Order Submission Strategies of Institutional and Individual Investors

Huu Nhan Duong

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Department of Accounting and Finance
Faculty of Business and Economics
Monash University

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Huu Nhan Duong

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Abstract

This thesis provides three essays on the order submissions of institutional and individual investors in a limit order book market, the Australian Stock Exchange (ASX). In addition, the thesis examines the effect of the removal of broker identifications (IDs) on investors' order submissions on the ASX.

Using the concept of order aggressiveness, which reflects investors' impatience for trading, the first essay investigates the decision of institutional and individual investors to demand liquidity (submit market orders) and supply it (place limit orders). The findings indicate that the order aggressiveness of institutional and individual investors is positively related to the same-side market depth and negatively related to the opposite-side market depth and the bid-ask spread. Institutional investors are also more aggressive in their order submissions when volatility increases in large capitalization (cap) stocks, whereas both institutional and individual investors are less aggressive when volatility increases in medium (mid) cap stocks. Institutions and individuals follow different order submission patterns throughout the trading day, with institutions being more aggressive early in the trading day and individuals becoming more aggressive as trading progresses. Finally, following the removal of broker IDs on the ASX, both institutional and individual investors become less aggressive and more willing to supply liquidity and display their orders in the central limit order book.

The second essay focuses on the information content of the limit order book and examines how it is impacted by the removal of broker IDs. This essay documents a negative relation between future volatility and variations in the liquidity provision in the order book, as captured by the order book slope. This essay also shows that the slope of the limit order book on the demand (buy) side is more informative about future volatility than the slope of the limit

order book on the supply (sell) side. Institutional investors' limit orders are also more informative about future volatility than individual limit orders. Finally, institutional limit orders become more informative about future volatility after the removal of broker IDs on the ASX, whereas minimal impact is observed for the informativeness of individual limit orders. Overall, the results in the first and second essays imply that the removal of broker IDs on the ASX makes investors more willing to submit and expose their informative limit orders in the limit order book. Therefore, this thesis supports the ASX's decision to stop disclosing broker identity information in the central limit order book.

The third essay examines the volume-volatility relation and the roles of the number of trades and average trade size, institutional trading and individual trading, and order imbalance in the volume-volatility relation. This essay provides evidence supporting a positive relation between trading volume and volatility. In addition, the number of trades has a more significant effect on volatility than average trade size. When the number of trades is decomposed into the number of trades of different sizes, the number of trades in the medium size category often has the most significant impact on volatility. This essay also shows that institutional trading and individual trading are positively related to volatility and individual trading often has a more significant effect on volatility than institutional trading. Finally, the findings in this essay indicate that on the ASX, a limit order book market, order imbalance is not the main factor behind the volume-volatility relation.

Declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other institution and that, to the best of my knowledge this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Huu Nhan Duong Date: 18 / 06 / 2009

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Part of the results presented in Chapter 2 of this thesis is accepted for publication in the forthcoming Pacific-Basin Finance Journal special issue on Market Microstructure. I would like to thank the Editor, Professor Ghon Rhee, the Guest-Editor, Associate Professor Carole Comerton-Forde and an anonymous referee for providing various comments and suggestions that improves the paper. I also thank the Financial Management Association (FMA) for awarding the paper developed from Chapter 3, the best PhD paper in the 2009 FMA European Conference. This thesis has been benefited from various comments and suggestions from participants at the FMA Doctorial Consortium, Orlando 2007; the 20th Australasian Finance and Banking Conference, Sydney 2007; the 2nd University of Sydney Microstructure Conference, Sydney 2008; the 4th Annual Central Bank Workshop on Microstructure of Financial Markets, Hong Kong 2008; and the FMA European Conference, Turin 2009.

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Chapter 1: Introduction and Overview

1.1 Introduction

Liquidity plays an important role in financial markets. According to Harris (2003, p. 394), traders like liquidity because it allows them to implement their trading strategies cheaply. Stock exchanges like liquidity because it helps them attract and retain traders, which has important implications for a stock exchange's competitiveness. Regulators also like liquidity because liquid markets are also less volatile markets.

This thesis investigates investors' order submissions to provide insights into issues related to the demand and supply of liquidity on a limit order book market, the Australian Stock Exchange (ASX). In particular, this thesis presents three essays related to the demand and supply of liquidity for two distinct classes of investors: institutional investors and individual investors. The first essay examines the factors affecting institutional and individual investors' decisions to demand and supply liquidity. In a limit order book market without market makers, the supply of liquidity is determined solely by the submission of limit orders, while the placement of market orders represents the demand for liquidity.[1] Therefore, the first essay focuses on the institutional and individual investors' decisions to submit limit orders and provide liquidity or to place market orders and consume liquidity. The second essay investigates the information content of the provision of liquidity in the limit order book on future volatility and the informativeness of institutional versus individual liquidity provisions. The third essay considers the demand side of liquidity and analyzes the impact on volatility

[1] Since all orders on the ASX are priced, technically, there is no market order on the ASX and all orders are limit orders. Some limit orders can, however, be priced aggressively and result in immediate executions. These aggressively priced limit orders are marketable limit orders and are referred to in this thesis simply as market orders, for brevity.

of trading volume, number of trades, average trade size, institutional trading, individual trading, and order imbalance.

The research issues in all three essays are examined in the light of an important change in the structure of the ASX. Despite the common belief that increasing market transparency will improve market quality (see, for example, Madhavan, 1996; Pagano and Roell, 1996; Glosten, 1999), from 28 November 2005, the ASX decided to switch to an anonymous trading system by removing the identifications (IDs) of brokers submitting orders in the central limit order book. The main motivation for this decision was to enhance market liquidity (Australian Stock Exchange, 2005). It is therefore important to address questions on the effect of anonymity on investors' order choice decisions, the information content of the limit order book and the volume-volatility relation. The results of this investigation will provide implications for the success of the ASX's decision.

The three essays are presented individually in Chapters 2, 3, and 4. Each chapter deals with separate research questions and thus the literature relevant to the research questions is discussed and reviewed separately within each chapter. The remainder of this chapter presents an overview of each essay and discusses the contributions of this thesis.

1.2 Overview of the Study

Chapter 2 investigates the order choice decisions of institutional and individual investors on the ASX. The analysis is carried out based on the concept of order aggressiveness, which indicates the level for impatience for trading of investors. A high level of order aggressiveness reflects a high level of an investor's impatience for trading. Chapter 2 documents that the order aggressiveness of institutional and individual investors is positively related to the same-side market depth and negatively related to the opposite-side market depth. When the bid-ask spread widens, both institutions and individuals tend to be less aggressive in their order submissions. Moreover, institutional investors place more aggressive orders when volatility increases in large cap stocks, whereas both institutional and individual investors are less aggressive when volatility increases in mid cap stocks. Institutional investors are more aggressive early on in the trading day, while individual investors increase their order aggressiveness as trading progresses. Finally, both groups of investors are less aggressive after the move to anonymity, with stronger results observed for individual investors.

Chapter 3 examines the information content of the limit order book and the impact of anonymity on the information content of the limit order book. This chapter documents a negative relation between future volatility and slope of the limit order book. The order book slope of the buy side is also more informative than that of the sell side and institutional investors' limit orders are also more informative about future volatility than individual limit orders. Finally, this chapter shows that the removal of broker IDs on the ASX has a significant impact on the predictive power of the limit order book. The move to anonymity increases the informativeness of institutional limit orders and has little effect on the informativeness of individual limit orders.

Chapter 4 investigates the volume-volatility relation and the effect of the number of trades and average trade size, institutional and individual trading, and order imbalance on volatility. The results in this chapter indicate a positive volume-volatility relation. Moreover, the number of trades is more important than average trade size in explaining volatility. This chapter also documents that medium-sized trades have a more significant impact on volatility than large- and small-sized trades. The trading activity of both institutions and individuals are positively related to volatility, with individual trading has a more significant role in explaining volatility than institutional trading. Finally, this chapter shows that order imbalance is not the main factor behind the volume-volatility relation on the ASX.

1.3 Contributions

This thesis considers issues associated with investors' order aggressiveness, limit order book informativeness, trader anonymity, and the volume-volatility relation in a limit order book market. This thesis makes the following contributions to the current literature.

First, this thesis investigates the order aggressiveness of institutional and individual investors. While there are extensive empirical studies on the order choice or order aggressiveness of investors, few studies have made a distinction between institutional and individual investors' orders in their investigation of order aggressiveness. Differentiating between institutional and individual orders while examining investors' order aggressiveness is important because these two classes of investors potentially differ in their possession of private information.[2] Moreover, individual investors are also an important investment group in Australia, with 55% of the adult Australian population owning shares. In terms of market value, individual investors possess at least 22% of the Australian equity market and their trading activities account for about 51% of the market turnover as measured by the number of transactions (D'Aloisio, 2005).

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[2] Szewczyk et al. (1992), Alangar et al. (1999) and Dennis and Weston (2001) find evidence that institutional investors are better informed than individual investors. Chakravarty (2001) documents that medium-sized institutional orders have a significantly greater cumulative stock price impact than individual orders. Moreover, Anand et al. (2005) also show that institutional limit orders outperform retail limit orders.

To the best of my knowledge, Aitken, Almeida, Harris and McInish (2007) and Aitken, Brown and Wee (2007) are the only studies that distinguish between institutional and individual investors' orders while analyzing order aggressiveness. The main focus of Aitken, Almeida, Harris and McInish (2007) is, however to compare the aggressiveness in the liquidity supply of proprietary trading desks and hedge funds with mutual funds, index funds, and insurance companies. In other words, they examine the aggressiveness of limit orders after these orders have already been submitted into the order book. This thesis differs from Aitken, Almeida, Harris and McInish (2007) by analyzing the factors affecting the order aggressiveness of institutional and individual investors at the time of their order submissions. This includes the choice of limit orders and market (marketable limit) orders of institutional and individual investors. This thesis also differs from Aitken, Brown and Wee (2007) by not only analyzing the factors affecting investors' order aggressiveness but also by highlighting whether these factors similarly affect both institutional and individual investors' order aggressiveness. The results of this thesis will enhance the understanding of the similarities as well as the differences in the supply and demand of liquidity of institutional and individual investors in order-driven markets.

Second, this thesis contributes to the current debate regarding whether informed traders use limit orders by examining the informativeness of the limit order book for future price volatility. If informed traders base their trades solely on market orders, as suggested by Glosten (1994) and Seppi (1997), the limit order book should not convey any information regarding future price movements. In contrast, if limit orders are an important component of the order submission strategies of informed traders, as highlighted by Chakravarty and Holden (1995), Bloomfield et al. (2005), Anand et al. (2005), Wald and Horrigan (2005), and Kaniel and Liu (2006), the limit order book should be informative about future price volatility. Analysis of the information content of the limit order book is based on the order book slope (Naes and Skjeltorp, 2006), which describes how the quantity supplied in the order book changes as a function of prices. The use of the order book slope also extends prior work which examines the informativeness of the limit order book based on the quantity (measured by the number of shares or orders) or the order imbalance in the demand and supply side of the order book (Ahn et al., 2001; Pascual and Veredas, 2006). In addition, since different volatility components might exist at the intraday level,[3] this thesis focuses mainly on the predictive power of the limit order book on the permanent (long-run) component of volatility.

Third, this thesis contributes to the current literature by analyzing the effect of a change in the degree of market transparency on institutional and individual investors' order aggressiveness and the information content of the limit order book. This analysis is based on a natural experiment where the same market is examined during two different periods with the only difference being the anonymity of liquidity suppliers. This is different from prior studies which focus on the anonymity of liquidity demanders (see, among others, Seppi, 1990; Forster and George, 1992; Benveniste et al., 1992; Madhavan and Cheng, 1997; Garfinkel and Nimalendran, 2003; Theissen, 2003; Reiss and Werner, 2004). The analysis is also undertaken for the same market and thus, does not rely on the comparison between different markets (see, for example, Garfinkel and Nimalendran, 2003; Heidle and Huang, 2002) or different trading venues within the same markets (see, among others, Grammig et al., 2001; Theissen, 2002; Simaan et al., 2003; Reiss and Werner, 2004).

[3] See, for example, Andersen and Bollerslev (1997a) and Muller et al. (1997).

Foucault et al. (2007) provide a theoretical model suggesting that the move to anonymity increases (decreases) the aggressiveness of uninformed investors if the participation rate of the informed traders in the trading process is low (high). If the participation rate of the informed traders is low, a move to anonymity will therefore increase the order aggressiveness of uninformed investors, which in turn reduce the bid-ask spread and its correlation with future volatility. Empirical evidence regarding the effect of the removal of broker IDs is relatively sparse and often focuses almost exclusively on the effect on the bid-ask spread.[4] To the best of my knowledge, Comerton-Forde and Tang (2008) is the only study that analyzes the effect of removing broker IDs on investors' order aggressiveness. Their study documents a reduction in investors' order aggressiveness following the move to anonymity. The effect of anonymity on the information content of the order book is documented in Foucault et al. (2007). Foucault et al. (2007) present evidence of a decline in the informativeness of the bid-ask spread, which reflects the information contained in the first step of the limit order book, after the move to anonymity on the Euronext Paris.

This study differs from Comerton-Forde and Tang (2008) by differentiating between institutional and individual orders when investigating the impact of reducing market transparency on investors' order aggressiveness. Specifically, this thesis examines whether institutional and individual investors become more or less aggressive following the move to anonymity and whether these two groups of investors react in a similar or different fashion to this change in market transparency. The current study also extends the analysis of Foucault et al. (2007) by investigating the effect of anonymity on the informativeness of the limit order book slope. If, as suggested by Foucault et al. (2007), investors are less aggressive in their order submissions when they expect price volatility to increase, the results will be a widening

[4] See, for example, Comerton-Forde et al. (2005), Haig et al. (2006), Foucault et al. (2007), Comerton-Forde and Tang (2008) and the Securities and Derivatives Industry Association (2007).

of the bid-ask spread and a gentler order book slope.[5] This suggests that the order book slope also contains information on future price volatility. The focus on the order book slope also complements Foucault et al.'s (2007) analysis by providing evidence of the impact of anonymity on the information content of the limit order book beyond the best quotes. The importance of the limit order book beyond the best quote as demonstrated in Cao et al. (2008, 2009) provides support for this examination.

In addition, this thesis analyzes the impact of anonymity on the information content of the slope of the order book based on institutional and individual limit orders. To the best of my knowledge, this is the first study to investigate the impact of anonymity on the information content of the order submissions of two classes of investors with different levels of information and monitoring activity. This investigation, together with the examination of the impact of anonymity on institutional and individual order aggressiveness, provides insights into the question whether and which investor class is more willing to display their orders in the central limit order book and, if they do so, whether and which investor class is more willing to also display informative limit orders in the central limit order book. Since the main purpose of the ASX when removing broker IDs is to counter front-running activities and encourage investors to execute transactions inside the central limit order book (Australian Stock Exchange, 2005), the results documented in this thesis have important implications for the success of the ASX's decision.

