paper makes a number of important findings with a focus on how microstructural and stock-specific factors affect resiliency. The authors find the price level, trade size and a stock's volatility are negatively related to resiliency while trading activity has a positive relation. Information asymmetry is also found to play an important role in resiliency and there is evidence of commonality in resiliency. However, Dong et al. (2007) examine resiliency only from a price recovery perspective on a market supported by designated market makers. We take a broader view of resiliency and examine how resiliency is affected by different liquidity shocks. In this sense, our study complements the work of Dong et al. (2007).

We also note these aforementioned studies examining resiliency utilise data that is now over a decade old with the most recent time period examined being from September 2003 to November 2004 by Hmaied et al. (2006). The growth in algorithmic trading in the past decade suggests an empirical investigation of resiliency over a more recent time period is warranted.

Lastly, our work is related to empirical studies on order aggressiveness (Griffiths et al., 2000, Ranaldo, 2004). These authors find that traders incorporate information on the state of the limit order book in their order submission strategies, confirming a number of theoretical predictions of order choice (Foucault, 1999, Parlour, 1998). For example, order aggressiveness is weaker when spreads are wide and depth on the same side of the limit order book is thin suggesting limit order markets can be resilient. However, this does not explicitly address resiliency as the modelling framework ignores the timing of these order arrivals.

## 2.3 Data

In this study, we utilised the order data described in Section 1.2 for a sample of 30 ASX-listed stocks covering a three-month period from September to November 2009. To provide for adequate representation of stocks with different levels of liquidity, the 30 stocks chosen covered different industries with precisely 10 stocks in the large, mid and small capitalisation categories as classified by S&P/ASX indices on the first trading day of the sample period. All priority crossing and off-market trades were removed as the focus is on liquidity that can be consumed in the limit order book. All limit order book records prior to 10:15 am and after 3:45 pm were also discarded as they may be contaminated with effects from the opening and closing call auctions. It is worthwhile noting that unlike other exchanges, hidden order functionality was not available for traders on the ASX ITS trading system over the period in which our data was collected. However, traders can still implement strategies that conceal their full trading intentions. Table 2.1 presents summary statistics of the companies included in our study. As expected, larger capitalisation stocks have significantly more trading and limit order activities and a lower duration between order events.

Table 2.1: Descriptive Statistics on the Sample

This table provides summary statistics on trade and order book data. The sample contains 30 companies listed on the ASX. The top 10 companies are large capitalisation stocks, the following 10 are mid-capitalisation stocks and the bottom 10 companies are small capitalisation stocks. Order book depth is measured in thousands of shares. L1 denotes the first (topmost) price level of the limit order book. L2-5 denotes order book price levels 2 to 5. The mean values of bid and ask prices, volumes and duration between order events (measured in seconds) are reported. The sample period covers every trading day from 1 September to 30 November 2009.

| Size Category | Stocks | # Buy Trades | # Sell Trades | # Order Events | L1 Bid Price | L1 Ask Price | L1 Bid Volume (x1000) | L2-5 Bid Volume (x1000) | L1 Ask Volume (x1000) | L2-5 Ask Volume (x1000) | Duration (secs) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Large | ANZ | 2178 | 1945 | 36511 | 22.94 | 22.95 | 6.360 | 30.557 | 6.506 | 26.854 | 0.54 |
| | BHP | 2863 | 2540 | 40852 | 38.41 | 38.42 | 5.654 | 28.541 | 6.273 | 30.918 | 0.48 |
| | CBA | 2436 | 2376 | 41718 | 51.43 | 51.45 | 1.793 | 7.470 | 1.745 | 6.611 | 0.47 |
| | MQG | 1709 | 1659 | 26506 | 51.74 | 51.76 | 0.952 | 3.463 | 0.946 | 3.175 | 0.75 |
| | ORG | 1169 | 1014 | 17900 | 15.91 | 15.92 | 3.479 | 19.014 | 3.686 | 17.231 | 1.10 |
| | QBE | 1580 | 1372 | 24268 | 22.93 | 22.95 | 4.157 | 18.278 | 3.377 | 13.671 | 0.82 |
| | RIO | 2310 | 2099 | 32372 | 63.95 | 63.97 | 1.233 | 4.112 | 1.451 | 5.222 | 0.61 |
| | WES | 1474 | 1548 | 23509 | 27.02 | 27.03 | 2.075 | 9.661 | 2.182 | 9.582 | 0.84 |
| | WOW | 1405 | 1245 | 22024 | 28.76 | 28.78 | 2.693 | 13.685 | 2.705 | 11.022 | 0.90 |
| | WPL | 1893 | 1781 | 29869 | 49.88 | 49.90 | 0.986 | 4.479 | 1.021 | 4.362 | 0.66 |
| Mid | BBG | 646 | 616 | 10598 | 10.80 | 10.81 | 2.032 | 9.897 | 2.127 | 8.504 | 1.87 |
| | BEN | 505 | 529 | 8657 | 8.94 | 8.95 | 3.964 | 16.573 | 4.115 | 17.198 | 2.29 |
| | BLD | 575 | 604 | 9133 | 5.83 | 5.84 | 9.838 | 47.676 | 10.147 | 45.583 | 2.17 |
| | CTX | 568 | 628 | 8923 | 11.16 | 11.18 | 3.829 | 17.811 | 3.420 | 10.490 | 2.22 |
| | DJS | 573 | 495 | 8148 | 5.55 | 5.56 | 14.724 | 80.144 | 14.447 | 76.665 | 2.43 |
| | GFF | 465 | 379 | 6075 | 1.61 | 1.62 | 63.246 | 197.948 | 60.926 | 170.142 | 3.26 |
| | HVN | 587 | 545 | 9238 | 4.24 | 4.25 | 22.250 | 92.376 | 24.623 | 92.883 | 2.14 |
| | JHX | 687 | 717 | 10731 | 7.45 | 7.46 | 4.861 | 21.753 | 4.795 | 22.882 | 1.84 |
| | MTS | 440 | 409 | 6682 | 4.54 | 4.55 | 33.053 | 195.439 | 30.960 | 161.215 | 2.96 |
| | UGL | 572 | 650 | 9267 | 14.23 | 14.24 | 1.397 | 4.209 | 1.560 | 4.526 | 2.13 |
| Small | BWP | 188 | 175 | 2583 | 1.75 | 1.76 | 12.211 | 65.231 | 13.920 | 56.471 | 7.64 |
| | CAB | 255 | 268 | 4177 | 5.97 | 5.98 | 4.704 | 17.252 | 4.783 | 19.950 | 4.73 |
| | EQN | 266 | 280 | 3879 | 3.72 | 3.73 | 14.821 | 61.614 | 15.505 | 62.151 | 5.10 |
| | IRE | 311 | 349 | 5713 | 8.10 | 8.12 | 1.652 | 5.346 | 1.624 | 5.182 | 3.46 |
| | MAH | 203 | 163 | 2322 | 0.63 | 0.63 | 205.973 | 1187.783 | 197.279 | 1102.765 | 8.51 |
| | NXS | 125 | 103 | 1663 | 0.34 | 0.35 | 857.584 | 4016.943 | 668.653 | 3360.231 | 11.88 |
| | SKE | 104 | 93 | 1095 | 2.18 | 2.19 | 2.882 | 13.406 | 3.212 | 13.846 | 17.92 |
| | SUL | 88 | 89 | 945 | 5.36 | 5.38 | 1.127 | 3.479 | 1.425 | 4.122 | 20.83 |
| | TPI | 259 | 242 | 3501 | 1.50 | 1.50 | 37.283 | 150.240 | 33.808 | 130.523 | 5.65 |
| | WTF | 303 | 248 | 4900 | 5.81 | 5.83 | 3.343 | 8.502 | 3.592 | 9.917 | 4.04 |

## 2.4 Method

This section presents the econometric methodology used to examine the dynamics of liquidity. The first methodological choice is the sampling frequency. Typically, this choice is between event time or calendar time. Studies based on calendar time (Coppejans et al., 2004, Hmaied et al., 2006) suffer from two drawbacks. Firstly, calendar time necessitates choosing an interval length for time aggregation. The appropriate interval length would likely vary among stocks in the sample depending on the level of limit order activity. For instance, Large (2007) finds that using data on a London Stock Exchange-listed stock, when the order book does replenish after a large trade, it does so fairly quickly and 'too fast to be captured by 5 min sampling'. Secondly, the time aggregation of data containing all order events occurring within an interval results in a potential loss of information and introduces contemporaneous dependencies in the dynamics we are seeking to examine. In this study, order event time provides a more natural sampling frequency for our dataset of order events.

### 2.4.1 Variable Definition

The vector of endogenous variables in the model is given by

$$x_t = \{p_t^a, p_t^b, x_t^b, x_t^s, v_t^{b,1}, v_t^{b,25}, v_t^{a,1}, v_t^{a,25}, d_t\}'. \tag{2.1}$$

Each increment in $t$ represents one of four order events (ENTER, AMEND, TRADE, DELETE) described in Section 1.2 that impact the first five price levels of the limit order book. The values contained in the variables at each time $t$ represent what is observed immediately following the arrival of the $t$th order event. In other words, the variables at time $t$ incorporate the information from the $t$th order event.

Table 2.2: Variable Definition

| Variable | Description |
|---|---|
| $p_t^a$ | Log of the ask price ($) |
| $p_t^b$ | Log of the bid price ($) |
| $x_t^b$ | Buy trade dummy variable |
| $x_t^s$ | Sell trade dummy variable |
| $v_t^{b,1}$ | Log depth at the best bid price (thousands) |
| $v_t^{b,25}$ | Log of the cumulative depth from 2nd to 5th bid price step (thousands) |
| $v_t^{a,1}$ | Log depth at the best ask price (thousands) |
| $v_t^{a,25}$ | Log of the cumulative depth from 2nd to 5th ask price step (thousands) |
| $d_t$ | Log of duration since the previous order book event (seconds) |
| $s_t$ | Spread in logs ($s_t = p_t^a - p_t^b$) |
| $q_t$ | Mid-quote ($q_t = 0.5(p_t^a + p_t^b)$) |

Table 2.2 provides a brief description of each variable. $p_t^b$ and $p_t^a$ are the logarithms of the best bid and ask prices respectively. The trading process is endogenised through the trading indicator variables. This allows us to distinguish between trading and order cancellation events. The choice of including two separate trade indicator variables, $x_t^b$ and $x_t^s$ which identify the occurrence of a buy and sell trade respectively, allows the model to capture potential asymmetric effects that have been found by Engle and Patton (2004) and Hautsch and Huang (2012). The discreteness of these variables did not introduce difficulties in estimation but residuals are heteroskedastic and White standard errors are used for statistical inference.

The $v_t$ variables represent the volume of waiting limit orders in the market. Volume at the best prices and volume behind the market are defined separately. There are strong reasons for including depth information beyond the best prices. Firstly, evidence suggests that there is information content in the limit order book beyond the best prices. Cao et al. (2009) find that order book information behind the market is moderately informative of price discovery based on the Hasbrouck information share measure (Hasbrouck, 1995). Secondly, a trader's intention may be to execute a large order that is unable to be filled by depth at the best prices. The volume of standing limit orders behind the best prices will influence execution strategy as it determines the cost of immediate execution. $v_t^{b,1}$ is defined as the log depth available at the first occupied bid price level (L1) and $v_t^{b,25}$ is defined as the log cumulative depth from the second to the fifth price levels (L2-5) of the limit order book. $v_t^{b,1}$ has a natural interpretation as the volume of trading necessary to move the price by at least one price level while the sum of $v_t^{b,1}$ and $v_t^{b,25}$ represents the volume of trading required to move the price by at least five price levels.[1] Separate variables are defined to measure volume on the bid and ask sides of the limit order book. Hautsch and Huang (2012) consider price impacts on liquid assets where price gaps, defined as levels in the limit order book with no displayed volume, are assumed never to occur. In contrast, this study examines a representative sample of small capitalisation stocks where price gaps are often observed. Hence, depth behind the market is defined as the aggregated volume of limit orders at a fixed price distance away from the best prices. We follow Hautsch and Huang (2012) in modelling quotes and depths in logarithms. Volume variables are characterised by occassional spikes and the logarithmic transformation reduces the impact large volumes may have on the estimation. The coefficients of the volume variables should be interpreted as elasticities.

While the informational role of time between trades is well established in the extant literature (Easley and O'Hara, 1992)[2], less is known about the information carried by the duration between order events. We endogenise duration between order events[3] in our specification to allow for any potential joint dynamics. Endogenising duration also plays a secondary role in facilitating the translation from order event time to calendar time.

### 2.4.2 Model Specification

We consider a high frequency cointegrated VAR that jointly models bid and ask quotes and limit order book depths. The model choice closely resembles that

[1] Hautsch and Huang (2012) find that the most significant price effects are for limit orders submitted up to the third price level. Defining $v_t^{b,25}$ to the fifth level of the limit order book should suffice as an adequate representation of order book depth behind the market.

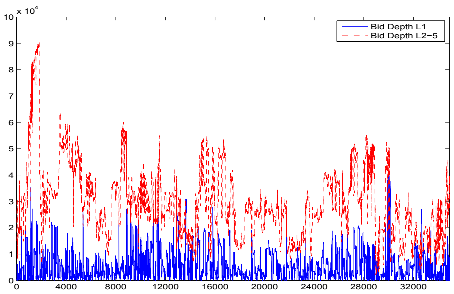
[2] Under the Easley and O'Hara (1992) model, the time between trades indicates the likelihood of an information event and the presence of informed trading.

[3] Duration is measured in seconds with precision to the nearest millisecond.

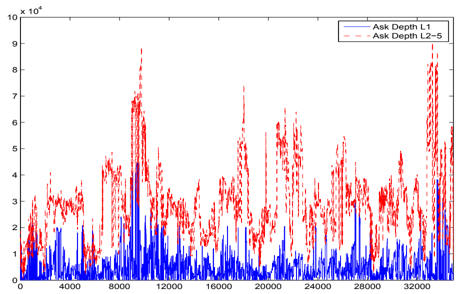
of Hautsch and Huang (2012). The cointegrated VAR in vector error correction (VEC) form is given by

$$\Delta x_t = \mu + \alpha\beta' x_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + D_0 z_t + \epsilon_t, \tag{2.2}$$

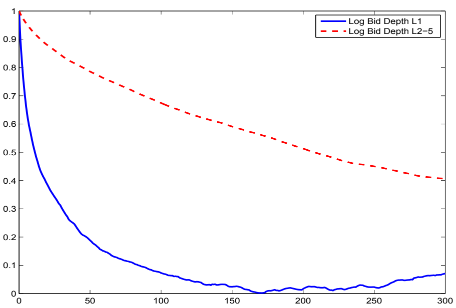
where $z_t$ is a vector containing a set of diurnal dummies that controls for intraday periodicities in the data series. The trading day is divided into six intervals, the first representing order events from 10:15 am to 11:00 am, then one for every hour till 3:00 pm and the last from 3:00 pm to 3:45 pm.



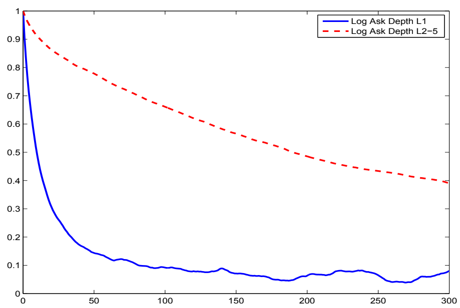

(a) Time Series of Bid Depths




(b) Time Series of Ask Depths




(c) Autocorrelation Functions of Bid Depths




(d) Autocorrelation Functions of Ask Depths

FIGURE 2.1: Plots of Order Book Depth

Time series and autocorrelation function plots of order book depth for BHP Billiton (BHP) on Monday 07 Sep 2009. The solid line displays L1 depth and the dotted line displays cumulative L2-5 depth.

We examine the statistical properties of our constructed order book depth variables. Figure 2.1 displays the time series and autocorrelation plots of order book depth for BHP Billiton on a representative trading day. There are strong positive co-movements between order book volume levels at the best prices and volume levels behind the market. The sample autocorrelations of our $v_t$ variables indicate persistent but potentially stationary processes with a lower level of persistence observed for order book depth at the best prices relative to depth behind the market.[4] This is an intuitive result as depth at the best prices inherits an additional source of variability from trading. The stationary properties of each endogenous variable are shown in Table 2.3, which reports the results of the Augmented Dickey-Fuller (ADF) test conducted on our full sample of stocks for each of the 65 trading days. The results are consistent with the generally accepted view that the log bid and ask price series ($p_t^b$ and $p_t^a$) are non-stationary processes but the spread ($s_t = p_t^a - p_t^b$) and change in mid-quote ($\Delta q_t$) are stationary processes. There is strong support for stationarity in the other remaining variables. In particular, the $v_t^{b,25}$ and $v_t^{a,25}$ series representing depth beyond the best prices reject the null hypothesis of a unit root on 100% of daily samples for large stocks, over 95% of daily samples for mid-capitalisation stocks and on over 75% of samples for small capitalisation stocks. Overall, the results suggest an adequate specification of the cointegrating matrix $\beta$ is given by

$$\beta = \begin{pmatrix} 1 & 0 & \dots & \dots & 0 \\ -1 & 0 & \dots & \dots & 0 \\ 0 & 1 & 0 & \dots & \vdots \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ 0 & \dots & \dots & \dots & 1 \end{pmatrix},$$

where the first column represents the log spread and the other co-integrating vectors account for the remaining $I(0)$ variables. This represents an important methodological difference to Hautsch and Huang (2012) who estimate the cointegrating relations assuming depth is potentially non-stationary.

[4] The rate of decay of the ACF for L2-5 depth indicates that this time series could alternatively be modelled as a fractionally integrated process. However, at the time of writing the properties of fractionally integrated processes in the context of a cointegrated system of equations have not been fully developed and is left for future research (Johansen and Nielsen, 2012).

TABLE 2.3: Stationarity Tests on Endogenous Variables

Augmented Dickey-Fuller (ADF) tests were conducted on the sample of 30 stocks for each trading day. Rejections of the null hypothesis of a unit root provides evidence of stationarity. The chosen lag length for the test is 30. The table reports both the number of rejections and the proportion of rejections at the 1% significance level across large, mid and small stocks.

| | Large Stocks | | Mid Stocks | | Small Stocks | |
|---|---|---|---|---|---|---|
| Variable | Number | (%) | Number | (%) | Number | (%) |
| $p_t^a$ | 192 | 32.0% | 274 | 45.7% | 271 | 45.2% |
| $p_t^b$ | 194 | 32.3% | 266 | 44.3% | 262 | 43.7% |
| $s_t$ | 600 | 100.0% | 599 | 99.8% | 570 | 95.0% |
| $\Delta q_t$ | 600 | 100.0% | 600 | 100.0% | 597 | 99.5% |
| $x_t^b$ | 600 | 100.0% | 600 | 100.0% | 590 | 98.3% |
| $x_s^b$ | 600 | 100.0% | 600 | 100.0% | 594 | 99.0% |
| $v_t^{b,1}$ | 600 | 100.0% | 599 | 99.8% | 576 | 96.0% |
| $v_t^{b,25}$ | 600 | 100.0% | 570 | 95.0% | 462 | 77.0% |
| $v_t^{a,1}$ | 600 | 100.0% | 600 | 100.0% | 583 | 97.2% |
| $v_t^{a,25}$ | 600 | 100.0% | 576 | 96.0% | 452 | 75.3% |
| $d_t$ | 600 | 100.0% | 600 | 100.0% | 587 | 97.8% |

The model is recast to represent the dynamics in terms of the spread and change in the mid-quote. This representation is appealing as the spread is explicitly modeled and the interactions between the spread and depth can be directly observed.

The following rotation matrix

$$R = \begin{pmatrix} 1 & -1 & 0 & \dots & 0 \\ 0.5 & 0.5 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & & & \ddots & \\ 0 & \dots & & \dots & 1 \end{pmatrix}$$

applied to Equation (2.2) achieves the transformation from changes in the bid and ask quotes into changes in the spread and mid-quote:

$$R\Delta x_t = R\mu + R\alpha\beta' x_{t-1} + \sum_{i=1}^{p-1} R\Gamma_i R^{-1} R\Delta x_{t-i} + RD_0 z_t + R\epsilon_t. \tag{2.3}$$

With further manipulation, this can be re-specified as

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + B_0 z_t + u_t, \tag{2.4}$$

where $y_t = \{s_t, \Delta q_t, x_t^b, x_t^s, v_t^{b,1}, v_t^{b,25}, v_t^{a,1}, v_t^{a,25}, d_t\}'$ and $A_p$ is a $q$ x $q$ matrix having a second column of zeros. This is a stationary VAR($p$) system with coefficient restrictions which can be estimated equation by equation without loss of efficiency.

Estimation was conducted for all thirty stocks. The large number of observations in our data permits a separate estimation of Equation (2.4) for each Monday to Friday trading week from September to November 2009, resulting in a total of 360 separate VAR models.[5] This provides a balance between retaining a sufficient number of observations and addressing possible structural instabilities in the liquidity dynamics over time.[6] To control for the absence of trading during overnight periods, a set of pre-sample values were taken on every trading day and incorporated into the estimation. The lag length chosen for the estimation depended upon the market capitalisation tertile of the stock. Larger stocks tended to have higher quoting activity and slower decaying ACF profiles, necessitating a higher lag order to capture the underlying dynamics. Ten lags for each endogenous variable ($p = 10$) was chosen for large capitalisation stocks while eight lags ($p = 8$) and six lags ($p = 6$) were chosen for mid and small capitalisation stocks respectively. In determining the appropriate lag length, the choice was guided by both residual diagnostic tests and information criteria. At the chosen lags, Ljung-Box serial correlation tests reported almost no remaining serial correlation across all estimations. Section 2.6 discusses the robustness of our results to the choice of lag order in the VAR specification.

[5]There were 12 Monday to Friday trading weeks from September to November 2009 resulting in a total of 30 x 12 = 360 separate VAR estimations.

[6]Hautsch and Huang (2012) estimate their model on each trading day to reduce the impact of possible structural breaks on their results. Their sample of stocks, however, represents the most actively traded stocks on Euronext.

### 2.4.3 Estimation Results

In addition to facilitating the construction of impulse response functions for measuring resiliency, the results presented in this section capture a rich set of liquidity dynamics and interactions between different liquidity variables. For brevity, only cross-sectional summary statistics are reported of the individual model estimations for each variable group. A variable group is defined as the co-efficients on all lags of a variable in each equation of the VAR specification. The summary statistics reported are the median sum of co-efficient values for each variable group and the number and proportion of variable groups that are positive (negative) and significantly different from zero. Using a White heteroskedasticity consistent covariance estimator, joint Wald tests were conducted to examine the significance of the entire variable group.

Table 2.4 reports a cross-sectional summary of the VAR estimation results on bid depth for each firm-trading week. Panel A shows that best bid depth reacts positively to both best ask depth and bid depth beyond the best prices, but responds negatively to the spread. Depth at the best bid also seems to improve with buyer initiated trading, although it is only negative and significant in 32% of estimated models. Panel B indicates a negative relation between bid depth behind the market and lagged values of bid depth at the best prices, which is statistically significant in 57% of estimated models. These results are consistent with the discretionary timing hypothesis of Admati and Pfleiderer (1988), where uninformed traders act strategically in timing their trades during high liquidity periods. These results are also consistent with the information effects of Biais et al. (1995). In times of high information asymmetry, liquidity declines as traders cancel their orders to avoid adverse selection. This can lead to both a reduction in limit order book depth and a widening of the bid-ask spread. The liquidity clustering effects observed are also documented in Coppejans et al. (2004).

Analogous estimation results are presented in Table 2.5 on ask side depth. The

Table 2.4: Estimation Results: Bid Market Depth

The table presents a summary of the VAR estimation results on $v_t^{b,1}$ and $v_t^{b,25}$ for each firm-trading week. Panel A reports the estimation results of the L1 bid depth equation ($v_t^{b,1}$). Panel B reports the estimation results of L2-5 bid depth equation ($v_t^{b,25}$). Column 2 reports the median sum of coefficient estimates across all firm-trading weeks. Column 3 (5) reports the number of firm-trading weeks with positive (negative) and significant joint Wald test statistics for the entire variable group. Column 4 (6) reports the percentage of firm-trading weeks that are positive (negative) and significant. There are a total of 30 x 12 = 360 firm-trading weeks in our sample. The significance level chosen is 1%.

Panel A: $v_t^{b,1}$ equation

| Variable | Median Sum of Coeffs | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | -80.9771 | 1 | 0.3% | 328 | 91.1% |
| $\Delta q_t$ | -0.86399 | 33 | 9.2% | 71 | 19.7% |
| $x_t^b$ | -0.06074 | 4 | 1.1% | 114 | 31.7% |
| $x_t^s$ | -0.01409 | 17 | 4.7% | 51 | 14.2% |
| $v_t^{b,1}$ | 0.90372 | 360 | 100.0% | 0 | 0.0% |
| $v_t^{b,25}$ | 0.01998 | 221 | 61.4% | 6 | 1.7% |
| $v_t^{a,1}$ | 0.02127 | 292 | 81.1% | 0 | 0.0% |
| $v_t^{a,25}$ | 0.00566 | 87 | 24.2% | 8 | 2.2% |
| $d_t$ | 0.00182 | 65 | 18.1% | 16 | 4.4% |

Panel B: $v_t^{b,25}$ equation

| Variable | Median Sum of Coeffs | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | -1.34920 | 56 | 15.6% | 98 | 27.2% |
| $\Delta q_t$ | 0.00993 | 40 | 11.1% | 22 | 6.1% |
| $x_t^b$ | 0.00475 | 29 | 8.1% | 4 | 1.1% |
| $x_t^s$ | 0.00661 | 46 | 12.8% | 9 | 2.5% |
| $v_t^{b,1}$ | 0.00274 | 205 | 56.9% | 7 | 1.9% |
| $v_t^{b,25}$ | 0.97712 | 360 | 100.0% | 0 | 0.0% |
| $v_t^{a,1}$ | 0.00051 | 69 | 19.2% | 26 | 7.2% |
| $v_t^{a,25}$ | 0.00037 | 16 | 4.4% | 18 | 5.0% |
| $d_t$ | 0.00010 | 16 | 4.4% | 9 | 2.5% |

same corresponding relationships are observed. In particular, Panel A shows that best ask depth responds positively to best bid depth and to ask depth beyond the best prices, but responds negatively to the spread. Panel B indicates ask depth beyond the best prices responds to ask depth at the best prices.

Panel A of both Table 2.4 and Table 2.5 reported a statistically significant negative relation between depth at the best prices and past values of the log spread. The estimation results on the spread equation in Table 2.6 also report a negative relation between the spread and past values of best bid and ask depth, suggesting that

Table 2.5: Estimation Results: Ask Market Depth

The table presents a summary of the VAR estimation results on $v_t^{a,1}$ and $v_t^{a,25}$ for each firm-trading week. Panel A reports the estimation results of the L1 ask depth equation ($v_t^{a,1}$). Panel B reports the estimation results of L2-5 ask depth equation ($v_t^{a,25}$). Column 2 reports the median sum of coefficient estimates across all firm-trading weeks. Column 3 (5) reports the number of firm-trading weeks with positive (negative) and significant joint Wald test statistics for the entire variable group. Column 4 (6) reports the percentage of firm-trading weeks that are positive (negative) and significant. There are a total of 30 x 12 = 360 firm-trading weeks in our sample. The significance level chosen is 1%.

Panel A: $v_t^{a,1}$ equation

| Variable | Median Sum of Coeffs | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | -83.6549 | 2 | 0.6% | 328 | 91.1% |
| $\Delta q_t$ | 0.76446 | 83 | 23.1% | 35 | 9.7% |
| $x_t^b$ | -0.01893 | 12 | 3.3% | 48 | 13.3% |
| $x_t^s$ | -0.06731 | 8 | 2.2% | 120 | 33.3% |
| $v_t^{b,1}$ | 0.02152 | 303 | 84.2% | 1 | 0.3% |
| $v_t^{b,25}$ | 0.00461 | 75 | 20.8% | 12 | 3.3% |
| $v_t^{a,1}$ | 0.90607 | 360 | 100.0% | 0 | 0.0% |
| $v_t^{a,25}$ | 0.01943 | 228 | 63.3% | 3 | 0.8% |
| $d_t$ | 0.00268 | 80 | 22.2% | 5 | 1.4% |

Panel B: $v_t^{a,25}$ equation

| Variable | Median Sum of Coeffs | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | -1.54550 | 52 | 14.4% | 91 | 25.3% |
| $\Delta q_t$ | -0.03196 | 27 | 7.5% | 40 | 11.1% |
| $x_t^b$ | 0.00517 | 29 | 8.1% | 6 | 1.7% |
| $x_t^s$ | 0.00939 | 47 | 13.1% | 3 | 0.8% |
| $v_t^{b,1}$ | 0.00050 | 70 | 19.4% | 28 | 7.8% |
| $v_t^{b,25}$ | 0.00044 | 28 | 7.8% | 14 | 3.9% |
| $v_t^{a,1}$ | 0.00329 | 228 | 63.3% | 8 | 2.2% |
| $v_t^{a,25}$ | 0.97620 | 360 | 100.0% | 0 | 0.0% |
| $d_t$ | 0.00026 | 21 | 5.8% | 2 | 0.6% |

there is a bi-directional Granger causal relation between the two variables. The results also suggest the spread responds negatively to depth beyond the best prices. However, there is a stronger relation to depth at the best prices as the median sum of co-efficients is more negative and is statistically significant in more estimated models. Overall, our results are consistent with the predictions of Kyle (1985) and Glosten and Milgrom (1985), that times of greater information asymmetry lead to both wider spreads and lower depths.

Table 2.7 highlights the existence of significant relations involving the duration

Table 2.6: Estimation Results: Spread

The table presents a summary of the VAR estimation results on $s_t$ for each firm-trading week. Column 2 reports the median sum of coefficient estimates across all firm-trading weeks. Column 3 (5) reports the number of firm-trading weeks with positive (negative) and significant joint Wald test statistics for the entire variable group. Column 4 (6) reports the percentage of firm-trading weeks that are positive (negative) and significant. There are a total of 30 x 12 = 360 firm-trading weeks in our sample. The significance level chosen is 1%.

| Variable | Median Sum of Coeffs (x$10^4$) | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | 9114.00 | 360 | 100.0% | 0 | 0.0% |
| $\Delta q_t$ | 0.05430 | 11 | 3.1% | 12 | 3.3% |
| $x_t^b$ | 0.25393 | 168 | 46.7% | 5 | 1.4% |
| $x_t^s$ | 0.30589 | 173 | 48.1% | 1 | 0.3% |
| $v_t^{b,1}$ | -0.07940 | 0 | 0.0% | 313 | 86.9% |
| $v_t^{b,25}$ | -0.02872 | 18 | 5.0% | 123 | 34.2% |
| $v_t^{a,1}$ | -0.08161 | 0 | 0.0% | 322 | 89.4% |
| $v_t^{a,25}$ | -0.03531 | 7 | 1.9% | 146 | 40.6% |
| $d_t$ | -0.00740 | 24 | 6.7% | 65 | 18.1% |

Table 2.7: Estimation Results: Duration between Order Events

The table presents a summary of the VAR estimation results on $d_t$ for each firm-trading week. Column 2 reports the median sum of coefficient estimates across all firm-trading weeks. Column 3 (5) reports the number of firm-trading weeks with positive (negative) and significant joint Wald test statistics for the entire variable group. Column 4 (6) reports the percentage of firm-trading weeks that are positive (negative) and significant. There are a total of 30 x 12 = 360 firm-trading weeks in our sample. The significance level chosen is 1%.

| Variable | Median Sum of Coeffs | # Pos and Sig | % Pos and Sig | # Neg and Sig | % Neg and Sig |
|---|---|---|---|---|---|
| $s_t$ | -113.170 | 13 | 3.6% | 301 | 83.6% |
| $\Delta q_t$ | -0.49495 | 41 | 11.4% | 64 | 17.8% |
| $x_t^b$ | -1.19630 | 4 | 1.1% | 348 | 96.7% |
| $x_t^s$ | -1.29720 | 0 | 0.0% | 359 | 99.7% |
| $v_t^{b,1}$ | 0.04743 | 316 | 87.8% | 7 | 1.9% |
| $v_t^{b,25}$ | 0.01643 | 136 | 37.8% | 68 | 18.9% |
| $v_t^{a,1}$ | 0.05627 | 330 | 91.7% | 2 | 0.6% |
| $v_t^{a,25}$ | 0.02094 | 160 | 44.4% | 51 | 14.2% |
| $d_t$ | 0.49564 | 360 | 100.0% | 0 | 0.0% |

between order book events. Firstly, the duration decreases with the presence of trading relative to other order events. The increased intensity of limit order activities reflects traders' reactions to the information content inferred from the observed trade. Secondly, the duration between order events is positively related to existing depth in the limit order book, particularly at the best prices. A low level of existing order book liquidity tends to increase the intensity of limit order activities. This is consistent with the existence of an order book resilience effect where a depleted limit order book entices liquidity provision through the submission of new limit orders (Biais et al., 1995, Degryse et al., 2005, Hedvall and Niemeyer, 1996). However, duration is not a significant variable in the spread or depth equations, suggesting that spreads and depth are not affected by periods of high (or low) order activity.

## 2.5 Measuring Resiliency

To quantify resiliency, we examine the effect of liquidity shocks on $y_t$ using the following impulse response function

$$I(h;\delta) = E[y_{t+h}|y_t + \delta_y, y_{t-1}, ...] - E[y_{t+h}|y_t, y_{t-1}, ...], \tag{2.5}$$

where the shock vector $\delta_y$ measures the change in the values of $y_t$ from the occurrence of a liquidity shock and $h$ is the number of future time steps. Hence, $I(h;\delta)$ measures the expected shift in the values of $y_t$ from a liquidity shock captured by the VAR model.

### 2.5.1 Identifying Liquidity Shocks

The application of Equation (2.5) requires a set of liquidity shocks to be defined and the pre-shock state of the system to be initialised. For each liquidity shock, all continuous variables in $y_t$ are initialized to their long run equilibrium values. The buy-sell trade indicator variables are set to zero so the most recent order events do not result in trading. We examine the impulse responses for five liquidity shock scenarios that result in a withdrawal of visible liquidity on the bid side of the limit order book. Analogous scenarios have been defined on the ask side. Recognising the high proportion of quote to trade activity in the market, liquidity shocks are not restricted to the occurrence of large trades (Large, 2007) but are also represented by order cancellations. The five scenarios we consider are:

1. Market Order (MO): Arrival of a sell market order that reduces the volume of waiting limit orders at the best bid by one half.

2. Order Cancellation (OC): Arrival of an instruction to cancel an existing limit order at the best bid, reducing the volume of waiting limit orders at the best bid by one half.

3. Aggressive Market Order (AMO): Arrival of a sell market order with volume exactly equal to the volume of waiting limit orders at the best bid. This scenario represents a trader who monitors the limit order book and chooses to limit the size of their market order to the quantity available at the best bid. By definition, this removes all the L1 bid depth and increases the bid-ask spread. To determine the new level of the spread $s_t$, the current best bid price $p_t^b$ is initialized to its average value over the estimation period. The current best ask $p_t^a$ is then inferred based on $p_t^b$ and the equilibrium value of the spread $s_t$. As the market order eliminates all existing volume at the best bid, $p_t^b$ is reduced by one price level and the spread $s_t$ and $\Delta q_t$ are re-computed at the new best bid. We denote $s_t^*$ and $\Delta q_t^*$ to be the re-computed values of the spread and change in mid-quote respectively. The construction of $\delta y$ requires some additional information on the volume of the limit order book behind the best prices. For the purposes of illustration, we assume that the initial state of the limit order book is such that the L1 bid volume

is equivalent to the L2 bid volume and L5 bid volume is equivalent to L6 bid volume. In this case, the sell market order has no effect on the values of any depth variables.

4. Aggressive Order Cancellation (AOC): Arrival of an instruction to cancel an existing limit order with volume equal to the volume of waiting limit orders at the best bid. This would occur if the cancelled limit order represented the only limit order at the best bid. The same assumptions and procedures are adopted as described in scenario AMO.

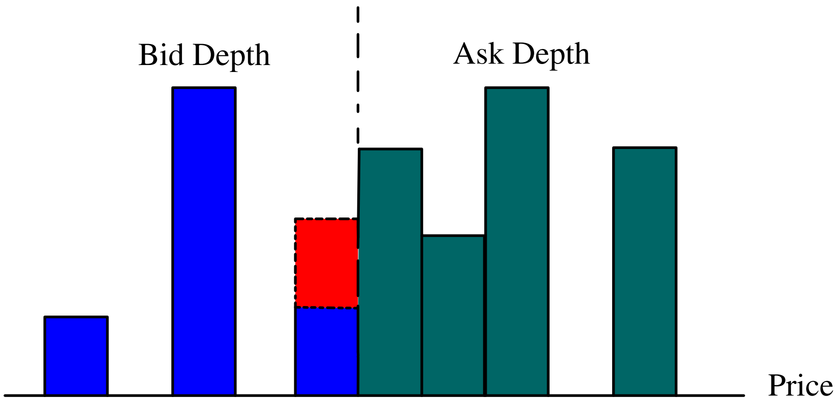
5. Order Cancellation Behind The Market (OCBM): Arrival of an instruction to cancel an existing bid limit order that reduces the volume of waiting limit orders between L2 and L5 by one half. This would occur if the trader previously submitted a bid limit order with volume exactly equal to one half of the current cumulative volume between L2 and L5.

TABLE 2.8: Shock Vectors Representing Liquidity Shocks

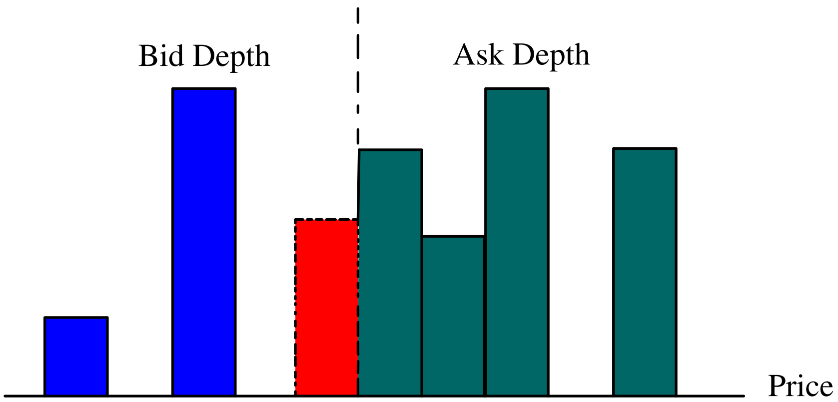
The table presents how each shock vector $\delta_y$ is constructed to represent the five liquidity shock scenarios. All continuous variables are initialised to its long run equilibrium values. The buy-sell trade indicator variables are set to zero so the most recent order events do not result in trading.

| $\delta_y$ | 1 (MO) | 2 (OC) | 3 (AMO) | 4 (AOC) | 5 (OCBM) |
|---|---|---|---|---|---|
| $s_t$ | 0 | 0 | $s_t^* - s_t$ | $s_t^* - s_t$ | 0 |
| $\Delta q_t$ | 0 | 0 | $\Delta q_t^* - \Delta q_t$ | $\Delta q_t^* - \Delta q_t$ | 0 |
| $x_t^b$ | 0 | 0 | 0 | 0 | 0 |
| $x_t^s$ | 1 | 0 | 1 | 0 | 0 |
| $v_t^{b,1}$ | -0.69 | -0.69 | 0 | 0 | 0 |
| $v_t^{b,25}$ | 0 | 0 | 0 | 0 | -0.69 |
| $v_t^{a,1}$ | 0 | 0 | 0 | 0 | 0 |
| $v_t^{a,25}$ | 0 | 0 | 0 | 0 | 0 |
| $d_t$ | 0 | 0 | 0 | 0 | 0 |

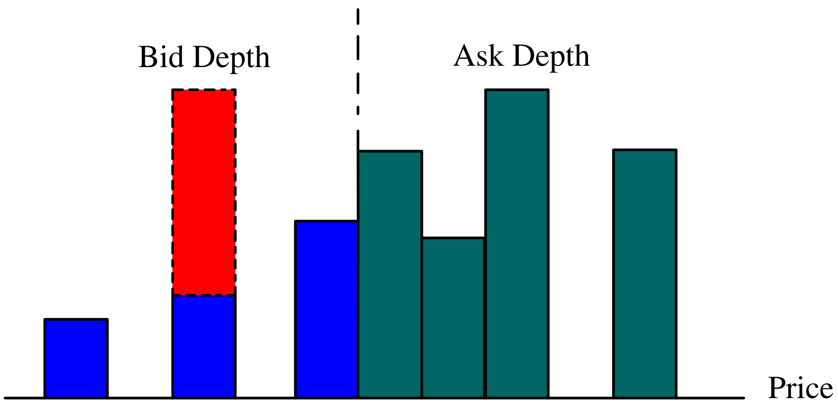
Figure 2.2 presents a graphical illustration of the effect of each liquidity shock on a hypothetical limit order book. Scenarios MO and OC reduce the volume of limit orders at the best bid by one half. Scenarios AMO and AOC exactly remove all the volume at the best bid thus increasing the bid-ask spread. Scenario OCBM represents an order cancellation that reduces the cumulative volume of bid limit




(a) Liquidity Shock - Scenario MO and OC




(b) Liquidity Shock - Scenario AMO and AOC




(c) Liquidity Shock - Scenario OCBM

FIGURE 2.2: Illustration of Liquidity Shocks
The figures above depict the effect of each liquidity shock on a hypothetical limit order book. Scenarios MO and OC reduce the volume of limit orders at the best bid by one half. Scenarios AMO and AOC remove all the volume at the best bid thus increasing the bid-ask spread. Scenario OCBM reduces the cumulative volume of bid limit orders from L2 to L5 by one half.

orders from L2 to L5 by one half. Table 2.8 summarises how each shock vector $\delta_y$ is constructed for each of the five liquidity shock scenarios. While the size of the shocks appear somewhat arbitrary, they are specified to facilitate cross-sectional comparisons. There is little loss of generality as the size of the shock has no impact on the shape of the impulse responses due to the linear structure of the VAR. The choice to model liquidity dynamics in order event time enables us to construct the shock vectors $\delta_y$ that capture all the contemporaneous relationships between the variables. Hautsch and Huang (2012) examine price effects from scenarios representing incoming limit orders with different levels of price aggressiveness. In contrast, our interest is on scenarios that have a liquidity impact such as a market order or an order cancellation.

### 2.5.2 Impulse Responses

To compute the impulse responses, we follow Hautsch and Huang (2012) and consider the companion form for the VAR($p$) process given in Equation (2.4):

$$Y_t = \mu + AY_{t-1} + Bz_t + U_t, \tag{2.6}$$

where

$$Y_t = \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ \vdots \\ y_{t-p+1} \end{pmatrix}, \mu = \begin{pmatrix} A_0 \\ 0 \\ \vdots \\ \vdots \\ 0 \end{pmatrix}, B = \begin{pmatrix} B_0 \\ 0 \\ \vdots \\ \vdots \\ 0 \end{pmatrix}, U_t = \begin{pmatrix} u_t \\ 0 \\ \vdots \\ \vdots \\ 0 \end{pmatrix},$$

and

$$A = \begin{pmatrix} A_1 & \dots & \dots & A_{p-1} & A_p \\ I_k & 0 & \dots & \dots & 0 \\ \vdots & I_k & & & \vdots \\ \vdots & \vdots & & & \vdots \\ 0 & \dots & & I_k & 0 \end{pmatrix}.$$

By repeated substitution of Y, Equation (2.6) can then be expressed as a vector moving average (VMA) process

$$Y_t = M_t + \sum_{i=0}^{t-1} A^i U_{t-i}, \tag{2.7}$$

where $M_t = \sum_{i=0}^{t-1} A^i \mu + A^t Y_0 + \sum_{i=0}^{t-1} A^i B z_{t-i}$ contains a constant, the initial condition and the effect of the exogenous variables. Let $J = [I_K 0 \dots 0]$ be a selection matrix such that $JY_t = y_t$ and $U_t = J' u_t$. Pre-multiplying $J$ on both sides of Equation (2.7) gives

$$y_t = JM_t + \sum_{i=0}^{t-1} JA^i J' u_{t-i} \tag{2.8}$$

and the linear impulse-response function can be estimated by

$$\hat{f}(h; \delta) = J \hat{A}^h J' \delta_y. \tag{2.9}$$

The asymptotic distribution of the impulse response function follows from Lutkepohl (1990)

$$\sqrt{T}(\hat{f} - f) \to N(0, G_h \Sigma_\alpha G_h'), \tag{2.10}$$

where $\alpha = vec(A_1, \dots, A_p)$, $G_h = \partial vec(f)/\partial vec(A_1, \dots, A_p)'$ and $\hat{\alpha}$ is a consistent estimator such that

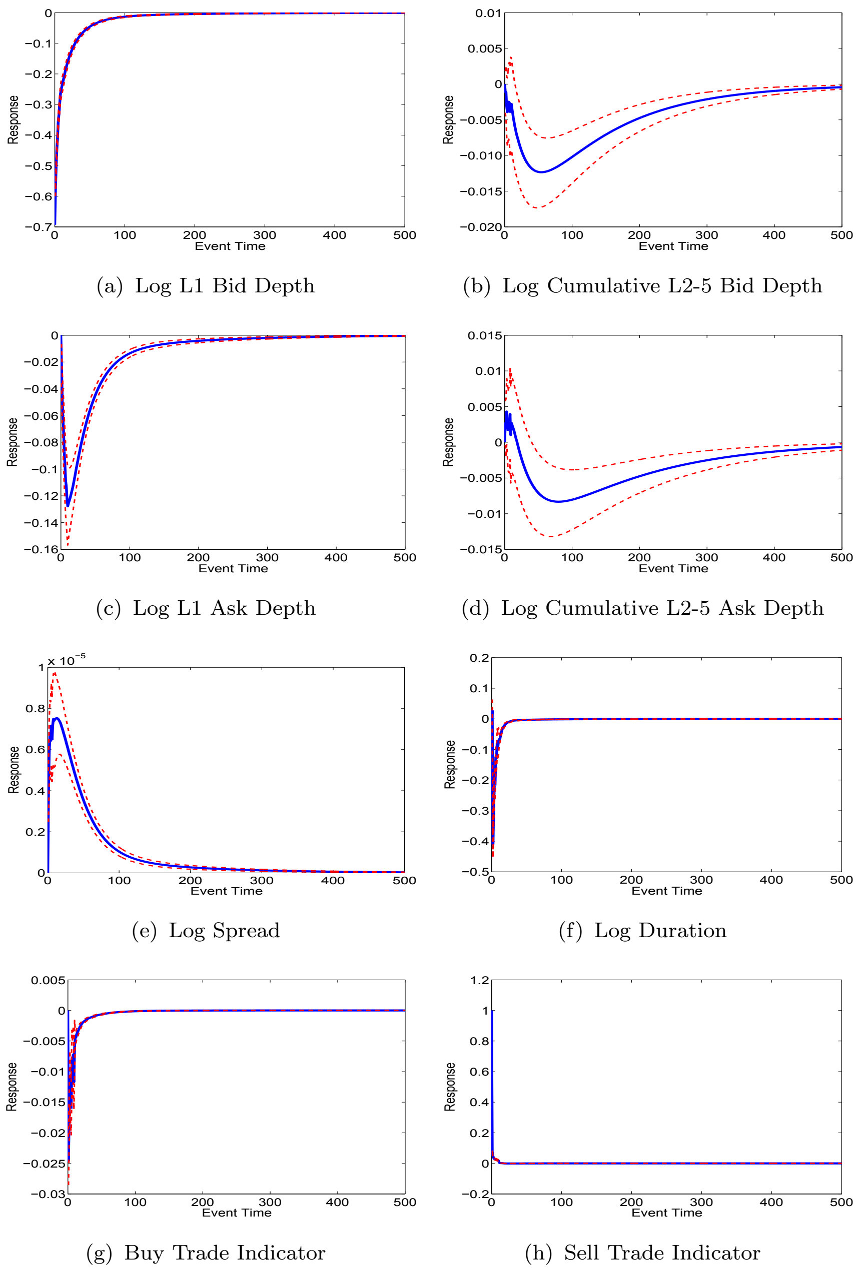
$$\sqrt{T}(\hat{\alpha} - \alpha) \to N(0, \Sigma_\alpha). \tag{2.11}$$

Confidence intervals are constructed using the diagonal elements of $G_h\hat{\Sigma}_\alpha G_h'$ and a White consistent estimator used for computing $\hat{\Sigma}_\alpha$. Due to the restrictions placed on the coefficients of lagged $\Delta q_t$ in our specification, $\alpha = vec(A_1, \ldots, A_p^*)$ is actually estimated where $A_p^*$ is $A_p$ with the second column of zeros removed.

### 2.5.3 Responses to Liquidity Shocks

This section presents the impulse responses generated by the VAR specification for the set of liquidity shocks defined in Section 2.5.1. The impulse responses illustrate the dynamic effects and adjustment path to equilibrium of each variable. To illustrate the effects of different liquidity shocks, impulse responses are presented for BHP Billiton (BHP) over the trading week beginning 7 September 2009. However, the effects observed from the impulse response profiles are representative of the broad cross-section of stocks. The full set of impulse responses, defined on both bid and ask side liquidity shocks for all firm-trading weeks, are provided electronically as supplementary results accompanying this thesis.

Figure 2.3 displays the impulse responses after a market sell order (MO). This liquidity shock is found to impact both sides of the limit order book with depth at the best ask also deteriorating in response to a reduction in best bid depth caused by the market order. This deterioration begins to reverse after 10 order book updates with the effect largely dissipated after 100 order events. To gauge the economic magnitude, the impulse response profile on best ask depth indicates that a reduction in depth at the best bid by 50% from a market order (MO) results in a subsequent deterioration in best ask depth by approximately 12% before recovery begins. In contrast, the economic effect on order book depth behind the market is significantly weaker. The same market sell order is found to reduce subsequent depth beyond the best prices by approximately 1% before recovery begins. These effects are consistent with the theoretical predictions of Parlour (1998) and Rosu (2009). Traders who wish to sell after the shock may respond to the reduced




(a) Log L1 Bid Depth

(b) Log Cumulative L2-5 Bid Depth

(c) Log L1 Ask Depth

(d) Log Cumulative L2-5 Ask Depth

(e) Log Spread

(f) Log Duration

(g) Buy Trade Indicator

(h) Sell Trade Indicator

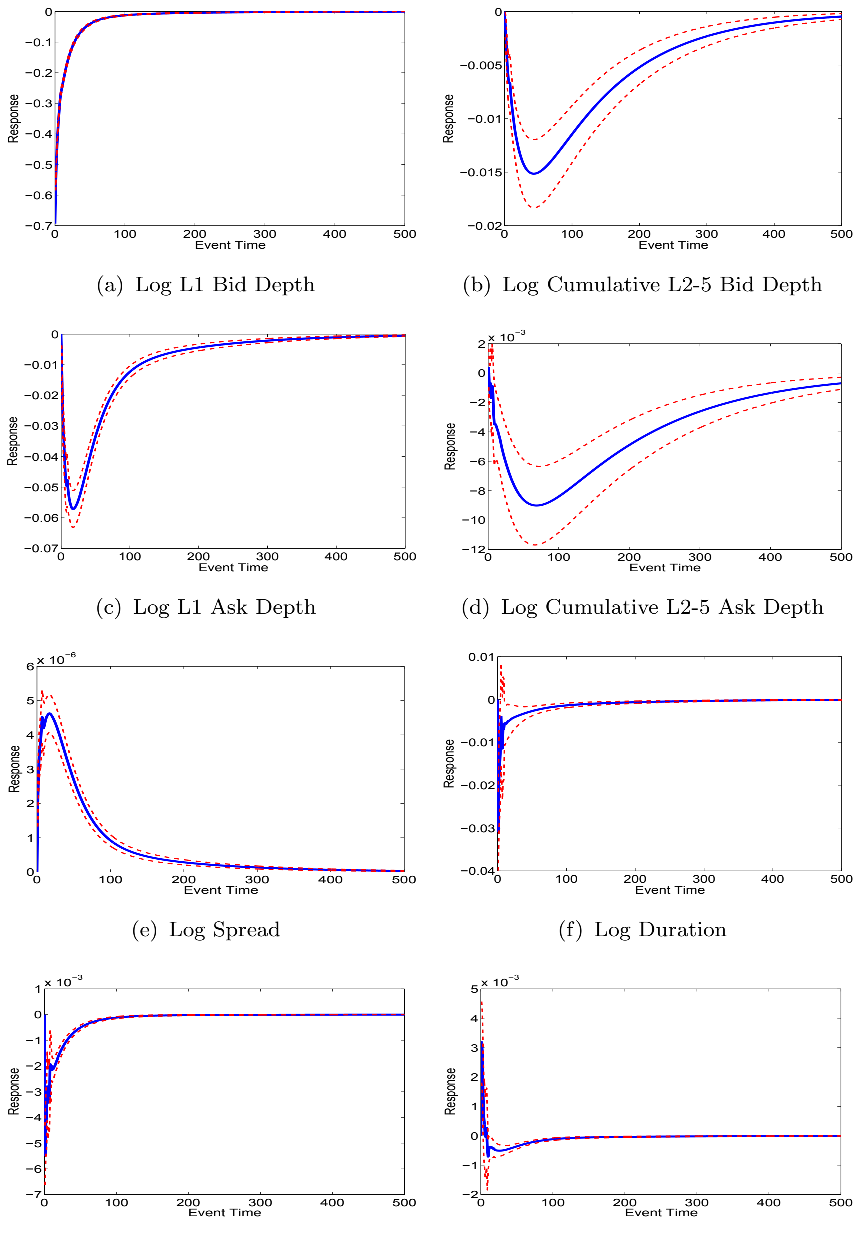
FIGURE 2.3: Response to a Liquidity Shock - Scenario MO

This figure presents the impulse responses resulting from the arrival of a sell market order that reduces the volume of waiting limit orders at the best bid by one half. Dashed lines represent 95% confidence intervals. The impulse responses presented are for BHP estimated over the trading week beginning Monday 7 September 2009.

depth at the best bid by switching their standing limit orders to market orders. For traders whose intention is to buy, limit orders become more attractive than market orders which supports the recovery. The execution probability of a bid limit order has increased while the expected waiting costs are lower than before the shock.

Given that an order cancellation (scenario OC) has the same initial effect on the limit order book as a market sell order (scenario MO), are there differences in the way liquidity is replenished? The impulse responses after a bid order cancellation for the same volume as a sell market order are shown in Figure 2.4. The two impulse responses display a similar recovery profile with no noticeable differences observed in the rate of recovery in bid depth. This is perhaps a surprising finding since if one expects the perception of prevailing information asymmetry associated with trading to be greater than from order cancellations, traders may be more reluctant to provide liquidity immediately following trading. The most noticeable differences are observed in the impulse responses of the duration variables. Market orders are found to significantly increase quote activity relative to order cancellations. This is consistent with two effects. First, traders may be observing and reacting immediately to the trade by revising or withdrawing their orders. Secondly, autocorrelation is observed in trading and a sell market order increases the arrival probability of another sell market order relative to an order cancellation.

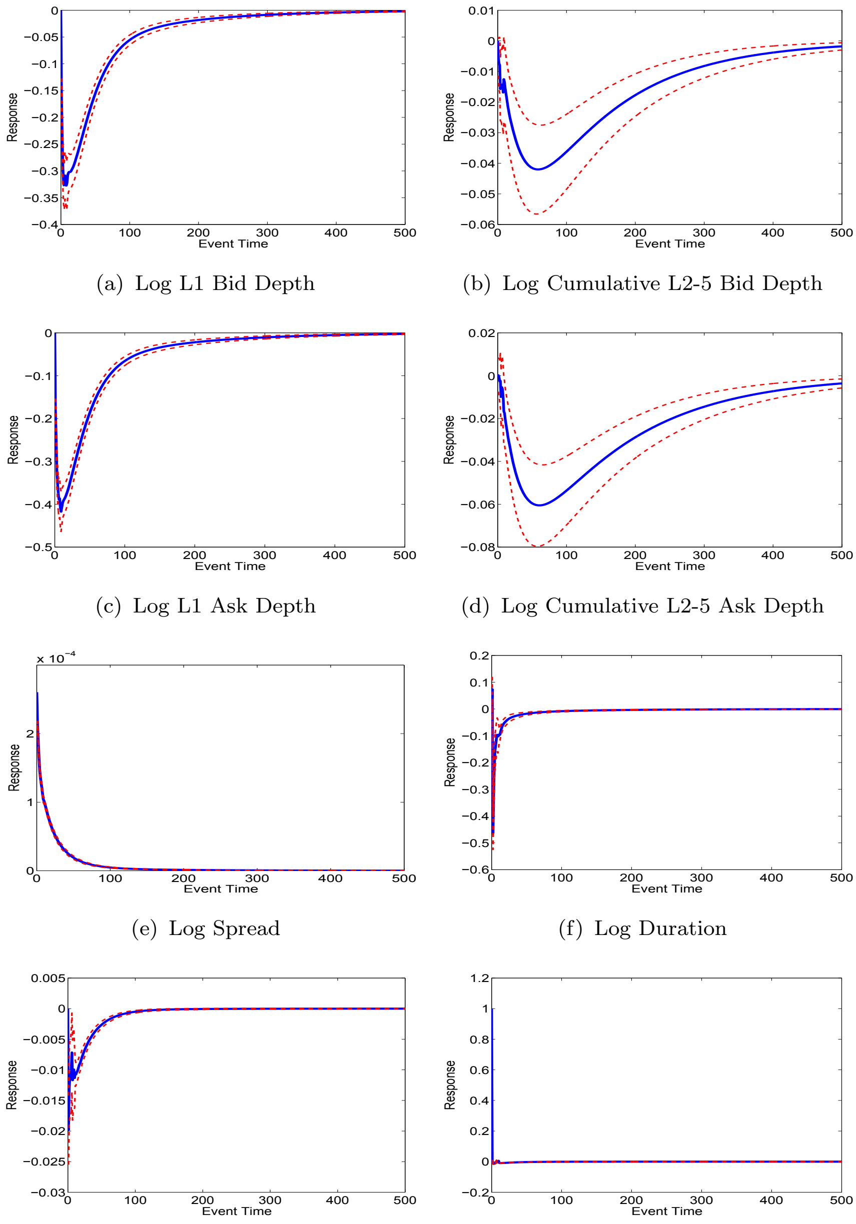
The immediate effect on the limit order book from an aggressive sell market order (AMO) is an increase in the bid-ask spread. The impulse responses induced by this liquidity shock are presented in Figure 2.5. The spread is found to be resilient with an increase in the spread subsequently inducing fresh price improving limit orders such that the effect has largely dissipated after 100 order events. While the liquidity shock has, by design, no direct impacts on order book depth, an aggressive market order has economically significant effects on future order book depth. Firstly, depth at the best prices on both sides of the order book deteriorates immediately following an aggressive sell market order that widens the spread. Secondly,




(a) Log L1 Bid Depth
(b) Log Cumulative L2-5 Bid Depth
(c) Log L1 Ask Depth
(d) Log Cumulative L2-5 Ask Depth
(e) Log Spread
(f) Log Duration
(g) Buy Trade Indicator
(h) Sell Trade Indicator

FIGURE 2.4: Response to a Liquidity Shock - Scenario OC

This figure presents the impulse responses resulting from the arrival of a cancellation instruction on an existing limit order at the best bid, reducing the volume of waiting limit orders at the best bid by one half. Dashed lines represent 95% confidence intervals. The impulse responses presented are for BHP estimated over the trading week beginning Monday 7 September 2009.




(a) Log L1 Bid Depth
(b) Log Cumulative L2-5 Bid Depth
(c) Log L1 Ask Depth
(d) Log Cumulative L2-5 Ask Depth
(e) Log Spread
(f) Log Duration
(g) Buy Trade Indicator
(h) Sell Trade Indicator

FIGURE 2.5: Response to a Liquidity Shock - Scenario AMO

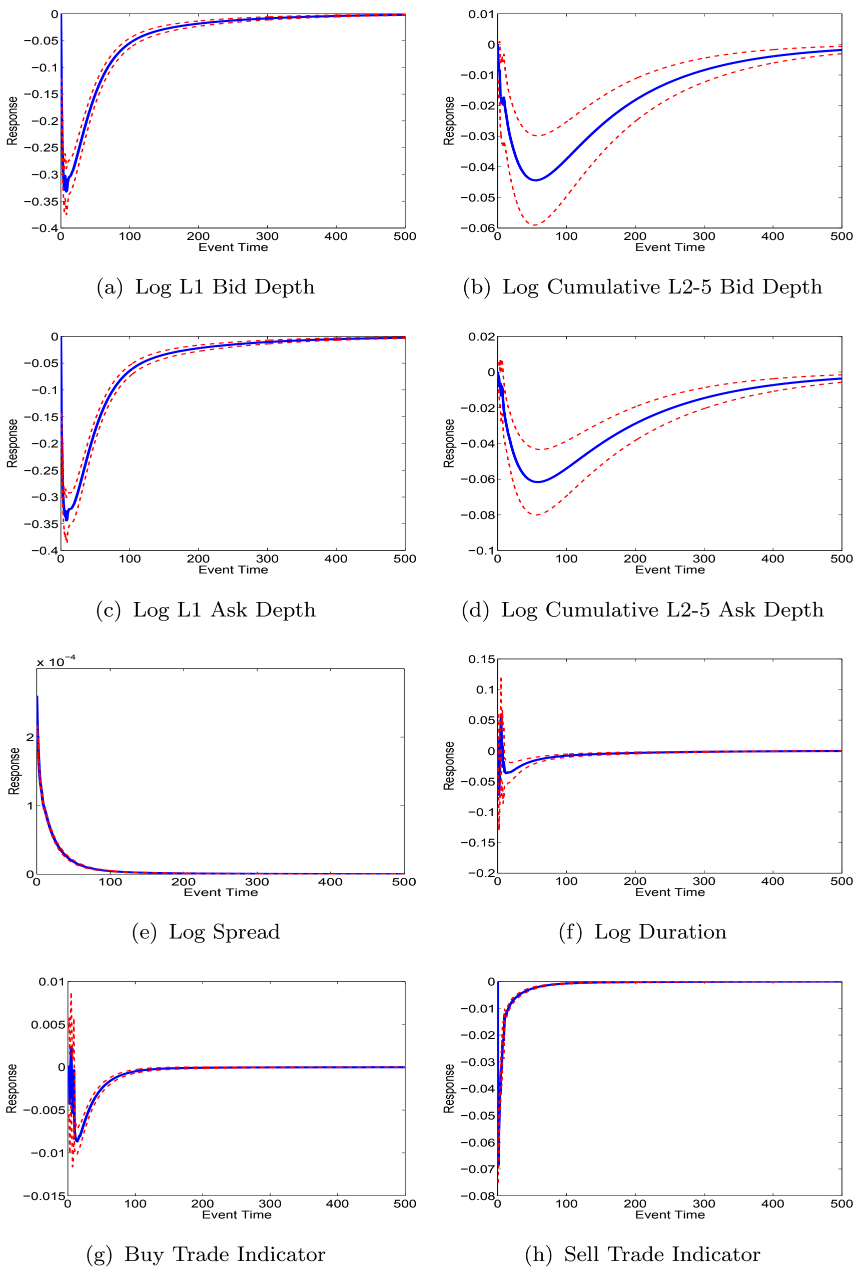
This figure presents the impulse responses resulting from the arrival of an aggressive sell market order that precisely removes all the volume of waiting limit orders at the best bid. This increases the spread but the state of the limit order book is such that even though the market order 'shifts' the limit order book, the depth at L1 and the cumulative depth at L2-5 remain unchanged. Dashed lines represent 95% confidence intervals. The impulse responses presented are for BHP estimated over the trading week beginning Monday 07 September 2009.

a deterioration in order book depth behind the market is also observed but with less severity and a slower recovery rate. Hence, sell market orders that consume all liquidity at the best bid also affect liquidity well beyond the best prices. Based on the impulse responses, depth at the best bid (ask) deteriorates by approximately 25% (30%) while L2-5 bid (ask) depth deteriorates by approximately 4% (6%) before recovery begins. The deterioration in liquidity occurs rapidly for order book depth at the best prices. After approximately 10 order events, best bid and ask depths begin to recover, although the time to recovery is slower than in scenario MO with the effect of the shock largely dissipated after 150 order events. Thirdly, the impulse response on the duration variable indicates that scenario AMO results in a significant increase in order book activity consistent with what was observed for scenario MO.

Figure 2.6 displays the impulse response profiles after an aggressive order cancellation that increases the spread (AOC). A comparison of these results with those displayed in Figure 2.5 (AMO) highlights similarities in the rate of recovery of both spreads and depths. Similar to our previous findings, there is no evidence to indicate differences in either spread or depth resiliency to trading relative to order cancellation events. The most noticeable difference lies again with the duration, as trading induces significantly more order activity than an order cancellation.

Figure 2.7 shows that limit order cancellations behind the market can have negative effects on depth at the best prices. Both best bid and best ask depth deteriorate immediately following this liquidity shock, although a larger response is observed on the bid side. The impulse responses imply that best bid (ask) depth deteriorates by approximately 12% (6%) before recovery begins. A comparison of the impulse responses on $v_t^{b,25}$ for scenario OCBM relative to $v_t^{b,1}$ for scenario MO indicates that depth resiliency behind the market is significantly weaker than depth resiliency at the best prices.

While not the central focus of this study, our model can examine the permanent price impact from our liquidity shocks. Prior studies have examined the price




(a) Log L1 Bid Depth

(b) Log Cumulative L2-5 Bid Depth

(c) Log L1 Ask Depth

(d) Log Cumulative L2-5 Ask Depth

(e) Log Spread

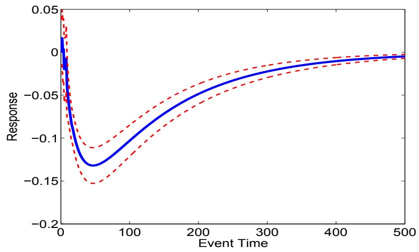
(f) Log Duration

(g) Buy Trade Indicator

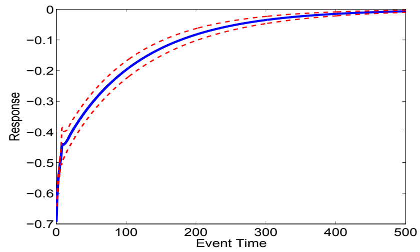
(h) Sell Trade Indicator

FIGURE 2.6: Response to a Liquidity Shock - Scenario AOC

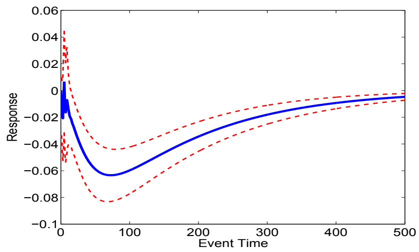
This figure presents the impulse responses resulting from the arrival of an aggressive cancellation instruction that precisely removes all the volume of waiting limit orders at the best bid. This increases the log spread but the state of the limit order book is such that even though the market order 'shifts' the limit order book, the depth at L1 and the cumulative depth at L2-5 remain unchanged. Dashed lines represent 95% confidence intervals. The impulse responses presented are for BHP estimated over the trading week beginning Monday 07 September 2009.



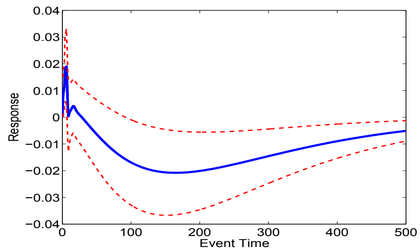

(a) Log L1 Bid Depth




(b) Log Cumulative L2-5 Bid Depth

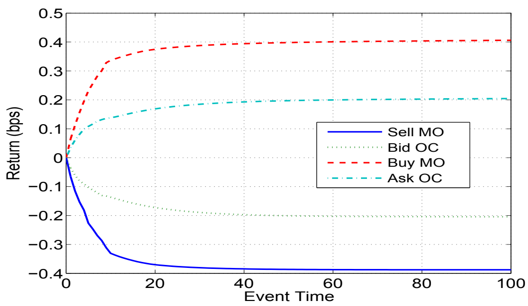



(c) Log L1 Ask Depth

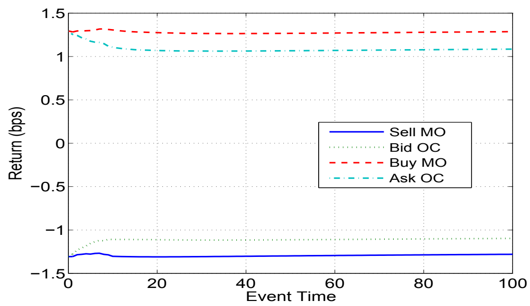



(d) Log Cumulative L2-5 Ask Depth

FIGURE 2.7: Response to a Liquidity Shock - Scenario OCBM
This figure presents the impulse responses resulting from the arrival of a cancellation instruction that reduces the volume of waiting limit orders between L2 and L5 by one half. Dashed lines represent 95% confidence intervals. The impulse responses presented are for BHP estimated over the trading week beginning Monday 07 September 2009.




(a) Scenario MO and OC




(b) Scenario AMO and AOC

FIGURE 2.8: Cumulative Price Impact of Trading vs Order Cancellations
This figure presents the cumulative price impact of market orders relative to order cancellations. The impulse responses presented are for BHP estimated over the trading week beginning Monday 07 September 2009.

impact from trading (Engle and Patton, 2004, Hasbrouck, 1991) and limit order submissions (Hautsch and Huang, 2012). However, as far as we know there is no empirical evidence on the impact of order cancellations under this framework.

The cumulative price impact on the bid and ask sides of the limit order book for the first four liquidity shocks are displayed in Figure 2.8. Figure 2.8(a) shows that order cancellations have a permanent price impact, indicating that these order events contribute to price discovery. However, market orders have a higher price impact than cancellation of existing orders. This confirms that traders do perceive market orders as carrying greater private information but this is reflected in the price levels at which liquidity is offered as opposed to a reluctance to provide liquidity after observing the shock. Prices are resilient as the adjustment process occurs relatively quickly, reaching its permanent level after approximately 40 order events. Our model generates the same price effects from trading as those documented in the extant literature (Hasbrouck, 1991, Hautsch and Huang, 2012) which should provide assurance on the results we present regarding resiliency.

Figure 2.8(b) shows the immediate impact on the mid-quote induced by an increase in the bid-ask spread from scenarios AMO and AOC. The shift in the mid-quote is permanent under an aggressive market order, while some reversion is observed when it is due to an aggressive order cancellation.

### 2.5.4 Time to Recovery

The impulse responses illustrate the dynamic adjustment path of a liquidity shock in order event time. While this may provide an appropriate cross-sectional comparison of the dynamic responses to shocks, practitioners are particularly interested in determining the resiliency of liquidity to shocks in calendar time. The speed of recovery measured in calendar time is a function of the frequency of order book events which varies substantially between stocks.

The time between order events is endogenised in our dynamic system and resiliency, measured in calendar time, can be estimated using the forecasts of $d_t$ in our VAR specification. The issue of translating event time to calendar time has also been addressed in Dufour and Engle (2000). In comparison to our approach, the authors employ a Weibull Autoregressive Conditional Duration (WACD) model to simulate the future stochastic path of time durations which requires the assumption of strong exogeneity in the trade arrival process.

The $d_t$ forecasts obtained are on the log transformed durations and consideration is required on how to recover the original duration forecast. Arino and Franses (2000) consider precisely this issue of forecasting the levels of a log-transformed time series in a vector autoregressive system and provide expressions for the unbiased h-step ahead forecasts under a Gaussian VAR. However, Bardsen and Luetkepohl (2009) found that under a controlled simulation experiment, the unbiased forecast was inferior to the naive forecast obtained by applying the exponential transformation. Hence, we use the naive forecast to recover the durations from the log transformed $d_t$ variable.

Table 2.9 provides a broader picture of the resiliency on the Australian equity market. We report 50% (half-life) and 90% recovery times to summarise the resiliency of the liquidity variable directly impacted by each liquidity shock. The 50% (90%) recovery time is defined as the estimated time for the initial effect of a liquidity shock to have dissipated by at least 50% (90%).[7] Table 2.9 shows that the rate of recovery from our set of liquidity shocks is high and robust across the sample of large stocks, but displays greater variation among smaller stocks. For large stocks, the median time for the effect of a market sell order (MO) on best bid depth to dissipate by 50% is less than a second and the effect of the shock will have dissipated by at least 90% after 5 seconds. For other liquidity shocks,

[7]The liquidity shocks defined in Section 2.5.1 affect the bid-side of the limit order book. In Table A.1 of Appendix A, we also report the recovery estimates by re-defining liquidity shocks to impact the ask-side of the limit order book.

TABLE 2.9: Time to Recovery

The table summarises the resiliency of each liquidity shock across all firm-trading weeks. Resiliency is measured as the time required for the effect of a representative liquidity shock to dissipate by a certain percentage (%). The reported levels are 50% (half-life) and 90%, and they are measured on two time scales. Order event time measures the number of limit order book updates observed from the time of the liquidity shock until the effect of the shock on the liquidity variable has declined by 50% or 90%. Calendar time (measured in seconds) is estimated by applying the exponential transformation to forecasts of $d_t$ obtained from the VAR specification. For each liquidity shock, the median, standard deviation, minimum and maximum recovery times are reported across different size categories.

Panel A: Half-life Estimates

| | | | Order Event Time | | | | Time in Seconds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Variable | Size Category | Median | Stdev | Min | Max | Median | Stdev | Min | Max |
| MO | $v_t^{b,1}$ | Large | 8 | 1.6 | 6 | 13 | 0.9 | 0.3 | 0.4 | 1.8 |
| | | Mid | 10 | 4.6 | 5 | 34 | 2.3 | 4.5 | 0.5 | 38.3 |
| | | Small | 9 | 4.7 | 2 | 25 | 5.3 | 9.4 | 0.5 | 52.0 |
| OC | $v_t^{b,1}$ | Large | 7 | 0.8 | 6 | 9 | 0.9 | 0.3 | 0.5 | 1.7 |
| | | Mid | 7 | 3.7 | 5 | 32 | 2.4 | 4.3 | 0.7 | 38.7 |
| | | Small | 9 | 4.0 | 3 | 26 | 7.4 | 9.1 | 1.8 | 65.5 |
| AMO | $s_t$ | Large | 14 | 5.2 | 7 | 31 | 1.7 | 0.7 | 0.5 | 3.6 |
| | | Mid | 8 | 2.6 | 4 | 17 | 1.9 | 2.0 | 0.7 | 21.2 |
| | | Small | 9 | 4.1 | 3 | 28 | 5.2 | 6.4 | 1.8 | 39.7 |
| AOC | $s_t$ | Large | 13 | 3.8 | 6 | 25 | 1.8 | 0.6 | 0.6 | 3.4 |
| | | Mid | 7 | 2.2 | 4 | 16 | 2.3 | 2.5 | 0.8 | 26.7 |
| | | Small | 9 | 3.3 | 3 | 26 | 6.1 | 14.2 | 1.8 | 132.5 |
| OCBM | $v_t^{b,25}$ | Large | 19 | 11.4 | 9 | 63 | 2.8 | 1.6 | 0.8 | 8.6 |
| | | Mid | 59 | 125.7 | 10 | 724 | 19.0 | 102.6 | 1.7 | 857.2 |
| | | Small | 44.5 | 97.5 | 5 | 547 | 34.7 | 153.7 | 3.1 | 695.7 |

Panel B: 90% Recovery Estimates

| | | | Order Event Time | | | | Time in Seconds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Variable | Size Category | Median | Stdev | Min | Max | Median | Stdev | Min | Max |
| MO | $v_t^{b,1}$ | Large | 44 | 7.3 | 30 | 62 | 5.2 | 1.9 | 2.5 | 11.0 |
| | | Mid | 54 | 27.1 | 25 | 222 | 16.4 | 33.5 | 4.7 | 310.3 |
| | | Small | 49 | 24.6 | 4 | 161 | 35.0 | 55.1 | 2.0 | 301.2 |
| OC | $v_t^{b,1}$ | Large | 37 | 5.9 | 28 | 52 | 4.4 | 1.8 | 2.5 | 10.6 |
| | | Mid | 46 | 27.2 | 23 | 221 | 14.8 | 32.5 | 4.1 | 297.1 |
| | | Small | 45 | 21.9 | 12 | 146 | 36.3 | 50.8 | 7.9 | 308.8 |
| AMO | $s_t$ | Large | 74 | 21.5 | 45 | 134 | 9.7 | 3.2 | 2.7 | 17.4 |
| | | Mid | 40 | 10.8 | 20 | 80 | 10.8 | 11.4 | 4.9 | 125.5 |
| | | Small | 37 | 19.4 | 11 | 126 | 24.6 | 28.8 | 8.2 | 178.1 |
| AOC | $s_t$ | Large | 71 | 19.2 | 44 | 129 | 9.4 | 3.0 | 2.8 | 17.1 |
| | | Mid | 39 | 10.4 | 20 | 80 | 11.3 | 11.7 | 5.3 | 128.7 |
| | | Small | 38 | 17.9 | 10 | 109 | 25.9 | 31.8 | 8.2 | 194.3 |
| OCBM | $v_t^{b,25}$ | Large | 107 | 60.6 | 52 | 340 | 13.9 | 9.2 | 5.3 | 49.4 |
| | | Mid | 255 | 321.3 | 43 | >1000 | 84.8 | 302.0 | 7.5 | >2791.5 |
| | | Small | 193 | 298.9 | 23 | >1000 | 145.0 | 557.1 | 12.4 | >2299.4 |

the median half-life estimates range between 1 and 3 seconds with no half-life estimates exceeding 9 seconds.