Finally, this thesis contributes to the current literature by investigating the roles of number of trades and average trade size, institutional and individual trading, and order imbalance in the

[5] According to Naes and Skjeltorp (2006), when the majority of the share volume in the order book is concentrated near the best quotes, the limit order book slope will be steep. In contrast, a gentle order book slope arises when a greater share volume in the order book is distributed away from the best quotes. Therefore, if investors are less aggressive in their order submissions, a greater share volume will be located away from the best quotes. This results in a gentler limit order book slope.

volume-volatility relation on a limit order book market. Jones et al. (1994) document evidence that for NASDAQ stocks, the volume-volatility relation is driven by the relation between the number of trades and volatility. The average trade size has no information on volatility beyond that contained in the number of trades. Shalen (1993) and Daigler and Wiley (1999) argue that the trading activity of the less informed investors is the key factor behind the volume-volatility relation. In a more recent study, Chan and Fong (2000) provide evidence that order imbalance explains the majority of the volume-volatility relation for a sample of NYSE and NASDAQ stocks.

This thesis argues that it may be premature to conclude that order imbalance plays a dominant role in the volume-volatility relation. The theoretical framework for the role of order imbalance on volatility is based on the argument that market makers infer information from the order flow and adjust their quotes accordingly. Whether this argument holds for an order-driven market with no designated market makers is an empirical question. Existing studies on this issue focus exclusively on the U.S. market, with the presence of specialists or dealers. The use of the Lee and Ready's (1991) algorithm for identifying the initiating side of the transaction, as in Chan and Fong (2000 is also associated with potential classification errors, as suggested by Odders-White (2000), Ellis et al. (2000), Finucane (2000), Theissen (2001), and Boehmer et al. (2007), among others.

Furthermore, although some prior studies have examined the impact of the number of trades and average trade size on volatility for order-driven markets,[6] to the best of my knowledge, none of them take into consideration the possibility that large and aggressive orders can walk up or down the limit order book and create several transactions. In an order-driven market,

[6] See, for example, Song et al. (2005), Tai et al. (2006) and Ciner and Sackley (2007).

such as the ASX, when an aggressive order whose size exceeds the opposite-side market depth arrives at the market, it walks up or down the book and is executed against several smaller orders.[7] Therefore, the arrival of an aggressive order whose size exceeds the opposite-side market depth will result in multiple executions and can inflate the number of trades measure as well as deflates the average trade size measure.

The current study examines the impact of the number of trades and average trade size on volatility when the number of trades and average trade size are calculated without considering the multiple executions from one large order or when several smaller transactions initiated by a large order are grouped together. The thesis also contributes to the literature by examining the role of order imbalance in the volume-volatility relation for a pure limit order book market with no designated market maker. In addition, since institutions and individuals potentially differ in their possession of private information and monitoring activity, the analysis of the impact of institutional and individual trading on volatility in this thesis also provides evidence regarding whether the volume-volatility relation is driven by the trading activity of the less informed investors (Shalen, 1993 and Daigler and Wiley, 1999). Using a proprietary dataset that provides a complete record of all institutional and individual trading in the central limit order book, this thesis overcomes the data limitation encountered in prior literature[8] and thus provides direct evidence of the effect of institutional and individual trading on volatility. Moreover, since specific information on the initiating side of the transaction is known, the study overcomes the potential order imbalance measurement

[7] These orders continue walking up or down the order book until either the orders are fully executed or the order price cannot be matched with any other orders on the opposite side of the book.

[8] Prior studies (see, for example, Reiley and Wachowicz, 1979; Lee and Ward, 1980; Sias, 1996; Dennis and Strickland, 2002; Bohl and Brzeszczynski, 2006; Chiyachantana et al., 2006; Bohl et al., 2008) often rely on the use of changes in institutional ownership or trades executed by a subset of institutions when testing the relation between institutional trading and volatility.

problem that arises due to the application of the Lee and Ready's (1991) algorithm for identifying buyer- and seller-initiated transactions.

Overall, the results of this thesis provide insights into the decision to demand and supply liquidity of institutional and individual investors, the information content of their liquidity provisions, and the impact of their demand of liquidity on volatility. This thesis also highlights the impact of the removal of broker IDs on a limit order market on investors' willingness to supply liquidity, the information content of their liquidity provision, and the impact of their liquidity demand on volatility. The important role of the limit order market as a form of security market organization[9] illustrates the importance of analyzing these issues for this type of market. The findings of this thesis are also relevant for specialist and dealer markets such as the NYSE and the NASDAQ since the limit order book is an important part of these markets' trading (see, among others, Harris and Hasbrouck, 1996; Chung et al., 1999; Bloomfield et al., 2005; Moulton, 2006; Hendershott and Moulton, 2008).

1.4 Structure of the Thesis

The structure of this thesis is as follows: Chapter 2 discusses the order aggressiveness of institutional and individual investors and the effect of anonymity on investors' order aggressiveness. Chapter 3 focuses on the information content of the limit order book and the impact of anonymity on limit order book informativeness. Chapter 4 analyzes the volume-volatility relation and the roles of the number of trades and average trade size, institutional and individual trading, and order imbalance in the volume-volatility relation. Chapter 5 summarizes and concludes the thesis and provides suggestions for future research.

[9] Glosten (1994) provides the theoretical background for the importance of order-driven markets. Jain (2003) documents that at the end of 1999, 26 of the 51 stock markets in his study were limit order markets. Virtually all of the stock markets in Europe are also organized as limit order markets (Handa et al., 2003). For an extensive review of the research on limit order markets, see Parlour and Seppi (2008).

Chapter 2: Order Aggressiveness of Institutional and Individual Investors

2.1 Introduction

2.1.1 Purpose and Motivation

This chapter investigates the factors determining the order aggressiveness of institutional and individual investors on the Australian Stock Exchange (ASX). In addition, the chapter also examines the effect of the removal of broker IDs on the ASX on institutional and individual investors' order aggressiveness. Utilizing a proprietary ASX dataset that identifies institutional and individual order submissions, this chapter addresses three research questions. First, what are the factors affecting the order aggressiveness of institutional and individual investors? Second, do these factors influence institutional and individual investors' order aggressiveness in a similar way? Third, how do institutional and individual investors respond to the change in market transparency; in particular, are institutional and individual investors more or less aggressive following the removal of broker IDs on the ASX?[10]

The investigation of investors' order aggressiveness is important for various reasons. First, according to Harris (1998), understanding the factors that affect order submission strategies (order aggressiveness) will enable traders to decide what type of orders to submit, how to determine order price, and how and when to revise or cancel their orders, if necessary. Therefore, evidence regarding the order aggressiveness of institutional and individual investors will facilitate traders to optimize their trading strategies, which, in turn, will result in lower transaction costs and higher portfolio returns.

[10] From 28 November 2005, brokers can no longer observe the IDs of other brokers submitting orders on the ASX. Prior to this change, brokers were able to identify in real-time the broker number associated with every order (the broker IDs) in the central limit order book for each security traded on the ASX (Australian Stock Exchange, 2005).

Second, unlike a quote-driven market where market makers are obliged to provide liquidity, in an order-driven market such as the ASX, liquidity provision relies solely on the submission of orders (Bloomfield et al., 2005). The submission of limit orders is viewed as the provision (supply) of liquidity, whereas market orders consume (demand) liquidity. Therefore, for the market as a whole, analyzing traders' order submission strategies will help understand the market conditions under which traders are willing to supply (submit limit orders) and demand (place of market orders) liquidity. This will improve the understanding of the price formation process (Ellul et al., 2007) and the fundamental issues of how order-driven markets function (Bloomfield et al., 2005).

Furthermore, examining the changing behavior of institutional and individual investors in different market transparency regimes will provide a better understanding of investors' demand and supply of liquidity in response to a reduction in market transparency. These findings will be helpful to market regulators in designing the market mechanism that will enhance the overall market liquidity.

2.1.2 Main Findings

The order aggressiveness of institutional and individual investors is examined for 30 large cap, 30 mid cap, and 30 small cap stocks traded on the ASX for the period between 1 August 2005 and 31 March 2006. This chapter finds the order aggressiveness of institutional and individual investors to be positively (negatively) related to the same-side (opposite-side) market depth. In addition, a negative relation between order aggressiveness and the bid-ask spread is also observed, except in the small cap stocks for individual investors. The relation between order aggressiveness and volatility is less conclusive, with institutions (institutions and individuals) tending to increase (decrease) their order aggressiveness when volatility increases in large (mid) cap stocks.

This chapter also highlights differences in the order aggressiveness patterns of institutional and individual investors over the course of the trading day. Specifically, institutional investors are more aggressive during the first trading hour, whereas individual investors are less aggressive early in the day and tend to increase their order aggressiveness as the end of the trading day approaches. In addition, individual investors are less aggressive when submitting large orders while institutional investors tend to increase their aggressiveness when submitting large orders, except in small cap stocks. The differences in order aggressiveness patterns and responses to changes in order size between institutional and individual investors are stronger in the anonymous market than in the transparent market. Moreover, institutional and individual investors are more aggressive in their selling activities than in their buying activities in mid cap and small cap stocks. Different responses of individual buyers and sellers to changes in spread and volatility are also documented in mid cap stocks.

Finally, both institutional and individual investors become less aggressive in their order submissions following the removal of broker IDs on the ASX. The reduction in order aggressiveness is, however, much stronger for individual investors than for institutional investors. This finding suggests that following the move to anonymity, both institutional and individual investors are more willing to supply liquidity and display their orders in the central limit order book. Overall, this evidence supports the decision by the ASX to remove broker IDs in order to enhance the overall market liquidity.

2.1.3 Chapter Outline

The rest of the chapter is organized as follows. Section 2.2 provides a review of the current literature and develops the hypotheses to be examined in this chapter. Section 2.3 describes the data utilized for investigating institutional and individual investors' order aggressiveness. Section 2.4 explains the research methods and Section 2.5 discusses the results and implications. The conclusion of the chapter is provided in Section 2.6.

2.2 Literature Review and Hypotheses Development

2.2.1 Determinants of Order Aggressiveness

When making trading decisions, traders can choose to submit limit orders and supply liquidity to the market or post market orders and consume liquidity. This choice reflects the trade-off between the costs and benefits of one particular type of order over the other's. The advantage of using market orders is the immediacy of the order execution, but it comes with the cost of potentially paying higher execution prices. In contrast, limit orders provide price improvement over market orders but are associated with the risk of non-execution. Moreover, since the limit price is fixed over time and monitoring can be costly, limit orders can become mispriced and thus be executed at unfavorable prices. This is often referred to in the literature as the risk of being "picked-off" or "picking-off" risk. The trade-offs among execution probability, price improvement, and "picking-off" risk play a key role in determining traders' order choices.[11] Aitken, Almeida, Harris and McInish (2007) argue that active institutional traders such as hedge funds expend resources monitoring the status of orders while passive traders such as pension funds and individual investors do not. Hence, the "picking-off" risk is relevant to some of the institutional investors and to the majority of individual investors.

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[11] Hollifield et al. (2004) suggest a method to determine if traders' order submissions are consistent with the theory of trade-offs among order price, execution probability and "picking-off" risk. Discussions of the profitability of limit order trading are provided by Handa and Schwartz (1996), Harris and Hasbrouck (1996), Wald and Horrigan (2005) and Hollifield et al. (2006).

Developing a one-tick dynamic model of a limit order market without asymmetric information, Parlour (1998) highlights that the decision to submit a market order or a limit order depends critically on the market depth on either side of the order book. Since this is a one-tick model, traders can either submit a market order, place a limit order which has a lower time priority than existing limit orders, or choose not to trade. Therefore, the execution probability of limit orders depends on the size of the book (market depth) and on the agent's belief about future order arrivals. Parlour (1998) shows that an increase in the buy-side (sell-side) market depth reduces the execution probability of buy (sell) limit orders and induces incoming traders to submit buy (sell) market orders. Furthermore, sellers (buyers) also rationally anticipate the crowding out of limit orders on the buy (sell) side and in this way limit sell (buy) orders become more attractive than market sell (buy) orders. Thus, there is a positive (negative) relation between same-side (opposite-side) market depth and order aggressiveness. Consistent with Parlour (1998), Handa et al. (2003) also show that the greater the excess market depth of the buy (sell) side relative to the market depth of the sell (buy) side, the higher the execution risk to buyers (sellers). Therefore, the larger the imbalance between the buy (sell) side relative to the sell (buy) side, the more likely buyers (sellers) are to use market orders rather than limit orders.

Foucault (1999) develops a game theoretic model of price formation and order placement decisions in a dynamic limit order market where investors differ in their valuations but not in their private information. The author suggests that higher volatility implies a greater risk of being "picked-off" for limit order submitters. Thus, limit order traders will demand a larger compensation for the higher "picking-off" risk in a more volatile market. This in turn results in a larger spread and a higher cost of trading with market orders. Hence, more traders find it optimal to carry out their trades with limit orders rather than market orders. Drawing on this intuition, the model predicts that the proportion of limit orders in the order flow is positively related to price volatility and the bid-ask spread in limit order markets. The prediction of a positive relation between limit order submissions and the bid-ask spread is also consistent with the theoretical model of Cohen et al. (1981), in which limit orders become more attractive as the bid-ask spread increases.

Empirical analysis of investors' order submission strategies generally provides support for theoretical predictions of the effect of spread and market depth on the order aggressiveness of investors. This empirical evidence is consistent and robust for different markets and over different sample periods (see for example Biais et al., 1995; Griffiths et al., 2000; Al-Suhaibani and Kryzanowski, 2000; Ranaldo, 2004; Verhoeven et al., 2004; Beber and Caglio, 2005; Hall and Hautsch, 2006; Ellul et al., 2007; Aitken, Brown and Wee, 2007; Cao et al., 2008).

Past research on the effect of volatility on order aggressiveness is less conclusive. Bae et al. (2003), Ranaldo (2004) and Beber and Caglio (2005) document a positive relation between the placement of limit orders and volatility, as predicted by Foucault (1999). In contrast, Hasbrouck and Saar (2002), Wald and Horrigan (2005) and Aitken, Brown and Wee (2007) find that investors actually decrease their usage of limit orders relative to market orders when volatility increases. The differences in the empirical evidence regarding the effect of volatility on order aggressiveness may be attributed to the assumption of risk-neutral investors in the Foucault (1999) model. Hasbrouck and Saar (2002) suggest that Foucault's (1999) prediction might not be applicable to risk-averse investors.[12] Higher volatility also

[12] Wald and Horrigan (2005) observe that for a risk-averse investor, higher volatility increases the execution probability of limit orders, but it is also associated with greater adverse selection costs. The higher adverse selection costs associated with increased volatility can outweigh the benefits of higher fill rates for limit orders. Thus, a rise in volatility would result in a decline in the use of limit orders relative to market orders.

implies greater costs of order monitoring and management, which in turn reduces the use of limit order strategies. Moreover, if information asymmetry exists among investors, agents with private information can exploit their information and place market orders when the asset is more volatile (Goettler et al., 2008).