Among smaller stocks, greater variability is observed in the level of resiliency. The median half life estimate from different liquidity shocks represented by all scenarios with the exception of scenario OCBM range between 2 and 7 seconds while half-life estimates vary from less than a second to over 2 minutes. For order cancellations behind the market (OCBM), significantly less resiliency is observed and the impact of the order cancellation can persist over a long time period. The median half life estimate is 19 seconds for mid stocks and 35 seconds for small stocks. Table 2.9 confirms the findings that while spreads and depths at the best prices have similar levels of resiliency, the recovery rate of depth behind the market occurs at a much slower pace. This is particularly prominent in small stocks where less activity is observed behind the market.

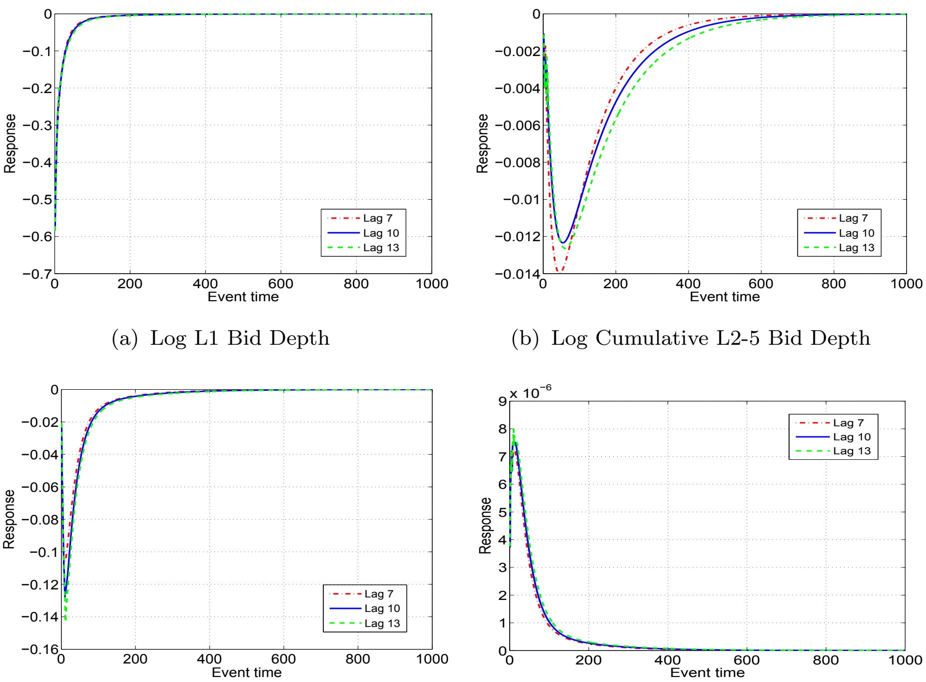
When resiliency is measured in order event time, the recovery rates of the spread in scenarios AMO and AOC are higher in smaller stocks than in large stocks. This is consistent with one of the predictions of Foucault et al. (2005), that spread resiliency is negatively related to order arrival rates. Smaller stocks tend to have lower order arrival rates and limit order traders, facing larger expected waiting times become more aggressive in their price improvements.

The speed at which the limit order book recovers, particularly in large stocks, suggests that computerized algorithms as opposed to human traders are playing an important role in identifying and responding to liquidity imbalances in the limit order book. The results also suggest caution should be exercised in the use of time-aggregated data when examining resiliency.

It is difficult to make direct comparisons of the levels of resiliency with those documented in the empirical literature, as liquidity shocks are defined differently in different studies. Coppejans et al. (2004) report that on the Swedish stock index futures market, all of the impact occurs within the first ten minutes following the liquidity event. Hmaied et al. (2006) show that for Tunisian stocks, the median time to recovery depends on the nature of the shock but ranges from 15 to 50 minutes. However, these studies use 10 and 15 minute sampling intervals respectively in their analysis. Large (2007) finds that for Barclays shares traded on the London Stock Exchange, the order book replenishes reliably after a large trade only 40% of the time, and if it does replenish, has a half life of around 20 seconds. In relation to these findings, the speed of order book replenishment appears to be faster than previously documented.

## 2.6 Robustness of Results

To examine the robustness of our results to lag order misspecification in the VAR model, all estimations were repeated at different lag lengths from $p = 2$ to $p = 15$. At lower lags than the original lag $p$ chosen for the estimation, a greater proportion of the estimated models contained significant serial correlation in the residuals, indicating an underspecified VAR model. At higher lags than the original lag choice $p$, some of the estimated impulse responses had a distinctly jagged appearance, evidence of potential overparameterisation. For these alternative specifications, the dynamic relationships revealed in the estimated coefficients are present across all lag lengths and the profiles of the impulse responses are remarkably similar. Figure 2.9 compares the estimated impulse response profiles from a liquidity shock defined by scenario MO for our representative stock, BHP, at two alternative lag lengths $p = 7$ and $p = 13$. Table 2.10 provides a comparison of the median half-life estimates across the entire sample against two alternative VAR specifications at three fewer and three greater lags than the original lag choice. The half-life estimates are robust to alternative lag order specifications and there is no indication of a lag truncation bias from underspecification.




(a) Log L1 Bid Depth

(b) Log Cumulative L2-5 Bid Depth

(c) Log L1 Ask Depth

(d) Log Spread

FIGURE 2.9: Robustness of Impulse Responses to Lag Order Mis-specification
This figure compares the impulse response profiles resulting from the arrival of a sell market order defined by Scenario MO under two alternative VAR specifications, $p = 7$ and $p = 13$. The impulse responses presented are for BHP estimated over the trading week beginning Monday 7 September 2009.

TABLE 2.10: Robustness of Recovery Estimates to Lag Order Mis-specification

The table presents a summary of 50% recovery (half-life) estimates computed at two alternative lag specifications. The alternative lag specifications are three lags fewer and three lags greater than the original lag choice. The median half-life is reported across stocks in the same size category. Order event time measures the number of limit order book updates observed from the time of the liquidity shock until the effect of the shock on the liquidity variable has declined by 50% or 90%. Calendar time (measured in seconds) is estimated by applying the exponential transformation to forecasts of $d_t$ obtained from the VAR specification.

| Scenario | Variable | | Order Event Time | | | Time In Seconds | | |
|---|---|---|---|---|---|---|---|---|
| | | Lag Adjustment | -3 | 0 | 3 | -3 | 0 | 3 |
| MO | $v_t^{b,1}$ | Large | 10 | 8 | 8 | 0.9 | 0.8 | 0.8 |
| | | Mid | 10 | 9.5 | 8 | 2.5 | 2.2 | 2.0 |
| | | Small | 10 | 9 | 7 | 6.2 | 5.1 | 4.7 |
| OC | $v_t^{b,1}$ | Large | 7 | 7 | 7 | 0.9 | 0.9 | 0.8 |
| | | Mid | 8.5 | 7 | 7 | 2.8 | 2.4 | 2.2 |
| | | Small | 10 | 9 | 7 | 7.3 | 7.4 | 6.5 |
| AMO | $s_t$ | Large | 14 | 14 | 13 | 1.7 | 1.7 | 1.6 |
| | | Mid | 8 | 8 | 8 | 2.1 | 1.9 | 1.9 |
| | | Small | 9 | 9 | 8 | 5.0 | 5.1 | 5.0 |
| AOC | $s_t$ | Large | 13 | 13 | 11 | 1.9 | 1.8 | 1.7 |
| | | Mid | 8 | 7 | 7 | 2.6 | 2.3 | 2.3 |
| | | Small | 9 | 9 | 8 | 6.2 | 6.1 | 5.7 |
| OCBM | $v_t^{b,25}$ | Large | 20.5 | 19 | 18 | 2.9 | 2.8 | 2.4 |
| | | Mid | 59 | 59 | 58 | 18.8 | 19.0 | 18.2 |
| | | Small | 43 | 44.5 | 41.5 | 31.6 | 34.7 | 33.5 |

## 2.7 Conclusion

Motivated by the importance of resiliency as a market attribute, this study examines empirically the resiliency of a cross-section of stocks on the Australian equity market. Resiliency is central to market structures that rely solely on endogenous liquidity provision, and the success of order splitting strategies depend upon limit order books exhibiting a sufficient degree of resilience.

This chapter develops a high frequency VAR specification that captures different dimensions of liquidity in the limit order book. A measure of resiliency is proposed under a set of common liquidity shocks from the impulse responses generated by this VAR specification. These liquidity shocks capture both trading and order cancellation activities.

Overall, we show that although liquidity shocks that directly impact one dimension of liquidity have detrimental effects on other dimensions of liquidity, the replenishment process generally occurs quickly, indicating limit order books are resilient. Examining resiliency along different dimensions, we find that spreads and depth at the best prices have similar levels of resiliency, while resiliency is lower for depth beyond the best prices.

Cross-sectionally, we observe a consistently high level of resiliency for all firm-trading weeks across large stocks. The timescales over which the limit order book is replenished suggest that automated liquidity provision is pervasive among these stocks. These liquidity suppliers seem to play a pivotal role in supporting the market's 'self-correcting' ability (Coppejans et al., 2004), and the widespread use of order splitting strategies by institutional investors to minimise transaction costs. Our findings also indicate the difficulty in using time aggregated data to capture short term liquidity dynamics and resiliency.

Greater variation in resiliency is observed across smaller stocks. This is consistent with the findings of Anand and Venkataraman (2012), that liquidity provision in smaller stocks can be 'sparse and opportunistic'. We hope our results motivate further research on whether a permanent market maker presence in less actively traded stocks may improve resiliency.

# Chapter 3

# Limit Order Behaviour and Execution Costs of Retail and Non-Retail Investors

## 3.1 Introduction

There has been a longstanding interest in understanding the trading behaviour and performance of institutional and retail investors in financial markets. The consensus in the existing literature suggests that institutional investors largely gain from trading at the expense of retail investors. Prior studies also find significant disparity in their trading behaviour with these investors differing in their reactions to past price performance and in the degree to which they follow momentum and contrarian strategies. While the existing literature offers important insights, its focus is on investment time horizons typically spanning several days, weeks or months. In contrast, little empirical research exists on the order execution costs of the two groups of investors, which can only be measured over very short time horizons using high frequency data. An examination of their order execution costs can provide insights on the effectiveness with which these two groups of investors manage the trading process.

The superior investment performance of institutional investors over longer horizons has been attributed to their greater levels 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) find evidence of private information gathering while Campbell et al. (2009) show that institutions anticipate earnings surprises. On the other hand, retail investors are seen to be noise traders who are susceptible to behavioural biases, which contributes to their underperformance.

The sources of potential trading advantages of institutional investors in order execution are significantly different to the advantages they have over longer time horizons, with many believing their edge arises from their access to trading technology. A strong dichotomy exists between institutional and retail investors. Institutional investors are a diverse group which includes proprietary trading desks, market makers, investment managers, brokers and hedge funds, most of whom have access to algorithmic trading systems for a variety of trading tasks, Retail investors, on the other hand, are typically non-algorithmic market users. Among institutional investors, investment in superior technology and the level of sophistication of their computerised trading algorithms is viewed as vital for economic success.[1]

A review conducted by the Australian Securities Exchange (ASX) estimated algorithmic trading represents 30-40% of total volumes traded, with high frequency trading (HFT) representing about 10% of all algorithmic trading (ASX, 2010). In Australia, algorithmic trading is more dominated by agency algorithms than it is

[1] To gain a better understanding on the importance of algorithms to investors, 'Trade' magazine surveyed institutional buy side investors on their main reasons 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.

in the US equity market, where HFT estimates are reported to be between 50-70% of total volume traded (Brogaard, 2010, Sussman et al., 2009).

The benefits offered by algorithmic trading are wide ranging. They include faster identification of, and reaction to, liquidity opportunities (Biais et al., 2012) and greater technical ability to monitor limit order risks. They also enable the implementation of superior trading strategies. The extent to which these benefits translate to better order execution outcomes is ultimately an empirical question.

This chapter compares the limit order execution costs of the different classes of investors in Australia utilising a unique dataset containing over five million non-marketable limit order submissions from more than a hundred market participants. We focus on limit orders which, as opposed to market orders, require continuous monitoring of limit order risks after order submission. Limit order submission, revision and cancellation activities represent a significant proportion of total order activity and have only increased, in some cases at an alarming rate, with the widespread adoption of algorithmic trading. Limit orders play an important role in lowering overall execution costs as they offer price improvement at the expense of exposure to limit order risks. We separate out market makers from the class of institutional investors as they likely have different motives for trading than other institutional investors. Limit order execution costs are evaluated based on the ex post cost measure of Harris and Hasbrouck (1996) which measures the adverse selection costs of executed limit orders and the implementation shortfall (Perold, 1988) which incorporates a penalty for non-execution.

We also examine the trading behaviour of institutional investors, retail investors and market makers through their limit order activities. The richness of the data allows order revisions, cancellations and executions to be observed for each submitted limit order. Understanding the limit order behaviour of different investors is important for at least two reasons. Firstly, it increases our understanding of the evolution of liquidity and the price formation process in limit order markets.

Secondly, it sheds light on the sources of any observed differences in the order execution costs of different groups of investors. If algorithmic trading is at the heart of these differences, it would be of interest to determine whether non-retail investors (algorithmic users) engage in dynamic strategies which are fundamentally different to retail investors (non-algorithmic users).

While there is an extensive literature on order choice (Bloomfield et al., 2005, Griffiths et al., 2000), fewer studies have examined limit order behaviour subsequent to order submission. The literature has tended to focus on order cancellations (Chakrabarty et al., 2006, Hasbrouck and Saar, 2009, Lo et al., 2002) as opposed to limit order revisions (Fong and Liu, 2010) despite evidence from Liu (2009) documenting that more orders are revised than cancelled. A related paper by Duong et al. (2009) investigate the determinants of order aggressiveness between institutional and retail investors, but the focus is solely on their order placement decisions as opposed to decisions made subsequent to order submission. As far as we know, this is the first empirical study comparing the limit order revision and cancellation activities of retail and non-retail investors.

Liu (2009) and Fong and Liu (2010) identify two sources of risk motivating limit order revision and cancellation activities. The first source, *picking-off* risk[2], 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 this risk better than other traders. Recent developments in theoretical models of limit order books examining the effects of high frequency trading (Biais et al., 2012, Hoffmann, 2012) typically incorporate trader heterogeneity where traders can compete on speed and impose negative externalities by picking off the stale limit orders of slower traders.

[2]This is referred to as *free-option* risk by Liu (2009).

The limit order trader also bears *non-execution* risk, which represents the opportunity cost suffered when the limit order fails to achieve execution. Hasbrouck and Saar (2009) finds evidence supporting the *chasing* hypothesis as an explanation for the cancellation behaviour of traders, consistent with the management of non-execution risk. According to this hypothesis, as the market moves away from the limit price of an order, traders with a desire to transact reposition their limit orders more aggressively in order to increase their chances of execution.

Prior literature using survival analysis (Chakrabarty et al., 2006, Hasbrouck and Saar, 2009, Lo et al., 2002) adopted a single risk approach where the event of interest is either order cancellation or execution and the alternative risk events are 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 the type of limit order revision allows us to disentangle how investors respond to these two types of risks. The analysis is conducted under a competing risks framework, in which an individual limit order can subsequently be cancelled, executed (full or partial) or revised (price or volume). These outcomes are represented as potential risk events for the limit order. The hazard rate for the risks of interest can be modelled separately using the Cox proportional hazards duration model (Cox, 1972). We incorporate time varying covariates 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) examines 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 help them manage their execution, and these agency algorithms significantly reduce the costs of monitoring limit orders. Hence, these investors are unlikely to be subject to the same trade-offs between monitoring costs and limit order submission risks as retail investors.

This study is related to the burgeoning literature on algorithmic trading. The existing literature has focussed on the impact of algorithmic trading on a range of market quality measures such as liquidity, volatility and price discovery (e.g. Hendershott et al., 2011, Boehmer et al., 2012). The results of these studies generally conclude that increased algorithmic trading has led to an overall improvement in market quality.

Two recent studies focus specifically on the impact of high frequency traders (a subcategory of algorithmic trading known for its low latency, level of sophistication of its algorithms and high levels of order message activity) on the execution costs of other investors. The public opinion over high frequency trading remains divided. The IOSCO (2011, p.10) consultation report noted comments from other investors that the presence of HFT 'discourages them from participating as they feel they are at an inherent disadvantage' because they lack the superior technology used in HFT trading. In response, regulators in many countries are considering proposals to regulate HFT and one of the main concerns cited are the increased costs imposed on less sophisticated investors. However, the findings from these two studies do not provide empirical support for these concerns. Malinova et al. (2013) examine the introduction of a per-message fee model in the Canadian market that led to a decrease in HFT activity. Their results indicate the new fee model actually caused an increase in spreads and an increase in the trading costs of retail investors. Brogaard et al. (2013) focus on the effect of HFTs on the execution costs of non-HFT institutional investors. The authors find that latency changes from technology upgrades on the London Stock Exchange are associated with HFT activity but no statistically significant relationship is found between these latency changes and institutional investors' execution costs.

In high frequency tick datasets, it is generally not possible to distinguish between the limit order activities of computers and human traders, making it difficult for a direct comparison to be made between the activities of algorithmic and non-algorithmic market users. Notable exceptions are Brogaard et al. (2013) who exploit a pricing scheme by Deutsche Bank to identify algorithmic trading activity and Brogaard (2010) who obtained a unique NASDAQ dataset identifying high frequency traders (HFTs) and non-HFTs. The Australian Stock Exchange (ASX) does not require its market participants to flag whether orders are submitted through algorithmic trading engines and market participants may not always be aware of how their clients are conducting their trading (ASX, 2010). Nevertheless, the widespread adoption of algorithmic trading by non-retail investors suggests that an analysis of limit order execution costs can shed light on the disproportionate effects of algorithmic trading between different classes of investors.

Our findings are as follows. Under two measures of limit order execution costs, our analysis fails to find substantive evidence of retail investors suffering significant losses relative to institutional investors. However, when we examine the ex post cost of limit orders based on the counterparty triggering limit order execution, we find that non-retail investors extract significant rents from retail limit orders which suffer significant adverse selection costs.

We also find fundamental differences in the limit order behaviour of institutional investors, retail investors and market makers. Both institutional investors and market makers use more order revisions and react more quickly to liquidity opportunities. Fleeting orders are more commonly used by institutional investors to search for latent liquidity. The results from proportional hazard models confirm that all investors respond to changes in limit order risks. However, institutional investors are found to be more responsive to changes in non-execution risks, leading to lower opportunity costs but a higher price impact relative to retail investors. This reflects the greater willingness by institutional investors to trade relative to retail investors, but may also reflect their improved ability of manage non-execution risks.

## 3.2 Data

We studied the limit order activities of 75 randomly chosen firms over the month of November 2009, a period before market fragmentation. The order data was sourced from the Australian Equities Tick History database and is described in more detail in Section 1.2. The selected firms cover a broad cross-section of constituents in the S&P/ASX 300 and are ranked into market capitalisation tertiles. The sample is restricted to limit order submission, revision and cancellation activities during continuous trading hours from 10:10 am to 4:00 pm as these orders are constantly exposed to non-execution and picking-off risk. Orders that are not cancelled by the close of trading are treated as right censored observations. The limit order analysis is confined to standard limit orders, excluding orders associated with priority crossings (including dark trades), off-market trades, Fill and Kill and All or Nothing orders. Priority crossing trades are excluded because these orders do not follow standard price-time priority rules. Fill and Kill and All or Nothing order types are excluded as they do not allow orders to stand in the limit order book. In this chapter, we focus on the limit order activities of institutional investors (INST), retail investors (RET) and market makers (MM). Section 1.3 provides further details on how we classify market participants.

## 3.3 Limit Order Activities Across Investors

### 3.3.1 Statistics of Limit Order Submissions

Over the full sample across all investors, we find that 50% of all non-marketable limit orders are cancelled, 33% of orders have been revised one or more times and 49% achieve full or partial execution. Table 3.1 presents summary statistics of new

TABLE 3.1: Frequency of Limit Order Events

This table presents summary statistics of new limit order submissions on the selected sample of 75 stocks. The sample period is the month of November 2009, consisting of 21 trading days. Only standard orders submitted between 10:10 am and 4:00 pm are included in the analysis. Stocks are ranked by market capitalisation and grouped into tertiles with summary statistics reported for each size tertile. The % of non-marketable limit orders 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, expressed as a percentage. % Buy and % Sell represents the proportion of bid and ask non-marketable limit orders. The table also reports the percentage breakdown of all non-marketable limit orders experiencing certain order events. % Cancelled represents the proportion of orders subsequently cancelled, % Revised represents the proportion of orders with at least one revision, % Executed represents those orders which are subsequently executed (including partial execution) and % Censored represents those orders remaining in the order book at the close of trading. As these events are not mutually exclusive, the percentages do not necessarily add to 100%.

Panel A: Large Stocks

| Investor Category | Total Non-marketable Limit Orders | % Non-marketable Limit Orders | % Buy | % Sell | % Cancelled | % Revised | % Executed | % Censored |
|---|---|---|---|---|---|---|---|---|
| INST | 2,846,721 | 79.1% | 49.8% | 50.2% | 49.1% | 32.2% | 51.9% | 0.3% |
| RET | 127,748 | 55.0% | 54.1% | 45.9% | 16.7% | 24.1% | 58.5% | 24.9% |
| MM | 400,002 | 84.1% | 46.4% | 53.6% | 67.8% | 41.5% | 33.6% | 0.1% |

Panel B: Medium Stocks

| Investor Category | Total Non-marketable Limit Orders | % Non-marketable Limit Orders | % Buy | % Sell | % Cancelled | % Revised | % Executed | % Censored |
|---|---|---|---|---|---|---|---|---|
| INST | 1,174,489 | 78.8% | 51.0% | 49.0% | 52.4% | 31.8% | 48.9% | 0.3% |
| RET | 46,226 | 60.3% | 55.5% | 44.5% | 16.9% | 26.3% | 55.5% | 27.7% |
| MM | 98,261 | 80.6% | 48.2% | 51.8% | 54.9% | 41.5% | 46.4% | 0.3% |

Panel C: Small Stocks

| Investor Category | Total Non-marketable Limit Orders | % Non-marketable Limit Orders | % Buy | % Sell | % Cancelled | % Revised | % Executed | % Censored |
|---|---|---|---|---|---|---|---|---|
| INST | 393,772 | 76.5% | 50.9% | 49.1% | 53.3% | 32.9% | 47.9% | 0.4% |
| RET | 26,106 | 63.6% | 51.2% | 48.8% | 17.2% | 25.5% | 48.4% | 34.6% |
| MM | 43,601 | 83.5% | 52.3% | 47.7% | 61.7% | 37.2% | 39.9% | 0.3% |

Panel D: All Stocks

| Investor Category | Total Non-marketable Limit Orders | % Non-marketable Limit Orders | % Buy | % Sell | % Cancelled | % Revised | % Executed | % Censored |
|---|---|---|---|---|---|---|---|---|
| INST | 4,414,982 | 78.8% | 50.2% | 49.8% | 50.3% | 32.2% | 50.7% | 0.3% |
| RET | 200,080 | 57.2% | 54.1% | 45.9% | 16.8% | 24.8% | 56.5% | 26.8% |
| MM | 541,864 | 83.4% | 47.2% | 52.8% | 65.0% | 41.2% | 36.4% | 0.2% |

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 tertiles, accounting for 78.8% of all orders by institutional investors and 83.4% by market makers compared to 57.2% by 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 utilise 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 computerised algorithms reduces the cost of monitoring limit orders. Market makers have the greatest propensity to revise and cancel their limit orders consistent with their liquidity provision role. Limit orders that remain in the order book at the close of trading are censored and originate primarily from retail investors. The percentage of censored orders increases for smaller stocks, indicating that these stocks contain a greater proportion of stale limit orders. A decrease in execution rates is also observed on limit orders placed by institutional and retail investors in smaller stocks, which are generally less liquid and have lower order arrival rates.

### 3.3.2 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 therefore reveal important information about the dynamic trading strategies employed by investors. There are several different types of limit order revisions. For an upward (downward) limit order revision in price, the limit price is revised closer to (further from) the market with the limit order placed at the end of the priority queue at the new price level. Increasing the volume of a limit order also results in the creation of a

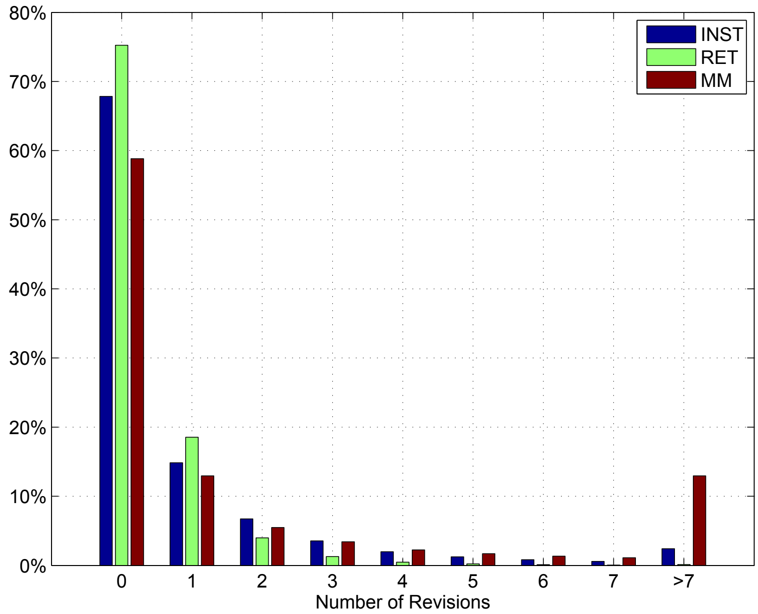



FIGURE 3.1: Number of Limit Order Revisions
This figure presents the percentage breakdown of the total number of revisions observed on non-marketable limit orders by investor category. It is based on all standard orders submitted between 10:10 am and 4:00 pm on the sample of 75 stocks.

new order for the additional order volume. The existing order retains its priority while the new limit order is placed at the end of the queue. However, reducing the volume of a limit order does not affect its position in the queue. Figure 3.1 displays the percentage breakdown of the total number of order revisions made to each non-marketable limit order among institutional investors, retail investors and market makers. Across all investors, a large proportion of limit orders are not revised. Retail investors are the least active users of limit order revisions and more than 70% of their limit orders are not revised. In contrast, market makers are more active users of revisions, with over 10% of their limit orders experiencing more than seven subsequent revisions.

Table 3.2 presents information on the type of order revisions employed by different investors. A transition frequency matrix of order revision activity is estimated where each state represents a level of order aggressiveness and each element of the matrix represents the migration frequency from one level of order aggressiveness to another level. No state change occurs for revisions made only to limit order

TABLE 3.2: 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 observing the order revision and each column represents the order aggressiveness level of the revised order. The most aggressive limit order (inside spread) is placed with a limit price that narrows the bid-ask spread. L$x$ represents a limit order placed at price level $x$ (for example, L1 refers to an order placed at the best bid or offer). L$x$-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 |

volume, while state changes reflect a change to the limit price (and possibly order volume).

Some striking differences are found in the types of order revisions employed by investors. Firstly, institutional investors have the greatest propensity to make revisions to limit order volume, with no changes to their limit price. For limit orders positioned at the best prices, institutional investors made 72.4% of revisions to limit order volume with no change to limit order prices. In comparision, we observe this type of revision accounts for 28.7% of all order revisions at the best prices from market makers and 12.5% from retail investors. The popularity of VWAP-style algorithms employed by institutional investors provides a possible explanation for these findings. Under a VWAP benchmark, the trader attempts to execute an order in line with the volume in the market. Revisions to the order volume of existing limit orders may reflect the trader responding to or anticipating changes in trading volume. Secondly, for limit orders positioned on the second and third price level of the limit order book, upward price revisions are significantly more common than downward price revisions for institutional investors and retail investors, but not for market makers. Non-execution risk appears to be of greater concern to institutional and retail investors and this behaviour is consistent with the chasing hypothesis. Under the chasing hypothesis, an investor revises the limit price to bring it closer to the best prices to improve their chances of execution. Among institutional investors, orders are most commonly revised to the best prices while retail investors' limit orders are frequently converted to market orders. This behaviour is consistent with the higher costs of monitoring imposed on retail investors. In contrast, market makers are less aggressive with their order revisions than institutional and retail investors. Their observed frequencies of upward and downward price revisions indicates more symmetric concerns for non-execution and picking-off risk.

### 3.3.3 Order Exposure

Limit order events are modelled under a competing risks framework. Within this framework, a limit order is at risk from multiple causes of failure[3] (such as an execution, cancellation or a revision order event). Limit orders that remain in the limit order book after the close of the day's 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 risk events. This is not strictly true in the presence of data where we can observe limit order revisions. We accomodate this behaviour within 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, limit orders that are subsequently revised will spawn multiple observations in our sample.

We analyse exposure times of limit orders prior to observing an order revision, execution or cancellation. The Kaplan-Meier estimator is a common procedure

[3] The terminology is adopted from the survival analysis literature.

in the survival analysis literature on censored data. However, in the presence of competing risks the Kaplan-Meier estimator tends to overestimate the incidence rates of a particular risk event (Pintilie, 2006). An alternative approach is to use cumulative incidence functions, which quantify the cumulative probability of observing event $C = j$ in the interval $(0, t]$, without assumptions about the dependence between these events (Kalbfleisch and Prentice, 1980). The cumulative incidence function (CIF) from risk event $j$ is defined by

$$F_j(t) = P(T \leq t; C = j) = \int_0^t \lambda_j(u)S(u)du, \qquad j = 1, ...., J \tag{3.1}$$

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

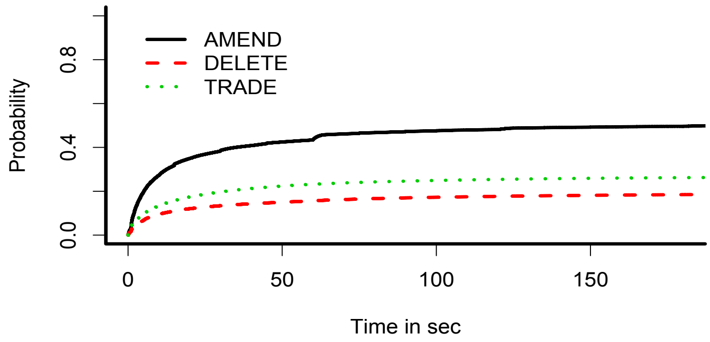
$$\lambda_j(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P(t \leq T \leq t + \Delta t, C = j | T \geq t) \tag{3.2}$$

and $S(t) = P(T > t)$ is the survivor 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

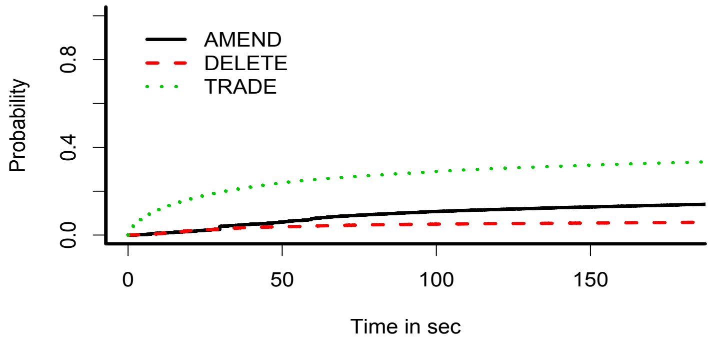
$$\hat{F}_j(t) = \sum_{i:t_i \leq t} \frac{d_{ji}}{n_i} \hat{S}(t_i), \tag{3.3}$$

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

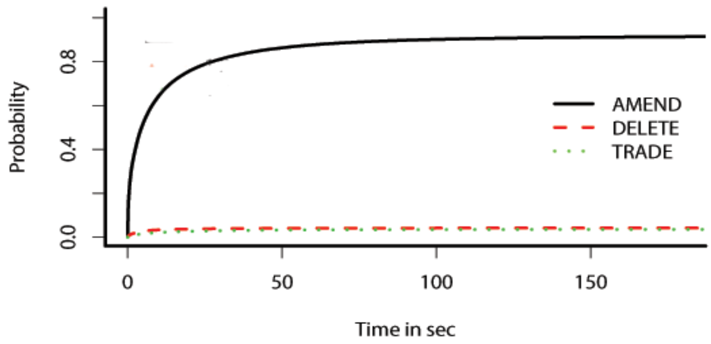
Figure 3.2 displays the estimated CIFs of order revision, cancellation and execution events across investor categories for a representative stock, BHP Billiton (BHP). Both institutional investors and market makers are found to be active users of limit order revisions. Market makers are most active, with over 80% of limit orders revised within the first minute, while cancellations are more prevalent




(a) Institutional Investors (INST)




(b) Retail Investors (RET)




(c) Proprietary Trading and Market Makers (MM)

FIGURE 3.2: Cumulative Incidence Plots for BHP

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

## TABLE 3.3: Cumulative Incidence Function Estimates

The table presents the cumulative incidence function estimates of order revision (AMEND), cancellation (DELETE) and execution (TRADE) events at various timepoints. Cumulative incidence functions are estimated separately for each of the 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 revision. The analysis is based on all standard orders submitted between 10:10 am and 4:00 pm.

Panel A: Large Stocks

| | 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: Medium Stocks

| | 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 Stocks

| | 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% |

among institutional investors. In contrast, execution is the most common outcome for a retail investor's limit order. The findings observed for BHP are robust across stocks. Table 3.3 summarises these results, reporting the cross-sectional averages of estimated CIFs for each investor category across size tertiles. The CIFs of limit order cancellations and revisions from non-retail investors rise very sharply before levelling off, consistent with these investors actively managing their limit order strategies. Retail investors experience high execution rates with few limit order cancellations or revisions observed within 30 seconds of 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 orders that are cancelled (or revised) within two seconds (Hasbrouck and Saar, 2009). Fleeting orders are almost entirely placed by institutional investors and market makers. Focusing on institutional limit orders, the average cumulative incidence of order revisions after two seconds is 8.6% for large stocks and falls to 4.9% for small stocks. For order cancellations, it is 5.3% for large stocks and 6.2% for smaller stocks. The cumulative incidence of fleeting order revisions for market makers is significantly higher at 21.2% for large stocks but falls to just 5.4% for small stocks.

Hasbrouck and Saar (2009) assert that the search for latent liquidity is a motive behind dynamic strategies utilising 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. Even in markets which do not provide hidden liquidity, 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 3.4 presents statistics on 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 capitalisation. The results also provide insights into how retail investors adjust their order submission strategies in the presence of algorithmic trading. Significant order shading is observed from retail investors' limit orders with 65.5% of retail investors' limit orders placed more than three price levels from the best prices for large stocks. Retail investors compensate for their lack of attention in monitoring orders by placing their orders further behind the limit order book.

Table 3.4: Limit Order Placement: Fleeting vs Non-Fleeting Orders

This table presents statistics on the price aggressiveness of newly submitted non-marketable limit orders categorised 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 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). Only non-fleeting orders are tabulated for retail investors as they do not submit fleeting orders. An order revision is considered to be both a cancellation and a resubmission for the purposes of classifying fleeting orders. Only standard limit orders submitted between 10:10 am and 4:00 pm are included. The most aggressive limit order (inside spread) is placed with a limit price that narrows the bid-ask spread. L$x$ represents a limit order placed at price level $x$ (for example, L1 refers to an order placed at the best bid or offer). L$x$-L$(x+1)$ represents an order with limit price placed between price level $x$ and $x+1$. A chi-square test is used to test the equality of the proportion of fleeting vs non-fleeting orders at each order placement level. The symbol * denotes a rejection of the null hypothesis of equality at the 1% level.

Panel A: Large Stocks

| | Fleeting Orders $\leq$ 2s | | Non-Fleeting Orders $>$ 2s | | | Fleeting vs Non-Fleeting Orders | |
|---|---|---|---|---|---|---|---|
| | INST | MM | INST | MM | RET | INST | MM |
| 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: Medium Stocks

| | Fleeting Orders $\leq$ 2s | | Non-Fleeting Orders $>$ 2s | | | Fleeting vs Non-Fleeting Orders | |
|---|---|---|---|---|---|---|---|
| | INST | MM | INST | MM | RET | INST | MM |
| 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 Stocks

| | Fleeting Orders $\leq$ 2s | | Non-Fleeting Orders $>$ 2s | | | Fleeting vs Non-Fleeting Orders | |
|---|---|---|---|---|---|---|---|
| | INST | MM | INST | MM | RET | INST | MM |
| 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% | * | * |

To examine the likely beneficiaries of the liquidity provided by fleeting orders, we estimate cumulative probabilities of limit order execution conditioning on the type of investor triggering execution and price aggressiveness. These probabilities are estimated for each stock across different time intervals and Table 3.5 reports the cross-sectional average of these estimated cumulative probabilities. Marked differences exist in the distributions of execution times for limit orders placed inside the spread relative to limit orders placed at lower aggressiveness levels. We find that 54.7% (68.0%) of limit orders in large stocks are executed within two seconds by an institutional investor (market maker) after observing a limit order placed inside the spread. The estimated cumulative probability falls to 35.5% (37.6%) for small stocks. In contrast, 14.4% of limit orders in large stocks placed inside the spread are executed by retail investors within two seconds, falling to just 4.9% for small stocks.[4] The results are consistent with non-retail investors closely monitoring the market for trading opportunities and suggests that the speed advantages offered by trading technology allow them to react to fleeting opportunities while fleeting order liquidity is largely inaccessible to retail investors.

## 3.4 Limit Order Risks

### 3.4.1 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 better at monitoring markets, their order revision and cancellation activity will respond more quickly to changes in these limit order

[4] An incoming market order could be matched against a limit order submitted immediately prior by chance without the trader having observed and reacted to the new liquidity opportunity.

## Table 3.5: Time to Limit Order Execution By Initiating Investor and Price Aggressiveness

This table reports the cumulative probabilities of limit order execution conditioning on the type of investor triggering execution and limit order price aggressiveness. The cumulative probabilities are estimated separately for each stock and the cross-sectional averages of these cumulative probabilities are reported across different time intervals. For revised orders, limit order execution times are measured from the last order revision. The analysis is based on all standard orders submitted between 10:10 am and 4:00 pm.

Panel A: Large Stocks

| | 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: Medium Stocks

| | 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 C: Small Stocks

| | 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% |

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 3.6 is expanded to incorporate different types of limit order revisions in order to disentangle how investors respond to these risks. The cause-specific hazards of particular interest are limit order revisions where traders decide to move their limit price towards the top of the order book (AMEND+) as well as limit order revisions away from the top of the book (AMEND-).

TABLE 3.6: List of Competing Risk Events

| Risk Event | Definition |
|---|---|
| DELETE | Limit order cancellation |
| AMEND+ | Upward price revision of existing limit order (non-marketable) |
| AMEND+MKT | Existing limit order revised to market order |
| AMEND- | Downward price revision of existing limit order |
| AMEND0 | Volume revision of existing limit order |
| TRADE | Limit order execution (full or partial) |

Following Hasbrouck and Saar (2009), we model the cause-specific hazard function $\lambda_j(t; X(t))$ given by

$$\lambda_j(t; X(t)) = \lim \frac{1}{\Delta t} P(t \leq T \leq t + \Delta t, C = j | T \geq t, X(t)). \tag{3.4}$$

$\lambda_j(t; X(t))$ 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 $\lambda_j(t; X(t))$ takes the following semi-parametric form

$$\lambda_j(t; X(t)) = \lambda_{0j}(t) exp(\beta_j' X(t)), \tag{3.5}$$

where $\lambda_{0j}(t)$ is an arbitrary, unspecified baseline hazard rate and $\beta_j$ is a vector of coefficients related to event $j$. This is the Cox (1972) proportional hazards duration model.[5] Let $t_{j1} < t_{j2} < .... < t_{jk_j}$ denote the $k_j$ ordered times at which risk event $j$ is observed, $j = 1, ...., J$, and let $X_{ji}(t_{ji})$ be the value of the set of covariates for the $i$th limit order that experiences event $j$ at time $t_{ji}$. The partial likelihood function (Kalbfleisch and Prentice, 1980) is

$$L(\beta_1, ..., \beta_J) = \prod_{j=1}^{J} \prod_{i=1}^{k_j} \frac{exp(\beta_j' X_{ji}(t_{ji}))}{\sum_{\ell \epsilon R(t_{ji})} exp(\beta_j' X_\ell(t_{ji}))}, \tag{3.6}$$

where the risk set, $R(t_{ji})$ represents the set of limit orders at risk immediately prior to $t_{ji}$. The coefficient vectors are estimated using the Efron (1977) approximation of the partial maximum likelihood function.

The set of explanatory variables controls for the effects of limit order characteristics and market conditions prevailing at the time of order submission. The two variables capturing order characteristics are order size, computed as the log of the order value in millions of dollars ($m), and price aggressiveness, computed for a bid limit order as 100(limit price − best bid$_{t=0}$)/(best bid$_{t=0}$) and for an ask limit order as 100(best ask$_{t=0}$ − limit price)/(best ask$_{t=0}$). Market condition variables include: trading activity, calculated as the log of the cumulative trading value in the prior five-minute interval in millions of dollars ($m), volatility measured as the sum of absolute mid-quote changes in the prior five-minute interval, and the percentage spread defined as 100(ask price - bid price)/(mid price). These variables are supplemented with institutional and market maker dummies to account for differences in the use of limit order revision and cancellation activities across investors.

The model also incorporates the time-dependent covariates of Hasbrouck and Saar

[5] 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 than a fully parametric model where we have no strong a priori knowledge of the specific functional of the hazard rate.

(2009) to track price movements in bid and ask prices subsequent to order submission. For a bid limit order, these are defined as

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

where $t = 0^+$ represents the instant after submission. Positive values for $\Delta q_{same}$ and $\Delta q_{opp}$ indicate the best bid and ask prices have moved higher, decreasing the chance of limit order execution. Negative values for $\Delta q_{same}$ and $\Delta q_{opp}$ suggest the market is moving towards the limit price, increasing the chance of execution. Ask limit orders are defined in an analogous manner but with an opposite sign. These variables are most important to our investigation and capture the quote monitoring intensity across investors and their strategic responses to changes in limit order risks. All explanatory variables, excluding dummy variables, are standardised (within each stock) to have zero mean and unit variance.

### 3.4.2 Empirical Results

This section presents estimation results under two specifications of the Cox model. The first model specification incorporates $\Delta q_{same}$ and $\Delta q_{opp}$ to capture how upward order revision intensity relates to changes in bid and ask quotes after order submission. The second model specification includes interaction terms to examine whether differences exist across investors. The full sample of limit orders imposes significant computational constraints on the estimation. To overcome this, a stratified sampling approach was adopted by randomly sampling 1,000 limit orders across each stock and investor category[6] with the final sample constructed by pooling all the randomly chosen stratified sub-samples. Time-dependent explanatory variables are constructed using the counting process formulation of Andersen

[6]For stock and investor category partitions where less than 1,000 limit orders are observed, the sub-sample contains all available limit orders.

and Gill (1982) with each limit order tracked through the first three minutes. The results reported here are robust to the length of time chosen to track the limit order. However, an attenuation effect is observed with longer tracking periods as the estimation results become unduly affected by the stale limit orders that are standing in the limit order book but which do not respond to market price movements.

Table 3.7 reports the estimation results for upward limit order revisions. The coefficient on order size is negative and significant in estimations across all size tertiles, implying that upward order revision intensity increases for smaller orders. In contrast, Fong and Liu (2010) document that limit order revisions increase with order size as non-execution risk is higher for larger orders. Our results may be explained by the use of order splitting, a common strategy under algorithmic trading. Small limit orders are likely to be part of a dynamic strategy with those algorithms capable of intensely monitoring exposed orders for limit order risks. There is a positive effect from volatility on the rate of upward order revisions, indicating greater attention is paid to non-execution risk during times of high volatility. The positive coefficient on the spread suggests the intensity of upward limit order revisions increases when spreads are wide. A wide spread increases the cost of immediacy as it reduces the attractiveness of revising a limit order to a market order while also providing more price levels for undercutting activity to occur. Hasbrouck and Saar (2009) documents that a wider spread could lead to an increase in fleeting limit orders placed inside the bid-ask spread to search for latent liquidity. The positive spread coefficient may also be partially capturing this effect via upward limit order revisions. A negative relationship is observed between price aggressiveness and upward order revision intensity, but only for mid and small sized stocks. Orders placed further behind the limit order book experience higher non-execution risk, increasing the chance that they will be repositioned more aggressively. Institutional and market maker dummies account for differences in the baseline hazard and as expected, the coefficients indicate that both classes

## Table 3.7: Hazard Model of Upward Limit Order Revisions ($AMEND+$)

This table reports the parameter estimates $\beta$ from two specifications of a time varying proportional Cox hazards model where the risk event is an upward limit order revision ($AMEND+$). The sample is constructed by selecting 1,000 limit orders across each stock and investor category. Orders are tracked through the first three minutes. The explanatory variables are: Order Size computed as the log of the order value in millions of dollars ($m); Trading Activity computed as the log of the cumulative trading value in the prior five-minute interval in millions of dollars ($m); Volatility measured as the sum of absolute mid-quote changes in the prior five-minute interval; Spread defined as 100(ask price - bid price)/ mid price; Price Aggressiveness, which is computed for a bid limit order as 100(limit price $-$ best bid$_{t=0}$)/(best bid$_{t=0}$); Dummy variables that take the value of 1 if the limit order comes from an institutional investor or market maker, or 0 otherwise. $\Delta q_{same}$ and $\Delta q_{opp}$ are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission (Hasbrouck and Saar, 2009). All explanatory variables apart from the indicator variables are standardised within each stock to have zero mean and unit variance. The reported $p$-values are calculated using robust standard errors clustered by stock.

Panel A: Large Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.140 | 0.869 | <0.001 | -0.149 | 0.861 | <0.001 |
| Trading Activity | 0.033 | 1.034 | 0.226 | 0.031 | 1.032 | 0.252 |
| Volatility | 0.060 | 1.062 | 0.013 | 0.061 | 1.063 | 0.017 |
| Spread | 0.132 | 1.141 | <0.001 | 0.123 | 1.131 | <0.001 |
| Price Aggressiveness | 0.001 | 1.001 | 0.982 | 0.002 | 1.002 | 0.975 |
| Institutional Dummy | 1.723 | 5.599 | <0.001 | 1.600 | 4.953 | <0.001 |
| Market Maker Dummy | 2.814 | 16.669 | <0.001 | 2.818 | 16.748 | <0.001 |
| $\Delta q_{same}$ | 0.226 | 1.254 | 0.005 | 0.153 | 1.165 | 0.094 |
| $\Delta q_{opp}$ | 0.522 | 1.686 | <0.001 | 0.562 | 1.754 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.745 | 2.107 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | -0.288 | 0.750 | 0.029 |
| Institutional x $\Delta q_{opp}$ | | | | -0.274 | 0.761 | 0.034 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.042 | 1.043 | 0.727 |

Panel B: Medium Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.218 | 0.804 | <0.001 | -0.227 | 0.797 | <0.001 |
| Trading Activity | 0.000 | 1.000 | 0.994 | 0.001 | 1.001 | 0.959 |
| Volatility | 0.140 | 1.151 | <0.001 | 0.129 | 1.138 | <0.001 |
| Spread | 0.091 | 1.095 | <0.001 | 0.097 | 1.102 | <0.001 |
| Price Aggressiveness | -0.058 | 0.943 | <0.001 | -0.059 | 0.943 | <0.001 |
| Institutional Dummy | 1.780 | 5.932 | <0.001 | 1.684 | 5.387 | <0.001 |
| Market Maker Dummy | 2.842 | 17.148 | <0.001 | 2.825 | 16.863 | <0.001 |
| $\Delta q_{same}$ | 0.311 | 1.365 | <0.001 | 0.221 | 1.247 | 0.025 |
| $\Delta q_{opp}$ | 0.343 | 1.409 | <0.001 | 0.356 | 1.428 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.551 | 1.734 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | -0.270 | 0.764 | 0.017 |
| Institutional x $\Delta q_{opp}$ | | | | -0.046 | 0.955 | 0.705 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.029 | 1.029 | 0.767 |

Panel C: Small Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.191 | 0.827 | <0.001 | -0.195 | 0.823 | <0.001 |
| Trading Activity | -0.010 | 0.990 | 0.644 | -0.012 | 0.988 | 0.594 |
| Volatility | 0.100 | 1.105 | <0.001 | 0.102 | 1.108 | <0.001 |
| Spread | -0.024 | 0.976 | 0.590 | -0.028 | 0.973 | 0.551 |
| Price Aggressiveness | -0.070 | 0.932 | <0.001 | -0.070 | 0.933 | <0.001 |
| Institutional Dummy | 1.913 | 6.771 | <0.001 | 1.814 | 6.137 | <0.001 |
| Market Maker Dummy | 3.052 | 21.153 | <0.001 | 2.972 | 19.529 | <0.001 |
| $\Delta q_{same}$ | 0.495 | 1.641 | <0.001 | 0.076 | 1.079 | 0.322 |
| $\Delta q_{opp}$ | 0.160 | 1.174 | 0.018 | 0.430 | 1.537 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.469 | 1.598 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | 0.374 | 1.453 | <0.001 |
| Institutional x $\Delta q_{opp}$ | | | | -0.195 | 0.823 | 0.079 |
| Market Maker x $\Delta q_{opp}$ | | | | -0.369 | 0.692 | 0.005 |

Panel D: All Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.188 | 0.829 | <0.001 | -0.191 | 0.826 | <0.001 |
| Trading Activity | 0.004 | 1.004 | 0.780 | 0.006 | 1.006 | 0.659 |
| Volatility | 0.095 | 1.100 | <0.001 | 0.094 | 1.098 | <0.001 |
| Spread | 0.078 | 1.081 | <0.001 | 0.082 | 1.085 | <0.001 |
| Price Aggressiveness | -0.049 | 0.952 | <0.001 | -0.050 | 0.951 | <0.001 |
| Institutional Dummy | 1.725 | 5.613 | <0.001 | 1.654 | 5.227 | <0.001 |
| Market Maker Dummy | 2.875 | 17.729 | <0.001 | 2.856 | 17.396 | <0.001 |
| $\Delta q_{same}$ | 0.381 | 1.463 | <0.001 | 0.194 | 1.214 | <0.001 |
| $\Delta q_{opp}$ | 0.302 | 1.352 | <0.001 | 0.413 | 1.511 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.353 | 1.423 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | -0.107 | 0.899 | 0.158 |
| Institutional x $\Delta q_{opp}$ | | | | -0.061 | 0.941 | 0.386 |
| Market Maker x $\Delta q_{opp}$ | | | | -0.055 | 0.946 | 0.438 |

of investors experience a higher rate of upward order revision activity, relative to retail investors.

Moving on to the time-dependent covariates, the coefficients on both $\Delta q_{same}$ and $\Delta q_{opp}$ are positive and significant, consistent with traders 'chasing' market prices (Hasbrouck and Saar, 2009) by revising their limit orders more aggressively. There are some interesting effects when the model is expanded to include the interaction terms. The coefficient on Institutional x $\Delta q_{same}$ is positive and significant across all size tertiles but this is partially offset by the negative coefficient on Institutional x $\Delta q_{opp}$, although it is only significant for large stocks. This suggests that, relative to retail investors, the upward order revision activity of institutional investors responds more to changes in same-side quotes but less to changes in quotes on the opposite side. In other words, institutional investors are more active in repositioning existing limit orders in response to undercutting, but less to changes in the costs of immediate trading.

Overall, the results support the greater responsiveness of institutional investors to changes in non-execution risk. Focusing on the estimation results across all stocks, the hazard ratio of 1.214 for $\Delta q_{same}$ implies a percentage increase (decrease) in the intensity of upward order revisions of 21% for a one standard deviation increase (decrease) in the same-side quote for a retail investor. In contrast, a one standard deviation increase (decrease) in the same-side quote for an institutional investor results in a 73% increase (decrease) in the intensity of upward order revisions.

The negative coefficent estimates for Market Maker x $\Delta q_{same}$ for large and mid-sized stocks are generally consistent with the behaviour of electronic liquidity providers. For example, if the best bid moves towards a market maker's limit price and this is perceived to be non-information driven, market makers may revise an existing bid limit order to replenish the order book at the original price level. The Market Maker x $\Delta q_{same}$ term is significant for large and mid-sized stocks where market makers are more active. In addition, when the best bid moves away, market makers with no precommitment to trade are less likely to 'chase' the market.

## Table 3.8: Hazard Model of Downward Limit Order Revisions ($AMEND-$)

This table reports the parameter estimates $\beta$ from two specifications of a time varying proportional Cox hazards model where the risk event is a downward limit order revision ($AMEND-$). The sample is constructed by selecting 1,000 limit orders across each stock and investor category. Orders are tracked through the first three minutes. The explanatory variables are: Order Size computed as the log of the order value in millions of dollars ($m); Trading Activity computed as the log of the cumulative trading value in the prior five-minute interval in millions of dollars ($m); Volatility measured as the sum of absolute mid-quote changes in the prior five-minute interval; Spread defined as 100(ask price - bid price)/ mid price; Price Aggressiveness, which is computed for a bid limit order as 100(limit price − best bid$_{t=0}$)/(best bid$_{t=0}$); Dummy variables that take the value of 1 if the limit order comes from an institutional investor or market maker, or 0 otherwise. $\Delta q_{same}$ and $\Delta q_{opp}$ are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission (Hasbrouck and Saar, 2009). All explanatory variables apart from the indicator variables are standardised within each stock to have zero mean and unit variance. The reported $p$-values are calculated using robust standard errors clustered by stock.

Panel A: Large Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.067 | 0.935 | 0.042 | -0.070 | 0.932 | 0.034 |
| Trading Activity | 0.004 | 1.004 | 0.879 | 0.005 | 1.005 | 0.867 |
| Volatility | 0.077 | 1.080 | <0.001 | 0.073 | 1.075 | 0.002 |
| Spread | 0.091 | 1.096 | <0.001 | 0.092 | 1.097 | <0.001 |
| Price Aggressiveness | 0.699 | 2.012 | 0.014 | 0.690 | 1.993 | 0.016 |
| Institutional Dummy | 1.666 | 5.291 | <0.001 | 1.603 | 4.969 | <0.001 |
| Market Maker Dummy | 3.643 | 38.216 | <0.001 | 3.664 | 39.010 | <0.001 |
| $\Delta q_{same}$ | -0.832 | 0.435 | <0.001 | -0.378 | 0.685 | 0.020 |
| $\Delta q_{opp}$ | 0.143 | 1.153 | 0.004 | -0.245 | 0.782 | 0.144 |
| Institutional x $\Delta q_{same}$ | | | | -0.761 | 0.467 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | -0.439 | 0.645 | 0.018 |
| Institutional x $\Delta q_{opp}$ | | | | 0.382 | 1.466 | 0.071 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.435 | 1.545 | 0.017 |

Panel B: Medium Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.009 | 0.991 | 0.885 | -0.008 | 0.992 | 0.903 |
| Trading Activity | -0.044 | 0.957 | 0.149 | -0.044 | 0.957 | 0.149 |
| Volatility | 0.150 | 1.162 | <0.001 | 0.150 | 1.162 | <0.001 |
| Spread | 0.081 | 1.084 | <0.001 | 0.080 | 1.084 | <0.001 |
| Price Aggressiveness | 0.306 | 1.358 | 0.050 | 0.307 | 1.359 | 0.050 |
| Institutional Dummy | 1.421 | 4.139 | <0.001 | 1.433 | 4.189 | <0.001 |
| Market Maker Dummy | 3.467 | 32.038 | <0.001 | 3.525 | 33.961 | <0.001 |
| $\Delta q_{same}$ | -0.421 | 0.656 | <0.001 | -0.418 | 0.659 | <0.001 |
| $\Delta q_{opp}$ | 0.058 | 1.059 | 0.267 | -0.139 | 0.870 | 0.148 |
| Institutional x $\Delta q_{same}$ | | | | -0.268 | 0.765 | 0.192 |
| Market Maker x $\Delta q_{same}$ | | | | 0.040 | 1.041 | 0.699 |
| Institutional x $\Delta q_{opp}$ | | | | 0.176 | 1.192 | 0.216 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.217 | 1.242 | 0.083 |

Panel C: Small Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | 0.099 | 1.105 | 0.105 | 0.098 | 1.103 | 0.114 |
| Trading Activity | -0.051 | 0.951 | 0.004 | -0.050 | 0.951 | 0.005 |
| Volatility | 0.112 | 1.119 | <0.001 | 0.107 | 1.113 | 0.001 |
| Spread | -0.058 | 0.944 | 0.161 | -0.058 | 0.944 | 0.159 |
| Price Aggressiveness | 0.874 | 2.396 | <0.001 | 0.873 | 2.395 | <0.001 |
| Institutional Dummy | 1.701 | 5.478 | <0.001 | 1.714 | 5.552 | <0.001 |
| Market Maker Dummy | 3.601 | 36.648 | <0.001 | 3.596 | 36.443 | <0.001 |
| $\Delta q_{same}$ | -0.119 | 0.888 | 0.293 | -0.072 | 0.930 | 0.835 |
| $\Delta q_{opp}$ | -0.171 | 0.843 | 0.055 | -0.196 | 0.822 | 0.645 |
| Institutional x $\Delta q_{same}$ | | | | 0.295 | 1.343 | 0.432 |
| Market Maker x $\Delta q_{same}$ | | | | -0.209 | 0.811 | 0.577 |
| Institutional x $\Delta q_{opp}$ | | | | -0.060 | 0.942 | 0.896 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.111 | 1.117 | 0.808 |

Panel D: All Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.011 | 0.989 | 0.742 | -0.010 | 0.990 | 0.758 |
| Trading Activity | -0.035 | 0.965 | 0.036 | -0.035 | 0.966 | 0.037 |
| Volatility | 0.111 | 1.118 | <0.001 | 0.110 | 1.117 | <0.001 |
| Spread | 0.060 | 1.062 | <0.001 | 0.060 | 1.062 | <0.001 |
| Price Aggressiveness | 0.549 | 1.731 | <0.001 | 0.547 | 1.729 | <0.001 |
| Institutional Dummy | 1.530 | 4.616 | <0.001 | 1.511 | 4.531 | <0.001 |
| Market Maker Dummy | 3.548 | 34.748 | <0.001 | 3.585 | 36.057 | <0.001 |
| $\Delta q_{same}$ | -0.461 | 0.631 | <0.001 | -0.346 | 0.707 | 0.004 |
| $\Delta q_{opp}$ | -0.045 | 0.956 | 0.293 | -0.216 | 0.806 | 0.085 |
| Institutional x $\Delta q_{same}$ | | | | -0.168 | 0.846 | 0.256 |
| Market Maker x $\Delta q_{same}$ | | | | -0.116 | 0.890 | 0.340 |
| Institutional x $\Delta q_{opp}$ | | | | 0.014 | 1.014 | 0.918 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.229 | 1.258 | 0.083 |

The estimation results of the hazard model for downward order revisions are presented in Table 3.8. The coefficients on order size, volatility, spread and the investor dummies are generally consistent with those reported in Table 3.7. The intensity of downward order revisions is found to increase with more aggressive limit order placement, as these limit orders are most exposed to picking-off risk. The coefficients on $\Delta q_{same}$ and $\Delta q_{opp}$ are negative and significant, indicating that investors pay attention to picking-off risk. There is some evidence that institutional investors are more responsive to picking-off risk than retail investors, but only for large stocks.

Table 3.9: Hazard Model of Order Cancellations ($DELETE$)

This table reports the parameter estimates $\beta$ from two specifications of a time varying proportional Cox hazards model where the risk event is an order cancellation ($DELETE$). The sample is constructed by selecting 1,000 limit orders across each stock and investor category. Orders are tracked through the first three minutes. The explanatory variables are: Order Size computed as the log of the order value in millions of dollars ($m); Trading Activity computed as the log of the cumulative trading value in the prior five-minute interval in millions of dollars ($m); Volatility measured as the sum of absolute mid-quote changes in the prior five-minute interval; Spread defined as 100(ask price - bid price)/ mid price; Price Aggressiveness, which is computed for a bid limit order as 100(limit price $-$ best bid$_{t=0}$)/(best bid$_{t=0}$); Dummy variables that take the value of 1 if the limit order comes from an institutional investor or market maker, or 0 otherwise. $\Delta q_{same}$ and $\Delta q_{opp}$ are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission (Hasbrouck and Saar, 2009). All explanatory variables apart from the indicator variables are standardised within each stock to have zero mean and unit variance. The reported $p$-values are calculated using robust standard errors clustered by stock.

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.301 | 0.740 | <0.001 | -0.303 | 0.738 | <0.001 |
| Trading Activity | 0.082 | 1.085 | <0.001 | 0.081 | 1.085 | <0.001 |
| Volatility | 0.063 | 1.065 | 0.007 | 0.064 | 1.066 | 0.006 |
| Spread | 0.143 | 1.153 | <0.001 | 0.144 | 1.155 | <0.001 |
| Price Aggressiveness | 0.199 | 1.220 | 0.029 | 0.202 | 1.224 | 0.028 |
| Institutional Dummy | 1.526 | 4.598 | <0.001 | 1.505 | 4.503 | <0.001 |
| Market Maker Dummy | 1.241 | 3.458 | <0.001 | 1.222 | 3.393 | <0.001 |
| $\Delta q_{same}$ | 0.350 | 1.419 | <0.001 | 0.126 | 1.134 | 0.040 |
| $\Delta q_{opp}$ | 0.117 | 1.124 | 0.004 | 0.147 | 1.158 | 0.015 |
| Institutional x $\Delta q_{same}$ | | | | 0.301 | 1.352 | <0.001 |
| Market Maker x $\Delta q_{same}$ | | | | 0.000 | 1.000 | 0.997 |
| Institutional x $\Delta q_{opp}$ | | | | 0.013 | 1.013 | 0.823 |
| Market Maker x $\Delta q_{opp}$ | | | | 0.021 | 1.021 | 0.823 |

Table 3.9 reports the estimation results for order cancellations on the full sample of stocks. As discussed, the motive behind order cancellations is unclear and the effect of changes in the same-side ($\Delta q_{same}$) and opposite-side ($\Delta q_{opp}$) quotes reflects two opposing influences. On the one hand, cancellations may intensify as the best price moves away from the limit price and the probability of execution is reduced. On the other, cancellations can also intensify when market prices move towards the

limit price if there is a perceived increase in information asymmetry and traders react to prevent their limit orders from being picked off. The positive coefficients on $\Delta q_{same}$ and $\Delta q_{opp}$ under the first specification indicates that across all investors, non-execution risks appear to be the dominant influence on order cancellations. The second model specification provides insights into the cancellation intensities of different investors to movements in bid and ask quotes. While all investors appear to care more about non-execution risk than picking-off risk, the positive coefficient for Institutional x $\Delta q_{same}$ indicates that this concern is most significant among institutional investors.

To investigate the cost of immediacy hypothesis (Hasbrouck and Saar, 2009), Table 3.10 reports the estimation results for limit orders that are subsequently revised to market orders. Under the first model specification, the positive coefficient for $\Delta q_{same}$ indicates that increases in non-execution risk drive investors to revise limit orders to market orders with greater intensity. The negative coefficient for $\Delta q_{opp}$, measuring changes in the cost of immediate execution subsequent to order submission, is consistent with the cost of immediacy hypothesis. The intensity at which limit orders are revised to market orders should increase as the cost of immediacy decreases. The coefficients on Institutional x $\Delta q_{opp}$ are negative and significant for large stocks while the coefficients on Market Maker x $\Delta q_{opp}$ are negative and significant for all size tertiles. Market makers appear to be best able to capture liquidity opportunities from price improving limit orders. In contrast, while Table 3.2 highlights that it is common among retail investors to convert existing limit orders to market orders, the evidence points to institutional investors and market makers responding more rapidly to decreases in the cost of immediate execution, relative to retail investors.

Table 3.10: Hazard Model of Upward Limit Order Revision to Market Order ($AMEND + MKT$)

This table reports the parameter estimates $\beta$ from two specifications of a time varying proportional Cox hazards model where the risk event is an amendment from a limit order to a market order ($AMEND + MKT$). The sample is constructed by selecting 1,000 limit orders across each stock and investor category. Orders are tracked through the first three minutes. The explanatory variables are: Order Size computed as the log of the order value in millions of dollars ($m); Trading Activity computed as the log of the cumulative trading value in the prior five-minute interval in millions of dollars ($m); Volatility measured as the sum of absolute mid-quote changes in the prior five-minute interval; Spread defined as 100(ask price - bid price)/ mid price; Price Aggressiveness, which is computed for a bid limit order as 100(limit price − best bid$_{t=0}$)/(best bid$_{t=0}$); Dummy variables that takes the value of 1 if the limit order comes from an institutional investor or market maker, or 0 otherwise. $\Delta q_{same}$ and $\Delta q_{opp}$ are the two time varying covariates tracking the evolution of bid-ask quotes subsequent to order submission (Hasbrouck and Saar, 2009). All explanatory variables apart from the indicator variables are standardized within each stock to have zero mean and unit variance. The reported $p$-values are calculated using robust standard errors clustered by stock.

Panel A: Large Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.784 | 0.457 | <0.001 | -0.783 | 0.457 | <0.001 |
| Trading Activity | 0.115 | 1.122 | <0.001 | 0.113 | 1.120 | <0.001 |
| Volatility | -0.131 | 0.878 | 0.074 | -0.131 | 0.878 | 0.078 |
| Spread | -0.409 | 0.664 | <0.001 | -0.421 | 0.656 | <0.001 |
| Price Aggressiveness | 1.238 | 3.448 | <0.001 | 1.237 | 3.446 | <0.001 |
| Institutional Dummy | -1.523 | 0.218 | <0.001 | -1.673 | 0.188 | <0.001 |
| Market Maker Dummy | -2.234 | 0.107 | <0.001 | -2.493 | 0.083 | <0.001 |
| $\Delta q_{same}$ | 1.195 | 3.304 | <0.001 | 1.087 | 2.966 | <0.001 |
| $\Delta q_{opp}$ | -1.244 | 0.288 | <0.001 | -1.032 | 0.356 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.337 | 1.401 | 0.148 |
| Market Maker x $\Delta q_{same}$ | | | | 0.141 | 1.151 | 0.666 |
| Institutional x $\Delta q_{opp}$ | | | | -0.825 | 0.438 | <0.001 |
| Market Maker x $\Delta q_{opp}$ | | | | -1.065 | 0.345 | 0.003 |

Panel B: Medium Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.738 | 0.478 | <0.001 | -0.739 | 0.478 | <0.001 |
| Trading Activity | 0.171 | 1.187 | <0.001 | 0.170 | 1.186 | <0.001 |
| Volatility | -0.125 | 0.883 | 0.074 | -0.128 | 0.880 | 0.066 |
| Spread | -0.443 | 0.642 | <0.001 | -0.446 | 0.640 | <0.001 |
| Price Aggressiveness | 1.045 | 2.842 | <0.001 | 1.045 | 2.842 | <0.001 |
| Institutional Dummy | -0.990 | 0.372 | 0.001 | -0.997 | 0.369 | 0.002 |
| Market Maker Dummy | -1.897 | 0.150 | <0.001 | -2.121 | 0.120 | <0.001 |
| $\Delta q_{same}$ | 0.696 | 2.005 | <0.001 | 0.742 | 2.100 | <0.001 |
| $\Delta q_{opp}$ | -0.856 | 0.425 | <0.001 | -0.816 | 0.442 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | -0.185 | 0.831 | 0.365 |
| Market Maker x $\Delta q_{same}$ | | | | -0.087 | 0.917 | 0.796 |
| Institutional x $\Delta q_{opp}$ | | | | 0.035 | 1.035 | 0.865 |
| Market Maker x $\Delta q_{opp}$ | | | | -0.822 | 0.440 | 0.006 |

Panel C: Small Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.651 | 0.521 | <0.001 | -0.653 | 0.521 | <0.001 |
| Trading Activity | 0.195 | 1.216 | <0.001 | 0.195 | 1.215 | <0.001 |
| Volatility | -0.045 | 0.956 | 0.558 | -0.044 | 0.957 | 0.565 |
| Spread | -0.474 | 0.622 | <0.001 | -0.486 | 0.615 | <0.001 |
| Price Aggressiveness | 0.950 | 2.585 | <0.001 | 0.957 | 2.603 | <0.001 |
| Institutional Dummy | -0.411 | 0.663 | 0.342 | -0.412 | 0.662 | 0.339 |
| Market Maker Dummy | -2.055 | 0.128 | <0.001 | -2.348 | 0.096 | <0.001 |
| $\Delta q_{same}$ | 0.462 | 1.587 | <0.001 | 0.451 | 1.570 | 0.004 |
| $\Delta q_{opp}$ | -0.491 | 0.612 | <0.001 | -0.461 | 0.631 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | 0.008 | 1.008 | 0.960 |
| Market Maker x $\Delta q_{same}$ | | | | 0.502 | 1.653 | 0.239 |
| Institutional x $\Delta q_{opp}$ | | | | 0.008 | 1.008 | 0.944 |
| Market Maker x $\Delta q_{opp}$ | | | | -1.301 | 0.272 | <0.001 |

Panel D: All Stocks

| | Coefficient | Exp(Coefficient) | $p$-value | Coefficient | Exp(Coefficient) | $p$-value |
|---|---|---|---|---|---|---|
| Order Size | -0.713 | 0.490 | <0.001 | -0.713 | 0.490 | <0.001 |
| Trading Activity | 0.155 | 1.168 | <0.001 | 0.154 | 1.166 | <0.001 |
| Volatility | -0.097 | 0.908 | 0.047 | -0.096 | 0.909 | 0.048 |
| Spread | -0.410 | 0.664 | <0.001 | -0.421 | 0.657 | <0.001 |
| Price Aggressiveness | 1.016 | 2.761 | <0.001 | 1.018 | 2.768 | <0.001 |
| Institutional Dummy | -0.902 | 0.406 | <0.001 | -0.919 | 0.399 | <0.001 |
| Market Maker Dummy | -2.028 | 0.132 | <0.001 | -2.291 | 0.101 | <0.001 |
| $\Delta q_{same}$ | 0.554 | 1.739 | <0.001 | 0.578 | 1.783 | <0.001 |
| $\Delta q_{opp}$ | -0.627 | 0.534 | <0.001 | -0.581 | 0.560 | <0.001 |
| Institutional x $\Delta q_{same}$ | | | | -0.070 | 0.932 | 0.427 |
| Market Maker x $\Delta q_{same}$ | | | | 0.258 | 1.295 | 0.160 |
| Institutional x $\Delta q_{opp}$ | | | | -0.077 | 0.926 | 0.316 |
| Market Maker x $\Delta q_{opp}$ | | | | -1.123 | 0.325 | <0.001 |

## 3.5 Limit Order Execution Costs

The evidence presented thus far suggests that there are fundamental differences in the limit order behaviour across investors. In this section, we measure differences in the limit order execution costs between institutional investors, retail investors and market makers. Execution cost measures are based only on the implicit costs of limit order trading as we are unable to observe explicit costs which include commissions, market, settlement and clearing fees and transaction taxes as well as any investment costs in developing trading technology.

A common assumption among theoretical models examining the effects of high frequency trading (Biais et al., 2012, Hoffmann, 2012) is that these traders enjoy a speed advantage, allowing them to react faster to new information and impose an externality cost to the slower (retail) traders. To examine the adverse selection costs on these investors from their orders being picked off, we employ the Harris and Hasbrouck (1996) ex post cost measure on executed limit orders.

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

For limit buy orders, the ex post cost is the difference between the execution price ($p_{\text{fill}}$) and the best bid price ten minutes after execution ($q^{\text{bid}}_{\text{fill}+10}$). The benefits of technology are likely to flow from the speed advantages in gathering and processing information on order flow and market conditions, and the nature of this information is likely to be short-lived. This measure is open to two interpretations. First, it can be viewed as the realised cost of reversing the trade at market prices a short time later. Alternatively, it can be viewed as the difference between the price at which the trader was willing to buy (sell) at the time of execution relative to the price at which the market is willing to buy (or sell) a short time later. Harris and Hasbrouck (1996) identifies the ex post cost 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.

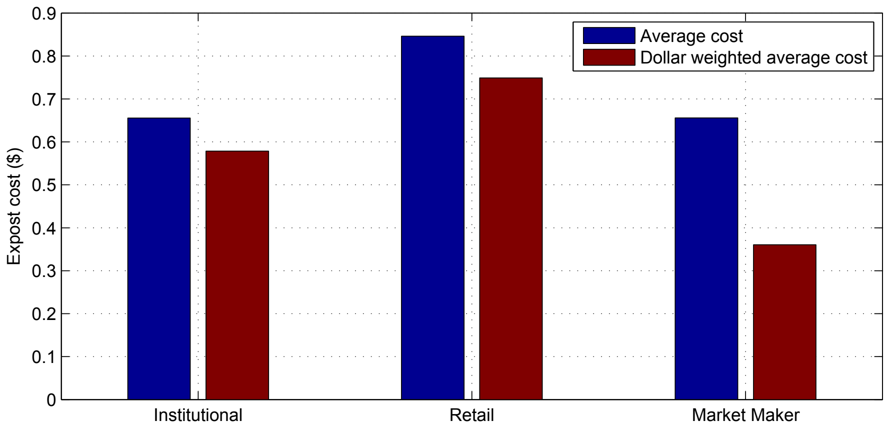



FIGURE 3.3: Ex post Cost of Executed Limit Orders

This figure displays the ex post cost of executed limit orders by institutional investors, retail investors and market makers for a limit order of 1,000 shares. The ex post cost is computed for a bid limit order as the difference between the execution price ($p_{\text{fill}}$) and the best bid price ten minutes after execution ($q^{\text{bid}}_{\text{fill}+10}$). The ex post cost is calculated across all orders on an equal weighted and dollar weighted average cost basis.

In Figure 3.3, we report the average ex post cost of all executed limit orders for institutional investors, retail investors and market makers. Overall, the ex post costs are higher for retail investors than both institutional investors and market makers on both an equal weighted and dollar weighted average cost basis.

We further investigate differences in the ex post costs between investors within a regression framework. Table 3.11 presents the estimation results from two specifications. The first regression specification controls only for the trade direction and intraday seasonalities. As trading technology is likely to be a key driver behind the observed differences in the limit order behaviour of retail and non-retail investors, access to superior trading technology could result in better order placement decisions or improved market timing ability. The coefficients for the investor dummies from this specification can capture differences in ex post costs arising from these factors. The second regression specification examines differences in their ex post costs controlling for order characteristics and market conditions. The coefficients for order size, price aggressiveness and spread are statistically significant, suggesting that these factors do influence order execution costs.

Table 3.11: Regressions of Ex post Cost

This table reports the regression coefficients of the Harris and Hasbrouck (1996) ex post cost measure (in cents) controlling for order characteristics and market conditions. For limit buy orders, the ex post cost is the difference between the execution price and the best bid price ten minutes after execution. The sample includes all standard non-marketable limit orders submitted during between 10:10 am and 4:00 pm that subsequently achieve execution (full or partial). The explanatory variables in both regressions are: Price Aggressiveness, which is computed for a bid limit order as 100(limit price - best $\text{bid}_{t=0}$) / best $\text{bid}_{t=0}$; Order Size computed as the log of the order value in millions of dollars ($m), Buy dummy variable that takes a value of 1 if it is a buy limit order, or 0 if it is a sell limit order; Spread defined as 100(ask price - bid price) / mid price at the time of order submission or revision; Volatility defined as the sum of absolute mid-quote changes in the half-hour interval prior to order submission or revision; Trading Activity as the log of the value of shares traded in millions of dollars ($m) over the previous half-hour interval prior to order submission or revision; Time of Day dummies for five intraday time intervals. The regressions are estimated with stock fixed effects and $p$-values are calculated using two-way clustered standard errors, where the cluster is defined by stock and day.