Based on the previous theoretical models and empirical results, the hypotheses regarding the effects of market depth, bid-ask spread and volatility on order aggressiveness are formulated as follows[13]:

H_1: Order aggressiveness is positively (negatively) related to the same-side (opposite-side) market depth.

H_2: Order aggressiveness is negatively related to the bid-ask spread.

H_3: Order aggressiveness is negatively related to price volatility.

Prior literature also suggests that the order aggressiveness of investors might exhibit an intraday pattern. Harris (1998) derives a model for optimal dynamic order submission strategies, which encompasses three types of traders: uninformed liquidity traders, informed traders and value-motivated traders. In this model, both liquidity and informed traders become more aggressive as trading progresses. Liquidity traders are more aggressive toward the end of the trading session to achieve their daily targets while the increasing aggressiveness of informed traders is due to the revelation of their "information" at the end of the trading day. Beber and Caglio support Harris's (1998) argument by documenting the increasing aggressiveness of orders throughout the day in their analysis of 10 stocks traded on the NYSE during the period from November 1990 to January 1991.

[13] All the hypotheses in this chapter are stated in the alternative form.

Bloomfield et al. (2005) provide experimental evidence that informed traders are more aggressive and trade mostly with market orders early in the trading day. However, in contrast to Harris (1998), they document that toward the end of the trading day, rather than becoming more aggressive, informed traders, on average, trade more with limit orders than market orders. Uninformed investors behave in the opposite fashion. They are less aggressive early on in the trading day and become more aggressive as the trading day comes to a close. Anand et al. (2005) and Ellul et al. (2007) offer empirical support for the experimental evidence of Bloomfield et al. (2005). Drawing on the findings in prior literature that institutional traders are informed and individual traders are uninformed, Anand et al. (2005) show that institutional (informed) investors are more aggressive and use more market orders in the first half of the trading day than in the second half. In addition, Ellul et al. (2007) observe a positive (negative) relation between elapsed trading time and the probability of limit orders (market sell orders) for 148 stocks traded on the NYSE during the week of April 30 to May 4, 2001.

Based on the evidence presented in Bloomfield et al. (2005), Anand et al. (2005), and Ellul et al. (2007) and on findings in prior studies that institutional investors are better informed,[14] the following hypothesis is formulated regarding the pattern of investors' order aggressiveness over the course of the trading day:

H_4: Institutional (individual) investors are more (less) aggressive early on in the trading day than at the end of the trading day.

[14] See, for example, Szewczyk et al. (1992), Alangar et al. (1999), Dennis and Weston (2001) and Chakravarty (2001).

2.2.2 Order Aggressiveness and the Removal of Broker IDs

The literature on the informativeness of broker identification is relatively sparse and often focuses on the effect of withdrawing (or disclosing) broker IDs on the bid-ask spread.[15] Foucault et al. (2007) develop a theoretical model for limit order markets to explain the changing aggressiveness of informed and uninformed traders after the removal of brokers IDs. In a transparent market, uninformed investors infer information about future price movements from observing the quotation behavior of informed traders. They try to front-run the informed traders to benefit from the information by setting more competitive quotes than those posted by the informed traders. Informed traders respond by sometimes engaging in bluffing strategies, posting non-aggressive orders, and setting wider spreads than appropriate. In an anonymous trading system, uninformed traders cannot distinguish the informed traders' orders from those of uninformed traders. They submit orders based on their belief about the identity of the traders with the orders in the limit order book. In this case, if the participation rate of informed traders is low (high), uninformed traders will be more (less) aggressive, and improve on the already posted orders more (less) often.

Alternatively, Simaan et al. (2003) propose the collusion hypothesis, which argues that a non-anonymous trading system facilitates collusion among liquidity suppliers. Therefore, traders' aggressiveness is lower under the non-anonymous trading system compared to the anonymous system. In support of this hypothesis, Simaan et al. (2003) document evidence that dealers post more aggressive quotes in an anonymous market (the ECNs) than in a transparent market where dealers' IDs are displayed (the NASDAQ). Since the ASX is a limit order market, this study formulates the hypothesis regarding the effect of the removal of

[15] Comerton-Forde et al. (2005), Foucault et al. (2007), and Comerton-Forde and Tang (2008) observe a reduction in the bid-ask spread following the move to anonymity on the Euronext Paris, the Tokyo Stock Exchange, and the ASX. On the other hand, Comerton-Forde et al. (2005) document a larger spread after the Korea Stock Exchange started disclosing broker IDs information.

broker IDs on the ASX on investors' order aggressiveness based on Foucault et al.'s (2007) model.

Prior to 28 November 2005, the ASX disseminated, in real-time, the broker IDs associated with every order in the central limit order book for each security traded on the ASX. However, the broker IDs information associated with individual orders and trades was only disseminated to the broker community. From 28 November 2005, brokers can no longer observe the identification of other brokers submitting orders on the ASX. The ASX provides market share information only at the end of the trading day and releases the full trading history with broker IDs only after a delay of three days. The main reason for the ASX to stop disclosing broker IDs is that exposing broker IDs fosters front-running activities. These activities suppress liquidity and impose extra costs on investors. This results in investors seeking execution outside the central market (the limit order book), which in turn, impairs the overall market liquidity (Australian Stock Exchange, 2005). In addition, although the release of broker IDs information to third parties is strictly prohibited, the Australian Stock Exchange (2005) states that constant breaches in the confidentiality agreement, which explicitly prohibits brokers from telling their clients regarding who is buying and selling, is also a major factor behind the move to anonymity. Ostensibly, institutional clients and very high net worth individuals often request and receive this information from their brokers. This creates an information advantage for those investors using full advisory broking services over those making their own trading decisions (Australian Stock Exchange, 2003).[16]

[16] Empirical evidence on the impact of anonymity on the market quality of the ASX is documented in Comerton-Forde and Tang (2008). The authors observe a reduction in bid-ask spreads, adverse selection risk, trade execution costs, and order exposure risk after the removal of broker IDs on the ASX. They also find a reduction in order aggressiveness following the move to anonymity

Drawing on the insights of Foucault et al. (2007), this thesis argues that if institutional investors are better informed than individual investors, in the non-anonymous trading system they will submit aggressive orders to minimize the risk of being front-run by other traders. Since the risk of front-running activities is reduced in an anonymous trading system, institutional investors will be less aggressive and submit limit orders more often after the removal of broker IDs on the ASX. For individual investors, the move to anonymity reduces the ability of other traders to distinguish their orders and those submitted by institutional investors. Therefore, for individual orders, the move to anonymity will reduce the risk of being "picked-off" by better-informed investors. Thus, individual investors are less aggressive and more willing to expose their orders after the move to anonymity on the ASX.

Based on the above discussion, the following hypothesis regarding the effect of the move to anonymity on investors' order aggressiveness is formulated:

H_5: A move to anonymity decreases institutional and individual investors' order aggressiveness.

2.3 Data

The determinants of order aggressiveness are investigated for 30 large cap, 30 mid cap, and 30 small cap stocks traded on the ASX between August 2005 and March 2006. The selection criteria for these stocks include both stock market capitalization and trading activity. First, this study considers only seasoned stocks that are included in the S&P/ASX 200 index on 1 August 2005. The choice of this index ensures the representation of large cap, mid cap, and small cap stocks as well as the institutional trading interest and the liquidity of the stocks under investigation. Consistent with the ASX's classification, large cap stocks are defined as those included in the S&P/ASX 50 index. Mid cap stocks are defined as those included in the

S&P/ASX 100 index but not in the S&P/ASX 50 index, while stocks included in S&P/ASX 200 index but not in the S&P/ASX 100 index are small cap stocks. Second, all large cap, mid cap, and small cap stocks are ranked based on the daily average number of trades for the three-month period (May to July 2005) before the sample period. The 30 large cap stocks and 30 small cap stocks chosen are the 30 most traded large cap stocks and the 30 least traded small cap stocks, based on the daily average number of trades for the period between May and July 2005, respectively. The 30 mid cap stocks chosen are the 15 stocks above and the 15 stocks below the stocks with median daily average number of trades for the period between May and July 2005.

Two different datasets from the Securities Industry Research Centre of Asia-Pacific (SIRCA) are collected for the investigation of the order aggressiveness of institutional and individual investors. The first dataset is the proprietary Order Book Dataset which records the details for each order, including the order type (submission, revision, cancellation, execution), the date and time to the nearest hundredth of a second, stock code, order price, order volume, and order direction (buy or sell order). Each new order is assigned a unique identification number so that the order can be tracked from its submission through to any revision, cancellation, or execution. A unique feature of this dataset is the provision of the confidential dummy variable, which indicates whether the order is submitted by an institutional or an individual investor. The confidential classification of institutional and individual orders is provided on an aggregated basis by SIRCA, after the approval to release confidential data from the ASX.

The second dataset is the Market Depth Dataset, also provided by SIRCA, which contains information on the market depth of a particular stock. Specifically, it details the 10 best limit prices on the bid and ask side, in association with the total volume (number of shares) and the total number of orders at each price level. This dataset is updated whenever there is a change to the prices and/or volumes of any of these 10 best limit prices. All the records in the Market Depth Dataset in which the bid price is greater than the ask price at any of the 10 limit price levels, are removed. All observations where the bid (ask) prices are not in strict descending (ascending) order from the first to the 10th best prices are also excluded from the sample.

In this study, the Order Book Dataset is matched to the Market Depth Dataset to obtain a final dataset that contains detailed information on every institutional or individual order submission, revision or cancellation together with the market depth information at that time. In addition, only orders submitted in the continuous trading session (from 10:10 to 16:00) are included. All crossing orders, All or Nothing orders and Fill and Kill orders are also excluded from the sample.[17]

2.4 Research Methodology

Consistent with Biais et al. (1995), orders are classified into six levels of order aggressiveness. Category 1, the most aggressive orders, are buy (sell) orders with prices greater (less) than the best ask (bid) quote and the size of the orders exceeds the market depth at the best ask (bid) quote. These buy (sell) orders are executed against the volume at the ask (bid) and in part against the market depth available higher (lower) in the book up to the order price. The unfilled portion of the order enters as a limit order in the order book. Category 2 orders are buy (sell) orders with prices equal to the best ask (bid) quote and demand more volume than the market depth at the best ask (bid) quote. These orders are executed immediately and the unfilled portion the order becomes a limit order at that price in the limit

[17] If an investor submits an All or Nothing order, the order is to be filled in full, or else cancelled. In contrast, if an investor places a Fill and Kill order, the intention is to fill the order as much as possible and to cancel the unexecuted part.

order book. Category 3 orders are orders with price equal to the opposite best quote and demand less volume than the market depth at the opposite best quote. These orders are executed immediately and in full. Category 4 and 5 orders are limit orders within and at the prevailing quotes, respectively. Category 6 orders are the least aggressive, in the sense that they are buy (sell) orders with prices less (greater) than the best bid (ask) quote. Based on this classification, Category 1, 2 and 3 can be classified as market orders, since they result in immediate execution[18], while Category 4, 5 and 6 orders are limit orders, as they are not executed immediately. These orders stand in the limit orders book, waiting for execution.

The following example illustrates the classification of order aggressiveness for buy and sell orders in this chapter. Suppose stock AAA has a best bid (ask) quote at time t of B_1 (A_1) and the market depth available at this quote is V_{B1} (V_{A1}). The order aggressiveness level ($OA_{i,t}$) of the incoming buy order i at time t with price P_i and size V_i is determined as follows:

$$OA_{i,t} = \begin{cases} 1 \text{ if } \mathrm{P_i} > A_1 \,\&\, V_i > V_{A1} \\ 2 \text{ if } \mathrm{P_i} = A_1 \,\&\, V_i > V_{A1} \\ 3 \text{ if } \mathrm{P_i} = A_1 \,\&\, V_i \le V_{A1} \\ 4 \text{ if } \mathrm{A_1} > \mathrm{P_i} > B_1 \\ 5 \text{ if } \mathrm{P_i} = B_1 \\ 6 \text{ if } \mathrm{P_i} < B_1 \end{cases} \tag{2.1}$$

If, instead, a sell order i at time t with price P_i and size V_i is submitted, the order aggressiveness level ($OA_{i,t}$) of this order is determined as follows:

[18] Since all orders on the ASX are priced, Category 1, 2 and 3 orders should be classified as marketable limit orders. For brevity, this thesis refers to them as market orders.

$$OA_{i,t} = \begin{cases} 1 \text{ if } \mathrm{P_i} < B_1 \;\&\, V_i > V_{B1} \\ 2 \text{ if } \mathrm{P_i} = B_1 \;\&\, V_i > V_{B1} \\ 3 \text{ if } \mathrm{P_i} = B_1 \;\&\, V_i \le V_{B1} \\ 4 \text{ if } \mathrm{A_1} > \mathrm{P_i} > B_1 \\ 5 \text{ if } \mathrm{P_i} = A_1 \\ 6 \text{ if } \mathrm{P_i} > A_1 \end{cases} \tag{2.2}$$

The determinants of institutional and individual investors' order aggressiveness are investigated based on the ordered probit model, which consists of two parts. The first part relates the observable action types (R_i) to the latent linking variable (Z_i) as follows:

$$R_i = \begin{cases} 1 \text{ if } \mathrm{Z_i} \in (-\infty, \mu_1] \\ 2 \text{ if } \mathrm{Z_i} \in (\mu_1, \mu_2] \\ 3 \text{ if } \mathrm{Z_i} \in (\mu_2, \mu_3] \\ 4 \text{ if } \mathrm{Z_i} \in (\mu_3, \mu_4] \\ 5 \text{ if } \mathrm{Z_i} \in (\mu_4, \mu_5] \\ 6 \text{ if } \mathrm{Z_i} \in (\mu_5, \infty) \end{cases} \tag{2.3}$$

where R_i is the order aggressiveness, classified as suggested by Biais et al. (1995) and μ_1, μ_2, μ_3, μ_4, and μ_5 are the intercept parameters to be estimated. In the second part of the model, the latent variable Z_i is in turn modelled as follows:

$$Z_i = \beta_1\, \mathrm{Depth}_{same,i} + \beta_2\, \mathrm{Depth}_{opposite,i} + \beta_3\, \mathrm{Spread}_i + \beta_4\, \mathrm{Vola}_i + \beta_5\, \mathrm{FirstInt}_i + \beta_6\, \mathrm{Size}_i$$

$$+ \beta_7\, \mathrm{Direction}_i + \beta_8\, \mathrm{Anonymous}_i + \varepsilon_i\,, \tag{2.4}$$

where $Depth_{same,i}$ ($Depth_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. $Spread_i$ is the relative bid-ask spread, measured as the percentage of the bid-ask spread over the bid-ask mid-point, at the time of order submission. Following Ranaldo (2004), $Vola_i$ is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. $FirstInt_i$ is a dummy variable that equals one for orders submitted between 10:10 and 11:00 and zero otherwise. $Direction_i$ is a dummy variable that equals one for sell orders and zero otherwise. $Size_i$ is the natural logarithm of the number of shares in a particular order. $Anonymous_i$ is a dummy variable that takes on the value of one for orders submitted from 28 November 2005 onward (in the anonymous trading system) and zero otherwise.