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | $p$-value | Coefficient | $p$-value |
| Institutional Dummy | 0.012 | <0.001 | -0.001 | 0.741 |
| Market Maker Dummy | 0.008 | 0.036 | -0.003 | 0.426 |
| Price Aggressiveness | | | 0.076 | 0.001 |
| Order Size | | | -0.003 | <0.001 |
| Buy Dummy | 0.004 | 0.694 | 0.003 | 0.717 |
| Spread | | | -0.098 | <0.001 |
| Volatility | | | 0.030 | 0.263 |
| Trading Activity | | | -0.002 | 0.288 |
| Time 11:00-12:00 | -0.008 | 0.022 | -0.008 | 0.012 |
| Time 12:00-13:00 | -0.010 | 0.008 | -0.011 | 0.002 |
| Time 13:00-14:00 | -0.010 | 0.008 | -0.012 | 0.003 |
| Time 14:00-15:00 | -0.016 | <0.001 | -0.017 | <0.001 |
| Time > 15:00 | -0.020 | <0.001 | -0.021 | <0.001 |

The coefficient estimates for the investor dummies in the first specification are positive and significant at the 5% level, which indicates that retail investors have lower ex post costs. This result appears to conflict with the higher ex post costs observed in Figure 3.4. We find that this could be attributed to the preferences of retail investors for trading in smaller stocks which on average have higher ex post costs. The regressions estimated in Table 3.11 include stock fixed effects, which control for cross-sectional variation in ex post costs. In the second regression specification, we find no statistically significant differences in the ex post costs between retail and non-retail investors when we also control for order characteristics and market conditions.

Next, we examine whether retail investors experience higher ex post costs when their limit orders are triggered by non-retail investors. Table 3.12 presents the ex post regression results for the sample of retail limit orders where the market order dummy variables indicate whether the retail limit order was triggered by an

Table 3.12: Ex post Cost of Retail Limit Orders

This table reports the regression coefficients of the Harris and Hasbrouck (1996) ex post cost measure (in cents) on the sample of executed limit orders submitted by retail investors between 10:10 am and 4:00 pm. The Market Order dummy variables indicate whether the retail limit order was triggered by an institutional investor or market maker. See Table 3.11 for a description of the remaining explanatory variables. The regressions are estimated with stock fixed effects and $p$-values are calculated using two way clustered standard errors, where the cluster is defined by stock and day.

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | $p$-value | Coefficient | $p$-value |
| Institutional Market Order Dummy | 0.034 | <0.001 | 0.032 | <0.001 |
| Market Maker Market Order Dummy | 0.052 | <0.001 | 0.050 | <0.001 |
| Price Aggressiveness | | | 0.089 | 0.043 |
| Order Size | | | -0.009 | <0.001 |
| Buy Dummy | -0.006 | 0.537 | -0.004 | 0.751 |
| Spread | | | -0.095 | 0.113 |
| Volatility | | | -0.039 | 0.688 |
| Trading Activity | | | -0.007 | 0.518 |
| Time 11:00-12:00 | -0.026 | 0.185 | -0.022 | 0.216 |
| Time 12:00-13:00 | -0.021 | 0.234 | -0.023 | 0.227 |
| Time 13:00-14:00 | -0.005 | 0.812 | -0.014 | 0.593 |
| Time 14:00-15:00 | -0.029 | 0.128 | -0.036 | 0.102 |
| Time > 15:00 | -0.030 | 0.170 | -0.038 | 0.129 |

institutional investor or market maker. The coefficient estimates on the market order dummies under both specifications indicate retail investors suffer significantly higher ex post costs when their limit orders are triggered by institutional investors and market makers.

In the second specification, the coefficients on the market order dummies imply that the ex post costs of retail limit orders increase by \$0.32 when triggered by an institutional investor and by \$0.50 when triggered by a market maker on a hypothetical 1,000 share limit order. The economic magnitude is substantial relative to the average ex post cost incurred across all retail limit orders of \$0.75 on a dollar weighted average basis.

Table 3.13 presents equivalent results for the ex post costs of institutional and market maker limit orders. Substantial differences are also found in their ex post costs conditional on the counterparty triggering execution. Institutional investors experience lower ex post costs when their limit orders are triggered by retail investors but higher ex post costs when they are triggered by market makers. Market makers achieve lower ex post costs when their limit orders are triggered by both institutional or retail investors. Collectively, the results reported in Table 3.12 and

Table 3.13: Ex post Cost of Non-Retail Limit Orders

This table reports the regression coefficients of the Harris and Hasbrouck (1996) ex post cost measure (in cents) separately on the sample of executed limit orders submitted by institutional investors and market makers between 10:10 am and 4:00 pm. The Market Order dummy variables indicate the counterparty that triggered execution of the limit order. See Table 3.11 for a description of the remaining explanatory variables. The regressions are estimated with stock fixed effects and $p$-values are calculated using two-way clustered standard errors, where the cluster is defined by stock and day.

Panel A: Institutional Investors

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | $p$-value | Coefficient | $p$-value |
| Retail Market Order Dummy | -0.021 | <0.001 | -0.020 | <0.001 |
| Market Maker Market Order Dummy | 0.014 | 0.002 | 0.015 | 0.002 |
| Order Exposure | | | | |
| Price Aggressiveness | | | 0.050 | 0.015 |
| Order Size | | | -0.002 | <0.001 |
| Buy Dummy | 0.004 | 0.649 | 0.004 | 0.679 |
| Spread | | | -0.091 | <0.001 |
| Volatility | | | 0.025 | 0.309 |
| Trading Activity | | | -0.002 | 0.236 |
| Time 11:00-12:00 | -0.007 | 0.037 | -0.008 | 0.024 |
| Time 12:00-13:00 | -0.009 | 0.025 | -0.011 | 0.010 |
| Time 13:00-14:00 | -0.009 | 0.016 | -0.012 | 0.005 |
| Time 14:00-15:00 | -0.015 | <0.001 | -0.017 | <0.001 |
| Time > 15:00 | -0.019 | <0.001 | -0.020 | <0.001 |

Panel B: Market Makers

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | $p$-value | Coefficient | $p$-value |
| Retail Market Order Dummy | -0.041 | <0.001 | -0.039 | <0.001 |
| Institutional Market Order Dummy | -0.018 | 0.007 | -0.018 | 0.005 |
| Order Exposure | | | | |
| Price Aggressiveness | | | 0.146 | <0.001 |
| Order Size | | | -0.001 | 0.237 |
| Buy Dummy | -0.005 | 0.635 | -0.005 | 0.644 |
| Spread | | | -0.133 | <0.001 |
| Volatility | | | 0.065 | 0.349 |
| Trading Activity | | | -0.002 | 0.591 |
| Time 11:00-12:00 | -0.006 | 0.475 | -0.006 | 0.518 |
| Time 12:00-13:00 | -0.011 | 0.312 | -0.010 | 0.352 |
| Time 13:00-14:00 | -0.017 | 0.034 | -0.015 | 0.041 |
| Time 14:00-15:00 | -0.021 | 0.012 | -0.018 | 0.020 |
| Time > 15:00 | -0.026 | 0.003 | -0.022 | 0.003 |

Table 3.13 suggest that market makers impose some adverse selection costs on institutional investors, and both institutional investors and market makers impose adverse selection costs on the limit orders of retail investors.

We also employ the implementation shortfall approach of Perold (1988) as a measure of limit order execution costs. The implementation shortfall consists of two component costs. Price impact is the signed difference between the volume weighted average fill price ($p_{\text{fill}}$) and the mid-quote at the time of order submission ($q^{\text{mid}}_{t=0}$). The price impact would be expected to be negative on executed limit

TABLE 3.14: Regressions of Implementation Shortfall

This table reports the regression coefficients of price impact, opportunity cost and implementation shortfall (in cents) on order characteristics and market conditions. The sample includes all standard limit order submissions between 10:10 am and 4:00 pm 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. 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. Coefficient estimates on price impact and opportunity cost regressions are reported separately for both the full sample and a restricted sample. For price impact regressions, the restricted sample contains only executed limit orders while for opportunity cost regressions, it contains only the unexecuted limit orders. The price impact (opportunity cost) on partially filled orders is based only on the executed (unexecuted) portion of the limit order. 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 3.11 for a description of the explanatory variables. The regressions are estimated with stock fixed effects and $p$-values are calculated using two-way clustered standard errors, where the cluster is defined by stock and day.

Panel A: All Controls

| Dependent Variable | Price Impact | | | | Opportunity Cost | | | | Implementation ShortFall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All Orders | | Executed Orders | | All Orders | | Unexecuted Orders | | All Orders | |
| | Coefficient | $p$-value | Coefficient | $p$-value | Coefficient | $p$-value | Coefficient | $p$-value | Coefficient | $p$-value |
| Institutional Dummy | 1.043 | <0.001 | 1.800 | <0.001 | -1.237 | 0.018 | -3.487 | 0.008 | -0.194 | 0.621 |
| Market Maker Dummy | 1.064 | <0.001 | 1.764 | <0.001 | -1.319 | 0.015 | -3.792 | 0.004 | -0.254 | 0.536 |
| Price Aggressiveness | -0.010 | 0.027 | 0.316 | 0.003 | -0.023 | 0.119 | 0.123 | 0.001 | -0.033 | 0.024 |
| Order Size | 0.009 | <0.001 | 0.012 | 0.005 | 0.047 | <0.001 | 0.042 | 0.018 | 0.056 | <0.001 |
| Buy Dummy | -0.032 | 0.291 | -0.070 | 0.296 | -0.187 | 0.371 | -0.422 | 0.386 | -0.220 | 0.349 |
| Spread | -0.082 | 0.011 | -0.459 | 0.002 | 1.556 | <0.001 | 1.399 | <0.001 | 1.474 | <0.001 |
| Volatility | -0.197 | 0.001 | -0.505 | 0.002 | 1.497 | 0.046 | 1.761 | 0.119 | 1.300 | 0.068 |
| Trading Activity | -0.029 | <0.001 | -0.054 | <0.001 | 0.021 | 0.573 | 0.150 | 0.251 | -0.008 | 0.821 |
| Time 11:00-12:00 | 0.015 | 0.188 | 0.005 | 0.847 | -0.116 | 0.011 | -0.310 | 0.001 | -0.101 | 0.076 |
| Time 12:00-13:00 | 0.024 | 0.044 | -0.004 | 0.888 | -0.192 | 0.015 | -0.499 | 0.008 | -0.168 | 0.063 |
| Time 13:00-14:00 | 0.022 | 0.102 | -0.016 | 0.565 | -0.166 | 0.140 | -0.373 | 0.158 | -0.144 | 0.214 |
| Time 14:00-15:00 | 0.036 | 0.030 | 0.015 | 0.646 | -0.232 | 0.034 | -0.528 | 0.033 | -0.197 | 0.072 |
| Time > 15:00 | 0.055 | 0.002 | 0.065 | 0.064 | -0.341 | 0.002 | -0.751 | <0.001 | -0.286 | 0.008 |

Panel B: Exclude Order Characteristics and Market Condition Controls

| Dependent Variable | Price Impact | | | | Opportunity Cost | | | | Implementation Shortfall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All Orders | | Executed Orders | | All Orders | | Unexecuted Orders | | All Orders | |
| | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value |
| Institutional Dummy | 1.020 | <0.001 | 1.812 | <0.001 | -1.331 | 0.014 | -3.351 | 0.008 | -0.311 | 0.448 |
| Market Maker Dummy | 1.048 | <0.001 | 1.771 | <0.001 | -1.378 | 0.013 | -3.623 | 0.005 | -0.330 | 0.436 |
| Buy Dummy | -0.034 | 0.267 | -0.070 | 0.302 | -0.193 | 0.358 | -0.424 | 0.383 | -0.227 | 0.334 |
| Time 11:00-12:00 | 0.029 | 0.019 | 0.038 | 0.186 | -0.186 | 0.001 | -0.414 | <0.001 | -0.157 | 0.017 |
| Time 12:00-13:00 | 0.047 | <0.001 | 0.053 | 0.086 | -0.312 | 0.001 | -0.680 | 0.001 | -0.265 | 0.011 |
| Time 13:00-14:00 | 0.060 | <0.001 | 0.073 | 0.032 | -0.334 | 0.006 | -0.665 | 0.007 | -0.275 | 0.024 |
| Time 14:00-15:00 | 0.062 | 0.002 | 0.083 | 0.036 | -0.386 | 0.003 | -0.757 | 0.005 | -0.324 | 0.010 |
| Time > 15:00 | 0.063 | 0.002 | 0.094 | 0.018 | -0.464 | <0.001 | -0.879 | 0.001 | -0.401 | 0.003 |

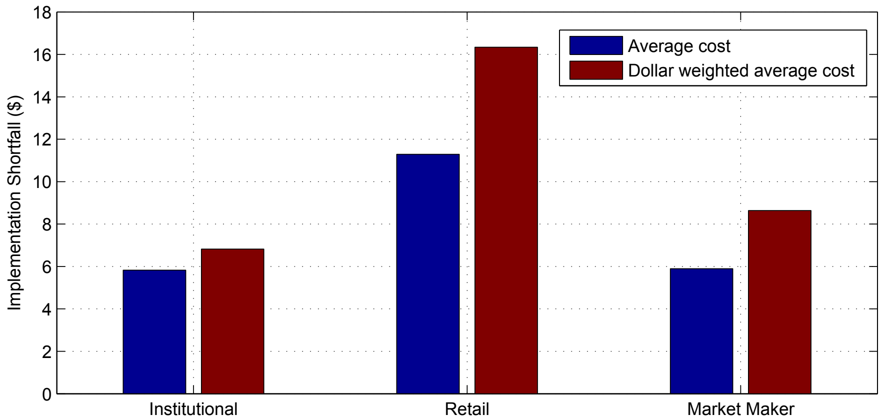



FIGURE 3.4: Implementation Shortfall of Non-Marketable Limit Orders
This figure displays the implementation shortfall cost (Perold, 1988) of non-marketable limit orders by institutional investors, retail investors and market makers for a limit order of 1,000 shares. The implementation shortfall is calculated across all orders on an equal weighted and dollar weighted average cost basis.

orders (without order revisions) and zero for unfilled limit orders. The opportunity cost is the signed difference between the reference price ($p_{\text{ref}}$) 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 if no cancellation takes place.[7]

$$\text{Price impact} = \begin{cases} p_{\text{fill}} - q^{\text{mid}}_{t=0} & \text{bid limit order} \\ q^{\text{mid}}_{t=0} - p_{\text{fill}} & \text{ask limit order} \end{cases}$$

$$\text{Opportunity cost} = \begin{cases} p_{\text{ref}} - q^{\text{mid}}_{t=0} & \text{bid limit order} \\ q^{\text{mid}}_{t=0} - p_{\text{ref}} & \text{ask limit order} \end{cases}$$

Harris and Hasbrouck (1996) motivate the use of the implementation shortfall as a measure of execution costs based on a trader with a precommitment to trade who will switch their cancelled limit orders to market orders if the order remains

[7] This measure of opportunity cost may exaggerate the penalty on limit orders that remain in the order book at the close of trading as the market price tends to move further away from the limit price with time. As a robustness check, we have replicated the analysis assuming that limit orders are cancelled one hour after order submission. These results, which are presented in Appendix B, do not change our conclusions.

unexecuted. Hence, this measure tends to exaggerate the penalty on unexecuted limit orders.

Figure 3.4 highlights differences in the implementation shortfall costs of non-marketable limit orders between institutional investors, retail investors and market makers. As with ex post costs, implementation shortfall is highest for retail investors ($16.34 compared to $6.82 for institutional investors and $8.64 for market makers on a dollar weighted average basis for a hypothetical 1,000 share limit order).

Table 3.14 presents the estimation results of regressions on the price impact, opportunity costs and implementation shortfall costs for all new limit order submissions during continuous trading hours. As expected, price impact and opportunity costs increase with order size. The coefficients for spreads and volatility are negative and significant in the price impact regressions but they reverse sign in the opportunity cost regressions. Limit orders submitted away from the mid-quote have a greater chance of execution during times when spreads are wider and volatility is higher. These executed limit orders incur a negative price impact which explains the negative relationship. On the other hand, the same uncertain market conditions also create higher opportunity costs. Price aggressiveness is negatively related to price impact based on the full sample as the relationship is affected by unexecuted orders which have zero price impact. When conditioned on order execution, price impact is larger for more aggressively placed limit orders as expected.

The price impact regressions indicate that institutional investors and market makers incur significantly higher price impact costs relative to retail investors. Across all orders, the coefficient estimates imply that on a 1,000 share limit order, institutional investors incur an additional price impact cost of $10.43, while market makers incur an additional cost of $10.64 compared to a retail investor's limit order. Variations in the execution rates of limit orders do not explain these results, as even higher price impact costs are incurred when conditioned on order execution.

The opportunity cost regressions show that the limit orders of institutional investors and market makers experience lower opportunity costs. Across all orders, the implied cost differential between an institutional investor (market maker) and a retail investor's limit order of 1,000 shares is \$12.37 (\$13.19). Restricting our sample to unexecuted limit orders, this cost differential increases to \$34.87 (\$37.92).

However, the coefficient estimates on the institutional and market maker dummies in the implementation shortfall regressions are not statistically significant. The lower opportunity costs experienced by non-retail investors are offset by the higher price impact on executed limit orders. These results are unaffected by controls on order characteristics and market conditions. The higher price impacts and lower opportunity costs among institutional investors are consistent with the earlier evidence of a strong preference for managing non-execution risks.

There are some limitations to our analysis. Our study of limit order execution costs considers the potential influence of differences in the behaviour and market timing ability of investors but we cannot alleviate all possible endogeneity concerns. For instance, traders may be conditioning their order placement decisions on the expected costs of trading or they may be able to anticipate changes in adverse selection risk and adjust the intensity with which they are monitoring their limit orders. We are unable to establish a true causal relation of the impact of trading technology on the welfare of investors. However, we can dismiss different order types and execution venues as potential explanations driving differences in the execution costs between investors. This is because our analysis is restricted to standard limit orders over a sample period where the ASX operated as the only stock exchange. Our results should be interpreted in light of these caveats.

## 3.6 Conclusion

This study employs a unique dataset to examine the limit order behaviour and execution costs of institutional investors, retail investors and market makers in the

Australian equity market. We document evidence consistent with the inequalities in access to algorithmic trading technology between retail and non-retail investors. In contrast to retail investors, non-retail investors use more order revisions, search for latent liquidity and react to fleeting liquidity opportunities. Investors are found to make different trade-offs between non-execution risk and picking-off risk, with non-execution risk the dominant effect behind order cancellations. Institutional investors are significantly more sensitive to non-execution risks than retail investors, consistent with institutional investors demanding immediacy. Market makers are significantly more responsive to changes in the cost of immediacy, suggesting that these investors are best able to capture liquidity opportunities from price improving limit orders.

After controlling for cross-sectional differences in execution costs between stocks, we do not find that the overall ex post costs of executed limit orders by retail investors are higher than non-retail investors. However, the limit orders of retail investors experience significantly higher ex post costs when their limit orders are triggered by institutional investors, and even higher ex post costs when triggered by market makers. Under the implementation shortfall measure, non-retail investors incur lower opportunity costs but this is offset by higher price impacts. Taken together, we find no evidence of differences in implementation shortfall costs between retail and non-retail investors. The evidence supports the common belief that faster traders can extract 'rents' from their speed advantages over retail investors but our findings fall short of supporting the view that algorithmic trading technology is severely disadvantaging retail investors.

Related findings from Malinova et al. (2013) and Brogaard et al. (2013) fail to establish causal relationships between an increase in HFT activity and the trading costs of retail and non-HFT institutional investors respectively. Negative perceptions are still held by many in the investment community, suggesting further empirical research is warranted on how technology impacts different investors.

# Chapter 4

# Investor Trading and Performance Around Earnings Announcements

## 4.1 Introduction

Fundamental to the integrity of the market is the full and fair disclosure of all material information to all investors. Significant regulations governing information disclosure exist in all countries around the world with the common objective of 'leveling the playing field' and reducing information asymmetries between investors. One of the justifications often cited for disclosure regulation is that it protects the welfare of retail investors, who are characterised as the most financially unsophisticated given the vast resources available to institutional investors for information acquisition. To date, there is limited empirical evidence on the impact of information disclosures on different types of investors.

In this study we adopt Livne's (2000) classification, which identifies two types of information-based trading that can arise around disclosures. First, the anticipation of news may stimulate the search for information in the pre-announcement period

(Kim and Verrecchia, 1994, Verrecchia, 1982). Given the heterogenous ability of investors in private information acquisition, this may result in a subset of investors gaining an information advantage. While a large body of literature suggests institutional investors as the ones most likely to be informed by sources such as access to management (Bushee et al., 2011) and analyst tipping (Irvine et al., 2007), robust empirical evidence has also emerged of informed trading by retail investors. Kaniel et al. (2012) examine pre-event trading by individual investors and find that they were able to predict returns on and after earnings announcements, consistent with these investors trading on their private information. Decomposing abnormal returns into liquidity provision and private information components, the authors attribute half the abnormal returns earned by retail investors to informed trading. To explain their findings, Kaniel et al. (2012) argue that individual investors are better able to act on their private information because they are more nimble in their trading and are not subject to the constraints of institutional investors. Kelley and Tetlock (2013) suggest that informed retail traders could obtain their information from their geographical proximity to firms (Berry and Gamble, 2013), relationships with employees or insights into customer tastes. We refer to the *anticipation* hypothesis as behaviour consistent with investors anticipating the content of the earnings announcement from their private information.

Second, irrespective of who may be informed of impending earnings announcements, evidence in favour of the anticipation hypothesis suggests that disclosure should decrease information asymmetry as public information supplants their private information (Diamond and Verrecchia, 1987, Foster and Viswanathan, 1990). However, the competing view is that contrary to its intention, complex disclosures such as earnings announcements can increase information asymmetries among investors with different information processing abilities (Fischer and Verrecchia, 1999, Kim and Verrecchia, 1994). The more efficient information processors make superior judgements about the implications of the earnings disclosure for the asset's fundamental value, thereby exacerbating information asymmetries. We call this proposition the *information processing* hypothesis.

This study tests for the presence of both forms of information-based trading among institutional and retail investors around earnings announcements. Earnings announcements are ideal information events for examining these hypotheses. The timing of these disclosures is generally known ex-ante, which motivates private information acquisition. Earnings announcements can also generate significant stock price reactions and their interpretation is generally non-trivial, thus representing a setting where trading opportunities could arise for the most efficient information processors.

The provision of broker identifiers in our data allows for more fine-tuned results on the population of institutional and retail investors. Prior studies have indicated substantial heterogeneity among institutional (Yan and Zhang, 2009) and retail investors (Kaniel et al., 2012, Kelley and Tetlock, 2013). We attempt to reduce heterogeneity among institutional investors based on the quality and reputation of the executing broker. One might expect that top-tier institutional investors, who trade through the most reputable brokers, have the greatest information advantages. Frino et al. (2013) argue that the superior research services offered by reputable brokers drive the preferences of institutional investors towards trading through these brokers. Following Fong et al. (2014), we also account for heterogeneity among retail investors along one dimension: whether they are using the services of a full-service broker or a discount broker. Fong et al. (2014) find that the trades from full-service retail brokers are more informative which they attribute to a clientele selection effect and the potential value of their advisory services. To the author's best knowledge, this is the first study examining differences in information-based trading around earnings announcements for these sub-populations of institutional and retail investors.

This study contributes to three streams of literature. First, within the informed trading literature, we verify the findings documented by Kaniel et al. (2012) in the United States of retail investors anticipating earnings announcements. The counterintuitive nature of their findings is novel, yet it remains subject to sample selection bias concerns along with prior studies relying on a subset of the retail trader population.[1] Australia also has a strong information environment, having adopted a continuous disclosure regime since 1994 where firms are required to make timely disclosures of any value relevant information. Our study benefits from using a high frequency dataset containing the complete records of all trading on the Australian equity market, allowing for a comprehensive investigation of the anticipation hypothesis and eliminating sample selection bias concerns.

Second, we contribute to the literature examining information asymmetry around earnings announcements. The theoretical literature offers conflicting predictions on whether information disclosures decrease or increase information asymmetries. Prior literature has focussed on testing predictions related to this issue by examining proxies for information asymmetries and there has been little research examining the consequences of information asymmetry on the welfare of different investors. An exception is Taylor (2010), who examines whether retail investors benefit from trading around earnings announcements using a database of individual trading records from a United States retail broker. Our study extends Taylor's findings of information-based trading for institutional and retail investors. The richness of our data allows us to directly control for adverse selection of stale limit orders (Linnainmaa, 2010), which could explain the poor performance of retail trades following earnings announcements documented in Taylor (2010).

Third, our examination of the validity of the anticipation hypothesis also has implications for the literature documenting the post-earnings announcement drift (PEAD) effect. Prior literature has suggested that the behaviour of retail investors may be a source of market price anomalies. Given the attention paid to this anomaly in the literature, there is surprisingly little direct evidence that retail investors contribute to PEAD. Hirshleifer et al. (2008) offer a direct test of

[1] Kelley and Tetlock (2013) highlights that the NYSE sample of retail orders used in Kaniel et al. (2012) may be biased towards full-service retail brokers as discount brokers that tend to cater for self-directed retail investors are incentivized to route their orders away from the NYSE.

whether the naivety of retail investors, trading contrary to earnings surprises, creates under-reaction and contributes to PEAD. They refer to the idea that retail investors contribute to PEAD as the *individual trading* hypothesis, but find no empirical support for it. The post-announcement trading patterns documented in Kaniel et al. (2012) are consistent with the individual trading hypothesis, but the authors argue that this is due to retail investors reversing the positions they entered into prior to earnings announcements in order to exploit their short-lived private information.

We find evidence in favour of the information processing and individual trading hypothesis, but very limited evidence to support earnings anticipation by investors. Following earnings announcements, institutional investors exhibit strong news-momentum behaviour while retail investors exhibit strong news-contrarian behaviour. However, no relation is found between earnings announcement period returns and aggregate pre-event trading by institutional or retail investors. Utilising more granular investor classifications, we find robust but weak evidence of earnings anticipation by full-service retail investors, consistent with the findings of Kaniel et al. (2012). News-contrarian trading is significantly driven by the limit order trades of discount retail investors, who are particularly strong net buyers after negative earnings news. In contrast, news-momentum trading is most significant among top-tier institutional investors, suggesting the observed post-event trading patterns reflect differential interpretation abilities of earnings information.

Next, we examined the impact of earnings announcements on the performance of trades by institutional and retail investors. The earnings announcement trades of retail investors underperform their trades in non-announcement periods, consistent with earnings disclosures impacting negatively on their welfare. Both the market and limit order trades of discount retail investors underperform and the poor performance of their limit order trades cannot be explained by the adverse selection of stale limit orders. There is weaker evidence of improved trading performance by top-tier institutional investors on earnings announcement days, suggesting that they may be able to trade advantageously at the expense of discount retail investors.

## 4.2 Background

### 4.2.1 Presence of Informed Trading

Prior theoretical literature offers several predictions on the trading strategies of those investors in possession of short-lived private information. Under a rational expectations model with risk averse investors, Hirshleifer et al. (1994) find that an investor who acquires the information early trades aggressively prior to the announcement, and partially reverses their position when the information is publicly revealed to avoid risk. Late-informed investors will trade in the direction of the information when it is announced and their trades are thus positively correlated with the trades of the earlier informed. Brunnermeier (2005) develops a model with risk-neutral informed traders who receive a noisy signal regarding an upcoming announcement. The informed trader exploits this information twice. First, they will trade in the direction of the signal before it is publicly revealed and second, they will find it optimal to partially reverse their position as prices on average tend to overshoot in the direction of the signal once the information is announced.

There is a large body of literature establishing institutions as investors with information advantages based on a number of different institutional databases. Among studies using ownership data from 13-F filings, Ali et al. (2004) and Baker et al. (2010) find a positive relation between changes in institutional holdings and subsequent abnormal earnings announcement returns, indicating that institutions have superior information on forthcoming earnings announcements. Campbell et al.

(2009) propose a method of inferring daily institutional trading by linking quarterly changes in ownership with daily trade data from TAQ and conclude that institutions anticipate earnings surprises and exploit the PEAD effect. Puckett and Yan (2011) highlight that institutions also earn significant abnormal returns from interim trading that is not revealed in quarterly ownership data. More confirmatory evidence is provided by Berkman and McKenzie (2012) who examine the Dataexplorers database containing information on both institutional ownership and short interest. The authors find stronger evidence of earnings anticipation by institutional investors than by short sellers.

Studies of institutional trading on the Australian equity market include Gallagher and Looi (2006) who find that active equity managers are able to successfully exploit private information more readily in smaller stocks, for which the degree of analyst coverage, information flow and market efficiency are lower than for large-cap stocks. Gallagher et al. (2010) examine the trades of active Australian equity fund managers around earnings announcements and they document trading behaviour consistent with the anticipation hypothesis, but only prior to positive earnings news.

In contrast, retail investors are often characterised as uninformed and subject to behavioural biases. Empirical studies examining retail trading over longer horizons have typically supported this view (Barber et al., 2009, Barber and Odean, 2000). On the other hand, studies examining retail trading over shorter time horizons have found evidence of return predictability (Jackson, 2003, Kaniel et al., 2008). Kaniel et al. (2008) argue that this predictability is consistent with individuals being compensated for providing liquidity to institutions that require immediacy.

While Kaniel et al. (2012) provide the strongest evidence of informed trading by retail investors, this is also supported by Kelley and Tetlock (2013) who finds that net retail trading can anticipate the tone of news articles and the direction of earnings surprises but only on aggressive orders. The counterintuitive nature of these findings motivates our investigation of whether the trading patterns of institutional and retail investors are consistent with the anticipation hypothesis. Our data permits such an investigation as we are able to simultaneously observe trading by institutional and retail investors. Following Kaniel et al. (2012), we test the anticipation hypothesis by examining whether a positive relation exists between pre-announcement net trading and subsequent earnings announcement returns.

### 4.2.2 Post-Earnings Announcement Drift

There exists an extensive literature documenting the post earnings announcement drift (PEAD) effect, one of the longest surviving market anomalies. Bernard and Thomas (1989, 1990) provide evidence in favour of a behavioural explanation of this phenomenon. This explanation is that PEAD is due to the failure of naive investors to recognise the implications of current earnings for future earnings. Earlier studies were based on the behaviour of small and large traders around earnings announcements and provides mixed evidence on whether retail traders drive PEAD. Bhattacharya (2001) documents that abnormal trading volumes from small traders increase with the magnitude of seasonal random walk earnings surprises, while Battalio and Mendenhall (2005) find that small trades ignore earnings signals based on analyst forecasts and respond to signals from a naive time series model. However, Lee (1992) and Shanthikumar (2004) find positive small trade imbalances after both good and bad earnings news consistent with an earnings attention effect.

Using a proprietary sample of individual trades from a single discount brokerage firm, Hirshleifer et al. (2008) provide a direct test for whether retail investors contribute to PEAD. Hirshleifer et al. (2008) conjecture that 'if individuals were causing PEAD, then they would engage in earnings-contrarian trading - buying aggressively after extreme negative earnings news and selling after extreme positive earnings news'. They find that individual investors are net buyers of stocks after both positive and negative earnings surprises which is consistent with attention-driven buying (Barber and Odean, 2008) but does not support the individual trading hypothesis.

### 4.2.3 Information Asymmetry Around Announcements

There are two opposing views on how earnings announcements could affect information asymmetry. Under the anticipation hypothesis, information asymmetries increase as some investors gather private information in the pre-announcement period, which then dissipates as the information is disclosed (Diamond, 1985, Foster and Viswanathan, 1990, Verrecchia, 1982). Regulations that strengthen the information environment reduce the incentives for private information acquisition and informed trading prior to earnings announcements. The competing view is that public disclosure is a source of private information for investors with superior information processing abilities. Kim and Verrecchia (1994) state that disclosures 'stimulate informed judgments among traders who process public disclosure into private information. The ability of information processors to produce superior assessments of a firms performance on the basis of an earnings announcement provides them with a comparative information advantage'. Kandel and Pearson (1995) suggest that the same information release can generate differential interpretations among traders with different abilities to process and interpret information. These competing predictions on how information asymmetry is affected by disclosure have vastly different policy implications.

The empirical literature has tended to focus on this issue by examining proxies for information asymmetry. Lee et al. (1993) find that spreads increase while depth decreases in anticipation of upcoming earnings announcements as traders respond to increased information asymmetry risks. The increase in the spread persists until the day after the earnings announcement. Brooks (1996) adopts the Hasbrouck (1991) decomposition of the price variance into a trade component and a random walk component. Using the trade component of the price variance as the information asymmetry measure, Brooks (1996) documents a reduction in the level of information asymmetry for earnings, but not for dividend announcements, consistent with earnings announcements leveling the information playing field. Chae (2005) finds that the cumulative trading volume decreases before scheduled earnings announcements and is negatively correlated with levels of information asymmetry.

Our approach provides a different perspective to the current literature on whether disclosures tend to alleviate or exacerbate information asymmetries. This study examines these conflicting predictions by examining the consequences of disclosure on the welfare of different investors. If disclosures decrease information asymmetry, the performance of trades by retail investors should improve following earnings announcements compared to the non-announcement period. On the other hand, if consistent with the information processing hypothesis, disclosures increase information asymmetries, we would expect the post-announcement trades by retail investors to underperform their non-announcement period trades. Hence, our results could be viewed as reflecting the influence of these two countervailing effects.

## 4.3 Data and Methodology

We filter the order data described in Section 1.2 for the subset of trades, and this filtering suffices for the majority of the analysis. As each trade during continuous trading hours represents a market order executing against a limit order, the extent to which our results are driven by the limit order effect (Linnainmaa, 2010) can be examined by linking the limit order trade to the time of submission. For trade data, both the buyer and seller identification codes are provided. The order identifier reveals unambiguously the side that initiated the transaction, removing the need to infer trade direction. The broker identification code reveals the brokerage firm on each side of the trade. The dataset captures all trading in the Australian equity market, including trades on Chi-X over the period between January 1, 2007 and December 31, 2013.

To mitigate survivorship bias and the impact of index membership changes, the initial sample includes all stocks that had ever been included in the S&P/ASX300 index between January 1, 2007 and July 31, 2013 with at least one periodic earnings announcement over this period.[2] In Australia, companies typically report earnings on a semi-annual basis. Interim and final half-yearly earnings announcement dates and times were obtained from the SIRCA company announcements database. We restrict our sample of earnings announcements to days where market-adjusted return data is available and we were able to derive values for our net trading measures. This results in a total sample of 470 stocks releasing 4,362 earnings announcements. Daily return data is calculated from price data retrieved from IRESS and is adjusted for corporate actions. Accounting data (book values) are obtained from Worldscope, while data on market values and shares outstanding come from Datastream. Further restrictions are imposed on the earnings announcement sample in some of the analysis presented in Section 4.4 based on the availability of accounting, stock or trade data.

Each ASX market participant has a unique broker identification code which is assigned to an investor category. The investor classification procedure is detailed in Section 1.3. We also examine investor trading from the use of market and limit orders during continuous trading hours. Kelley and Tetlock (2013) suggest that trader's active decisions towards using market or limit orders may reflect different underlying motives for trading. Among retail investors, they find that only market orders can predict earnings surprises, while limit orders are primarily used to provide liquidity.

Table 4.1 presents descriptive trade statistics for our sample of 470 firms by investor category. There are 123 brokerage firms operating as ASX market participants over

[2]We tracked ASX code changes throughout the sample period in constructing our sample of stocks.

Table 4.1: Descriptive Trade Statistics by Investor Category

This table presents descriptive statistics of the trade data on our sample of 470 Australian firms from January 1, 2007 to December 31, 2013 by investor category. Brokerage firms are classified into investor categories from hand-collected information based on each firm's investor clientele. All brokers in the dataset are classified as an institutional, retail or other investor. Retail investors are further sub-categorised as full-service retail, discount retail or mixed retail. The other category is also partitioned into proprietary traders and market makers, mixed institutional, mixed retail plus a small number of unclassified brokers.

| | Number of Brokerage Firms | Total Dollar Volume (A$bn) | | Percentage of all trades (by value) |
|---|---|---|---|---|
| | | Buy | Sell | |
| Institutional | 36 | 5124.139 | 5115.526 | 79.07% |
| - Top-tier Inst | 12 | 4729.977 | 4737.930 | 73.11% |
| - Second-tier Inst | 24 | 394.162 | 377.596 | 5.96% |
| Retail | 32 | 734.235 | 733.449 | 11.33% |
| - Full-service Retail | 19 | 178.471 | 185.528 | 2.81% |
| - Discount Retail | 12 | 540.731 | 532.881 | 8.29% |
| - Mixed Retail | 1 | 15.032 | 15.040 | 0.23% |
| Other | 55 | 616.674 | 626.072 | 9.60% |
| - Proprietary Trading and Market Makers | 23 | 312.558 | 317.727 | 4.87% |
| - Mixed Institutional/Retail | 27 | 303.880 | 308.106 | 4.73% |
| - Unclassified | 5 | 0.236 | 0.240 | 0.00% |
| Total | 123 | 6475.047 | 6475.047 | 100.00% |

the full sample period with a total of \$6.475 trillion dollars worth of transactions recorded in those 470 stocks. These statistics also highlight the dominance of institutions in the Australian market landscape. Less than 30% of all brokerage firms are classified as institutional brokers but they account for 79% of total dollar volume.[3] There is a high level of concentration among institutional brokers, with top-tier brokers capturing the majority of the order flow. Collectively, institutional and retail trading accounts for over 90% of total dollar volume traded. While there are more retail brokers providing advisory services (full-service), discount brokers account for a larger proportion of dollar volume. Our classification approach identified 27 diversified brokerage houses providing services for both institutional and retail investors, but they accounted for a total of just 4.73% of total dollar volume traded.