Besides spread, market depth, and volatility, a dummy variable for the first trading hour is included to examine the potential differences in the order aggressiveness of institutional and individual investors in the early part of the trading day, as suggested by Bloomfield et al. (2005) and Anand et al. (2005). The dummy variable $Direction_i$ is included to control for the potential asymmetry between buy and sell orders, as documented Ranaldo (2004). $Size_i$ is also incorporated in the ordered probit regression to examine the relation between order size and order aggressiveness. Finally, $Anonymous_i$ is included to investigate the effect of the removal of broker IDs on investors' order aggressiveness. If investors are more (less) aggressive following the move to anonymity, β_8 should be negative (positive) and significant. In order to highlight the potentially different impact an explanatory variable might have on the order aggressiveness of institutional and individual investors, the ordered probit model as given with Equation (2.4) is estimated separately for institutional and individual orders.

Analysis of the institutional and individual investors' order aggressiveness for buy and sell orders is also performed separately to highlight the potential differences in the determinants of order aggressiveness of buyers and sellers as documented in Ranaldo (2004). The following ordered probit model is estimated for institutional and individual investors' buy and sell orders:

$$Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Anonymous}_i + \varepsilon_i \quad (2.5)$$

In addition to incorporating the dummy variable for orders submitted in the anonymous market as in Equation (2.4) and (2.5), the effect of the move to anonymity on investors' order aggressiveness is also examined by analyzing the determinants of institutional and individual investors' order aggressiveness separately for the transparent and the anonymous market. The model is specified as follows:

$$Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \varepsilon_i \quad (2.6)$$

2.5 Results and Discussion

2.5.1 Statistics of Order Submissions

Table 1 provides summary statistics for the orders submitted for the 90 stocks under investigation. In total, 16,438,201 orders are investigated, including 7,207,314 orders submitted by institutional investors and 9,230,887 orders submitted by individual investors. Similar to Aitken, Brown and Wee (2007), Category 5 orders are the most common orders for institutional investors, while the most common orders for individual investors are Category 6 orders. In addition, consistent with Parlour (1998) and Handa et al. (2003), both institutional and individual investors tend to submit aggressive (market) orders when the same-side market depth is higher than the opposite-side market depth. This observation presents early support for the positive (negative) relation between same-side (opposite-side) market depth and order aggressiveness, as specified in Hypothesis 1. For both institutional and individual investors, the relative bid-ask spread is also higher at the time of limit order submissions than at the time of market order submissions. This observation suggests that, consistent with Hypothesis 2, investors tend to be less aggressive and use more limit orders when the bid-ask spread is wide. Volatility is also higher at the time of limit order submissions for individual investors. However, for institutional investors, there is not a significant difference in volatility at the time of limit order submissions and market order submissions.

Table 1: Descriptive statistics of order submissions

This table presents summary statistics of the order submissions of the institutional and individual investors. The sample period is between 1 August 2005 and 31 March 2006, totalling 171 trading days. Following Biais et al. (1995), orders are classified into six aggressiveness levels. Category 1 orders are buy (sell) orders with the prices greater (less) than the best ask (bid) quote and the order size exceeds the market depth at the best ask (bid) quote. Category 2 orders are buy (sell) orders with prices equal to the best ask (bid) quote and demand more volume than the market depth at the best ask (bid) quote. Category 3 orders are orders with price equal to the opposite best quote and demand less volume than the market depth at the opposite best quote. Category 4 and 5 orders are limit orders within and at the prevailing quotes, respectively. Category 6 orders are buy (sell) orders with prices less (greater) than the best bid (ask) quotes. "Frequency" is the number of orders submitted at a particular aggressiveness level. "Percentage of All Orders" is the percentage of the number of orders in a particular order aggressiveness level over all orders. "Order Size" is the average number of shares submitted in an order. "Depth at Best Same (Opposite)" is the average number of shares at the best same-side (opposite-site) quote at the time of order submission. "Depth at Same (Opposite)" is the average number of shares at the 10 best same-side (opposite-side) quote at the time of order submission. "Relative Spread" is the average relative spread, calculated as the percentage of the bid-ask spread over the bid-ask mid-point, at the time of the order submission. "Volatility" is the average volatility, which is calculated as the standard deviation of the most recent 20 mid-quote returns, at the time of order submission multiplied by 100.

Panel A: Institutional orders

Aggressiveness Level	Frequency	Percentage of All Orders	Order Size	Depth at Best Same	Depth at Best Opposite	Depth at Same	Depth at Opposite	Relative Spread	Volatility
1	109,097	1.51%	6,913	7,492	1,647	67,648	62,783	0.1974	0.0187
2	531,215	7.37%	16,232	26,536	7,256	192,121	183,360	0.1154	0.0343
3	1,691,793	23.47%	4,150	52,741	42,792	387,009	378,632	0.1725	0.0309
4	741,463	10.29%	2,708	9,508	9,053	77,498	77,738	0.2907	0.0414
5	2,827,552	39.23%	4,577	36,230	45,792	352,889	354,237	0.1562	0.0338
6	1,306,194	18.12%	5,501	16,768	22,653	183,594	189,667	0.1676	0.0258

Panel B: Individual orders

Aggressiveness Level	Frequency	Percentage of All Orders	Order Size	Depth at Best Same	Depth at Best Opposite	Depth at Same	Depth at Opposite	Relative Spread	Volatility
1	159,935	1.73%	6,533	9,458	1,708	88,605	80,792	0.2031	0.0248
2	524,809	5.69%	11,649	26,167	5,294	198,326	181,578	0.1353	0.0396
3	2,198,717	23.82%	4,009	97,022	80,293	739,030	712,801	0.1691	0.0295
4	713,470	7.73%	3,103	11,813	10,401	91,927	90,202	0.3495	0.0475
5	2,525,904	27.36%	5,382	62,758	76,078	587,172	592,409	0.2082	0.0395
6	3,108,052	33.67%	8,935	52,632	59,792	511,331	509,305	0.2023	0.0351

2.5.2 Distribution of Order Aggressiveness Levels

Table 2 provides information regarding the distribution of order aggressiveness levels over the course of the trading day, where the trading day is partitioned into six intervals: 10:10–11:00, 11:00–12:00, 12:00–13:00, 13:00–14:00, 14:00–15:00 and 15:00–16:00.

From Table 2, it is observed that the order aggressiveness of institutional investors has a U-shaped pattern. Institutional investors are more aggressive and demand more liquidity (place more market orders) early in the trading day than in other intervals. As the trading day progresses, institutional investors become less aggressive and submit fewer market orders and more limit orders. Toward the end of the trading day, institutional investors increase their order aggressiveness. However, the order aggressiveness of institutional investors at the end of the trading day is not as high as it is at the beginning of the trading day. Individual investors behave in an opposite fashion. They are less aggressive early in the day and become more aggressive as the end of the trading day approaches. This is reflected by the increase (decrease) in the use of market (limit) orders toward the end of the trading day.

Table 2: Distribution of order aggressiveness levels over the trading day

This table presents the distribution of order aggressiveness levels over the trading day. Following Biais et al. (1995), orders are classified into six aggressiveness levels. Category 1 orders are buy (sell) orders with the prices greater (less) than the best ask (bid) quote and the order size exceeds the market depth at the best ask (bid) quote. Category 2 orders are buy (sell) orders with prices equal to the best ask (bid) quote and demand more volume than the market depth at the best ask (bid) quote. Category 3 orders are orders with price equal to the opposite best quote and demand less volume than the market depth at the opposite best quote. Category 4 and 5 orders are limit orders within and at the prevailing quotes, respectively. Category 6 orders are buy (sell) orders with prices less (greater) than the best bid (ask) quotes. Orders with aggressiveness levels from 1 to 3 are market orders and orders with aggressiveness levels from 4 to 6 are limit orders. The trading day is divided into six intervals: 10:10–11:00, 11:00–12:00, 12:00–13:00, 13:00–14:00, 14:00–15:00, and 15:00–16:00. "MO" ("LO") refers to the total number of market (limit) orders in a particular interval. "Total" is the total number of orders submitted in a particular interval. "Percentage MO" ("Percentage LO") is the percentage of market (limit) orders out of all orders submitted in a particular interval.

Panel A: Institutional orders

Interval	Levels of Order Aggressiveness						MO	LO	Total	Percentage MO	Percentage LO
	1	2	3	4	5	6					
10:10–11:00	21,943	113,479	314,930	170,333	468,445	206,327	450,352	845,105	1,295,457	34.76%	65.24%
11:00–12:00	29,904	88,591	294,694	140,510	429,819	251,380	413,189	821,709	1,234,898	33.46%	66.54%
12:00–13:00	12,031	56,689	197,752	83,601	351,399	188,706	266,472	623,706	890,178	29.93%	70.07%
13:00–14:00	6,661	35,564	152,441	60,981	310,315	147,939	194,666	519,235	713,901	27.27%	72.73%
14:00–15:00	17,067	93,636	284,888	121,778	556,481	227,619	395,591	905,878	1,301,469	30.40%	69.60%
15:00–16:00	21,491	143,256	447,088	164,260	711,093	284,223	611,835	1159,576	1,771,411	34.54%	65.46%

Panel B: Individual orders

Interval	Levels of Order Aggressiveness						MO	LO	Total	Percentage MO	Percentage LO
	1	2	3	4	5	6					
10:10–11:00	37,639	114,474	429,256	174,945	511,381	728,550	581,369	1,414,876	1,996,245	29.12%	70.88%
11:00–12:00	39,242	88,731	399,647	131,958	417,144	629,005	527,620	1,178,107	1,705,727	30.93%	69.07%
12:00–13:00	20,453	62,788	295,059	90,382	342,058	433,258	378,300	865,698	1,243,998	30.41%	69.59%
13:00–14:00	14,277	42,032	220,244	62,354	260,894	314,822	276,553	638,070	914,623	30.24%	69.76%
14:00–15:00	20,109	85,691	351,401	104,574	417,444	450,128	457,201	972,146	1,429,347	31.99%	68.01%
15:00–16:00	28,215	131,093	503,110	149,257	576,983	552,289	662,418	1,278,529	1,940,947	34.13%	65.87%

2.5.3 Order Aggressiveness of Institutional and Individual Investors

Table 3 presents the results of investigating the determinants of order aggressiveness for institutional and individual investors, based on the ordered probit model specified in Equation (2.4). Since the aggressiveness levels are ranked from 1 (the most aggressive) to 6 (the least aggressive), a negative coefficient indicates a positive relation between the explanatory variable and investors' order aggressiveness.

The results in Table 3 indicate a positive (negative) and significant relation between the same-side (opposite-side) market depth and order aggressiveness for the majority of stocks under investigation. These results are consistent for both institutional and individual investors' orders and provide support for Hypothesis 1. Consistent with prior literature,[19] these findings suggest that the market depth can be viewed as a proxy for the execution probability and thus will affect investors' order aggressiveness. When the same-side market depth increases, the execution probability of the incoming limit order is reduced. Therefore, investors are more likely to submit more aggressive order to obtain higher execution priority in the book. In contrast, an increase in the market depth on the buy (sell) side increases the execution probability of limit orders on the sell (buy) side. This reduces the execution risk for limit orders and therefore, investors may prefer limit orders over market orders when the opposite-side market depth increases.

The majority of the coefficients for the bid-ask spread, as documented in Table 3, are positive and significant for institutional investors' orders. This finding supports Hypothesis 2, which suggests a negative relation between the order aggressiveness of institutional investors and the bid-ask spread. The order aggressiveness of individual investors is also negatively related

[19] See, for example, Biais et al. (1995), Parlour (1998), Griffiths et al. (2000), Ranaldo (2004), Beber and Caglio (2005), Hall and Hautsch (2006), Ellul et al. (2007), Aitken, Brown and Wee (2007) and Cao et al. (2008).

to the bid-ask spread, but only in the large cap and mid cap stocks. In small cap stocks, individual investors tend to submit more aggressive orders when the spread widens. This finding implies that the non-execution risk is a significant factor for individual investors while trading small cap stocks. Individual investors differ from institutional investors in their timely knowledge of the order book. This informational disadvantage induces them to place more aggressive orders even when the spread is high for small cap stocks.

The findings for the effect of volatility on investors' order aggressiveness are less conclusive. For large cap stocks, there is a positive relation between the order aggressiveness of institutional investors and volatility. In contrast, a negative relation between institutional investors' order aggressiveness and volatility is documented in mid cap stocks, whereas this relation is insignificant for the majority of small cap stocks. For individual investors, their order aggressiveness is negatively related to volatility in mid cap stocks but positively related to volatility in small cap stocks. In contrast, there is no clear-cut evidence regarding the direction or significance of the relation between volatility and individual investors' order aggressiveness for large cap stocks.[20]

The findings in Table 3 regarding the effect of volatility on order aggressiveness are similar to the mixed empirical evidence in prior literature. Consistent with Foucault's (1999) prediction, there is a negative relation between order aggressiveness and volatility in mid cap stocks. Volatility is positively related to institutional order aggressiveness in large cap stocks. Since higher volatility implies a greater "picking-off" risk (Foucault, 1999) and institutional

[20] Consistent with Ranaldo (2004), the effect of volatility on order aggressiveness is also examined with volatility as the only explanatory variable in the ordered probit model. In addition, besides calculating volatility based on the standard deviation most recent 20 mid-quote returns, volatility is also measured based on the standard deviation of the most recent 10 and 30 mid-quote returns. The results of these investigations, presented in Appendix 1, are qualitatively similar to those reported in Table 3.

investors often pay higher fees for more continuous monitoring of the state of the limit order book (Aitken, Almeida, Harris and McInish, 2007), the "picking-off" risk is more applicable to individual investors. Therefore, institutional investors have incentives to incur higher monitoring costs and place aggressive orders when volatility increases in order to profit from "picking-off" stale limit orders. This finding is also consistent with the prediction of Goettler et al. (2008) that informed traders will supply less liquidity and place more market orders when the asset is more volatile. Since monitoring is lower for mid and small cap stocks (Liu, 2009) and transaction costs are higher in those stocks compared to large cap stocks, it is much more difficult and less profitable for institutional investors to adopt this trading strategy in mid and small cap stocks. Thus, a positive relation between volatility and order aggressiveness is observed for institutional investors in large cap stocks but not in mid cap and small cap stocks. A positive relation between order aggressiveness and volatility for institutional investors is consistent with the notion that institutional investors monitor the limit order book more closely and "pick-off" stale limit orders when volatility increases.[21]

On the other hand, because the prices of small cap stocks are also relatively lower compared to large cap and mid cap stocks, a similar change in price will result in a larger absolute return in small cap stocks compared to large cap and mid cap stocks. Therefore, investors in small cap stocks are potentially more risk-averse than those in large and mid cap stocks. Hasbrouck and Saar (2002) and Wald and Horrigan (2005) suggest that for risk-averse investors, a rise in volatility results in an increase in the submission of market orders. Thus, the finding of a positive relation between order aggressiveness and volatility for individual investors in small cap stocks might reflect a higher risk-aversion of individual investors in those stocks in comparison to large cap and mid cap stocks.