For the purposes of our analysis, we aggregate the trade data to the daily level. An imbalance measure of investor trading ($NT$) is constructed for each investor category by subtracting the volume of shares sold from the volume of shares bought scaled by the number of shares outstanding. Expressing the volume imbalance

[3]This is similar to the US market where Jegadeesh and Tang (2011) report major institutional investors own about 73% of all publicly traded stocks.

to a relative measure in terms of the number of shares outstanding follows from previous studies (Griffin et al., 2010, Hirshleifer et al., 2008, Hvidkjaer, 2008, Irvine et al., 2007) with Irvine et al. (2007) stating that 'this normalization prevents institutional trading in large firms from biasing the results, as well as reduces cross-sectional variation in trading activity'.[4] For each stock, the net investor trading measure $NT[t]^i$ for investor category $i$ on day $t$ is

$$NT[t]^i = \frac{Buy\ volume[t]^i - Sell\ volume[t]^i}{Shares\ Outstanding[t]}. \tag{4.1}$$

The cumulative net investor trading over the period $[t, T]$ is given by

$$NT^i_{[t,T]} = \sum_{n=t}^{T} NT[n]^i, \tag{4.2}$$

where in event time analysis, the period is defined relative to the earnings announcement date (day 0). As some earnings announcements are released after the market close, we correct for event-day misalignment by identifying after-hours earnings announcements and re-assigning these to the following trading day.[5]

Throughout this chapter, we measure the cumulative abnormal return (CAR) as the buy and hold stock return minus the market return over the same period. The value-weighted portfolio return of all stocks in our sample is used as a proxy for the market return.

The literature has generally adopted two measures of the earnings announcement surprise. The more common measure uses consensus analyst forecasts as a proxy for the market's unobservable expectation of earnings. A standardised earnings surprise (SUE) is typically calculated as the difference between the announced

[4] As a robustness check, we also constructed an imbalance measure similar to Kaniel et al. (2012) for each investor category by subtracting the value of shares sold from the value of shares bought scaled by the average daily dollar volume in the calendar year. Qualitatively similar results were obtained and our findings presented in this chapter are unaltered under this alternative measure.

[5] Berkman and Truong (2009) show that the failure to correct for such announcements can lead to significant downward bias in calculating announcement day returns.

earnings and an analyst consensus normalised by a measure of earnings uncertainty. This study favours the market-adjusted return on the earnings announcement day (CAR0) as a measure of earnings surprise, removing the the requirement for the stock to have a sufficient level of analyst coverage. Brandt et al. (2008) show that the PEAD effect using this measure is stronger than the PEAD effect under SUE with the advantage of 'capturing the surprise in all aspects of the companys earnings announcement, and not just the surprises in earnings'.

## 4.4 Empirical Findings

### 4.4.1 Trading Patterns

We begin our investigation by documenting the aggregate trading behaviour of institutional and retail investors around earnings announcements. Announcements are first sorted into quintiles according to the magnitude of the earnings surprise, with announcements in quintile 1 (Q1) having the most negative earnings surprise. Table 4.2 presents event period averages of the cumulative net trading measure for institutional and retail investors across each earnings surprise quintile. Focusing first on post-event trading, Panel A of Table 4.2 shows that institutional investors engage in significant net buying following positive earnings news and net selling following negative earnings news. This evidence of news-momentum behaviour by institutional investors is consistent with these investors trading on their superior interpreting ability as well as exploiting the PEAD effect (Campbell et al., 2009). The behaviour of retail investors is a mirror image to that of institutional investors. Panel B of Table 4.2 shows that retail investors exhibit strong news-contrarian tendencies, suggesting that they may be contributing to the PEAD effect according to the individual trading hypothesis. Interestingly, net trading in the direction of the earnings surprise by institutional investors (and the opposite effect for retail investors) continues to increase up to three months following the

## Table 4.2: Net Institutional and Retail Investor Trading around Earnings Announcements

This table presents average net trading for institutional and retail investors around earnings announcements conditional on different levels of the earnings surprise. On any given day, the net trading measure is constructed by subtracting the daily volume of shares sold from the volume of shares bought and dividing this by the number of shares outstanding. This measure is then cumulated over different time periods before, during and after the earnings announcement. Announcements are sorted into quintiles with announcements in Q1 having the most negative earnings surprise. We report the estimated means across all earnings announcements in each surprise quintile along with cluster corrected t-statistics in parentheses (null hypothesis of zero net trading) based on semi-annual clustering. The symbols ** and * indicate the significance at the 1% and 5% level respectively.

Panel A: Institutional Investors

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q1 | Mean | -0.193% | -0.078% | -0.043%* | -0.015% | -0.082%** | -0.126%** | -0.147%** | -0.242%** | -0.388%** | -0.627%** |
| | t-stat | (-1.18) | (-1.88) | (-2.10) | (-1.41) | (-6.08) | (-6.62) | (-6.25) | (-5.78) | (-4.15) | (-2.75) |
| Q2 | Mean | 0.195%* | 0.042% | 0.028% | 0.020%* | -0.008%** | -0.015%** | -0.013% | -0.017% | -0.013% | 0.089% |
| | t-stat | (2.07) | (1.28) | (1.69) | (2.32) | (-2.68) | (-3.00) | (-1.25) | (-1.39) | (-0.37) | (1.48) |
| Q3 | Mean | 0.094% | 0.038% | 0.000% | -0.003% | -0.002% | -0.003% | -0.005% | 0.004% | 0.069% | 0.194% |
| | t-stat | (1.55) | (0.53) | (-0.01) | (-0.20) | (-0.28) | (-0.25) | (-0.20) | (0.11) | (1.34) | (1.11) |
| Q4 | Mean | 0.108% | 0.055% | 0.036% | 0.021% | 0.016%** | 0.016%* | 0.020%* | 0.056%** | 0.130%** | 0.258%** |
| | t-stat | (0.67) | (1.17) | (1.00) | (0.80) | (3.24) | (2.46) | (2.01) | (3.13) | (2.92) | (4.34) |
| Q5 | Mean | -0.169% | -0.133%* | -0.074%** | -0.066%* | 0.038%** | 0.046%** | 0.057%** | 0.088%** | 0.177%** | 0.319%* |
| | t-stat | (-1.26) | (-2.32) | (-2.66) | (-2.39) | (5.38) | (4.57) | (5.44) | (4.21) | (4.01) | (2.37) |
| Q5-Q1 | Mean | 0.024% | -0.055% | -0.031% | -0.051% | 0.120%** | 0.172%** | 0.204%** | 0.329%** | 0.566%** | 0.946%** |
| | t-stat | (0.12) | (-0.77) | (-0.89) | (-1.70) | (7.88) | (7.99) | (7.92) | (7.05) | (5.47) | (3.58) |

Panel B: Retail Investors

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q1 | Mean | 0.321%* | 0.132%* | 0.051%* | 0.018% | 0.077%** | 0.113%** | 0.119%** | 0.190%** | 0.296%** | 0.571%** |
| | t-stat | (2.04) | (2.19) | (2.18) | (1.55) | (9.97) | (10.20) | (6.81) | (5.95) | (4.35) | (2.81) |
| Q2 | Mean | -0.139%** | -0.046% | -0.025%* | -0.021%** | 0.007%* | 0.010%* | 0.002% | -0.002% | -0.002% | -0.057% |
| | t-stat | (-3.11) | (-1.94) | (-2.20) | (-3.03) | (2.40) | (1.99) | (0.21) | (-0.18) | (-0.09) | (-1.03) |
| Q3 | Mean | -0.038% | 0.012% | 0.015% | 0.012% | 0.003% | 0.006% | 0.025% | 0.016% | -0.042% | -0.122% |
| | t-stat | (-0.64) | (0.31) | (0.62) | (1.06) | (0.47) | (0.61) | (0.89) | (0.46) | (-1.10) | (-1.04) |
| Q4 | Mean | 0.031% | 0.015% | -0.007% | -0.005% | -0.010%** | -0.013%* | -0.016% | -0.037%* | -0.062% | -0.108% |
| | t-stat | (0.18) | (0.43) | (-0.34) | (-0.51) | (-3.59) | (-2.40) | (-1.52) | (-1.96) | (-1.67) | (-1.42) |
| Q5 | Mean | 0.166% | 0.112%* | 0.066%** | 0.064%** | -0.036%** | -0.044%** | -0.036%** | -0.059%** | -0.126%** | -0.112% |
| | t-stat | (1.52) | (2.15) | (2.92) | (2.71) | (-4.70) | (-4.40) | (-3.01) | (-3.69) | (-3.40) | (-0.86) |
| Q5-Q1 | Mean | -0.156% | -0.020% | 0.015% | 0.046% | -0.114%** | -0.157%** | -0.155%** | -0.249%** | -0.423%** | -0.682%** |
| | t-stat | (-0.81) | (-0.25) | (0.47) | (1.75) | (-10.38) | (-10.51) | (-7.32) | (-6.97) | (-5.45) | (-2.84) |

earnings announcement, suggesting that these observed trading patterns persist for an extended period.

Kaniel et al. (2012) explain that 'although trading in the opposite direction of the drift may slow the price adjustment process and may not, in isolation, be a good strategy, it is not necessarily an indication of irrational trading. Indeed, our findings ... suggest that individuals are profitably reversing positions that they entered into before the announcements'. Consistent with the hypothesis of informed trading by institutional or retail investors, we expect to observe an increase in net buying (selling) prior to positive (negative) earnings announcements in addition to the partial reversal of their positions in post-event trading, as predicted by Hirshleifer et al. (1994) and Brunnermeier (2005). Aggregate trading patterns observed prior to earnings announcements provide no evidence of earnings anticipation by institutional or retail investors. Among institutional investors, net selling is observed for the most negative earnings announcements, but is only significant in the $[-10, -1]$ window. More importantly, institutions are also net sellers for announcements in the quintile containing the most positive earnings news. Similarly, retail investors tend to be net buyers of stocks prior to both large positive and negative earnings surprises. The difference in net trading between the most positive (Q5) and the most negative (Q1) earnings announcements is not significant for institutional or retail investors across all pre-event trading windows.

Next, we examine net trading across finer partitions of investor and trade categories. For brevity, Table 4.3 reports just the differences in net trading between earnings announcements in the highest (Q5) and lowest (Q1) quintiles. The results suggest a partition across investor and trade categories is meaningful and yields additional insights. Based on net trading calculated from all trades, Panel A of Table 4.3 indicates the news-momentum behaviour is driven mostly by the trading activities of top-tier institutional investors, while the news-contrarian behaviour is driven mostly by discount retail investors. Panels B and C of Table 4.3 present the same results based on net trading calculated from the subsets of market and limit order trades respectively. Top-tier institutions are found to trade in the direction of earnings surprises utilising both market and limit orders. The difference between Q5 and Q1 net trading is positive and statistically significant across all post-event windows based on market and limit orders. This is in contrast to discount retail investors, whose contrarian behaviour is mainly driven by their executed limit orders. On day 0, Q5-Q1 net limit order trading by top-tier institutions based on market orders is 0.084% of shares outstanding compared to 0.023% of shares outstanding for limit orders, suggesting a preference for using aggressive orders immediately following the earnings announcement.

Some evidence also emerges of earnings anticipation by investors trading through full-service brokers. Panel A of Table 4.3 shows that the differences between Q5 and Q1 net trading of full service retail investors are 0.026% and 0.037% of shares outstanding over the [-10,-1] and [-21,-1] pre-event windows respectively. These results are statistically significant at the 1% level. In Appendix C, Panel A of Table C.1 reports net trading of full-service retail investors across all earnings surprise quintiles. Net selling is statistically significant in the [-10,-1] and [-21,-1] pre-event windows for the lowest earnings quintile (Q1) indicating that these investors may be more adept at anticipating bad news. Evidence of earnings anticipation is consistent with those reported by Kaniel et al. (2012) for the United States and Vieru et al. (2006) for Finland.

The results in Table 4.2 indicate strong asymmetries in the contrarian tendencies of retail investors to positive and negative earnings news. Over the 63 days immediately following the earnings announcement, retail investors are net buyers of 0.571% of shares outstanding on announcements in the lowest quintile but are net sellers of 0.112% of shares outstanding on announcements in the highest quintile. Earnings are highly visible events that demand attention and the strong contrarian effect after negative earnings surprises may be explained by attention-driven buying behaviour (Barber and Odean, 2008). In Appendix C, Table C.1 reports

## Table 4.3: Net Investor Trading around Earnings Announcements by Investor and Order Type

This table summarises net trading around earnings announcements for different investors and trade category. Institutional investors are partitioned based on whether they are trading through a top-tier or second-tier institutional broker while retail investors are partitioned based on whether they are trading through full-service or discount brokers. Panel A presents net trading calculated from all trades while Panels B and C present net trading calculated on market and limit orders respectively during continuous trading hours. On any given day, the net trading measure is constructed by subtracting the daily volume of shares sold from the volume of shares bought and dividing this by the number of shares outstanding. This measure is then cumulated over different time periods before, during, and after the announcement. Announcements are sorted into quintiles with announcements in Q1 having the most negative earnings surprises. The table reports just the difference between Q5 and Q1 net trading along with cluster-corrected t-statistics in parentheses (null hypothesis of zero net trading) based on semi-annual clustering. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: All Trades

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Top-tier Inst | Mean | 0.019% | -0.032% | -0.017% | -0.039% | 0.116%** | 0.167%** | 0.196%** | 0.302%** | 0.523%** | 0.918%** |
| | t-stat | (0.10) | (-0.49) | (-0.50) | (-1.24) | (9.09) | (9.54) | (7.77) | (6.97) | (5.95) | (3.77) |
| Second-tier Inst | Mean | 0.005% | -0.023% | -0.014% | -0.012% | 0.004% | 0.005% | 0.008% | 0.027% | 0.043% | 0.028% |
| | t-stat | (0.14) | (-1.24) | (-1.13) | (-1.33) | (0.63) | (0.56) | (0.83) | (1.43) | (1.27) | (0.61) |
| Full-service Retail | Mean | -0.030% | 0.037%** | 0.026%** | 0.030% | 0.000% | -0.007% | -0.028%** | -0.051%** | -0.093%** | -0.062% |
| | t-stat | (-0.66) | (3.00) | (2.83) | (1.36) | (-0.09) | (-1.19) | (-3.00) | (-3.15) | (-3.75) | (-1.11) |
| Discount Retail | Mean | -0.135% | -0.063% | -0.015% | 0.015% | -0.112%** | -0.147%** | -0.122%** | -0.188%** | -0.316%** | -0.590%** |
| | t-stat | (-0.82) | (-0.85) | (-0.50) | (0.98) | (-9.41) | (-10.81) | (-5.72) | (-6.04) | (-4.63) | (-2.93) |

Panel B: Market Orders

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Top-tier Inst | Mean | 0.046% | -0.017% | -0.014% | -0.032% | 0.084%** | 0.114%** | 0.092%** | 0.139%** | 0.241%** | 0.415%** |
| | t-stat | (0.44) | (-0.50) | (-0.86) | (-1.28) | (13.41) | (12.40) | (7.89) | (6.92) | (6.34) | (3.90) |
| Second-tier Inst | Mean | -0.001% | -0.015% | -0.009% | -0.007% | 0.011%** | 0.015%* | 0.011% | 0.025%* | 0.035%* | 0.052% |
| | t-stat | (-0.02) | (-1.65) | (-1.21) | (-1.68) | (2.82) | (2.53) | (1.77) | (2.20) | (1.96) | (1.91) |
| Full-service Retail | Mean | -0.021% | 0.010% | 0.010% | 0.004% | 0.008%** | 0.011%* | -0.004% | -0.013% | -0.029%* | -0.021% |
| | t-stat | (-1.16) | (1.34) | (1.71) | (1.00) | (3.68) | (2.56) | (-0.66) | (-1.46) | (-2.19) | (-0.70) |
| Discount Retail | Mean | -0.057% | -0.043% | -0.019% | 0.000% | 0.014% | 0.016%* | -0.014% | -0.025% | -0.074%* | -0.129% |
| | t-stat | (-0.77) | (-1.08) | (-1.54) | (0.05) | (1.92) | (2.06) | (-1.40) | (-1.69) | (-2.37) | (-1.34) |

Panel C: Limit Orders

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Top-tier Inst | Mean | -0.026% | -0.011% | 0.003% | -0.005% | 0.023%* | 0.036%** | 0.085%** | 0.131%** | 0.226%** | 0.381%** |
| | t-stat | (-0.32) | (-0.34) | (0.21) | (-0.46) | (2.47) | (3.63) | (5.21) | (5.41) | (5.02) | (2.86) |
| Second-tier Inst | Mean | 0.005% | -0.004% | -0.004% | -0.004% | -0.006%* | -0.007% | 0.000% | 0.007% | 0.011% | 0.005% |
| | t-stat | (0.38) | (-0.49) | (-0.84) | (-0.91) | (-2.44) | (-1.70) | (-0.07) | (1.04) | (0.81) | (0.26) |
| Full-service Retail | Mean | -0.005% | 0.023%* | 0.012%* | 0.025% | -0.010%** | -0.018%** | -0.021%** | -0.033%** | -0.049%** | -0.027% |
| | t-stat | (-0.21) | (2.15) | (2.21) | (1.20) | (-2.79) | (-6.35) | (-6.18) | (-4.64) | (-3.98) | (-1.05) |
| Discount Retail | Mean | -0.069% | -0.017% | 0.005% | 0.013% | -0.115%** | -0.150%** | -0.101%** | -0.153%** | -0.222%** | -0.426%** |
| | t-stat | (-0.60) | (-0.39) | (0.25) | (0.90) | (-15.20) | (-16.97) | (-6.94) | (-8.18) | (-5.14) | (-4.16) |

the results of all earnings surprise quintiles for full-service and discount retail investors. Full service retail investors appear to trade in a contrarian manner after positive earnings surprises but not after negative earnings surprises. The opposite pattern is observed with discount retail investors, who buy intensely after negative earnings surprises. This is consistent with discount retail investors being subject to the greatest attention constraints.

The effect of earnings surprises on post-announcement trading patterns is formalised in a regression setting that controls for other factors that may affect net trading. The following regressions are estimated on the sample of earnings announcements:

$$
\begin{aligned}
NT_{[1,10]} &= b_0 + b_1 CAR0 + b_2 MOM + b_3 BTM + b_4 MVE \\
&\quad + b_5 NT_{[-10,-1]} + e,
\end{aligned} \tag{4.3}
$$

$$
\begin{aligned}
NT_{[1,10]} &= b_0 + b_1 CAR0Q1 + b_2 CAR0Q2 + b_3 CAR0Q4 + b_4 CAR0Q5 \\
&\quad + b_5 MOM + b_6 BTM + b_7 MVE + b_8 NT_{[-10,-1]} + e,
\end{aligned} \tag{4.4}
$$

where the dependent variable is post-event net trading ($NT_{[1,10]}$) for each investor and trade category. The explanatory variables include either the earnings surprise (CAR0) or dummy variables representing the quintiles 1, 2, 4 and 5 of CAR0, momentum (MOM) defined as the market-adjusted buy and hold returns for the 126 trading days prior to the earnings announcement, the ratio of book-to-market equity using accounting data lagged six months (BTM), market value of equity (MVE) and net trading prior to the earnings announcement ($NT_{[-10,-1]}$) computed for each investor category. Following Taylor (2010), we use the decile ranks scaled from 0 to 1 for the variables BTM and MVE which reduces the effect of outliers.[6]

[6] The coefficients on the scaled decile variables can be interpreted as the differences in net trading between firms in the highest and lowest deciles.

## Table 4.4: Explaining Post-Announcement Net Trading

This table presents results on the relation between post-announcement net trading and the earnings surprise by investor and trade category. Regressions were estimated where the dependent variable is the cumulative net trading measure $NT_{[1,10]}$ calculated separately for each investor and trade category. The explanatory variables include either the earnings surprise (CAR0) or dummy variables representing quintiles 1, 2, 4 and 5 of CAR0, momentum (MOM) defined as the market-adjusted buy and hold returns for the 126 trading days prior to the earnings announcement date, the book-to-market ratio (BTM), market value of equity (MVE) and net trading prior to the earnings announcement ($NT_{[-10,-1]}$) computed for each investor across all trades. Following Taylor (2010), we use the decile ranks scaled from 0 to 1 for BTM and MVE. Only the coefficient estimates and t-stats of the earnings surprise measures are presented below. Cluster-corrected t-statistics are reported in parentheses besides the estimated coefficient based on semi-annual clustering. The symbols ** and * indicate significance at the 1% and 5% levels respectively. The control variables are not reported for brevity.

Panel A: All Trades

| | CAR0 | | CAR0Q1 | | CAR0Q2 | | CAR0Q4 | | CAR0Q5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 2.37** | (8.99) | -0.23** | (-6.42) | -0.04 | (-1.81) | 0.04* | (2.11) | 0.11** | (3.75) |
| - Top-tier Inst | 2.32** | (8.63) | -0.22** | (-5.37) | -0.06 | (-1.57) | 0.01 | (0.37) | 0.09* | (1.99) |
| - Second-tier Inst | 0.05 | (0.20) | -0.01 | (-0.43) | 0.02 | (1.02) | 0.03* | (2.12) | 0.02 | (1.39) |
| Retail | -1.83** | (-9.54) | 0.19** | (5.49) | 0.02 | (1.02) | -0.02 | (-1.22) | -0.08* | (-2.34) |
| - Full-service Retail | -0.39** | (-4.26) | 0.05** | (4.10) | 0.00 | (-0.13) | -0.01 | (-0.70) | -0.01 | (-0.78) |
| - Discount Retail | -1.38** | (-10.92) | 0.14** | (4.71) | 0.02 | (1.39) | -0.02 | (-0.98) | -0.06* | (-2.55) |

Panel B: Market Orders

| | CAR0 | | CAR0Q1 | | CAR0Q2 | | CAR0Q4 | | CAR0Q5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 0.98** | (2.96) | | | | | | | | |
| | | | -0.10** | (-5.58) | -0.01 | (-1.16) | 0.03* | (2.03) | 0.06** | (3.63) |
| - Top-tier Inst | 0.99** | (6.87) | | | | | | | | |
| | | | -0.09** | (-6.28) | -0.02 | (-1.47) | 0.01 | (1.01) | 0.05** | (2.71) |
| - Second-tier Inst | -0.01 | (-0.03) | | | | | | | | |
| | | | -0.01 | (-0.96) | 0.01 | (0.85) | 0.01 | (1.85) | 0.01 | (1.38) |
| Retail | -0.39** | (-2.59) | | | | | | | | |
| | | | 0.04 | (1.94) | -0.01 | (-0.96) | 0.00 | (-0.38) | -0.01 | (-0.76) |
| - Full-service Retail | -0.11 | (-1.93) | | | | | | | | |
| | | | 0.02* | (2.23) | 0.00 | (-0.59) | 0.00 | (0.02) | 0.00 | (-0.11) |
| - Discount Retail | -0.25* | (-2.31) | | | | | | | | |
| | | | 0.02 | (1.21) | 0.00 | (-0.93) | 0.00 | (-0.43) | -0.01 | (-0.84) |

Panel C: Limit Orders

| | CAR0 | | CAR0Q1 | | CAR0Q2 | | CAR0Q4 | | CAR0Q5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 1.24** | (4.92) | | | | | | | | |
| | | | -0.11** | (-3.95) | -0.02 | (-1.20) | 0.01 | (0.70) | 0.04 | (1.96) |
| - Top-tier Inst | 1.12** | (4.75) | | | | | | | | |
| | | | -0.11** | (-3.60) | -0.04 | (-1.37) | -0.01 | (-0.27) | 0.03 | (0.98) |
| - Second-tier Inst | 0.12* | (2.55) | | | | | | | | |
| | | | 0.00 | (0.31) | 0.01 | (1.38) | 0.02* | (1.98) | 0.01 | (1.75) |
| Retail | -1.34** | (-11.73) | | | | | | | | |
| | | | 0.13** | (9.06) | 0.03* | (1.96) | -0.02 | (-1.63) | -0.06** | (-3.22) |
| - Full-service Retail | -0.24** | (-5.92) | | | | | | | | |
| | | | 0.02** | (4.31) | 0.00 | (1.11) | -0.01 | (-1.72) | -0.01 | (-1.58) |
| - Discount Retail | -1.08** | (-11.54) | | | | | | | | |
| | | | 0.11** | (8.12) | 0.02 | (1.91) | -0.01 | (-1.19) | -0.04** | (-3.43) |

Table 4.4 reports for each regression the coefficient estimates on the earnings surprise variables. The $b_1$ coefficient in Equation (4.3) measures the sensitivity of post-event net trading to changes in the earnings surprise (CAR0), while $b_1$ to $b_4$ in Equation (4.4) measure this sensitivity for each earnings surprise quintile. For brevity, the results for the control variables are omitted. However, we observe the coefficient estimates of MOM, BTM and MVE are consistent across all our regressions. Table C.2 in Appendix C presents the full estimation results on net institutional and retail investor trading across all trades.

Collectively, Table 4.4 provides strong confirmation of our earlier findings. The earnings surprise positively (negatively) predicts post-event net trading of institutional (retail) investors when controlling for momentum, book-to-market, size and past trading. In Panel A, the coefficient on $CAR0$ for post-event net trading of top-tier institutional investors imply that a 1% increase in the earnings surprise results in an increase in net buying of 2.32% of shares outstanding. For discount retail brokers, the coefficient for $CAR0$ indicates that the same 1% increase leads to an increase in *net selling* of 1.38% of shares outstanding. Comparing the coefficients for $CAR0Q1$ and $CAR0Q5$ highlights the asymmetries in post-event trading patterns among institutional and retail investors when responding to positive and negative earnings news. Panels B and C of Table 4.4 present the same regression results on market and limit order net trading respectively. The results suggest that earnings surprises positively predict the post-event net trading of market and limit orders of top-tier institutional brokers. However, among discount retail brokers the effect of the earnings surprise on post-event limit order net trading is significantly stronger.

Griffin et al. (2003) document a strong cross-sectional relation between short-term stock returns and net trading by institutional and retail investors. Institutions are found to be net buyers of stocks experiencing large positive returns on the previous day while retail investors tend to be net sellers. The behavioural finance literature also reports retail investors as return contrarians over short horizons (Grinblatt

# Table 4.5: Predictability of Future Net Investor Trading on News and Non-News Days

This table examines the predictability of future net trading for each investor and trade category. Panel data regressions are estimated where the dependent variable is the cumulative net investor trading measure $NT_{[t+1,t+10]}$ calculated separately for each investor and trade category. RET0 is the market-adjusted return on day 0. News is an indicator variable that takes the value of 1 if an earnings announcement is released on day 0. MOM is defined as the market-adjusted buy and hold returns for the 126 trading days prior to the earnings announcement date, BTM is the ratio of book-to-market equity using accounting data lagged six months, MVE is the market value of equity and $NT_{[t-10,t-1]}$ captures past net trading and is calculated for each investor across all trades. The estimated regressions include stock fixed effects and t-statistics in parentheses are calculated from standard errors clustered by firm and date. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: All Trades

| | RET0 | | RET0xNews | | MOM | | BTM | | MVE | | $NT_{[t-10,t-1]}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 1.050** | (12.62) | 0.744* | (2.23) | 0.074 | (1.66) | -0.101** | (-2.95) | 0.223** | (3.95) | 72.541** | (14.86) |
| - Top-tier Inst | 0.903** | (11.94) | 0.921* | (2.55) | 0.065 | (1.62) | -0.125** | (-3.80) | 0.148** | (2.84) | 68.148** | (14.75) |
| - Second-tier Inst | 0.136** | (5.34) | -0.171 | (-0.69) | 0.011 | (1.75) | 0.024* | (2.26) | 0.085** | (4.45) | 42.820** | (8.84) |
| Retail | -0.765** | (-11.38) | -0.929** | (-5.09) | -0.055 | (-1.74) | 0.046 | (1.49) | -0.168** | (-3.47) | 61.601** | (13.05) |
| - Full-service Retail | -0.213** | (-8.00) | -0.148 | (-1.55) | -0.009 | (-1.26) | 0.002 | (0.14) | -0.024 | (-0.99) | 51.007** | (8.78) |
| - Discount Retail | -0.541** | (-9.43) | -0.736** | (-4.83) | -0.045 | (-1.80) | 0.045 | (1.77) | -0.152** | (-3.68) | 55.910** | (13.01) |

Panel B: Market Orders

| | RET0 | | RET0xNews | | MOM | | BTM | | MVE | | $NT_{[t-10,t-1]}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 0.506** | (11.81) | 0.184 | (0.67) | 0.037* | (1.98) | -0.072** | (-4.05) | 0.130** | (4.95) | 21.244** | (4.93) |
| - Top-tier Inst | 0.415** | (9.59) | 0.324* | (2.11) | 0.033* | (2.24) | -0.072** | (-4.43) | 0.087** | (3.92) | 18.808** | (4.23) |
| - Second-tier Inst | 0.088** | (6.12) | -0.138 | (-0.67) | 0.005 | (1.11) | -0.001 | (-0.23) | 0.045** | (4.34) | 18.001** | (8.83) |
| Retail | -0.159** | (-4.57) | -0.131 | (-0.98) | -0.011 | (-1.06) | -0.011 | (-0.56) | -0.040 | (-1.27) | 28.577** | (10.49) |
| - Full-service Retail | -0.056** | (-5.22) | -0.046 | (-0.96) | -0.001 | (-0.33) | -0.008 | (-1.07) | -0.005 | (-0.39) | 25.897** | (8.20) |
| - Discount Retail | -0.102** | (-3.25) | -0.051 | (-0.50) | -0.010 | (-1.26) | 0.001 | (0.07) | -0.037 | (-1.57) | 23.082** | (9.99) |

Panel C: Limit Orders

| | RET0 | | RET0xNews | | MOM | | BTM | | MVE | | $NT_{[t-10,t-1]}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat | Coeff(x100) | t-stat |
| Institutional | 0.451** | (9.78) | 0.554 | (1.91) | 0.049** | (5.96) | -0.009 | (-0.59) | 0.046 | (1.74) | 42.811** | (7.93) |
| - Top-tier Inst | 0.394** | (9.79) | 0.527* | (2.01) | 0.044** | (5.59) | -0.028 | (-1.82) | 0.019 | (0.77) | 40.416** | (8.64) |
| - Second-tier Inst | 0.048** | (4.18) | 0.030 | (0.48) | 0.007** | (3.51) | 0.019** | (3.60) | 0.034** | (3.81) | 19.743** | (7.00) |
| Retail | -0.544** | (-13.64) | -0.699** | (-5.51) | -0.048** | (-3.68) | 0.051** | (2.99) | -0.105** | (-4.13) | 26.607** | (9.90) |
| - Full-service Retail | -0.136** | (-9.13) | -0.084 | (-1.81) | -0.010** | (-3.05) | 0.008 | (1.29) | -0.015 | (-1.25) | 19.489** | (6.58) |
| - Discount Retail | -0.400** | (-12.63) | -0.606** | (-5.32) | -0.037** | (-3.60) | 0.040** | (2.66) | -0.094** | (-4.21) | 27.402** | (10.77) |

and Keloharju, 2000, Kaniel et al., 2008), suggesting that the trading patterns we have documented may be due to these investors reacting to return shocks observed on the earnings announcement date, as opposed to the information contained in the earnings release.

To explore this possibility, we run the following panel data regression:

$$\begin{aligned} NT_{s,[t+1,t+10]} &= \gamma_s + b_1 RET0_{s,t} + b_2 (RET0 \times News)_{s,t} + b_3 MOM_{s,t} \\ &\quad + b_4 BTM_{s,t} + b_5 MVE_{s,t} + b_6 NT_{s,[t-10,t-1]} + e_{s,t}, \end{aligned} \tag{4.5}$$

which predicts future net investor trading ($NT_{[t+1,t+10]}$) based on the current day's market-adjusted return (RET0), an interaction term that isolates market-adjusted returns observed on earnings announcement days (RET0xNews), our set of standard controls and stock fixed effects $\gamma_s$. The interaction term captures differences in how investors trade on days with and without earnings announcements.

Table 4.5 presents the results from estimating Equation (4.5) across all investor and trade categories. We first make some observations on the estimation results of our control variables. The coefficient on lagged trade imbalance ($NT_{[t-10,t-1]}$) is positive and highly significant in all regression specifications, indicating strong persistence in the daily trading patterns of institutional and retail investors as documented in previous studies. The signs of the coefficients for MOM are consistent with institutional investors in aggregate acting as momentum traders (Bennett et al., 2003), while retail investors tend to trade in the direction opposite to past price momentum. The coefficients for BTM and MVE suggest that institutional (retail) investors are net buyers of low (high) book-to-market and higher (lower) market capitalisation stocks, but these coefficients are not always significant.

Turning to the effect of return shocks, the coefficient estimates for RET0 confirm the momentum behaviour of institutional investors and contrarian behaviour of retail investors with respect to prior returns. Of primary interest is the interaction coefficient of RET0xNews, which indicates whether a distinct return-contrarian and news-contrarian effect is evident among retail investors. Retail investors are found to be significantly more contrarian to prior day returns, when they are also accompanied by an earnings announcement. A further partitioning of net retail trading indicates that the news-contrarian trading behaviour is mainly driven by the limit order trades of discount retail investors.

Our results are in stark contrast to Kelley and Tetlock (2013), who find investors are more contrarian to past returns that are *not* accompanied by news. If retail investors are acting as liquidity providers to institutions in response to return shocks, as portrayed by Kaniel et al. (2008), our results suggest that they supply more liquidity in the direction opposite to the earnings surprise on days accompanied by earnings announcements. This behaviour is consistent with retail investors driving the PEAD effect. Based on the regression of net limit order trading by discount retail investors, the coefficient for RET0 indicate that a 1% increase in the market-adjusted return increases net selling by 0.004% of shares outstanding, but the coefficient for RET0xNews implies that net selling more than doubles to 0.010% of shares outstanding if it is on the day of an earnings announcement.

The distinct news-momentum effect, on the other hand, is driven mainly by top-tier institutional investors utilising both market and limit orders. The coefficient for RET0xNews is positive and significant for all regressions of net trading by top-tier institutional investors, but insignificant in all regressions of net trading by second-tier institutional investors. Overall, the post-event trading responses to earnings surprises that we observe are consistent with the information processing hypothesis.

### 4.4.2 Earnings Anticipation

Examining trading patterns prior to earnings announcements revealed some evidence of informed trading by full-service retail investors. This section provides two further empirical tests of earnings anticipation. Similar to Kaniel et al. (2012), our first test examines market-adjusted returns over different earnings announcement windows conditional on pre-event net trading. Market-adjusted returns (CAR) calculated over a short window largely reflect the immediate impact of the earnings surprise, while longer announcement windows also incorporate the PEAD effect. Announcements are independently sorted into quintiles based on $NT_{[-10,-1]}$, calculated separately for each investor and trade category with announcements in Q1 having the largest pre-event net selling imbalances.

Table 4.6 summarises our results by reporting the differences in the cumulative abnormal returns (CAR) between stocks experiencing intense net investor buying (Q5) and intense net investor selling (Q1). CAR is measured over different post-event windows. No evidence is found of a positive relationship between aggregate pre-event trading and abnormal returns during or after earnings announcements. This is the case for both institutional and retail investors.

Examining the net trading of full-service retail investors, our results provide weak evidence of earnings anticipation. Panel A of Table 4.6 shows that the difference in average CAR between the stocks that full-service retail investors intensely bought (Q5) and sold (Q1) is positive across all post-event windows, but is only significant at the 5% level over the periods [0,1] and [1,5]. Panels B and C of Table 4.6 present the differences between Q5 and Q1 CAR from the net trading of market and limit orders respectively. The results indicate that full-service retail investors tend to use market orders to act on their private information.

In our second test, we employ a regression framework to test whether pre-event net trading can predict cumulative abnormal returns on and after the earnings announcement. We run the following regression on the sample of earnings announcements:

$$CAR_{[0,T]} = b_0 + b_1 NT_{[-10,-1]} + b_2 MOM + b_3 BTM + b_4 MVE + e, \tag{4.6}$$

## Table 4.6: Return predictability Using Net Investor Trading Prior to Earnings Announcements

This table summarises the predictability of pre-announcement net investor trading on the market-adjusted returns during and after earnings announcements. Announcements are sorted into quintiles according to $NT_{[-10,-1]}$, the level cumulative net investor trading calculated over the 10 days prior to the earnings announcement for each investor and trade category. Announcements in Q1 experience the most intense investor selling relative to buying prior to the earnings announcement. The table reports just the difference in $CAR_{[t,T]}$ between stocks in Q5 and Q1, where $CAR_{[t,T]}$ is the buy and hold stock return from day t to day T minus the market return over the same period. The market return is defined as the value-weighted portfolio return of all stocks within our sample. Cluster-corrected t-statistics are reported in parentheses based on semi-annual clustering. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: All Trades

| | | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] | [0 63] |
|---|---|---|---|---|---|---|---|---|
| Institutional Investors | Mean | -0.208% | -0.150% | 0.130% | 0.326% | -1.807% | -4.988% | -4.846% |
| | t-stat | (-0.52) | (-0.28) | (0.26) | (0.46) | (-0.83) | (-0.79) | (-0.82) |
| - Top-tier Inst | Mean | -0.185% | -0.122% | 0.080% | 0.241% | -1.971% | -5.028% | -4.956% |
| | t-stat | (-0.44) | (-0.24) | (0.16) | (0.31) | (-0.88) | (-0.82) | (-0.86) |
| - Second-tier Inst | Mean | -0.126% | -0.264% | 0.208% | 0.469% | 0.308% | 0.319% | 0.326% |
| | t-stat | (-0.40) | (-0.64) | (0.44) | (0.71) | (0.24) | (0.09) | (0.09) |
| Retail Investors | Mean | 0.336% | 0.109% | -0.196% | -0.447% | 1.503% | 2.652% | 2.742% |
| | t-stat | (0.95) | (0.23) | (-0.37) | (-0.57) | (0.73) | (0.44) | (0.48) |
| - Full-service Retail | Mean | 0.397% | 1.076%* | 1.346%* | 1.976% | 3.613% | 5.561% | 6.026% |
| | t-stat | (1.18) | (2.26) | (1.98) | (1.92) | (1.94) | (1.14) | (1.28) |
| - Discount Retail | Mean | 0.182% | -0.281% | -0.672% | -1.176% | 0.291% | 0.753% | 0.795% |
| | t-stat | (0.55) | (-0.61) | (-1.00) | (-1.29) | (0.13) | (0.11) | (0.12) |

Panel B: Market Orders

| | | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] | [0 63] |
|---|---|---|---|---|---|---|---|---|
| Institutional Investors | Mean | -0.423% | -0.416% | 0.483% | 0.542% | -0.818% | -2.508% | -2.793% |
| | t-stat | (-1.09) | (-0.84) | (0.90) | (0.66) | (-0.40) | (-0.41) | (-0.47) |
| - Top-tier Inst | Mean | -0.179% | -0.141% | 0.516% | 0.473% | -1.457% | -4.213% | -4.295% |
| | t-stat | (-0.44) | (-0.28) | (0.98) | (0.61) | (-0.65) | (-0.72) | (-0.75) |
| - Second-tier Inst | Mean | -0.453% | -0.584% | 0.103% | 0.150% | -0.126% | 0.042% | -0.209% |
| | t-stat | (-1.44) | (-1.39) | (0.29) | (0.20) | (-0.09) | (0.01) | (-0.05) |
| Retail Investors | Mean | -0.014% | 0.612% | 1.696%** | 1.671%* | 3.592% | 4.851% | 4.719% |
| | t-stat | (-0.03) | (1.19) | (3.22) | (1.97) | (1.89) | (0.97) | (1.00) |
| - Full-service Retail | Mean | 0.220% | 0.765% | 1.718%* | 2.081%* | 3.686%* | 4.558% | 5.031% |
| | t-stat | (0.63) | (1.66) | (2.39) | (2.13) | (2.12) | (1.18) | (1.32) |
| - Discount Retail | Mean | -0.110% | 0.192% | 0.893% | 0.512% | 2.358% | 2.607% | 2.321% |
| | t-stat | (-0.25) | (0.38) | (1.89) | (0.74) | (1.17) | (0.49) | (0.47) |

Panel C: Limit Orders

| | | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] | [0 63] |
|---|---|---|---|---|---|---|---|---|
| Institutional Investors | Mean | 0.083% | -0.058% | -0.415% | -0.625% | -2.802% | -4.939% | -4.568% |
| | t-stat | (0.21) | (-0.12) | (-0.82) | (-0.75) | (-1.50) | (-1.07) | (-1.07) |
| - Top-tier Inst | Mean | -0.146% | -0.386% | -0.581% | -0.707% | -2.565% | -5.595% | -5.457% |
| | t-stat | (-0.36) | (-0.80) | (-1.13) | (-0.82) | (-1.53) | (-1.19) | (-1.27) |
| - Second-tier Inst | Mean | 0.137% | -0.030% | -0.194% | -0.381% | -0.367% | -0.553% | -0.351% |
| | t-stat | (0.38) | (-0.06) | (-0.42) | (-0.56) | (-0.28) | (-0.15) | (-0.10) |
| Retail Investors | Mean | 0.287% | -0.018% | -0.866% | -1.256% | 0.662% | 1.954% | 1.996% |
| | t-stat | (0.84) | (-0.04) | (-1.61) | (-1.70) | (0.29) | (0.30) | (0.32) |
| - Full-service Retail | Mean | 0.125% | 0.449% | 0.180% | 0.338% | 1.700% | 2.179% | 2.062% |
| | t-stat | (0.38) | (1.02) | (0.28) | (0.35) | (0.86) | (0.39) | (0.39) |
| - Discount Retail | Mean | 0.156% | -0.306% | -0.699% | -1.345% | -0.215% | 0.818% | 0.828% |
| | t-stat | (0.49) | (-0.71) | (-1.02) | (-1.35) | (-0.09) | (0.13) | (0.13) |

Table 4.7: Return Predictive Regressions using Net Investor Trading prior to Earnings Announcements

This table presents the results from estimating regressions relating abnormal returns on and after earnings announcements to net investor trading prior to the announcement. The dependent variable in each regression is the cumulative abnormal return $CAR_{[0,T]}$, defined as the buy and hold stock return from day 0 to day T (inclusive) minus the market return over the same period. The explanatory variables are an intercept, pre-announcement net investor trading $NT_{[-10,-1]}$, momentum (MOM), book-to-market ratio (BTM) and the market value of equity (MVE). For brevity, only the coefficient estimate on $NT_{[-10,-1]}$ is reported below. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: All Trades

| | | [0,1] | [0,5] | [0,10] | [0,21] | [0,42] | [0,63] |
|---|---|---|---|---|---|---|---|
| Institutional Investors | Coeff | -0.1360 | -0.0414 | -0.0373 | -1.3457 | -2.9150 | -4.1336 |
| | t-stat | (-0.65) | (-0.13) | (-0.06) | (-0.99) | (-1.58) | (-1.47) |
| - Top-tier Inst | Coeff | -0.1220 | 0.0377 | 0.0733 | -1.2613 | -3.0671 | -4.5531 |
| | t-stat | (-0.49) | (0.12) | (0.16) | (-1.02) | (-1.70) | (-1.64) |
| - Second-tier Inst | Coeff | -0.2160 | -0.5166 | -0.7026 | -1.7972 | -1.8780 | -2.9702 |
| | t-stat | (-0.36) | (-0.35) | (-0.35) | (-1.03) | (-0.82) | (-0.95) |
| Retail Investors | Coeff | 0.1548 | 0.0359 | -0.0199 | 1.6904 | 2.9982 | 3.4981 |
| | t-stat | (0.71) | (0.10) | (-0.03) | (1.31) | (1.52) | (1.37) |
| - Full-service Retail | Coeff | 1.5651* | 1.5919 | 2.3620 | 4.5538* | 5.8119 | 7.7956 |
| | t-stat | (2.01) | (1.34) | (1.74) | (2.14) | (1.90) | (1.92) |
| - Discount Retail | Coeff | -0.3761 | -0.6387 | -1.1116 | 0.5363 | 1.8636 | 2.2236 |
| | t-stat | (-1.01) | (-1.60) | (-1.39) | (0.43) | (0.86) | (0.73) |

Panel B: Market Orders

| | | [0,1] | [0,5] | [0,10] | [0,21] | [0,42] | [0,63] |
|---|---|---|---|---|---|---|---|
| Institutional Investors | Coeff | -0.2165 | 0.1177 | -0.2752 | -1.6371 | -3.2860 | -7.2251 |
| | t-stat | (-0.50) | (0.21) | (-0.31) | (-0.94) | (-1.12) | (-1.35) |
| - Top-tier Inst | Coeff | -0.1240 | 0.3949 | 0.0393 | -1.3298 | -3.2185 | -7.3840 |
| | t-stat | (-0.26) | (0.72) | (0.07) | (-0.98) | (-1.20) | (-1.50) |
| - Second-tier Inst | Coeff | -1.0164 | -1.9936 | -2.8232 | -4.6357 | -5.0185 | -7.4644 |
| | t-stat | (-0.85) | (-0.70) | (-0.67) | (-1.15) | (-0.97) | (-0.94) |
| Retail Investors | Coeff | 0.1060 | 0.5371 | 0.7989 | 3.8816 | 6.3123* | 8.8212* |
| | t-stat | (0.20) | (0.60) | (0.82) | (1.88) | (2.37) | (2.26) |
| - Full-service Retail | Coeff | 2.6988 | 3.7058 | 5.6074 | 10.2948* | 14.5494* | 21.5623** |
| | t-stat | (1.47) | (1.30) | (1.83) | (2.31) | (2.44) | (2.90) |
| - Discount Retail | Coeff | -0.7825 | -0.5673 | -0.9799 | 2.4973 | 4.8748 | 6.6778 |
| | t-stat | (-1.43) | (-0.75) | (-0.92) | (1.17) | (1.67) | (1.46) |

Panel C: Limit Orders

| | | [0,1] | [0,5] | [0,10] | [0,21] | [0,42] | [0,63] |
|---|---|---|---|---|---|---|---|
| Institutional Investors | Coeff | -0.0051 | -0.0094 | 0.1680 | -0.6264 | -1.7150 | -4.0619 |
| | t-stat | (-0.07) | (-0.07) | (0.57) | (-0.68) | (-1.36) | (-1.75) |
| - Top-tier Inst | Coeff | -0.0403 | -0.0324 | 0.1197 | -0.6281 | -1.7605 | -4.4918 |
| | t-stat | (-0.41) | (-0.23) | (0.44) | (-0.70) | (-1.36) | (-1.89) |
| - Second-tier Inst | Coeff | 0.6906 | 0.4436 | 1.2234 | -0.9435 | -1.7641 | -3.6264 |
| | t-stat | (0.59) | (0.18) | (0.38) | (-0.34) | (-0.45) | (-0.65) |
| Retail Investors | Coeff | 0.1649 | -0.4533 | -0.7572 | 0.4477 | 1.1834 | -0.0430 |
| | t-stat | (0.34) | (-0.63) | (-0.78) | (0.26) | (0.42) | (-0.01) |
| - Full-service Retail | Coeff | 2.2364** | 0.8743 | 1.6163 | 5.0520 | 3.6225 | 0.6583 |
| | t-stat | (2.70) | (0.61) | (0.93) | (1.32) | (0.60) | (0.07) |
| - Discount Retail | Coeff | -0.2912 | -0.9238 | -1.5936 | -0.6046 | 0.5973 | -0.0861 |
| | t-stat | (-0.41) | (-1.08) | (-1.49) | (-0.40) | (0.21) | (-0.03) |

where the dependent variable $CAR_{[0,T]}$ is computed over different post-event windows. The explanatory variables include pre-event net trading $NT_{[-10,-1]}$, calculated for each investor and trade category, and our control variables MOM, BTM and MVE. Table 4.7 presents the results for the coefficient of interest, $b_1$ across all regression specifications. Consistent with our earlier results, some evidence is found of full-service retail investors trading in the direction of post-event CAR. Panel A shows the coefficients for $NT_{[-10,-1]}$ are positive across all post-event windows but are significant only for $CAR_{[0,1]}$ and $CAR_{[0,21]}$. Full-service retail investor's preferences for using market orders in pre-event trading are also observed. The coefficients for $b_1$ are larger in magnitude in all regresssions based on $NT_{[-10,-1]}$ calculated from market orders relative to limit orders. They are also significant at the 5% level in 3 out of 6 post-event windows, compared to 1 out of 6 post-event windows for limit orders. Among other investors, we find pre-event trading has no predictive power over post-event CAR.

Overall, our tests of the anticipation hypothesis suggests some retail investors trading through full-service brokers are able to successfully anticipate earnings news. These findings are consistent with but significantly weaker than the results documented in Kaniel et al. (2012). Our failure to find systematic evidence of informed trading prior to earnings announcements by institutional investors may not seem surprising as institutions dominate trading and are a diverse group. Our results do not preclude a select few who are privy to private information and whose trading cannot be identified based on the coarse categorisations of our data. Nevertheless, the lack of any discernable pre-event trading patterns is in stark contrast to the strong trading patterns observed in the post-event period.

### 4.4.3 Investor Trade Performance

Under the information processing hypothesis, earnings announcements exacerbate information asymmetries between investors with different information interpreting abilities. The strong post-event trading patterns that we report in Section 4.4.1 are consistent with this hypothesis. A consequence of this asymmetry is that the most efficient information processors are likely to be able to trade more advantageously following disclosures. For each group of investors, we examine whether there is any disparity in the aggregate performance of their trades following earnings announcements relative to the non-announcement period.

Table 4.8: Trading Performance around Earnings Announcements - Institutional and Retail Investors

This table reports the results of estimating panel regressions examining the trade performance of institutional and retail investors around earnings announcements with stock fixed effects. The dependent variable is the market-adjusted holding period return ($HPR_{[t,T+t]}$) to a representative investor who takes a position on the close of trading based on the net trade imbalance on the day. Ann is an indicator variable that takes the value of 1 if the investor placed a position on the day of the earnings announcement and Post-Ann is an indicator variable that takes the value of 1 if the investor placed a position in the post-event window $[1, 5]$. To account for daily variations in trade imbalances, regressions are estimated by weighting the trade return on each stock and day by the net dollar volume traded for each investor category. Coefficient estimates (x100) are reported along with t-statistics in parentheses calculated from robust standard errors clustered by firm and date. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: Institutional Investors

| | Time Horizon | | | | |
|---|---|---|---|---|---|
| | 5 | 10 | 21 | 42 | 63 |
| Ann | 0.283 | 0.922** | 1.042* | 1.202 | 1.383 |
| | (1.47) | (3.12) | (2.15) | (1.72) | (1.74) |
| PostAnn | 0.235* | 0.523* | 0.253 | 0.148 | 0.078 |
| | (2.00) | (2.32) | (0.88) | (0.36) | (0.19) |
| \|MOM\| | 0.126 | 0.058 | -0.131 | 0.584 | 0.972 |
| | (0.78) | (0.27) | (-0.41) | (0.68) | (1.06) |
| MVE | -0.461 | -0.419 | -0.336 | -0.373 | -1.780 |
| | (-0.80) | (-0.54) | (-0.27) | (-0.19) | (-0.67) |
| Trading Activity | -0.505** | -0.795** | -1.022** | -1.206 | -1.164 |
| | (-2.93) | (-3.01) | (-2.65) | (-1.48) | (-1.25) |
| Stock Vol | -0.276 | -0.419 | -0.551 | -0.676 | -0.872 |
| | (-1.07) | (-1.23) | (-1.16) | (-0.90) | (-0.96) |

Panel B: Retail Investors

| | Time Horizon | | | | |
|---|---|---|---|---|---|
| | 5 | 10 | 21 | 42 | 63 |
| Ann | -0.507** | -1.126** | -1.226** | -1.590* | -1.728* |
| | (-2.75) | (-4.11) | (-2.97) | (-2.44) | (-2.22) |
| PostAnn | -0.264** | -0.642** | -0.418 | -0.458 | -0.473 |
| | (-2.70) | (-3.11) | (-1.41) | (-1.05) | (-1.16) |
| \|MOM\| | -0.159 | -0.028 | 0.183 | 0.365 | 0.128 |
| | (-1.14) | (-0.15) | (0.61) | (0.88) | (0.24) |
| MVE | 0.464 | 0.387 | 0.120 | 0.741 | 1.098 |
| | (1.10) | (0.67) | (0.10) | (0.40) | (0.45) |
| Trading Activity | 0.410* | 0.507* | 0.527 | -0.048 | -0.684 |
| | (2.34) | (2.08) | (1.32) | (-0.09) | (-0.83) |
| Stock Vol | 0.197 | 0.452 | 0.731 | 1.313 | 1.908* |
| | (0.79) | (1.43) | (1.56) | (1.87) | (1.98) |

Specifically, we estimate the following panel regression:

$$\begin{aligned} HPR_{s,[t,T+t]} &= \gamma_s + b_1 Ann_{s,t} + b_2 PostAnn_{s,t} + b_3 |MOM|_{s,t} + b_4 MVE_{s,t} \\ &\quad + b_5 TradeActivity_{s,t} + b_6 StockVol_{s,t} + e_{s,t}, \end{aligned} \tag{4.7}$$

where the dependent variable ($HPR_{[t,T+t]}$) is the market-adjusted holding period return to a representative investor who mimics the aggregate trading behaviour of an investor and trade category. At the close of each day, this investor observes the trade imbalance of the stock and immediately places a position in the direction of the imbalance. $HPR_{[t,T+t]}$ is calculated as the buy and hold return of the investor's position for $T$ days minus the market return over the same period. All returns are calculated before transaction costs and for robustness, $HPR_{[t,T+t]}$ is calculated over five different holding periods $T$. Our approach of using closing prices follows from Seasholes and Zhu (2010) and alleviates potential microstructure effects.

The regression includes two explanatory variables to identify post-event trading. Ann is an indicator variable that takes the value of 1 if the investor placed a position on the day of the earnings announcement and Post-Ann is an indicator variable that takes the value of 1 if the investor placed a position between the first and the fifth days following the earnings announcement ([1,5] window). The control variables include the absolute value of the MOM variable ($|MOM|$), market value of equity (MVE), trade activity defined as the total dollar volume traded relative to its market capitalisation averaged over the previous 21 days and stock volatility measured as the standard deviation of daily stock returns over the previous 126 days. All these control variables are represented as scaled decile ranks to reduce the influence of outliers. The variable $|MOM|$ controls for investor trade performance that may be explained by the momentum strategy. The evidence indicates that investing in momentum stocks is on average profitable (Jegadeesh and Titman, 1993, 2001) and that retail investors tend to trade against past price momentum (Grinblatt and Keloharju, 2000), which suggests that retail trade performance can be negatively related to $|MOM|$.

To account for daily variations in trade imbalances, regressions are estimated by weighting each observation by the net dollar volume traded for each investor category. Test statistics are calculated based on robust standard errors clustered by stock and day which accounts for the correlation induced by overlapping time intervals.

Table 4.8 presents the results of estimating panel regressions examining the aggregate trade performance of institutional and retail investors following earnings announcements with stock fixed effects. For institutional investors, Panel A of Table 4.8 provides some evidence of an improvement in the performance of their earnings announcement trades. The coefficient estimates for the Ann and Post-Ann variables are all positive and statistically significant at the 5% level in 2 out of 5 holding periods.

Turning to the results in Panel B of Table 4.8, the coefficient estimates for the Ann variable are all negative and significant at the 5% level. Across all holding periods, retail investors' earnings announcement trades underperform their trades in non-announcement periods. The magnitude of the coefficients are also economically significant. The coefficient estimates for Ann imply the 5-day holding period return on earnings announcement trades are on average lower by 0.507% relative to non-announcement trades. This performance differential increases with the holding period, increasing to 1.728% after 63 days. The coefficients for PostAnn, which measures the relative performance of trades in the post-announcement window [1,5], are also negative across all holding periods but are statistically significant only for the 5-day and 10-day holding periods. This suggests that the impact of increased information asymmetries on retail investor performance appears to be isolated to a short time period following earnings disclosures.

In Table 4.9, we extend our results by estimating panel regressions examining the trade performance of different investor and trade categories. Some striking differences in the trading outcomes of different investors are observed in Panel A of Table 4.9 on earnings announcement dates. The earnings announcement trades of

Table 4.9: Investor Trading Performance around Earnings Announcements by Investor and Trade Type

This table summarizes the results on the relative trade performance of different investors and trade categories. Panel regressions are estimated to examine the trade performances of different investor and trade categories around earnings announcements with stock fixed effects. The dependent variable is the market-adjusted holding period return ($HPR_{[t,T+t]}$) to a representative investor who takes a position on the close of trading based on the net trade imbalance on the day. Ann is an indicator variable that takes the value of 1 if the investor placed a position on the day of the earnings announcement and Post-Ann is an indicator variable that takes the value of 1 if the investor placed a position in the post-event window $[1, 5]$. To account for daily variations in trade imbalances, regressions are estimated by weighting the trade return on each stock and day by the net dollar volume traded for each investor and trade category. Only the coefficient estimates for the Ann and PostAnn indicator variables are presented below. Coefficient estimates (x100) are reported along with t-statistics in parentheses calculated from robust standard errors clustered by firm and date. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

Panel A: All Trades

| | | Ann | | | | | PostAnn | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 5 | 10 | 21 | 42 | 63 | 5 | 10 | 21 | 42 | 63 |
| Top-tier Inst | Coeff(x100) | 0.336 | 0.751** | 0.749 | 0.913 | 1.313 | 0.149 | 0.410* | 0.117 | -0.063 | -0.037 |
| | t-stat | (1.66) | (2.68) | (1.58) | (1.31) | (1.61) | (1.34) | (2.01) | (0.43) | (-0.16) | (-0.09) |
| Second-tier Inst | Coeff(x100) | -0.244 | 0.358 | 0.694 | 0.692 | 0.009 | 0.152 | 0.174 | 0.274 | 0.498* | 0.243 |
| | t-stat | (-1.00) | (1.13) | (1.46) | (1.12) | (0.01) | (1.59) | (1.20) | (1.27) | (2.16) | (0.73) |
| Full-service Retail | Coeff(x100) | -0.088 | -0.344 | -0.392 | -0.225 | -0.441 | -0.093 | -0.232 | -0.124 | -0.080 | -0.168 |
| | t-stat | (-0.51) | (-1.04) | (-0.80) | (-0.32) | (-0.50) | (-0.94) | (-1.46) | (-0.59) | (-0.22) | (-0.51) |
| Discount Retail | Coeff(x100) | -0.634** | -1.315** | -1.362** | -1.904** | -2.002** | -0.308** | -0.749** | -0.482 | -0.493 | -0.433 |
| | t-stat | (-3.33) | (-4.68) | (-3.10) | (-3.12) | (-2.78) | (-2.65) | (-3.65) | (-1.54) | (-1.13) | (-0.97) |

Panel B: Market Orders

| | | Ann | | | | | PostAnn | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 5 | 10 | 21 | 42 | 63 | 5 | 10 | 21 | 42 | 63 |
| Top-tier Inst | Coeff(x100) | 0.525** | 0.729* | 0.687 | 0.629 | 0.887 | 0.054 | 0.209 | 0.102 | -0.221 | -0.089 |
| | t-stat | (2.91) | (2.45) | (1.46) | (1.09) | (1.22) | (0.52) | (1.61) | (0.55) | (-0.82) | (-0.25) |
| Second-tier Inst | Coeff(x100) | -0.166 | 0.421 | 0.672 | 0.744 | 0.035 | 0.174 | 0.153 | 0.265 | 0.550* | 0.591 |
| | t-stat | (-0.53) | (1.11) | (1.18) | (1.10) | (0.04) | (1.83) | (0.97) | (1.08) | (1.96) | (1.71) |
| Full-service Retail | Coeff(x100) | 0.182 | -0.202 | -0.393 | -0.148 | -0.309 | -0.072 | -0.265 | -0.254 | -0.180 | -0.234 |
| | t-stat | (0.66) | (-0.65) | (-0.93) | (-0.22) | (-0.41) | (-0.60) | (-1.41) | (-1.04) | (-0.44) | (-0.68) |
| Discount Retail | Coeff(x100) | -0.211 | -0.946** | -1.101* | -1.738* | -2.120** | -0.294** | -0.764** | -0.533 | -0.665 | -0.706 |
| | t-stat | (-1.17) | (-2.95) | (-2.01) | (-2.54) | (-2.93) | (-2.74) | (-3.50) | (-1.68) | (-1.44) | (-1.57) |

Panel C: Limit Orders

| | | Ann | | | | | PostAnn | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 5 | 10 | 21 | 42 | 63 | 5 | 10 | 21 | 42 | 63 |
| Top-tier Inst | Coeff(x100) | 0.041 | 0.382 | 0.457 | 0.712 | 1.065 | 0.135 | 0.341 | 0.048 | 0.074 | -0.040 |
| | t-stat | (0.21) | (1.70) | (1.35) | (1.38) | (1.67) | (1.47) | (1.63) | (0.19) | (0.20) | (-0.10) |
| Second-tier Inst | Coeff(x100) | -0.239 | 0.313 | 0.680 | 0.649 | 0.191 | 0.170 | 0.261 | 0.294 | 0.520* | 0.126 |
| | t-stat | (-1.19) | (1.09) | (1.65) | (1.19) | (0.28) | (1.63) | (1.58) | (1.29) | (2.04) | (0.32) |
| Full-service Retail | Coeff(x100) | -0.576** | -0.601 | -0.389 | -0.266 | -0.321 | -0.120 | -0.190 | 0.060 | 0.148 | 0.120 |
| | t-stat | (-3.76) | (-1.61) | (-0.58) | (-0.31) | (-0.31) | (-1.27) | (-1.26) | (0.32) | (0.46) | (0.34) |
| Discount Retail | Coeff(x100) | -0.914** | -1.418** | -1.450** | -1.962** | -2.005** | -0.289* | -0.618** | -0.345 | -0.340 | -0.302 |
| | t-stat | (-4.52) | (-5.15) | (-3.61) | (-3.41) | (-2.82) | (-2.27) | (-3.19) | (-1.22) | (-0.93) | (-0.74) |

discount retail investors underperform non-announcement trades across all holding periods, reaching a substantial difference of 2.002% for a 63-day holding period. The coefficents on Ann are significantly smaller in magnitude and are insignificant for full-service retail investors, indicating these investors are significantly less affected by earnings announcements.

In Panel B (C) of Table 4.9, the dependent variable in the regression is the market-adjusted holding period return to an investor who trades in the direction of the market (limit) order trade imbalances. The regressions are then weighted according to the net market (limit) order dollar volumes traded. The most significant result in Panel B is that the market order trades of discount retail investors during earnings announcement periods also experience poor performance compared to non-announcement periods. Panel C of Table 4.9 confirms the poor performance of discount retail investors' limit order trades following earnings announcements. The empirical evidence is consistent with the information processing hypothesis and earnings disclosures increasing information asymmetries. Discount retail investors appear to be most disadvantaged due to their limited information processing ability.

### 4.4.4 Stale Limit Orders

The evidence thus far indicates that the post-announcement trading patterns and poor trade performance of discount retail investors are driven substantially by their limit order trades. Linnainmaa (2010) shows that these results could arise mechanically from the limit order effect. This occurs when informed traders selectively trade against stale limit orders after an information release that changes the fundamental value of the asset. Discount retail investors, who are viewed as the most attention constrained and have the least resources available to monitor their limit orders, are most likely to suffer from this form of adverse selection.

To control for the limit order effect, we examine the passive side of every trade in our sample made during continuous trading hours. We classify a limit order as stale if it was submitted prior to the earnings announcement and it's execution was triggered after the announcement. For these limit orders, we assume that the investor has not had the chance to cancel their limit order prior to its execution following the earnings disclosure.

We distinguish this from the case where an investor responds to the earnings announcement with an active decision to place a limit order which subsequently achieves execution. We assume that investors submitting limit orders following earnings announcements are aware of their release to the market. This requirement is not unrealistic as all announcements, including earnings announcements, are submitted to the ASX on a centralized platform and are readily and publicly available in real time to all investors.[7] In addition, a trading halt is imposed by the exchange when any market sensitive announcement is released, which includes earnings announcements. This provides time for investors to process the information contained in the release.

Table 4.10 presents some statistics on the incidence of stale limit order executions on and after earnings announcement dates over the full sample. As expected, the proportion of stale limit order trades is highest on the day of the earnings announcement and declines in the days following the earnings announcement. The proportion of stale limit orders are also highest among discount retail investors and lowest among institutional investors. However, trading is not dominated by the triggering of stale limit orders on and after earnings announcements. The dollar volume traded from executing against the stale limit orders of discount retail investors never exceeds 12% of total limit order dollar volume traded by these investors. The low incidence of stale limit order trades suggests that the limit order effect is unlikely to significantly alter our findings.

[7] The ASX publishes all company announcements on their website. See http://www.asx.com.au/asx/statistics/todayAnns.do.

TABLE 4.10: Incidence of Stale Limit Order Executions

This table presents summary statistics on the incidence of stale limit order executions on and after earnings earnings announcements. We consider only orders executed during continuous trading hours. A limit order is classified as stale if it was submitted to the market prior to the earnings announcement but the time of execution occurs after the announcement. For each investor category, Panel A reports the total buy dollar volume of trades executed from stale limit orders and the proportion of total buy dollar volume represented by stale limit order executions over our entire sample. Panel B reports the same statistics for sell dollar volume.

Panel A: Buy Dollar Volume (A$bn)

| | | Days Relative to Earnings Announcement | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | >3 |
| Institutional | Stale | 0.166 | 0.035 | 0.018 | 0.005 | 0.049 |
| | Total | 22.392 | 19.221 | 15.337 | 14.089 | 1632.932 |
| | % | 0.74% | 0.18% | 0.11% | 0.04% | 0.00% |
| Retail | Stale | 0.354 | 0.104 | 0.034 | 0.023 | 0.123 |
| | Total | 5.262 | 4.072 | 3.084 | 2.864 | 293.319 |
| | % | 6.73% | 2.56% | 1.12% | 0.79% | 0.04% |
| - Full-service | Stale | 0.051 | 0.019 | 0.005 | 0.004 | 0.031 |
| | Total | 1.264 | 1.014 | 0.705 | 0.602 | 65.728 |
| | % | 4.07% | 1.84% | 0.75% | 0.64% | 0.05% |
| - Discount Retail | Stale | 0.302 | 0.085 | 0.029 | 0.019 | 0.092 |
| | Total | 3.907 | 2.989 | 2.319 | 2.217 | 222.179 |
| | % | 7.73% | 2.85% | 1.26% | 0.85% | 0.04% |

Panel B: Sell Dollar Volume (A$bn)

| | | Days Relative to Earnings Announcement | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | >3 |
| Institutional | Stale | 0.123 | 0.027 | 0.013 | 0.009 | 0.062 |
| | Total | 24.156 | 20.353 | 15.974 | 14.476 | 1651.277 |
| | % | 0.51% | 0.13% | 0.08% | 0.06% | 0.00% |
| Retail | Stale | 0.402 | 0.149 | 0.077 | 0.049 | 0.229 |
| | Total | 4.383 | 3.663 | 2.949 | 2.669 | 296.974 |
| | % | 9.17% | 4.08% | 2.61% | 1.83% | 0.08% |
| - Full-service | Stale | 0.049 | 0.026 | 0.014 | 0.008 | 0.048 |
| | Total | 1.135 | 0.972 | 0.797 | 0.719 | 70.913 |
| | % | 4.34% | 2.66% | 1.78% | 1.11% | 0.07% |
| - Discount Retail | Stale | 0.351 | 0.123 | 0.062 | 0.041 | 0.180 |
| | Total | 3.141 | 2.598 | 2.096 | 1.896 | 220.022 |
| | % | 11.17% | 4.74% | 2.98% | 2.15% | 0.08% |

To confirm this, Table 4.11 re-estimates Equation (4.7), controlling for the limit order effect. For each stock, the daily net dollar volume traded is calculated separately for each investor category on all limit order trades, excluding the trades of stale limit orders. The dependent variable in the regression is the market-adjusted holding period return to an investor who trades in the direction of this imbalance. The regression is then weighted by the net limit order dollar volume traded, excluding stale limit order trades. Table 4.11 confirms that our findings of poor relative trade performance during earnings announcements, particularly by discount retail investors, are unchanged after removing stale limit order trades.

We also examined whether excluding stale limit order trades affects the relation

## Table 4.11: Retail Limit Order Trading Performance Excluding Stale Limit Orders

This table reports the results of estimating panel regressions examining the trade performance of retail investors around earnings announcements with stock fixed effects. The dependent variable is the market-adjusted holding period return ($HPR_{[t,T+t]}$) to a representative investor who takes a position on the close of trading based on the net limit order trade imbalance excluding stale limit orders on the day. Ann is an indicator variable that takes the value of 1 if the investor placed a position on the day of the earnings announcement and Post-Ann is an indicator variable that takes the value of 1 if the investor placed a position in the post-event window $[1, 5]$. To account for daily variations in trade imbalances, regressions are estimated by weighting the trade return on each stock and day by the net dollar volume traded for all limit order trades, excluding stale limit orders, for each investor category. Coefficient estimates (x100) are reported along with t-statistics in parentheses calculated from robust standard errors clustered by firm and date. The symbols ** and * indicate significance at the 1% and 5% levels respectively

| | Announcement Date | | | | |
|---|---|---|---|---|---|
| | 5 | 10 | 21 | 42 | 63 |
| Retail | -0.790** | -1.182** | -1.190** | -1.550* | -1.607* |
| | (-4.07) | (-3.95) | (-2.64) | (-2.43) | (-1.96) |
| - Full-service Retail | -0.504** | -0.481 | -0.238 | -0.108 | -0.161 |
| | (-3.31) | (-1.26) | (-0.34) | (-0.12) | (-0.15) |
| - Discount Retail | -0.819** | -1.328** | -1.378** | -1.913** | -2.011** |
| | (-4.04) | (-4.78) | (-3.38) | (-3.36) | (-2.82) |

| | Post Announcement Window | | | | |
|---|---|---|---|---|---|
| | 5 | 10 | 21 | 42 | 63 |
| Retail | -0.260* | -0.531** | -0.269 | -0.262 | -0.251 |
| | (-2.27) | (-2.86) | (-1.00) | (-0.72) | (-0.66) |
| - Full-service Retail | -0.112 | -0.175 | 0.068 | 0.172 | 0.146 |
| | (-1.17) | (-1.17) | (0.36) | (0.54) | (0.42) |
| - Discount Retail | -0.279* | -0.611** | -0.345 | -0.333 | -0.292 |
| | (-2.22) | (-3.16) | (-1.21) | (-0.90) | (-0.72) |

## Table 4.12: Predictability of Future Net Investor Trading on News and Non-News Days

This table examines the predictability of future net trading of retail investors. Panel data regressions are estimated where the dependent variable is the cumulative net investor trading measure $NT_{[t+1,t+10]}$, but excludes stale limit orders. RET0 is the market-adjusted return on day 0. News is an indicator variable that takes the value of 1 if an earnings announcement is released on day 0. MOM is defined as the market-adjusted buy and hold returns for the 126 trading days prior to the earnings announcement date, BTM is the ratio of book-to-market equity using accounting data lagged six months, MVE is the market value of equity and $NT_{[t-10,t-1]}$ captures past net trading and is calculated for each investor across all trades. The estimated regressions include stock fixed effects and t-statistics in parentheses are calculated from standard errors clustered by firm and date. The symbols ** and * indicate significance at the 1% and 5% levels respectively.

| | RET0 | RET0xNews | MOM | BTM | MVE | NT[-10,-1] |
|---|---|---|---|---|---|---|
| Retail | -0.540** | -0.672** | -0.047** | 0.051** | -0.104** | 26.347** |
| | (-13.18) | (-5.48) | (-3.63) | (3.10) | (-4.20) | (9.79) |
| - Full-service Retail | -0.135** | -0.079 | -0.010** | 0.009 | -0.015 | 19.487** |
| | (-8.98) | (-1.72) | (-3.03) | (1.33) | (-1.25) | (6.57) |
| - Discount Retail | -0.397** | -0.585** | -0.037** | 0.040** | -0.093** | 27.139** |
| | (-12.27) | (-5.25) | (-3.54) | (2.74) | (-4.26) | (10.68) |

between prior returns, earnings news and the post-event trading patterns of retail investors. Table 4.12 re-estimates Equation (4.5) where the cumulative net trading measure, $NT_{[t+1,t+10]}$ is calculated excluding stale limit order trades. The interaction term RET0xNews remains statistically significant, indicating the distinct news-contrarian behaviour of discount retail investors cannot be explained by the limit order effect.

## 4.5 Conclusion

The theoretical literature arrives at competing predictions about whether earnings disclosures alleviate or exacerbate information asymmetries. If investors differ in their ability to discover and trade on private information prior to earnings announcements, earnings disclosures should decrease information asymmetries. On the other hand, heterogeneity in the ability of investors to process the information contained in the earnings release could lead to an increase in information asymmetries between investors.

We document strong post-announcement trading patterns with institutional investors exhibiting news-momentum behaviour which is mirrored by the news-contrarian behaviour of retail investors. The aggressive trading of retail investors against the direction of the earnings surprise could drive the PEAD effect, which supports the individual trading hypothesis. In contrast, we find only weak evidence of informed trading prior to earnings announcements by full-service retail investors, with no evidence of earnings anticipation by other investors. A possible explanation for our results is that full-service brokers reflect a more sophisticated retail investor clientele who are subject to less scrutiny than institutional investors, and may be more willing to trade on their inside information. At least for discount retail investors, the news-contrarian trading patterns observed are unlikely to be a part of a trading strategy to exploit private information as suggested by Kaniel et al. (2012).

However, we do find a deterioration in the performance of retail trades immediately following earnings announcements relative to non-announcement periods which we cannot attribute to the adverse selection of stale limit orders. Further investigation reveals that the poor performance of their earnings announcement trades are driven by discount retail investors, with institutional investors the likely beneficiaries. The evidence points to earnings disclosures increasing information asymmetries between investors, consistent with the information processing hypothesis. This has potentially significant policy implications for disclosure practices. Our results suggest that measures such as improving disclosure quality (Lawrence, 2013) could be important in leveling the playing field for these investors.

# Chapter 5

# Concluding Remarks

In this thesis, we presented three empirical studies on the Australian equity market examining important issues in the field of market microstructure and investor trading. The findings of this thesis have a number of significant policy implications, but would also be of interest to practitioners.

In Chapter 2, we proposed a high frequency vector autoregression (VAR) model to measure the resiliency of the limit order book. The model captured a rich set of liquidity dynamics. Liquidity shocks were found to have immediate detrimental effects on other dimensions of liquidity but the replenishment process generally occurs quickly, indicating limit order books are resilient. The prevalence of order splitting strategies is not surprising, as it has become a mechanism traders use to benefit from the resiliency of liquidity. A consistently high level of resiliency was found in large stocks, consistent with the activities of automated liquidity providers. However, greater variation in resiliency is observed across smaller stocks, which calls into question whether a permanent market maker presence in these stocks may improve resiliency.

There are many other potential avenues for further research on resiliency. A particularly important direction given the current debates over high frequency trading is the impact of technology changes on the resiliency of the limit order book. Price-time priority rules incentivise competing liquidity providers to invest in trading technology to increase the speed at which they can identify and respond to liquidity imbalances in the limit order book. While this could have a beneficial impact on resiliency, many are concerned over the resulting technology 'arms race' and the social value of improving resiliency over microsecond time horizons.

Chapter 3 compares the limit order behaviour and execution costs of retail and non-retail investors to provide insights into the extent to which technology benefits investors. We find fundamental differences in the trading behaviour between the two groups consistent with their inequalities in access to trading technology. Survival models indicate that institutional investors are more responsive than retail investors to non-execution risk, consistent with their demand for immediacy. However, market makers are the most responsive to the cost of immediacy, indicating that they are best able to capture liquidity opportunities from price improving limit orders.

The ex post cost of retail investor limit orders are significantly higher when they are triggered by institutional investors or market makers, suggesting they can extract 'rents' from their speed advantages at the expense of retail investors. However, our findings on their overall execution costs falls short of supporting the view that trading technology is severely disadvantaging retail investors.

While our study presents an important step towards assessing concerns raised over the unequal playing field created by access to trading technology, further investigation is warranted. Understanding how advances in technology improve the way investors manage the trading process and affect execution outcomes is relevant to both regulators and practitioners. Future research could also address some of the limitations in our analysis. In particular, one could take advantage of technology upgrades as exogenous events to shed further light as to the impact of algorithmic trading on the welfare of retail investors in the Australian equity market.

Finally, Chapter 4 examines information-based trading by institutional and retail investors around earnings announcements. Retail investors exhibit strong news-contrarian behaviour following earnings announcements, consistent with the individual trading hypothesis while institutional investors exhibit news-momentum behaviour. In contrast, we find only weak evidence of informed trading prior to earnings announcements by full-service retail investors, with no evidence of earnings anticipation by other investors. At least for discount retail investors, the news-contrarian trading patterns observed are unlikely to be a part of a trading strategy to exploit private information as suggested by Kaniel et al. (2012).