[21] "Picking-off" activities are more likely to originate from active institutions such as hedge funds and proprietary trading desks rather than mutual funds and insurance companies (Aitken, Almeida, Harris and McInish, 2007).

Institutional and individual investors also possess different order submission strategies in the first hour of the trading day. For institutional investors, negative and significant coefficient estimates for the *FirstInt* variable are observed for the majority of large cap, mid cap, and small cap stocks under investigation. This implies that institutional investors are more aggressive and demand liquidity in the first hour of the trading day. In contrast, for individual orders, the majority of the coefficient estimates for the *FirstInt* variables are positive and significant. This result indicates that individual investors are less aggressive and use more limit orders during the first trading hour.[22]

Overall, the results in Table 2 and the results regarding the *FirstInt* variable presented in Table 3 support Hypothesis 4. Institutional and individual investors in this study tend to behave similarly to informed and uninformed investors, as documented in Bloomfield et al. (2005) and Anand et al. (2005). Institutional investors are potentially the better-informed investors, they submit more aggressive orders early on in the trading, when information asymmetry is high and prices have not converged to their true values. As trading progresses and information is incorporated into prices, institutional investors switch to using limit orders and provide liquidity to the market. Individual investors behave in the opposite direction to institutional investors; they are less aggressive early in the trading day when information asymmetry and the "picking-off" risk are high. As trading progresses, individual investors become more aggressive in their order submissions, especially when the end of the trading day approaches. The increase in order aggressiveness of individual investors toward the end

[22] In addition to the dummy variable for the first trading hour, the remaining time (in hours) until market closing time (*TTC*) is also incorporated into the ordered probit regression. Negative (positive) and significant coefficient estimates for the *TTC* variable are observed for institutional (individual) investors in the majority of large cap, mid cap, and small cap stocks. This evidence indicates that institutional investors are more aggressive early on in the trading day, whereas individual investors are more aggressive in their order submission toward the end of the trading day. These results are consistent with those documented in Table 3 and are presented in Appendix 2.

of the trading day is consistent with the prediction of Harris (1998), where investors are more aggressive toward the end of the trading day to achieve their trading targets.

The results in Panel A of Table 3 also indicate that in large and mid cap stocks, the larger the institutional investors' orders, the more aggressive they are. In contrast, in small cap stocks, institutional investors are often less aggressive when they submit a large order. For individual investors, if they submit a large order, this order is often non-aggressive. This contrasting behavior of institutional and individual investors suggests that for institutional investors, the non-execution risk is more important than the "picking-off" risk when submitting large orders in large and mid cap stocks. In contrast, the "picking-off" risk appears to be more important for individual investors when placing large orders. Finally, the results in Table 3 show that institutional investors' sell orders are more aggressive than their buy orders, especially in mid cap and small cap stocks. In contrast, individual investors' sell orders are more (less) aggressive than buy orders in small cap and mid cap (large cap) stocks. This finding implies that institutional and individual investors consider a higher opportunity cost of non-execution for sell orders in mid and small cap stocks, whereas individual investors are more patient in their selling activities in large cap stocks.

Table 3: Determinants of institutional and individual order aggressiveness

This table presents the results of investigating the determinants of institutional and individual investors' order aggressiveness. The following ordered probit model is estimated for institutional and individual orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \beta_8 \text{Anonymous}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first trading hour of the trading day. Direction_i and Anonymous_i are the dummy variables for sell orders and for orders submitted from 28 November 2005 onward, respectively. Size_i is the natural logarithm of the number of shares in the particular order. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Institutional orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0823	0%	100.00%	-0.0686	13.33%	80.00%	-0.0687	20.00%	66.67%
$\text{Depth}_{opposite}$	0.1002	96.67%	0%	0.1138	90.00%	6.67%	0.0412	43.33%	13.33%
Spread	0.5522	86.67%	6.67%	0.1654	70.00%	3.33%	0.1394	86.67%	3.33%
Volatility	-0.3840	33.33%	66.67%	0.1141	50.00%	26.67%	-0.0408	13.33%	26.67%
FirstInt	-0.1081	0%	100.00%	-0.0699	6.67%	90.00%	-0.0275	10.00%	46.67%
Size	-0.1197	3.33%	96.67%	-0.0411	10.00%	90.00%	0.0385	66.67%	30.00%
Direction	-0.0038	36.67%	40.00%	-0.0066	26.67%	50.00%	-0.0309	30.00%	46.67%
Anonymous	0.0341	63.33%	20.00%	0.0338	50.00%	26.67%	0.0160	56.67%	20.00%

Panel B: Individual orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0856	0%	96.67%	-0.0632	0%	76.67%	-0.1123	3.33%	83.33%
$\text{Depth}_{opposite}$	0.0599	86.67%	6.67%	0.0431	76.67%	10.00%	0.0718	50.00%	10.00%
Spread	1.0103	93.33%	3.33%	0.0420	46.67%	33.33%	-0.0425	20.00%	50.00%
Volatility	-0.9454	33.33%	36.67%	0.0024	40.00%	16.67%	-0.1152	6.67%	50.00%
FirstInt	0.0544	93.33%	0%	0.0189	63.33%	6.67%	0.0483	73.33%	3.33%
Size	0.0260	60.00%	30.00%	0.0349	73.33%	16.67%	0.0402	73.33%	13.33%
Direction	0.0032	50.00%	26.67%	0.0003	40.00%	43.33%	-0.0474	20.00%	53.33%
Anonymous	0.0937	90.00%	3.33%	0.1555	96.67%	3.33%	0.2789	93.33%	6.67%

2.5.4 Order Aggressiveness of Buy and Sell Orders

Table 4 presents evidence regarding the order aggressiveness of institutional investors' buy and sell orders. Consistent results for both buy and sell orders are observed for the effects of the same-side market depth, the opposite-side market depth, the bid-ask spread, volatility, and order size on order aggressiveness. In addition, the majority of the coefficient estimates for the *FirstInt* variable in Panel A of Table 4 are negative and significant, which indicates that institutional investors tend to be more aggressive early in the trading day for buy orders. In contrast, a similar pattern in institutional sell orders exists only in large cap and mid cap stocks. For small cap stocks, the majority of the coefficient estimates for the *FirstInt* variable in Panel B of Table 4 are insignificant. This finding suggests that in small cap stocks, there is no tendency for institutional investors to be more aggressive in their selling activities early on in the day. This difference in results for buy and sell orders suggests that if the order submissions of institutional investors in the first trading hour can be explained by their information advantage over individual investors, institutional buy orders are more likely to be more informative than institutional sell orders. This finding is consistent with prior empirical evidence that buy orders are more likely to be motivated by information than sell orders (see, for example, Griffiths et al., 2000; Ranaldo, 2004).

The results of investigating the order aggressiveness of individual investors' buy and sell orders are given in Table 5. For individual investors, buy and sell order aggressiveness is positively related to the same-side market depth and negatively related to the opposite-side market depth and order size. In addition, the majority of the coefficient estimates for the *FirstInt* variable are positive and significant. This finding suggests that individual investors are less aggressive in both their buying and selling activities in the first trading hour. The most significant differences in the effect of spread and volatility on individual buy and sell orders are observed in mid cap stocks. In mid cap stocks, when the spread increases, individual investors tend to submit less aggressive buy orders but more aggressive sell orders. Similarly, a rise in volatility will result in the submission of less aggressive buy orders but more aggressive sell orders. These two findings suggest that individual investors are less sensitive to transaction costs while selling but are more concerned with non-execution risk when the bid-ask spread widens and volatility increases in mid cap stocks.

Table 4: Determinants of institutional buy and sell order aggressiveness

This table presents the results of investigating the determinants of institutional investors' buy and sell order aggressiveness. The following ordered probit model is estimated for institutional investors' buy and sell orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Anonymous}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first hour of the trading day. Size_i is the natural logarithm of the number of shares in the particular order. Anonymous_i is the dummy variable for orders submitted from 28 November 2005 onwards. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Institutional buy orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0767	0%	90.00%	-0.0673	20.00%	63.33%	-0.0413	16.67%	56.67%
$\text{Depth}_{opposite}$	0.1016	100.00%	0%	0.1350	70.00%	3.33%	0.0794	66.67%	10.00%
Spread	0.6356	80.00%	6.67%	0.1979	66.67%	13.33%	0.1500	83.33%	10.00%
Volatility	-0.2759	26.67%	53.33%	0.2095	60.00%	26.67%	-0.0371	33.33%	33.33%
FirstInt	-0.1108	3.33%	96.67%	-0.0668	6.67%	80.00%	-0.0519	10.00%	56.67%
Size	-0.1109	3.33%	96.67%	-0.0317	10.00%	90.00%	0.0498	70.00%	16.67%
Anonymous	0.0273	46.67%	33.33%	0.0330	50.00%	30.00%	0.0454	53.33%	20.00%

Panel B: Institutional sell orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0897	0%	96.67%	-0.0846	0%	70.00%	-0.1290	16.67 %	70.00%
$\text{Depth}_{opposite}$	0.1024	100.00%	0%	0.0976	73.33%	20.00%	0.0161	36.67 %	36.67%
Spread	0.4833	76.67%	6.67%	0.1333	63.33%	13.33%	0.1348	76.67 %	3.33%
Volatility	-0.5032	33.33%	60.00%	-0.0104	50.00%	30.00%	-0.0396	23.33 %	23.33%
FirstInt	-0.1043	3.33%	96.67%	-0.0716	6.67%	76.67%	-0.0035	26.67 %	26.67%
Size	-0.1290	3.33%	96.67%	-0.0524	6.67%	86.67%	0.0234	46.67 %	36.67%
Anonymous	0.0413	66.67%	16.67%	0.0415	56.67%	26.67%	-0.0006	43.33 %	26.67%

Table 5: Determinants of individual buy and sell order aggressiveness

This table presents the results of investigating the determinants of individual investors' buy and sell order aggressiveness. The following ordered probit model is estimated for individual investors' buy and sell orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Anonymous}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first hour of the trading day. Size_i is the natural logarithm of the number of shares in the particular order. Anonymous_i is the dummy variable for orders submitted from 28 November 2005 onwards. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Individual buy orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0875	0%	90.00%	-0.1078	13.33%	66.67%	-0.1064	10.00%	70.00%
$\text{Depth}_{opposite}$	0.0670	80.00%	10.00%	0.0547	63.33%	20.00%	0.0920	60.00%	10.00%
Spread	1.1959	90.00%	3.33%	0.1150	60.00%	33.33%	-0.0295	23.33%	43.33%
Volatility	-0.8287	33.33%	30.00%	-0.0079	53.33%	30.00%	-0.0415	20.00%	36.67%
FirstInt	0.0412	80.00%	3.33%	0.0329	53.33%	10.00%	0.0568	60.00%	10.00%
Size	0.0211	63.33%	36.67%	0.0430	76.67%	10.00%	0.0418	80.00%	13.33%
Anonymous	0.0993	86.67%	13.33%	0.2585	96.67%	0%	0.2979	90.00%	3.33%

Panel B: Individual sell orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0904	6.67%	83.33%	-0.0860	10.00%	80.00%	-0.1377	6.67%	70.00%
$\text{Depth}_{opposite}$	0.0564	83.33%	6.67%	0.0696	73.33%	16.67%	0.0672	53.33%	16.67%
Spread	0.8008	90.00%	0%	-0.0178	26.67%	36.67%	-0.0497	26.67%	43.33%
Volatility	-1.0234	33.33%	36.67%	-0.0387	33.33%	40.00%	-0.2086	13.33%	53.333%
FirstInt	0.0669	90.00%	0%	0.0230	53.33%	16.67%	0.0399	60.00%	13.33%
Size	0.0308	63.33%	26.67%	0.0555	80.00%	13.33%	0.0409	70.00%	20.00%
Anonymous	0.0930	86.67%	10.00%	0.1865	96.67%	0%	0.2605	93.33%	6.67%

2.5.5 Anonymity and Investors' Order Aggressiveness

The effect of the move to anonymity on order aggressiveness is examined in three ways. First, the effect of the removal of broker IDs on investors' order aggressiveness is investigated by comparing the proportion of market and limit orders submitted by institutional and individual investors before and after the move to anonymity. Second, a dummy variable indicating orders submitted in the anonymous trading system (orders submitted from 28 November 2005 onwards) is incorporated into the ordered probit model in Equations (2.4) and (2.5). The coefficient estimates as well as the significance of this dummy variable indicate whether investors become more or less aggressive after the move to anonymity. Finally, the determinants of institutional and individual investors' order aggressiveness are investigated in the transparent market (before 28 November 2005) and in the anonymous market (from 28 November 2005 onward), as specified in Equation (2.6).

Table 6 presents evidence of the distribution of investors' order aggressiveness in the transparent and anonymous markets. From Table 6, both institutional and individual investors appear to be less aggressive and reduce their use of market orders (Category 1, 2 and 3 orders) following the move to anonymity. In contrast, both groups of investors tend to increase their use of limit orders in the anonymous market, with the largest increases observed for Category 5 orders for institutional investors and Category 6 orders for individual investors. Thus, the findings in Table 6 imply a reduction in order aggressiveness for both institutional and individual investors after the removal of broker IDs on the ASX.

Table 6: Anonymity and the distribution of order aggressiveness

This table presents the distribution of institutional and individual order aggressiveness for two periods: Pre-Anonymity (before 28 November 2005) and Post-Anonymity (from 28 November 2005 onward). Following Biais et al. (1995), order are classified into six aggressiveness levels. Category 1 orders are buy (sell) orders with the prices greater (less) than the best ask (bid) quote and the order size exceeds the market depth at the best ask (bid) quote. Category 2 orders are buy (sell) orders with prices equal to the best ask (bid) quote and demand more volume than the market depth at the best ask (bid) quote. Category 3 orders are orders with price equal to the opposite best quote and demand less volume than the market depth at the best opposite quote. Category 4 and 5 orders are limit orders within and at the prevailing quotes, respectively. Category 6 orders are buy (sell) orders with prices less (greater) than the best bid (ask) quotes. "% Inst. Orders" and "% Indi. Orders" refers to the percentage of all institutional and individual orders, respectively.

Panel A: Institutional orders

Aggressiveness Level	Large Cap Stocks				Mid Cap Stocks				Small Cap Stocks			
	Pre-Anonymity		Post-Anonymity		Pre-Anonymity		Post-Anonymity		Pre-Anonymity		Post-Anonymity	
	Frequency	% Inst. Orders	Frequency	% Inst. Orders	Frequency	% Inst. Orders	Frequency	% Inst. Orders	Frequency	% Inst. Orders	Frequency	% Inst. Orders
1	21,145	1.06%	32,641	1.23%	17,274	2.14%	18,674	1.65%	8,618	3.17%	10,745	3.07%
2	183,110	9.15%	212,325	8.03%	47,162	5.85%	58,258	5.14%	13,543	4.99%	16,817	4.80%
3	439,600	21.96%	548,787	20.75%	205,405	25.49%	285,590	25.19%	88,938	32.74%	123,473	35.25%
4	205,911	10.29%	241,968	9.15%	98,173	12.18%	115,737	10.21%	38,816	14.29%	40,858	11.67%
5	816,715	40.80%	1,128,554	42.68%	291,641	36.20%	420,792	37.12%	69,423	25.56%	100,427	28.67%
6	335,372	16.75%	479,876	18.15%	146,080	18.13%	234,619	20.70%	52,317	19.26%	57,930	16.54%

Panel B: Individual orders

Aggressiveness Level	Large Cap Stocks				Mid Cap Stocks				Small Cap Stocks			
	Pre-Anonymity		Post-Anonymity		Pre-Anonymity		Post-Anonymity		Pre-Anonymity		Post-Anonymity	
	Frequency	% Indi. Orders	Frequency	% Indi. Orders	Frequency	% Indi. Orders	Frequency	% Indi. Orders	Frequency	% Indi. Orders	Frequency	% Indi. Orders
1	37,473	1.42%	44,767	1.45%	24,250	2.36%	22,774	1.64%	14,663	3.17%	16,008	2.51%
2	172,831	6.55%	180,721	5.87%	54,831	5.33%	65,051	4.70%	23,731	5.13%	27,644	4.34%
3	740,285	28.04%	776,187	25.22%	221,499	21.53%	263,803	19.05%	91,833	19.85%	105,110	16.51%
4	210,613	7.98%	200,577	6.52%	100,698	9.79%	95,328	6.88%	54,681	11.82%	51,573	8.10%
5	672,830	25.48%	819,425	26.63%	334,911	32.56%	395,509	28.56%	142,831	30.87%	160,398	25.20%
6	806,235	30.54%	1,055,936	34.31%	292,475	28.43%	542,566	39.17%	134,955	29.17%	275,885	43.34%

The results of the *Anonymous* variable in Tables 3, 4 and 5 also indicate a reduction in order aggressiveness after the move to anonymity. From Tables 3, 4 and 5, a positive and significant coefficient estimate for the *Anonymous* variable is observed for the majority of the stocks under investigation. This evidence is consistent for all three groups of stocks, for both buy and sell orders, and for both institutional and individual investors, with stronger results obtained for individual investors. This finding is also consistent with the observation of the reduction in the use of market orders for both institutional and individual investors in Table 6. Overall, the results in Tables 3, 4, 5 and 6 provide support for Hypothesis 5. The empirical evidence suggests that both institutional and individual investors are less aggressive in their order submissions and more willing to supply liquidity following the move to anonymity. This result is also consistent with the evidence documented in Comerton-Forde and Tang (2008) and provides support for the ASX's decision to cease displaying broker IDs in order to enhance the overall market liquidity.

Finally, the determinants of institutional and individual investors' order aggressiveness are investigated in the transparent and anonymous markets to highlight whether anonymity results in any significant change in the impact of these determinants on order aggressiveness. The results of this investigation are presented in Table 7 for institutional investors and Table 8 for individual investors.

Table 7 provides consistent results regarding the effects of market depth, spread, volatility, order size, and order direction (except in large cap stocks) in both the transparent and anonymous markets. The results regarding the *FirstInt* variable suggest that institutional investors are more aggressive in the first hour of the trading day, with stronger results observed in the anonymous market, especially for small cap stocks. This finding is consistent with Foucault et al.'s (2007) suggestion that the risk of front-running activities in the transparent market can result in the informed traders sometimes engaging in bluffing strategies and posting less aggressive orders than would be appropriate. In an anonymous market with smaller risk of front-running activities, institutional investors increase their submission of aggressive orders when their information advantage is arguably greatest (in the first hour of the trading day).

For individual investors, the most significant differences when examining the two market regimes are observed for the effects of order size and the first trading hour on order aggressiveness. Individual investors are less aggressive in the first trading hour in the anonymous market than in the transparent market, especially in mid cap and small cap stocks. This finding is consistent with Foucault et al.'s (2007) prediction that when the participation rate of informed traders is larger, uninformed investors will be less aggressive after the move to anonymity. Since information asymmetry is higher in the first hour of the trading day (Bloomfield et al., 2005) and individual investors are normally the less informed class of investors, individual investors are less aggressive in their order submissions during the first trading hour in the anonymous market than in the transparent market. In addition, in the transparent market, individual investors are more aggressive when submitting large orders. In contrast, they tend to be less aggressive when placing large orders in the anonymous market. Most large individual orders arguably emanate from high net worth individuals. When their orders are informative, they would be aggressive under a transparent market to preclude front-running. If their orders are uninformed and they place limit orders, they face a high chance of being "picked-off". Therefore, they are better-off using more aggressive market orders under transparent market conditions. Since the move to anonymity reduces the ability of other traders to distinguish individual investors' orders from those submitted by institutional investors, the “picking-off” risk faced by uninformed limit order traders is reduced in the anonymous market. Therefore, individual investors are more willing to place limit orders in an anonymous market when they are uninformed. Even when they are informed, individual investors have more incentives to use limit orders than market orders under anonymity because of a lower risk of front-running activity.

Table 7: Determinants of institutional order aggressiveness in the transparent and anonymous markets

This table presents the results of investigating the determinants of institutional investors' order aggressiveness in the transparent and anonymous markets. The following ordered probit model is estimated for institutional investors' orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first hour of the trading day. Size_i is the natural logarithm of the number of shares in the particular order. Direction_i is the dummy variable for sell orders. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Transparent market

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0481	10.00%	66.67%	-0.0373	26.67%	46.67%	-0.1090	13.33%	56.67%
$\text{Depth}_{opposite}$	0.1002	96.67%	0%	0.0995	66.67%	3.33%	0.0782	63.33%	3.33%
Spread	0.6383	83.33%	6.67%	0.1615	60.00%	20.00%	0.1203	80.00%	10.00%
Volatility	-0.6394	23.33%	70.00%	0.0065	40.00%	23.33%	-0.0881	10.00%	26.67%
FirstInt	-0.1046	0%	90.00%	-0.0429	13.33%	66.67%	0.0173	23.33%	13.33%
Size	-0.1301	0%	100.00%	-0.0509	6.67%	90.00%	0.0282	53.33%	26.67%
Direction	-0.0113	26.67%	60.00%	-0.0129	33.33%	50.00%	-0.0083	23.33%	43.33%

Panel B: Anonymous market

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.1141	0%	100.00%	-0.1022	6.67%	83.33%	-0.0621	16.67%	56.67%
$\text{Depth}_{opposite}$	0.1036	96.67%	0%	0.1261	76.67%	10.00%	0.0257	46.67%	20.00%
Spread	0.5243	83.33%	3.33%	0.1881	83.33%	3.33%	0.1815	83.33%	0%
Volatility	-0.1521	33.33%	56.67%	0.2163	46.67%	16.67%	0.0369	30.00%	23.33%
FirstInt	-0.1117	3.33%	96.67%	-0.0938	0%	93.33%	-0.0735	6.67%	63.33%
Size	-0.1118	3.33%	96.67%	-0.0334	10.00%	86.67%	0.0468	73.33%	20.00%
Direction	0.0033	40.00%	36.67%	-0.0029	33.33%	50.00%	-0.0361	30.00%	46.67%

Table 8: Determinants of individual order aggressiveness in the transparent and anonymous markets

This table presents the results of investigating the determinants of individual investors' order aggressiveness in the transparent and anonymous markets. The following ordered probit model is estimated for institutional investors' orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first hour of the trading day. Size_i is the natural logarithm of the number of shares in the particular order. Direction_i is the dummy variable for sell orders. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Transparent market

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0788	0%	93.33%	-0.0766	10.00%	76.67%	-0.1340	6.67%	73.33%
$\text{Depth}_{opposite}$	0.0614	86.67%	6.67%	0.0550	60.00%	6.67%	0.1147	66.67%	10.00%
Spread	0.9082	90.00%	6.67%	-0.0003	30.00%	40.00%	0.0061	40.00%	33.33%
Volatility	-0.9172	20.00%	36.67%	0.0805	46.67%	16.67%	-0.0562	16.67%	30.00%
FirstInt	0.0387	60.00%	0%	0.0073	36.67%	33.33%	0.0218	33.33%	6.67%
Size	-0.0373	16.67%	80.00%	-0.0469	13.33%	76.67%	-0.0205	26.67%	60.00%
Direction	0.0118	50.00%	30.00%	0.0339	60.00%	30.00%	-0.0286	33.33%	53.33%

Panel B: Anonymous market

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0959	3.33%	93.33%	-0.1105	3.33%	86.67%	-0.1128	10.00%	76.67%
$\text{Depth}_{opposite}$	0.0588	86.67%	6.67%	0.0639	66.67%	6.67%	0.0555	40.00%	36.67%
Spread	1.0783	93.33%	6.67%	0.0895	50.00%	26.67%	-0.0954	10.00%	76.67%
Volatility	-0.9364	40.00%	36.67%	-0.1279	30.00%	33.33%	-0.1467	6.67%	36.67%
FirstInt	0.0608	86.67%	3.33%	0.0459	76.67%	6.67%	0.0642	76.67%	0%
Size	0.0685	83.33%	16.67%	0.1111	100.00%	0%	0.0877	100.00%	0%
Direction	-0.0066	40.00%	33.33%	-0.0256	33.33%	53.33%	-0.0527	16.67%	53.33%

2.5.6 Robustness Tests

This section discusses various robustness tests for the results regarding the order aggressiveness of institutional and individual investors. In the current chapter and the following two empirical chapters, the confidential classification of institutional and individual orders is provided on an aggregated basis by SIRCA, after the approval to release confidential data from the ASX. The first robustness check performs an independent test for the ASX's classification of institutional and individual orders, based on a trade-by-trade data from IRESS. This dataset identifies the transaction details (date, time, price, volume, buyer or seller-initiated) and most importantly the identities of the buying and selling brokers. During the sample period under investigation, 89 brokers are identified in the IRESS data, with 79 brokers participating in trading activity of the stocks considered in this robustness test. Brokers are classified into those dealing with institutional investors, those with individual investors, and those with both groups of investors.[23] The first robustness test uses only transactions that have the buying or selling broker classified as doing business with either institutional or individual investors, based on IRESS data. The Order Book Dataset provided by the ASX allows the identification for every transaction, whether the buyer and seller is an institution or an individual, as classified by the ASX. The ASX classification of institutions and individuals is then compared with the classification based on brokers' identities provided by IRESS. The results of this robustness in Table 9 indicate that for the 15 randomly chosen large cap, mid cap and small cap stocks, a consistency of at least 98.62% in the institutional/individual orders classification is obtained.

[23] This classification is based on the brokers' names as well as on the description of their activities, services, and products provided on the brokers' websites and through telephone interviews.

Table 9: Robustness test on the institutional/individual investors classification

This table presents the results of the first robustness test, which performs an independent test for the ASX's classification of institutional and individual orders, based on a trade- by- trade data from IRESS. IRESS provides information on all transactions executed on the ASX, including transaction date and time, price, trading volume, trade direction, and most importantly, the identity of the buying and selling brokers. Based on their identities, brokers are then classified as dealing with institutional investors, individual investors and both groups of investors. The ASX classification of institutions and individuals is then compared with the classification based on brokers' identities provided by IRESS. The comparison is performed for five randomly selected larger cap stocks, five randomly selected mid cap stocks, and five randomly selected small cap stocks. "Stock Code" provides information on the code of the stock and "Stock Group" presents information on whether the stock under investigation is a large cap, mid cap, or small cap stock. "Consistent Buyer Classification" ("Consistent Seller Classification") shows the number of buy (sell) orders that are consistently identified as submitted by an institution or an individual by both the ASX and the classification scheme based on broker identities provided by IRESS. "Inconsistent Buyer Classification" ("Inconsistent Seller Classification") shows the number of buy (sell) orders that are inconsistently identified as submitted by an institution or an individual by both the ASX and the classification scheme based on broker identities provided by IRESS. "% Consistent Buyer Classification", "% Consistent Seller Classification", and "% Overall Classification" show the percentages of buy orders, sell orders, and both buy and sell orders that are consistently identified as submitted by an institution or an individual by both the ASX and the classification scheme based on broker identities provided by IRESS.

Stock Code	Stock Group	Consistent Buyer Classification	Inconsistent Buyer Classification	Consistent Seller Classification	Inconsistent Seller Classification	% Consistent Buyer Classification	% Consistent Seller Classification	% Overall Classification
BHP	Large Cap	341,566	2,463	372,368	2,288	99.28%	99.39%	99.34%
CBA	Large Cap	160,632	396	150,877	352	99.75%	99.77%	99.76%
RIO	Large Cap	152,769	549	167,384	541	99.64%	99.68%	99.66%
TLS	Large Cap	169,845	2,039	183,589	2,915	98.81%	98.44%	98.62%
WOW	Large Cap	101,079	213	101,375	224	99.79%	99.78%	99.78%
ASX	Mid Cap	45,579	59	40,369	48	99.87%	99.88%	99.88%
COH	Mid Cap	45,739	77	43,815	78	99.83%	99.82%	99.83%
DVC	Mid Cap	40,940	43	38,815	37	99.90%	99.90%	99.90%
OSH	Mid Cap	53,788	209	57,004	274	99.61%	99.52%	99.57%
WAN	Mid Cap	27,427	16	24,290	21	99.94%	99.91%	99.93%
ABC	Small cap	15,736	11	15,599	10	99.93%	99.94%	99.93%
GAS	Small cap	7,456	1	6,856	0	99.99%	100.00%	99.99%
SDG	Small cap	11,831	8	11,360	8	99.93%	99.93%	99.93%
SEV	Small cap	19,907	6	17,697	16	99.97%	99.91%	99.94%
TSE	Small cap	23,613	14	22,599	14	99.94%	99.94%	99.94%

In the second robustness test, besides relying on the coefficient estimates of the ordered probit regressions, the marginal effects induced by an incremental variation in the regressors is also examined to draw conclusion on the determinants of order aggressiveness. Specifically, if the latent order aggressiveness $Z = x^{'}\beta + \varepsilon$, the marginal effects of changes in the regressors are calculated as follows:

$$\frac{\partial \Pr[R=1]}{\partial x} = -\phi(\mu_1 - x^{'}\beta)\beta \tag{2.7}$$

$$\frac{\partial \Pr[R=m]}{\partial x} = [\phi(\mu_{m-1} - x^{'}\beta) - \phi(\mu_m - x^{'}\beta)]\beta \quad \text{for m} = 2,3,4,5 \tag{2.8}$$

$$\frac{\partial \Pr[R=6]}{\partial x} = \phi(\mu_5 - x^{'}\beta)\beta \quad , \tag{2.9}$$

where $\phi(.)$ is the density normal distribution, β (s) are the coefficient estimates from Equation (2.6). $\mu_1, \mu_2, \mu_3, \mu_4$, and μ_5 are the intercept parameters (limit points) estimated in Equation (2.6). This chapter utilizes the individual observations of the regressors rather than the regressors' mean value, as in Ranaldo (2004), for estimating the marginal effects. In other words, in Equations (2.7), (2.8) and (2.9), the value of $x^{'}\beta$ is calculated based on each individual value of the explanatory variables rather than the mean value of the regressors. The reported marginal probabilities will be the average of all the estimated marginal probabilities calculated based on the individual observations of the explanatory variables. The results of the robustness are given in Tables 10, 11 and 12.