However, we do find a deterioration in the performance of retail investor trades immediately following earnings announcements relative to non-announcement periods which we cannot attribute to the adverse selection of stale limit orders. Further investigation reveals that this is driven by discount retail investors, with institutional investors the likely beneficiaries. The evidence points to earnings disclosures increasing information asymmetries between investors, consistent with the information processing hypothesis. Our results suggest that measures such as improving disclosure quality (Lawrence, 2013) could be important in leveling the playing field for these investors. Future research could also examine the role of sell-side analysts in processing information contained in earnings disclosures.

# Appendix A

# Time to Recovery - Ask Side Shocks

All the liquidity shocks defined in Section 2.5.1 affected the bid side of the limit order book. Table A.1 reports the recovery estimates from the impulse responses generated by re-defining liqudity shocks to impact the ask-side of the limit order book. The results did not reveal any qualitative differences from our main findings.

## Table A.1: Time to Recovery - Ask Side Shocks

The table summarizes the resiliency of each liquidity shock across all firm-trading weeks. Resiliency is measured as the time required for the effect of a representative liquidity shock to dissipate by a certain percentage (%). The reported levels are 50% (half-life) and 90% and measured on two time scales. Order event time measures the number of limit order book updates observed from the time of the liquidity shock until the effect of the shock on the liquidity variable has declined by 50% or 90%. Calendar time (measured in seconds) is estimated by applying the exponential transformation to forecasts of $d_t$ obtained from the VAR specification. For each liquidity shock, the median, standard deviation, minimum and maximum recovery times are reported across different size categories.

Panel A: Half-life Estimates

| | | | Order Event Time | | | | Time in Seconds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Variable | Size Category | Median | Stdev | Min | Max | Median | Stdev | Min | Max |
| MO | $v_t^{b,1}$ | Large | 9 | 2.0 | 6 | 16 | 0.9 | 0.4 | 0.4 | 2.5 |
| | | Mid | 10.5 | 3.9 | 5 | 26 | 2.5 | 2.8 | 0.6 | 19.0 |
| | | Small | 10 | 4.8 | 2 | 36 | 5.1 | 8.4 | 0.5 | 44.9 |
| OC | $v_t^{b,1}$ | Large | 7 | 0.7 | 6 | 9 | 0.9 | 0.3 | 0.5 | 1.7 |
| | | Mid | 7 | 3.3 | 5 | 24 | 2.4 | 3.3 | 0.9 | 29.8 |
| | | Small | 9 | 4.1 | 3 | 32 | 6.9 | 8.0 | 2.0 | 40.3 |
| AMO | $s_t$ | Large | 14 | 5.2 | 8 | 30 | 1.7 | 0.7 | 0.5 | 3.7 |
| | | Mid | 8 | 2.7 | 4 | 21 | 2.0 | 3.1 | 0.7 | 34.5 |
| | | Small | 9 | 4.0 | 3 | 26 | 5.2 | 6.0 | 1.6 | 29.5 |
| AOC | $s_t$ | Large | 13 | 3.7 | 7 | 23 | 1.7 | 0.6 | 0.5 | 3.2 |
| | | Mid | 7 | 2.4 | 4 | 21 | 2.3 | 3.8 | 0.7 | 42.3 |
| | | Small | 9 | 3.3 | 3 | 21 | 6.2 | 7.0 | 1.9 | 32.1 |
| OCBM | $v_t^{b,25}$ | Large | 20 | 13.5 | 10 | 74 | 2.7 | 2.2 | 1.0 | 15.0 |
| | | Mid | 44 | 178.9 | 10 | >1000 | 14.5 | 115.9 | 1.9 | >657.4 |
| | | Small | 47 | 154.0 | 5 | >1000 | 39.2 | 261.0 | 3.7 | >1912.7 |

Panel B: 90% Recovery Estimates

| | | | Order Event Time | | | | Time in Seconds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Variable | Size Category | Median | Stdev | Min | Max | Median | Stdev | Min | Max |
| MO | $v_t^{b,1}$ | Large | 44 | 7.4 | 32 | 69 | 5.2 | 2.0 | 2.6 | 12.4 |
| | | Mid | 55.5 | 23.1 | 32 | 158 | 16.8 | 26.4 | 5.5 | 240.3 |
| | | Small | 49 | 21.1 | 5 | 127 | 36.9 | 45.9 | 2.3 | 216.4 |
| OC | $v_t^{b,1}$ | Large | 38 | 5.9 | 27 | 53 | 4.6 | 1.8 | 2.6 | 11.2 |
| | | Mid | 48 | 23.3 | 29 | 148 | 15.3 | 26.9 | 5.4 | 249.9 |
| | | Small | 45 | 19.2 | 17 | 128 | 37.1 | 42.5 | 8.4 | 206.3 |
| AMO | $s_t$ | Large | 74 | 21.5 | 46 | 134 | 9.7 | 3.2 | 2.6 | 17.4 |
| | | Mid | 40 | 10.9 | 21 | 85 | 10.2 | 12.2 | 4.2 | 135.2 |
| | | Small | 40 | 18.8 | 9 | 116 | 25.3 | 30.3 | 6.6 | 163.2 |
| AOC | $s_t$ | Large | 72 | 19.2 | 45 | 127 | 9.5 | 3.1 | 2.7 | 16.9 |
| | | Mid | 38.5 | 10.5 | 20 | 84 | 10.6 | 13.0 | 4.1 | 143.9 |
| | | Small | 38.5 | 18.1 | 9 | 117 | 27.0 | 30.6 | 6.8 | 167.7 |
| OCBM | $v_t^{b,25}$ | Large | 112 | 75.4 | 56 | 447 | 14.9 | 12.4 | 6.1 | 90.6 |
| | | Mid | 220 | 311.3 | 46 | >1000 | 74.8 | 306.3 | 9.2 | >2843.1 |
| | | Small | 209 | 321.6 | 20 | >1000 | 172.0 | 641.8 | 14.9 | >2807.9 |

# Appendix B

# Robustness of Implementation Shortfall Results

The measure of opportunity cost used in producing Table 3.14 may exaggerate the penalty on unexecuted limit orders that are not cancelled until the end of the trading day. As retail investors are more likely to leave their limit orders in the order book, this effect may account for the difference in the opportunity costs of retail and non-retail investors. As a robustness test, we propose an alternative definition of implementation shortfall by measuring the opportunity cost assuming all limit orders are cancelled one hour after order submission. Table B.1 presents the estimation results on this alternative implementation shortfall measure incorporating controls for order characteristics and market conditions. We note that this alternative measure will also affect price impact as limit orders that rested in the order book more than an hour prior to execution now receive zero price impact. Our findings remain unchanged under either measure.

## Table B.1: Regressions of Implementation Shortfall - Alternative Definition

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 between 10:10am and 4:00pm from institutions, market makers and retail investors. For a bid limit order, Price Impact is computed as the volume weighted average fill price minus the mid-quote at the time of order submission. Opportunity Cost is computed as the best ask at the time of order cancellation (or price at the close of trading) minus the mid-quote at the time of order submission. Limit orders are assumed to be cancelled after resting in the order book for one hour after order submission. Co-efficient estimates on price impact and opportunity cost regressions are reported separately for both the full sample and a restricted sample. For price impact regressions, the restricted sample contains only executed limit orders while for opportunity cost regressions, it contains only the unexecuted limit orders. For partially filled orders, the price impact (opportunity cost) is based only on the executed (unexecuted) portion of the limit order. 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. The estimated regressions include stock fixed effects. $p$-values are calculated using two way clustered standard errors, where the cluster is defined by stock and day.

| Dependent Variable | Price Impact | | | | Opportunity Cost | | | | Implementation Shortfall | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All Orders | | Executed Orders | | All Orders | | Unexecuted Orders | | All Orders | |
| | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value | Coeff | $p$-value |
| Institutional Dummy | 0.629 | <0.001 | 1.241 | <0.001 | -0.586 | 0.008 | -1.558 | 0.002 | 0.043 | 0.756 |
| Market Maker Dummy | 0.637 | <0.001 | 1.161 | <0.001 | -0.604 | 0.008 | -1.784 | <0.001 | 0.033 | 0.823 |
| Price Aggressiveness | -0.015 | <0.001 | 0.167 | 0.009 | -0.014 | 0.032 | 0.091 | <0.001 | -0.029 | <0.001 |
| Order Size | 0.011 | <0.001 | 0.020 | <0.001 | 0.031 | <0.001 | 0.019 | 0.014 | 0.042 | <0.001 |
| Buy Dummy | -0.024 | 0.264 | -0.050 | 0.317 | -0.050 | 0.534 | -0.090 | 0.610 | -0.074 | 0.452 |
| Spread | -0.089 | 0.004 | -0.445 | 0.001 | 1.699 | <0.001 | 1.648 | <0.001 | 1.610 | <0.001 |
| Volatility | -0.220 | 0.007 | -0.537 | 0.006 | 1.195 | 0.007 | 1.228 | 0.029 | 0.975 | 0.009 |
| Trading Activity | -0.027 | <0.001 | -0.053 | <0.001 | -0.015 | 0.202 | 0.055 | 0.109 | -0.042 | 0.002 |
| Time 11:00-12:00 | 0.015 | 0.132 | 0.011 | 0.645 | -0.064 | 0.160 | -0.200 | 0.042 | -0.049 | 0.305 |
| Time 12:00-13:00 | 0.018 | 0.035 | -0.006 | 0.797 | -0.112 | 0.049 | -0.338 | 0.003 | -0.094 | 0.114 |
| Time 13:00-14:00 | 0.010 | 0.281 | -0.029 | 0.212 | -0.139 | 0.025 | -0.358 | 0.002 | -0.129 | 0.040 |
| Time 14:00-15:00 | 0.010 | 0.369 | -0.024 | 0.326 | -0.136 | 0.019 | -0.358 | 0.001 | -0.126 | 0.025 |
| Time > 15:00 | 0.025 | 0.044 | 0.019 | 0.503 | -0.191 | 0.007 | -0.468 | <0.001 | -0.166 | 0.015 |

# Appendix C

# Additional Results on Net Investor Trading

This appendix presents two sets of additional results on the empirical study presented in Chapter 4. Table C.1 reports the net trading of full-service and discount retail investors around earnings announcements for all earnings surprise quintiles. Table C.2 presents the full results from estimating regression specifications (4.3) and (4.4) on net-institutional and retail investor trading. For robustness, we calculated post-event net trading for five different time horizons.

## Table C.1: Net Retail Investor Trading around Earnings Announcements

This table presents average net trading among full-service and discount retail investors around earnings announcements, conditional on different levels of the earnings surprise. On any given day, the net trading measure is constructed by subtracting the daily volume of shares sold from the volume of shares bought and dividing this by the number of shares outstanding. This measure is then cumulated over different time periods before, during and after the earnings announcement. Announcements are sorted into quintiles with announcements in Q1 having the most negative earnings surprise. We report the estimated means across all earnings announcements in each surprise quintile along with cluster corrected t-statistics in parentheses (null hypothesis of zero net trading) based on semi-annual clustering. The symbols ** and * indicates significance at the 1% and 5% level respectively.

Panel A: Full Service Retail Investors

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q1 | Mean | -0.048% | -0.026%** | -0.019%* | -0.005% | 0.000% | 0.002% | 0.004% | 0.014% | 0.017% | -0.033% |
| | t-stat | (-1.35) | (-3.66) | (-2.51) | (-1.12) | (-0.06) | (0.39) | (0.55) | (1.23) | (0.99) | (-0.86) |
| Q2 | Mean | -0.064% | -0.020% | -0.015% | -0.010%* | -0.001% | -0.004% | -0.014%** | -0.026%** | -0.030%* | -0.052%* |
| | t-stat | (-1.93) | (-1.22) | (-1.88) | (-2.20) | (-0.73) | (-1.54) | (-3.79) | (-4.17) | (-2.14) | (-1.96) |
| Q3 | Mean | -0.088%** | -0.043%* | -0.015% | -0.005% | 0.000% | 0.001% | -0.011% | -0.024%* | -0.067%** | -0.111%** |
| | t-stat | (-2.80) | (-2.26) | (-1.61) | (-1.48) | (0.10) | (0.14) | (-1.70) | (-2.35) | (-5.19) | (-3.74) |
| Q4 | Mean | -0.098% | -0.016% | -0.015% | -0.009% | -0.002% | -0.003% | -0.014%** | -0.032%** | -0.048%** | -0.094%** |
| | t-stat | (-1.88) | (-0.98) | (-1.17) | (-1.19) | (-1.43) | (-1.52) | (-4.74) | (-8.41) | (-2.69) | (-3.07) |
| Q5 | Mean | -0.078%** | 0.012% | 0.007% | 0.025% | -0.001% | -0.005% | -0.024%** | -0.037%** | -0.076%** | -0.096%* |
| | t-stat | (-2.74) | (1.13) | (1.35) | (1.17) | (-0.26) | (-1.69) | (-3.86) | (-3.23) | (-4.28) | (-2.38) |
| Q5-Q1 | Mean | -0.030% | 0.037%** | 0.026%** | 0.030% | 0.000% | -0.007% | -0.028%** | -0.051%** | -0.093%** | -0.062% |
| | t-stat | (-0.66) | (3.00) | (2.83) | (1.36) | (-0.09) | (-1.19) | (-3.00) | (-3.15) | (-3.75) | (-1.11) |

Panel B: Discount Retail Investors

| | | [-63 -1] | [-21 -1] | [-10 -1] | [-5 -1] | [0 0] | [0 1] | [1 5] | [1 10] | [1 21] | [1 63] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q1 | Mean | 0.379%** | 0.162%** | 0.073%** | 0.025%** | 0.078%** | 0.111%** | 0.113%** | 0.171%** | 0.273%** | 0.588%** |
| | t-stat | (2.78) | (2.66) | (3.32) | (2.84) | (8.26) | (11.31) | (7.05) | (6.17) | (4.33) | (3.36) |
| Q2 | Mean | -0.065% | -0.023% | -0.007% | -0.007% | 0.008%** | 0.014%** | 0.017%* | 0.026%** | 0.035% | 0.004% |
| | t-stat | (-1.23) | (-1.33) | (-0.81) | (-1.21) | (3.93) | (3.92) | (2.08) | (2.62) | (1.51) | (0.08) |
| Q3 | Mean | 0.064% | 0.062%* | 0.030% | 0.016% | 0.002% | 0.005% | 0.035% | 0.040% | 0.027% | -0.004% |
| | t-stat | (0.92) | (2.16) | (1.51) | (1.88) | (0.65) | (0.90) | (1.47) | (1.45) | (0.98) | (-0.04) |
| Q4 | Mean | 0.113% | 0.027% | 0.009% | 0.005% | -0.008%** | -0.009% | 0.002% | -0.002% | -0.011% | -0.015% |
| | t-stat | (0.86) | (1.11) | (0.61) | (1.09) | (-3.09) | (-1.61) | (0.15) | (-0.10) | (-0.43) | (-0.24) |
| Q5 | Mean | 0.244%* | 0.099%* | 0.058%** | 0.039%** | -0.034%** | -0.037%** | -0.008% | -0.018% | -0.043% | -0.003% |
| | t-stat | (2.58) | (2.33) | (3.00) | (3.27) | (-4.70) | (-3.87) | (-0.61) | (-1.23) | (-1.64) | (-0.03) |
| Q5-Q1 | Mean | -0.135% | -0.063% | -0.015% | 0.015% | -0.112%** | -0.147%** | -0.122%** | -0.188%** | -0.316%** | -0.590%** |
| | t-stat | (-0.82) | (-0.85) | (-0.50) | (0.98) | (-9.41) | (-10.81) | (-5.72) | (-6.04) | (-4.63) | (-2.93) |

## Table C.2: Explaining Post-Announcement Net Trading - Institutional and Retail Investors

This table presents results on the relation between post-announcement net institutional or retail trading and the earnings surprise. Regressions were estimated where the dependent variable is post-event net trading ($NT_{[1,T]}$) calculated separately for institutional and retail investors over different time periods. The explanatory variables include either the earnings surprise measure CAR0 or dummy variables for quintiles 1,2,4 and 5 of the earnings surprise measure CAR0, momentum (MOM) defined as the market-adjusted buy and hold returns for the 126 trading days prior to the earnings announcement date, the book-to-market ratio (BTM), market value of equity (MVE) and net trading prior to the earnings announcement ($NT_{[-T,-1]}$) computed for each investor across all orders. Following Taylor (2010), we use the decile ranks scaled from 0 to 1 for BTM and MVE. Cluster corrected t-statistics are reported in parentheses below besides the estimated coefficient (x100) based on semi-annual clustering. The symbols ** and * indicates significance at the 1% and 5% level respectively.

Panel A: Institutional Investors

| | $NT_{[1,5]}$ | $NT_{[1,10]}$ | $NT_{[1,21]}$ | $NT_{[1,42]}$ | $NT_{[1,63]}$ | $NT_{[1,5]}$ | $NT_{[1,10]}$ | $NT_{[1,21]}$ | $NT_{[1,42]}$ | $NT_{[1,63]}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.02 | -0.04 | -0.04 | -0.02 | 0.11 | 0.01 | -0.01 | 0.04 | 0.08 | 0.27 |
| | (-0.75) | (-1.26) | (-0.82) | (-0.16) | (0.64) | (0.18) | (-0.17) | (0.57) | (0.57) | (1.24) |
| CAR0 | 1.46** | 2.37** | 4.06** | 5.98** | 6.64** | | | | | |
| | (8.89) | (8.99) | (4.38) | (4.66) | (5.33) | | | | | |
| CAR0Q1 | | | | | | -0.15** | -0.23** | -0.41** | -0.56** | -0.71** |
| | | | | | | (-7.08) | (-6.42) | (-4.66) | (-4.83) | (-5.17) |
| CAR0Q2 | | | | | | -0.02 | -0.04 | -0.11* | -0.09 | -0.12 |
| | | | | | | (-1.79) | (-1.81) | (-2.33) | (-1.27) | (-0.99) |
| CAR0Q4 | | | | | | 0.01 | 0.04* | 0.07 | 0.14 | 0.10 |
| | | | | | | (1.25) | (2.11) | (1.60) | (1.87) | (0.62) |
| CAR0Q5 | | | | | | 0.07** | 0.11** | 0.18** | 0.23** | 0.22 |
| | | | | | | (3.63) | (3.75) | (3.04) | (2.82) | (1.83) |
| MOM | 0.11* | 0.19* | 0.39** | 0.67** | 0.84** | 0.11* | 0.19* | 0.39** | 0.67** | 0.84** |
| | (2.17) | (2.40) | (2.74) | (2.73) | (2.64) | (2.20) | (2.45) | (2.78) | (2.78) | (2.70) |
| $NT_{[-T,-1]}$ | 19.98 | 30.97 | 59.92* | 67.06 | 74.70 | 20.25 | 31.36 | 60.97* | 68.34 | 75.26 |
| | (1.58) | (1.77) | (2.27) | (1.79) | (1.66) | (1.59) | (1.77) | (2.31) | (1.81) | (1.67) |
| BTM | -0.05 | -0.08 | -0.23* | -0.35** | -0.42** | -0.04 | -0.08 | -0.22* | -0.35** | -0.42** |
| | (-1.49) | (-1.71) | (-2.57) | (-2.99) | (-2.93) | (-1.47) | (-1.69) | (-2.49) | (-3.06) | (-3.02) |
| MVE | 0.04 | 0.11* | 0.28** | 0.40* | 0.25 | 0.03 | 0.09 | 0.25** | 0.35* | 0.18 |
| | (1.06) | (2.02) | (3.05) | (2.54) | (1.29) | (0.79) | (1.74) | (2.94) | (2.38) | (1.02) |

Panel B: Retail Investors

| | $NT_{[1,5]}$ | $NT_{[1,10]}$ | $NT_{[1,21]}$ | $NT_{[1,42]}$ | $NT_{[1,63]}$ | $NT_{[1,5]}$ | $NT_{[1,10]}$ | $NT_{[1,21]}$ | $NT_{[1,42]}$ | $NT_{[1,63]}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.03 | 0.04 | 0.04 | 0.13 | 0.17 | 0.01 | 0.01 | -0.03 | 0.02 | 0.00 |
| | (1.14) | (1.34) | (0.88) | (1.17) | (1.08) | (0.43) | (0.28) | (-0.57) | (0.16) | (0.00) |
| CAR0 | -1.13** | -1.83** | -2.75** | -4.09** | -4.21** | | | | | |
| | (-8.61) | (-9.54) | (-4.87) | (-5.60) | (-5.04) | | | | | |
| CAR0Q1 | | | | | | 0.11** | 0.19** | 0.32** | 0.47** | 0.58** |
| | | | | | | (6.06) | (5.49) | (5.43) | (5.44) | (4.64) |
| CAR0Q2 | | | | | | 0.00 | 0.02 | 0.08* | 0.07 | 0.08 |
| | | | | | | (0.49) | (1.02) | (2.33) | (1.11) | (0.66) |
| CAR0Q4 | | | | | | -0.02 | -0.02 | 0.00 | -0.02 | 0.01 |
| | | | | | | (-1.59) | (-1.22) | (0.06) | (-0.28) | (0.10) |
| CAR0Q5 | | | | | | -0.05** | -0.08* | -0.11* | -0.12 | -0.07 |
| | | | | | | (-2.76) | (-2.34) | (-2.27) | (-1.69) | (-0.76) |
| MOM | -0.08* | -0.13** | -0.24* | -0.45* | -0.58* | -0.08* | -0.13** | -0.24* | -0.45* | -0.57* |
| | (-2.43) | (-2.60) | (-2.25) | (-2.32) | (-2.26) | (-2.50) | (-2.67) | (-2.29) | (-2.36) | (-2.33) |
| $NT_{[-T,-1]}$ | 27.59 | 40.62* | 57.63 | 68.70 | 76.04 | 27.53 | 40.55* | 57.92 | 68.49 | 75.33 |
| | (1.94) | (2.00) | (1.69) | (1.47) | (1.35) | (1.93) | (1.99) | (1.69) | (1.45) | (1.33) |
| BTM | 0.02 | 0.03 | 0.13 | 0.15 | 0.17 | 0.01 | 0.03 | 0.13 | 0.15 | 0.17 |
| | (0.67) | (0.82) | (1.77) | (1.29) | (1.27) | (0.61) | (0.78) | (1.72) | (1.32) | (1.30) |
| MVE | -0.03 | -0.07 | -0.19* | -0.37* | -0.41* | -0.02 | -0.06 | -0.17* | -0.33* | -0.35 |
| | (-0.98) | (-1.46) | (-2.20) | (-2.31) | (-2.11) | (-0.69) | (-1.14) | (-2.06) | (-2.15) | (-1.92) |

# Bibliography


Admati, A. and P. Pfleiderer (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies 1*, 3–40.

Alfonsi, A., A. Fruth, and A. Schied (2010). Optimal execution strategies in limit order books with general shape functions. *Quantitative Finance 10*(2), 143–157.

Ali, A., C. Durtschi, B. Lev, and M. Trombley (2004). Changes in institutional ownership and subsequent earnings announcement abnormal returns. *Journal of Accounting, Auditing, and Finance 19*, 221–248.

Anand, A. and K. Venkataraman (2012). Should exchanges impose market maker obligations? Working paper.

Andersen, P. and R. Gill (1982). Cox regression model counting process: A large sample study. *Annals of Statistics 10*, 1100–1120.

Arino, M. A. and P. H. Franses (2000). Forecasting the levels of vector autoregressive log-transformed time series. *International Journal of Forecasting 16*, 111–116.

ASX (2010). Algorithmic trading and market access arrangements. Technical report, ASX.

Australian Securities Exchange (2008). *Integrated Trading System Reference Manual.* Australian Securities Exchange.

Baker, M., L. Litov, J. A. Wachter, and J. Wurgler (2010). Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements. *Journal Of Financial And Quantitative Analysis 45*(5), 1111–1131.

Barber, B. M., Y.-T. Lee, Y.-J. Liu, and T. Odean (2009). Just how much do individual investors lose by trading? *Review of Financial Studies 22*, 609–632.

Barber, B. M. and T. Odean (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance 55*, 773–806.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*, 785–818.

Bardsen, G. and H. Luetkepohl (2009). Forecasting levels of log variables in vector autoregressions. Working Paper Series, Department of Economics, Norwegian University of Science and Technology.

Battalio, R. H. and R. R. Mendenhall (2005). Earnings expectations, investor trade size, and anomalous returns around earnings announcements. *Journal of Financial Economics 77*, 289–319.

Bennett, J., R. Sias, and L. Starks (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies 16*, 1203–1239.

Berkman, H. and M. D. McKenzie (2012). Earnings announcements: Good news for institutional investors and short sellers. *Financial Review 47*(1), 91–113.

Berkman, H. and C. Truong (2009). Event day 0? After-hours earnings announcements. *Journal of Accounting Research 47*(1), 71–103.

Bernard, V. L. and J. K. Thomas (1989). Post-earnings-announcement drift: Delayed price responses or risk premium. *Journal of Accounting Research 7*, 1–36.

Bernard, V. L. and J. K. Thomas (1990). Evidence that stock price do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics 13*, 305–340.

Berry, T. and K. J. Gamble (2013). Informed local trading prior to earnings announcements. *Journal of Financial Markets 16*, 505–525.

Bessembinder, H., J. Hao, and M. Lemmon (2011). Why designate market makers? Affirmative obligations and market quality. Working paper.

Bhattacharya, N. (2001). Investors trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review 76*(2), 221–244.

Biais, B., T. Foucault, and S. Moinas (2012). Equilibrium high-frequency trading. SSRN Working paper.

Biais, B., P. Hillion, and C. Spatt (1995). An empirical analysis of the limit order book and the order flow in the Paris Bourse. *Journal of Finance 50*, 1655–1689.

Bloomfield, R., M. OHara, and G. Saar (2005). The make or take decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics 75*, 165–199.

Boehmer, E., K. Y. L. Fong, and J. J. Wu (2012). International evidence on algorithmic trading. AFA 2013 San Diego Meetings Paper.

Brandt, M. W., R. Kishore, P. Santa-Clara, and M. Venkatachalam (2008). Earnings announcements are full of surprises. SSRN Working paper.

Brogaard, J. (2010). High frequency trading and its impact on market quality. Working paper, Northwestern University.

Brogaard, J., T. Hendershott, S. Hunt, T. Latza, L. Pedace, and C. Ysusi (2013). High-frequency trading and the execution costs of institutional investors. FSA Occasional Papers in Financial Regulation.

Brogaard, J., T. Hendershott, and R. Riordan (2013). High frequency trading and price discovery. Working paper.

Brooks, R. M. (1996). Changes in asymmetric information at earnings and dividend announcements. *Journal of Business Finance and Accounting 23*(3), 359–378.

Brunnermeier, M. K. (2005). Information leakage and market efficiency. *Review of Financial Studies 18*(2), 417–457.

Bushee, B. J., M. J. Jung, and G. S. Miller (2011). Do investors benefit from selective access to management? SSRN Working paper.

Campbell, J. Y., T. Ramadorai, and A. Schwartz (2009). Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics 92*(1), 66–91.

Cao, C., O. Hansch, and X. Wang (2009). The information content of an open limit-order book. *Journal of Futures Markets 29*(1), 16–41.

Chae, J. (2005). Trading volume, information asymmetry, and timing information. *Journal of Finance 60*(1), 413–442.

Chakrabarty, B., Z. Han, K. Tyurin, and X. Zheng (2006). A competing risk analysis of executions and cancellations in a limit order market. Working paper. Center for Applied Economics and Policy Research, Indiana University.

Copeland, T. and D. Galai (1983). Information effects on the bid-ask spread. *Journal of Finance 38*, 1457–1469.

Coppejans, M., I. Domowitz, and A. Madhavan (2004). Resiliency in an automated auction. Working paper, ITG.

Cox, D. (1972). Regression models and life tables. *Journal of the Royal Statistical Society, Series B 34*(2), 187–220.

Danielsson, J. and R. Payne (2012). Liquidity determination in an order driven market. *The European Journal of Finance 18*(9), 799–821.

De Winne, R. and C. D'hondt (2007). Hide-and-seek in the market: Placing and detecting hidden orders. *Review of Finance 11*(4), 663–692.

Degryse, H. F., M. D. Jong, M. V. Ravenswaaij, and G. Wuyts (2005). Aggressive orders and the resiliency of a limit order market. *Review of Finance 9*(4), 201–242.

Diamond, D. (1985). Optimal release of information by firms. *Journal of Finance 40*, 1071–1094.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics 18*, 277–311.

Dong, J., A. Kempf, and P. K. Yadav (2007). Resiliency, the neglected dimension of market liquidity: Empirical evidence from the New York Stock Exchange. SSRN Working paper.

Dufour, A. and R. Engle (2000). Time and the impact of a trade. *Journal of Finance 55*(6), 2467–2498.

Duong, H. N., P. Kalev, and C. Krishnamurti (2009). Order aggressiveness of institutional and individual investors. *Pacific-Basin Finance Journal 17*, 533–546.

Easley, D. and M. O'Hara (1992). Time and the process of security price adjustment. *Journal of Finance 47*(2), 576–605.

Efron, B. (1977). The efficiency of Cox's likelihood function for censored data. *Journal of the American Statistical Association 72*, 557–565.

Egginton, J. F., B. F. V. Ness, and R. A. V. Ness (2014). Quote stuffing. Working paper.

Engle, R. F. and A. J. Patton (2004). Impacts of trades in an error-correction model of quote prices. *Journal of Financial Markets 7*(1), 1–25.

Fischer, P. E. and R. E. Verrecchia (1999). Public information and heuristic trade. *Journal of Accounting and Economics 27*, 89–124.

Fong, K. Y. and W.-M. Liu (2010). Limit order revisions. *Journal of Banking and Finance 34*, 1873–1885.

Fong, K. Y. L., D. R. Gallagher, and A. D. Lee (2014). Individual investors and broker types. Journal of Financial and Quantitative Analysis forthcoming.

Foster, D. and S. Viswanathan (1990). A theory of the interday variations in volume, variance, and trading costs in securities markets. *Review of Financial Studies 3*(4), 593–624.

Foucault, T. (1999). Order flow composition and trading costs in a dynamic limit order market. *Journal of Financial Markets 2*, 99–134.

Foucault, T., O. Kadan, and E. Kandel (2005). Limit order book as a market for liquidity. *Review of Financial Studies 18*, 1171–1217.

Foucault, T., A. Roell, and P. Sandas (2003). Market making with costly monitoring: An analysis of the SOES controversy. *Review of Financial Studies 16*(2), 345–384.

Frino, A., D. Gallagher, G. Li, and V. Mollica (2013). Why do institutional investors use reputable brokers? Working paper.

Gallagher, D. R. and A. Looi (2006). Trading behaviour and the performance of daily institutional trades. *Accounting and Finance 46*, 125–147.

Gallagher, D. R., A. Looi, and M. Pinnuck (2010). Are active fund managers collectors of private information or fast interpreters of public information? *Accounting and Finance 50*, 635–662.

Garbade, K. (1982). *Securities Markets*. New York: McGraw Hill.

Glosten, L. R. and P. R. Milgrom (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*(1), 71–100.

Griffin, J., J. Harris, T. Shu, and S. Topaloglu (2011). Who drove and burst the tech bubble? *Journal of Finance 66*, 1251–1290.

Griffin, J. M., J. H. Harris, and S. Topaloglu (2003). The dynamics of institutional and individual trading. *The Journal Of Finance 58*(6), 2285–2320.

Griffin, J. M., T. Shu, and S. Topaloglu (2010). Examining the dark side of financial markets: Who trades ahead of major announcements. Working paper.

Griffiths, M. D., B. F. Smith, D. S. Turnbull, and R. W. White (2000). The costs and determinants of order aggressiveness. *Journal of Financial Economics 56*(1), 65 – 88.

Grinblatt, M. and M. Keloharju (2000). The investment behavior and performance of various investor-type: A study of Finland's unique data set. *Journal of Financial Economics 55*(1), 43–67.

Haldane, A. (2011). The race to zero. Bank of England Speeches, Speech given to the International Economic Association Sixteenth World Congress.

Harris, L. (1996). Does a minimum price variation encourage order exposure? Unpublished working paper, University of Southern California.

Harris, L. and J. Hasbrouck (1996). Market vs. limit orders: The superdot evidence on order submission strategy. *Journal of Financial and Quantitative Analysis 31*, 213–231.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance 46*, 179–207.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *Journal of Finance 50*, 1175–1199.

Hasbrouck, J. and G. Saar (2009). Technology and liquidity provision: The blurring of traditional definitions. *Journal of Financial Markets 12*, 143–172.

Hautsch, N. and R. Huang (2012). The market impact of a limit order. *Journal of Economic Dynamics and Control 36*(4), 501 – 522.

Hedvall, K. and J. Niemeyer (1996). Order flow dynamics: Evidence from the Helsinki Stock Exchange. Working paper.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). Does algorithmic trading improve liquidity? *Journal of Finance 66*(1), 33.

Hirshleifer, D., J. N. Myers, L. A. Myers, and S. H. Teoh (2008). Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades. *The Accounting Review 83*, 1521–1550.

Hirshleifer, D., A. Subrahmanyam, and S. Titman (1994). Security analysis and trading patterns when some investors receive information before others. *Journal of Finance 49*, 1665–1698.

Hmaied, D. M., A. Grar, and O. B. Sioud (2006). Dynamics of market liquidity of Tunisian stocks: An analysis of market resiliency. *Electronic Markets 16*(2), 140–153.

Hoffmann, P. (2012). A dynamic limit order market with fast and slow traders. SSRN Working paper.

Hvidkjaer, S. (2008). Small trades and the cross-section of stock returns. *Review of Financial Studies 21*(3), 1123–1151.

IOSCO (2011). Consultation report on regulatory issues raised by the impact of technological changes on market integrity and effciency. Technical report, IOSCO.

Irvine, P., M. Lipson, and A. Puckett (May 2007). Tipping. *Review of Financial Studies 20*(3), 741–768.

Jackson, A. (2003). The aggregate behaviour of individual investors. Working paper.

Jegadeesh, N. and Y. Tang (2011). Institutional trades around takeover announcements: skill vs. insider information. *The Review of Financial Studies 20*, 741–768.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*, 65–91.

Jegadeesh, N. and S. Titman (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance 56*, 699–720.

Johansen, S. and M. Nielsen (2012). Likelihood inference for a fractionally cointegrated vector autoregressive model. *Econometrica 80*(6), 2667–2732.

Kalbfleisch, J. and R. Prentice (1980). *The statistical analysis of failure time data.* John Wiley and Sons,Inc.

Kandel, E. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy 103*, 831–872.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2012). Individual investor trading and return patterns around earnings announcements. *Journal of Finance 67*(2), 639–680.

Kaniel, R., G. Saar, and S. Titman (2008). Individual investor trading and stock returns. *Journal of Finance 63*, 273–310.

Kelley, E. K. and P. C. Tetlock (2013). How wise are crowds? Insights from retail orders and stock returns. *Journal of Finance 68*(3), 1229–1265.

Kim, O. and R. E. Verrecchia (1994). Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics 17*, 41–67.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica 53*, 1315–1336.

Large, J. (2007). Measuring the resiliency of an electronic limit order book. *Journal of Financial Markets 10*(1), 1–25.

Lawrence, A. (2013). Individual investors and financial disclosure. *Journal of Accounting and Economics 56*, 130–147.

Lee, C. M. (1992). Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics 15*, 265–302.

Lee, C. M., B. Mucklow, and M. J. Ready (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies 6*, 345–374.

Linnainmaa, J. T. (2010). Do limit orders alter inferences about investor performance and behavior? *The Journal of Finance 65*(4), 1473–1506.

Liu, W.-M. (2009). Monitoring and limit order submission risks. *Journal of Financial Markets 12*, 107–141.

Livne, G. (2000). Information asymmetry, investment horizons, and the dual role of public announcements. *Review of Accounting Studies 5*, 127–153.

Lo, A. W., C. MacKinlay, and J. Zhang (2002). Econometric models of limit-order executions. *Journal of Financial Economics 65*(1), 31–71.

Lutkepohl, H. (1990). Asymptotic distributions of impulse response functions and forecast error variance decompositions of vector autoregressive models. *Review of Economics and Statistics 72*, 116–125.

Malinova, K., A. Park, and R. Riordan (2013). Do retail traders suffer from high frequency traders? Working paper.

Obizhaeva, A. A. and J. Wang (2013). Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets 16*(1), 1–32.

Pardo, A. and R. Pascual (2012). On the hidden side of liquidity. *The European Journal of Finance 18*(10), 949–967.

Parlour, C. A. (1998). Price dynamics in limit order markets. *Review of Financial Studies 11*, 789–816.

Perold, A. (1988). The implementation shortfall: Paper versus reality. *Journal ofPortfolio Management 14*(3), 4–9.

Pintilie, M. (2006). *Competing Risks: A Practical Perspective (Statistics in Practice)* (1 ed.). Wiley.

Puckett, A. and X. S. Yan (2011). The interim trading skills of institutional investors. *The Journal Of Finance 66*(2), 601–633.

Ranaldo, A. (2004). Order aggressiveness in limit order book markets. *Journal of Financial Markets 7*, 53–74.

Rosu, I. (2009). A dynamic model of the limit order book. *Review of Financial Studies 22*(11), 4601–41.

Seasholes, M. and N. Zhu (2010). Individual investors and location bias. *Journal of Finance 65*, 1987–2010.

Shanthikumar, D. (2004). Small and large trades around earnings announcements: Does trading behavior explain post-earnings-announcement drift? Working paper, Harvard Business School.

Sussman, A., L. Tabb, and R. Iati (2009). US equity high frequency trading: Strategies, sizing and market structure. Technical report, TABB Group.

Taylor, D. (2010). Individual investors and corporate earnings. SSRN Working paper.

Venkataraman, K. and A. C. Waisburd (2007). The value of the designated market maker. *Journal of Financial and Quantitative Analysis 42*(03), 735–758.

Verrecchia, R. E. (1982). The use of mathematical models in financial accounting. *Journal of Accounting Research 20*, 1–42.

Vieru, M., J. Perttunen, and H. Schadewitz (2006). How investors trade around interim earnings announcements. *Journal of Business Finance and Accounting 33*(1–2), 145–178.

Yan, X. S. and Z. Zhang (2009). Institutional investors and equity returns: Are short-term institutions better informed? *Review of Financial Studies 22*, 893–924.