The marginal effects analysis in Tables 10, 11 and 12 shows that a unit increase in the same-side (opposite-side) market depth is associated with a positive (negative) marginal reaction for market order traders and a negative (positive) marginal reaction for limit order traders. A change in the bid-ask spread is also generally associated with a negative reaction for market order traders and a positive reaction for limit order traders. The switching normally occurs between traders who place limit orders within the quotes (Category 4 orders) and those who submit orders at the quote (Category 5 orders). Consistent with the results in Tables 7 and 8, there is no conclusive evidence regarding the marginal effects for the *Volatility* and *Direction* variable. Institutional investors generally increase the probability of submitting aggressive orders during the first trading hour, whereas individual investors tend to decrease the probability of submitting aggressive orders during the same period. Finally, institutional and individual investors also differ in their marginal reactions to a change in the order size in large and mid cap stocks in the anonymous market regime and in small cap stocks in the transparent market regime. All of these results are generally consistent with the findings in Tables 7 and 8. Thus, the empirical findings are robust to the use of either the coefficient estimates or marginal probabilities analysis in interpreting results of the ordered probit models.

Table 10: Marginal probabilities for large cap stocks

This table presents the results of the marginal probabilities based on the investigation of institutional and individual investors' order aggressiveness in large cap stocks in the transparent and anonymous markets. The following ordered probit model is estimated: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \varepsilon_i$. The marginal probabilities are calculated as follows: $\partial \Pr[R=1]/\partial x = -\phi(\mu_1 - x'\beta)\beta$, $\partial \Pr[R=m]/\partial x = [\phi(\mu_{m-1} - x'\beta) - \phi(\mu_m - x'\beta)]\beta$ for m = 2, 3, 4, and 5, and $\partial \Pr[R=6]/\partial x = \phi(\mu_5 - x'\beta)\beta$, where $\phi(.)$ is the density normal distribution, β (s) are the coefficient estimates and μ_1, μ_2, μ_3, μ_4, and μ_5 are the intercept parameters (limit points) estimated in the ordered probit equation.

Panel A: Institutional orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth_{same}	0.0012	0.0065	0.0089	0.0016	-0.0067	-0.0115	0.0024	0.0133	0.0230	0.0032	-0.0147	-0.0272
$\text{Depth}_{opposite}$	-0.0022	-0.0138	-0.0186	-0.0029	0.0143	0.0232	-0.0022	-0.0124	-0.0207	-0.0029	0.0138	0.0244
Spread	-0.0163	-0.0999	-0.1027	-0.0199	0.0819	0.1569	-0.0142	-0.0733	-0.0883	-0.0179	0.0580	0.1357
Volatility	0.0237	0.1118	0.0792	0.0289	-0.0614	-0.1822	0.0288	0.0450	-0.0462	0.0334	0.0670	-0.1280
FirstInt	0.0024	0.0146	0.0189	0.0032	-0.0146	-0.0245	0.0029	0.0141	0.0209	0.0036	-0.0152	-0.0263
Size	0.0029	0.0182	0.0237	0.0038	-0.0185	-0.0301	0.0029	0.0146	0.0202	0.0039	-0.0152	-0.0264
Direction	1.61×10^{-5}	0.0016	0.0023	7.91×10^{-5}	-0.0021	-0.0018	-0.0002	-0.0013	0.0002	-0.0001	0.0008	0.0006

Panel B: Individual orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth_{same}	0.0025	0.0082	0.0179	0.0017	-0.0038	-0.0265	0.0026	0.0085	0.0215	0.0016	-0.0007	-0.0335
$\text{Depth}_{opposite}$	-0.0024	-0.0068	-0.0135	-0.0012	0.0033	0.0206	-0.0020	-0.0057	-0.0129	-0.0011	0.0018	0.0199
Spread	-0.0344	-0.1099	-0.1949	-0.0126	0.0445	0.3073	-0.0439	-0.1183	-0.2199	-0.0219	0.0384	0.3656
Volatility	0.0242	0.1073	0.1898	0.0222	0.0033	-0.3468	0.0196	0.0781	0.1431	0.0282	0.0786	-0.3476
FirstInt	-0.0009	-0.0037	-0.0096	-0.0006	0.0013	0.0135	-0.0021	-0.0060	-0.0133	-0.0013	0.0017	0.0210
Size	0.0019	0.0051	0.0067	0.0009	-0.0020	-0.0126	-0.0016	-0.0055	-0.0155	-0.0013	-0.0005	0.0244
Direction	-0.0011	-0.0024	-0.0006	-0.0007	0.0004	0.0044	-0.0002	-0.0003	0.0022	0.0001	0.0006	-0.0024

Table 11: Marginal probabilities for mid cap stocks

This table presents results of the marginal probabilities based on the investigation of institutional and individual investors' order aggressiveness in mid cap stocks in the transparent and anonymous markets. The following ordered probit model is estimated: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \varepsilon_i$. The marginal probabilities are calculated as follows: $\partial \Pr[R=1]/\partial x = -\phi(\mu_1 - x'\beta)\beta$, $\partial \Pr[R=m]/\partial x = [\phi(\mu_{m-1} - x'\beta) - \phi(\mu_m - x'\beta)]\beta$ for m = 2, 3, 4, and 5, and $\partial \Pr[R=6]/\partial x = \phi(\mu_5 - x'\beta)\beta$, where $\phi(.)$ is the density normal distribution, β (s) are the coefficient estimates and μ_1, μ_2, μ_3, μ_4, and μ_5 are the intercept parameters (limit points) estimated in the ordered probit equation.

Panel A: Institutional orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth_{same}	0.0023	0.0036	0.0077	0.0007	-0.0059	-0.0084	0.0035	0.0087	0.0238	0.0023	-0.0144	-0.0239
$\text{Depth}_{opposite}$	-0.0055	-0.0091	-0.0206	-0.0025	0.0137	0.0240	-0.0049	-0.0114	-0.0284	-0.0036	0.0164	0.0319
Spread	-0.0081	-0.0169	-0.0341	-0.0039	0.0239	0.0391	-0.0073	-0.0177	-0.0423	-0.0049	0.0292	0.0430
Volatility	0.0078	0.0009	-0.0280	0.0096	0.0457	-0.0360	-0.0014	-0.0216	-0.0851	0.0037	0.1025	0.0019
FirstInt	0.0023	0.0046	0.0091	0.0011	-0.0072	-0.0099	0.0030	0.0088	0.0222	0.0021	-0.0155	-0.0206
Size	0.0027	0.0056	0.0116	0.0009	-0.0103	-0.0105	0.0018	0.0047	0.0090	0.0010	-0.0099	-0.0066
Direction	-0.0003	0.0012	0.0028	0.0007	-0.0008	-0.0036	$4.97\text{x}10^{-6}$	0.0010	-0.0008	0.0002	0.0003	-0.0007

Panel B: Individual orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth_{same}	0.0039	0.0069	0.0152	0.0029	-0.0047	-0.0242	0.0046	0.0077	0.0197	0.0045	0.0044	-0.0409
$\text{Depth}_{opposite}$	-0.0030	-0.0043	-0.0102	-0.0027	0.0024	0.0178	-0.0025	-0.0050	-0.0118	-0.0022	-0.0023	0.0238
Spread	0.0002	-0.0035	-0.0009	0.0019	0.0018	0.0005	-0.0047	-0.0099	-0.0178	-0.0018	$-1.70\text{x}10^{-5}$	0.0342
Volatility	-0.0062	-0.0064	-0.0204	-0.0009	0.0150	0.0189	0.0004	0.0072	0.0203	0.0033	0.0176	-0.0488
FirstInt	0.0002	-0.0008	-0.0020	0.0002	-0.0001	0.0025	-0.0023	-0.0042	-0.0081	-0.0020	-0.0006	0.0172
Size	0.0030	0.0048	0.0083	0.0020	-0.0034	-0.0147	-0.0040	-0.0081	-0.0205	-0.0038	-0.0048	0.0412
Direction	-0.0024	-0.0025	-0.0060	-0.0012	0.0005	0.0116	0.0009	0.0024	0.0041	0.0011	0.0013	-0.0098

Table 12: Marginal probabilities for small cap stocks

This table presents the results of the marginal probabilities based on the investigation of institutional and individual investors' order aggressiveness in small cap stocks in the transparent and anonymous markets. The following ordered probit model is estimated: $Z_i = \beta_1$ Depth$_{same,i}$ + β_2 Depth$_{opposite,i}$ + β_3 Spread$_i$ + β_4 Vola$_i$ + β_5 FirstInt$_i$ + β_6 Size$_i$ + β_7 Direction$_i$ + ε_i. The marginal probabilities are calculated as follows: $\partial \Pr[R=1]/\partial x = -\phi(\mu_1 - x'\beta)\beta$, $\partial \Pr[R=m]/\partial x = [\phi(\mu_{m-1} - x'\beta) - \phi(\mu_m - x'\beta)]\beta$ for m = 2, 3, 4, and 5, and $\partial \Pr[R=6]/\partial x = \phi(\mu_5 - x'\beta)\beta$, where ϕ(.) is the density normal distribution, β (s) are the coefficient estimates and μ_1, μ_2, μ_3, μ_4, and μ_5 are the intercept parameters (limit points) estimated in the ordered probit equation.

Panel A: Institutional orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth$_{same}$	0.0067	0.0081	0.0236	0.0005	-0.0130	-0.0259	-0.0006	0.0045	0.0208	0.0011	-0.0101	-0.0157
Depth$_{opposite}$	-0.0057	-0.0062	-0.0177	0.0006	0.0111	0.0179	0.0002	-0.0025	-0.0093	-0.0005	0.0051	0.0070
Spread	-0.0082	-0.0108	-0.0286	0.0011	0.0221	0.0244	-0.0124	-0.0137	-0.0427	0.0007	0.0285	0.0396
Volatility	0.0012	0.0081	0.0177	0.0017	-0.0085	-0.0202	-0.0095	-0.0028	-0.0038	0.0024	0.0179	-0.0042
FirstInt	-0.0005	-0.0013	-0.0041	$6.36\text{x}10^{-5}$	0.0021	0.0038	0.0032	0.0059	0.0198	$7.95\text{x}10^{-5}$	-0.0131	-0.0158
Size	-0.0007	-0.0016	-0.0065	$5.30\text{x}10^{-5}$	0.0023	0.0065	-0.0015	-0.0032	-0.0125	$9.75\text{x}10^{-5}$	0.0075	0.0097
Direction	0.0013	0.0019	0.0041	-0.0008	-0.0071	0.0006	-0.0006	0.0034	0.0124	$-8.50\text{x}10^{-5}$	-0.0098	-0.0054

Panel B: Individual orders

	Transparent Market Levels of Order Aggressiveness						Anonymous Market Levels of Order Aggressiveness					
	1	2	3	4	5	6	1	2	3	4	5	6
Depth$_{same}$	0.0097	0.0105	0.0238	0.0051	-0.0045	-0.0446	0.0074	0.0073	0.0185	0.0050	0.0051	-0.0433
Depth$_{opposite}$	-0.0095	-0.0090	-0.0205	-0.0045	0.0051	0.0384	-0.0039	-0.0029	-0.0092	-0.0024	-0.0029	0.0213
Spread	-0.0012	-0.0019	-0.0013	0.0012	0.0023	0.0009	0.0054	0.0059	0.0161	0.0043	0.0051	-0.0368
Volatility	0.0022	0.0046	0.0094	0.0017	0.0034	-0.0213	0.0052	0.0107	0.0252	0.0042	0.0112	-0.0565
FirstInt	-0.0017	-0.0013	-0.0037	-0.0009	-0.0005	0.0081	-0.0042	-0.0043	-0.0104	-0.0033	-0.0024	0.0246
Size	0.0017	0.0015	0.0034	0.0013	-0.0017	-0.0062	-0.0054	-0.0062	-0.0146	-0.0039	-0.0036	0.0337
Direction	0.0016	0.0025	0.0051	0.0016	-0.0010	-0.0098	0.0028	0.0041	0.0088	0.0024	0.0021	-0.0202

The final robustness test presents the results of examining the determinants of institutional and individual order aggressiveness, when order cancellations are included together with new order submissions and order revisions. The results presented in the previous sections are based only on new order submissions and order revisions. This is motivated by the argument of Hall and Hautsch (2006) for the need to model order submissions and order cancellations differently. In the sample period under investigation, 25.70% of all orders are subsequently cancelled and order cancellation accounts for 16.11% of all new order submissions, order revisions and order cancellations.[24] For robustness check, order cancellations are also included in the investigation of order aggressiveness, with order cancellations classified as the least aggressive orders (Ranaldo, 2004).

The results of this investigation, as documented in Table 13, indicate a positive (negative) relation between same-side (opposite-side) market depth and order aggressiveness. Order aggressiveness is also negatively related to bid-ask spread. Institutions tend to increase (decrease) their order aggressiveness when volatility increases in large (mid) cap stocks, whereas individuals decrease (increase) their order aggressiveness when volatility increases in mid (small) cap stocks. Institutional (individual) investors are also more (less) aggressive in the first trading hour and when submitting large order. Both groups of investors are less aggressive after the move to anonymity. These results are consistent with those presented in Table 3, where order cancellations are excluded. Therefore, the results in this chapter are robust to the inclusion or exclusion of order cancellations.

[24] Traditional theoretical models of the limit order book often do not allow traders to return to the market and cancel or revise their orders. Order cancellations are allowed in more recent studies (see, for example, Goettler et al., 2005, 2008; Rosu, 2008, 2009; Liu, 2009). For more discussion on order cancellations on the ASX, see Fong and Liu (2006) and Liu (2009).

Table 13: Determinants of institutional and individual order aggressiveness with the inclusion of order cancellations

This table presents the results of investigating the determinants of institutional and individual investors' order aggressiveness with the inclusion of order cancellations as the least aggressive orders. The following ordered probit models are estimated for institutional and individual orders: $Z_i = \beta_1 \text{Depth}_{same,i} + \beta_2 \text{Depth}_{opposite,i} + \beta_3 \text{Spread}_i + \beta_4 \text{Vola}_i + \beta_5 \text{FirstInt}_i + \beta_6 \text{Size}_i + \beta_7 \text{Direction}_i + \beta_8 \text{Anonymous}_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $\text{Depth}_{same,i}$ ($\text{Depth}_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. Spread_i is the relative bid-ask spread at the time of order submission. Vola_i is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. FirstInt_i is the dummy variable for the first trading hour of the trading day. TTC_i is the remaining time (in hours) until market closing time. Direction_i and Anonymous_i are the dummy variables for sell orders and orders submitted from 28 November 2005 onward, respectively. Size_i is the natural logarithm of the number of shares in the particular order. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level.

Panel A: Institutional orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0333	16.67%	80.00%	-0.0352	23.33%	60.00%	-0.0451	23.33%	66.67%
$\text{Depth}_{opposite}$	0.0767	96.67%	3.33%	0.0855	86.67%	6.67%	0.0275	40.00%	13.33%
Spread	0.5525	93.33%	6.67%	0.1859	86.67%	0%	0.1334	86.67%	3.33%
Volatility	-0.2045	33.33%	56.67%	0.2717	63.33%	16.67%	0.0741	40.00%	30.00%
FirstInt	-0.0526	3.33%	93.33%	-0.0223	10.00%	50.00%	-0.0072	6.67%	26.67%
Size	-0.1152	0%	96.67%	-0.0689	10.00%	90.00%	0.0051	40.00%	43.33%
Direction	-0.0040	30.00%	33.33%	0.0051	43.33%	43.33%	-0.0204	26.67%	46.67%
Anonymous	0.0224	50.00%	30.00%	0.0216	56.67%	23.33%	0.0125	43.33%	23.33%

Panel B: Individual orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
Depth_{same}	-0.0685	0%	90.00%	-0.0525	6.67%	76.67%	-0.0749	10.00%	83.33%
$\text{Depth}_{opposite}$	0.0385	76.67%	16.67%	0.0454	76.67%	10.00%	0.0794	76.67%	6.67%
Spread	0.8906	96.67%	0%	0.0792	50.00%	20.00%	0.0064	36.67%	33.33%
Volatility	-0.9261	26.67%	30.00%	0.4057	50.00%	20.00%	-0.2812	3.33%	76.67%
FirstInt	0.0116	50.00%	26.67%	0.0143	53.33%	23.33%	0.0263	50.00%	10.00%
Size	0.0014	50.00%	33.33%	0.0468	86.67%	6.67%	0.0647	93.33%	6.67%
Direction	0.0094	53.33%	40.00%	0.0115	53.33%	26.67%	-0.0313	23.33%	53.33%
Anonymous	0.0423	63.33%	13.33%	0.0753	90.00%	6.67%	0.0917	76.67%	10.00%

2.6 Conclusions

This chapter investigates the factors affecting the order aggressiveness of institutional and individual investors and examines the effect of the removal of broker IDs on the ASX on the order aggressiveness of these two classes of investors. Investigating order submissions during the period between 1 August 2005 and 31 March 2006, this chapter provides supportive evidence for the positive relation between order aggressiveness and same-side market depth and a negative relation between order aggressiveness and opposite-side market depth. These findings indicate that traders consider non-execution risk while deciding on their order placement strategy. Both individual and institutional traders submit less aggressive orders when spreads are high while trading large cap stocks. Individual investors, however, switch to a more aggressive strategy while trading small cap stocks, even if spreads are wide. This difference between individual and institutional investors reflects their sensitivity to non-execution risk. Individual investors are at an informational disadvantage with respect to their timely knowledge of the order book compared to institutional investors and hence alter their strategy to cope with non-execution.

Volatility has different impacts on order aggressiveness in different groups of stocks. Both institutional and individual investors place less aggressive orders when volatility increases in mid cap stocks, whereas institutional investors increase their order aggressiveness when volatility increases in large cap stocks. Institutional investors submit more aggressive orders under volatile market conditions in large cap stocks, arguably to profit from "picking-off" stale limit orders. As monitoring is lower and transaction costs are higher for mid cap and small cap stocks, institutions are less aggressive in their order placements when volatility increases in these stocks. Institutional and individual investors also follow different order placement strategies at the beginning of the trading day. While institutional traders place more aggressive orders early in the trading day to exploit potential short-lived private information, their individual counterparts are less aggressive initially and become more aggressive as the trading day progresses. In addition, institutional investors are more likely to increase their aggressiveness when placing large orders in large and mid cap stocks, whereas large orders submitted by individual investors are more likely to be non-aggressive. These differences in the behavior of institutional and individual investors in the first trading hour and in response to changes in order size are stronger in the anonymous market than in the transparent market. Individual buyers and sellers also react differently to changes in spread and volatility in mid cap stocks.

Finally, both institutions and individuals become less aggressive in their order submission after the removal of broker IDs on the ASX, with stronger evidence documented for individual investors. This finding suggests an enhancement to market liquidity, where both institutional and individual investors tend to increase their supply of liquidity following the move to anonymity. In other words, investors are more willing to display their orders and seek execution in the central limit order book after the move to anonymity. Since enhancing liquidity and encouraging traders to display orders and execute transactions in the central limit order book is the main motivation for the ASX to remove broker IDs, the results of this chapter support the ASX's decision to remove broker IDs in the central limit order book.

Chapter 3: Order Book Slope and Price Volatility

3.1 Introduction

3.1.1 Purpose and Motivation

The purpose of this chapter is to examine how the information inherent in the contents of the limit order book influences price volatility on the ASX. More specifically, this chapter investigates the informativeness of variations in the liquidity provision in the limit order book, as captured by the limit order book slope, in explaining price volatility. In addition, the effect of a change in market transparency on the information content of the limit order book is analyzed. In doing so, this chapter addresses four research questions. First, is the slope of the limit order book informative about future price volatility? Second, which side of the limit order book is more informative about future price volatility, the buy (demand) side or the sell (supply) side? Third, are institutional investors' limit orders more informative than individual limit orders about future price volatility? Finally, does anonymity have any impact on the informativeness of the limit order book and if it does, are institutional or individual limit orders more affected by this change?

Investigating the informativeness of the limit order book slope about future price volatility is important because volatility is essential for pricing options and determining order choices (see, for example, Foucault, 1999; Hasbrouck and Saar, 2002; Bae et al., 2003; Ranaldo, 2004; Beber and Caglio, 2005; Wald and Horrigan, 2005). Fleming et al. (2001, 2003) also demonstrate the substantial value of volatility timing in the context of investment decisions. Fleming et al. (2003) suggest that an investor implementing the volatility timing strategies would be willing to pay on the order of 50 to 200 basis points per year to capture the incremental gains generated by the realized volatility-based estimator. Furthermore, an understanding of the relation between the limit order book slope and future price volatility can provide insights about the process through which information is incorporated into prices. In other words, the analysis undertaken in this chapter provides evidence regarding the order choices of informed traders when they exploit their private information. The inconclusive evidence in the current literature regarding the use of limit orders by informed traders[25] provides the motivation for the analysis on the information content of the limit order book, carried out in this chapter.

3.1.2 Main Findings

This chapter documents evidence supportive of the informativeness of the order book slope about future price volatility in the majority of the constituent stocks of the S&P/ASX 100 index during the period between 1 July 2005 and 30 June 2006. The informativeness of the order book slope is observed for both the overall volatility and the permanent component of volatility, with stronger results observed for the permanent component of volatility. Consistent with the theoretical models of Chakravarty and Holden (1995), Wald and Horrigan (2005), and Kaniel and Liu (2006), this finding supports the use of limit orders by informed traders on the ASX. This chapter also finds that the slope of the limit order book on the buy side is more informative than that on the sell side and institutional limit orders are more informative than individual limit orders about the future permanent component of volatility.

Consistent with Foucault et al. (2007), the empirical results in this chapter suggest that anonymity has a significant impact on the information content of the limit order book. The move to anonymity on the ASX has a significant impact on the informativeness of institutional limit orders but a minimal impact on individual limit orders. Finally, among the

[25] See, for example, Glosten (1994), Seppi (1997), Chakravarty and Holden (1995), Wald and Horrigan (2005) and Kaniel and Liu (2006).

stocks that experience significant changes in the informativeness of the limit order book slope, the limit order book slope tends to become more informative after the removal of broker IDs on the ASX, especially in large cap stocks.

3.1.3 Chapter Outline

The remainder of the chapter is organized as follows. Section 3.2 provides the literature review and development of hypotheses. Section 3.3 describes the data examined and the measurement of variables used. Section 3.4 explains the research methodology. Section 3.5 discusses the results and their implications and Section 3.6 concludes the chapter.

3.2 Literature Review and Hypotheses Development

3.2.1 The Information Content of the Limit Order Book

In the current literature, limit orders are viewed as the non-aggressive type of order, which supply liquidity to the market, whereas market orders are aggressive orders and demand liquidity. Therefore, the information content of the limit order book is linked to the question of whether informed traders use non-aggressive (limit) orders to exploit their information advantage. The current literature, however, is inconclusive with regards to this issue. Glosten (1994) and Seppi (1997) present theoretical models of limit order markets in which informed traders carry out their trades using market orders. This preference for market orders over limit orders reflects the presumed impatience of informed traders to capitalize on their information. Harris (1998) incorporates limit orders in the informed traders' order submission strategies but argues that informed traders are less likely than liquidity traders to use limit orders.

In contrast to the traditional theoretical models, more recent studies provide both theoretical background and empirical evidence supporting the use of limit orders by informed traders.

Chakravarty and Holden (1995) show that for a risk-neutral informed trader, combining market and limit orders can be more profitable than a strategy of only placing market orders. Similarly, Wald and Horrigan (2005) develop a theoretical model to derive the optimal limit and market order decisions from the perspective of risk-averse traders. The authors suggest that rather than submitting market orders, it is optimal for informed traders to place slightly discounted limit orders, often inside the bid-ask spread, because the execution risk for these limit orders is minimal.

Consistent with both Chakravarty and Holden (1995) and Wald and Horrigan (2005), Kaniel and Liu (2006) provide a Glosten-Milgrom (Glosten and Milgrom, 1985) type of theoretical model, supporting the use of limit orders by informed traders. The authors emphasize the role of the informed traders' private information horizon as the key determinant of their use of limit orders versus market orders. When the expected time horizon for their private information is high, informed traders are more likely to submit limit orders instead of market orders. Moreover, when the probability that the information is long-lived is high enough, limit orders might be more informative than market orders.

Bloomfield et al. (2005) also emphasize limit orders as important components of informed traders' order submission strategies. According to these authors, when trading begins, informed traders are much more likely to take liquidity (use market orders) to profit from their information advantage. As the trading day progresses and prices converge to their true values, informed traders switch to limit orders to earn profit based on the spread. Bloomfield et al. (2005) further argue that toward the end of the trading day, informed traders, on average trade more with limit orders than uninformed traders.

Foucault et al. (2007) develop a theoretical model for a limit order market where traders differ in terms of their private information on future volatility. According to these authors, the limit order book is a conduit for volatility information because of the option-like features of limit orders.[26] As prices of options depend on volatility, limit order traders should incorporate volatility information into their limit order submissions. Therefore, the limit order book should contain private volatility information. In particular, Foucault et al. (2007) document that it is optimal for informed traders with private information on volatility to bid less aggressively if volatility is expected to increase.

With the availability of order book data, the ability of information contained in the limit order book to predict future returns, volume, and volatility has been documented. Irvine et al. (2000) propose a measure of liquidity, the Cost of Round Trip measure, which aggregates the limit order book information at any moment in time as a measure of liquidity. The authors support the significance of this liquidity measure by showing its ability to predict the number of trades in forthcoming periods. Kavajecz and Odders-White (2004) highlight that some technical rules that are used to predict future price trends are related to the liquidity provision in the limit order book. Kalay and Wohl (2009) also show that their buying pressure (BP) measure, which is based on the slopes of the demand and supply schedules possess predictive power over future returns. Harris and Panchapagesan (2005) document that both asymmetry between buys and sells in terms of quantities as well as the option values provided by limit orders help explain future returns on the New York Stock Exchange (NYSE). Similarly, Cao et al. (2009) find empirical support for the role of imbalance between demand and supply in the order book of the 100 most actively traded stocks on the ASX in explaining future short-term returns.

[26] Copeland and Galai (1983) were the first to stress that a sell (buy) limit order is similar to a call (put) option with an exercise price equal to the limit order price.

Empirical findings regarding the informativeness of the limit order book for future volatility are presented in Ahn et al. (2001), Coppejans et al. (2004), Pascual and Veredas (2006), and Nigmatulin et al. (2007). Specifically, Ahn et al. (2001) and Coppejans et al. (2004) find a negative relation between market depth and future short-term price volatility for the 33 component stocks in the Hang Seng index of the Stock Exchange of Hong Kong and the Swedish stock index futures contracts, respectively. Decomposing volatility into transitory and informational components based on a dynamic state-space co-integration model for ask and bid quotes, Pascual and Veredas (2006) also provide evidence supporting the informativeness of the limit order book for the future informational component of price volatility. Nigmatulin et al. (2007) also observe that the limit order book contains information regarding future volatility and returns for Dow Jones Industrial Average (DJIA) stocks traded on the NYSE between 1 June 2006 and 31 July 2006.

This chapter, consistent with Foucault et al.'s (2007) model, expects investors to be less aggressive in their order submissions when they expect price volatility to increase. If investors are less aggressive in their order submissions, the bid-ask spread widens and a greater share volume will be located away from the best quotes (Foucault et al., 2007). When a greater share volume is distributed away from the best quotes, the order book slope becomes more gentle (Naes and Skjeltorp, 2006). This suggests that the order book slope is negatively related to future price volatility.[27] Based on this discussion, the following hypothesis regarding the informativeness of the limit order book slope over future volatility is formulated:[28]

H_1: The limit order book slope is negatively related to future price volatility.

[27] Naes and Skjeltorp (2006) document a negative contemporaneous relation between the order book slope and price volatility. They argue that the order book slope reflects investors' divergence of opinion and thus their results are consistent with the "Divergence of Opinion" model of Harris and Raviv (1993) and Shalen (1993). Bessembinder et al. (1996) also find support for the impact of divergence of opinion on trading volume.

[28] All the hypotheses in this chapter are stated in the alternative form.

Andersen et al. (1997a) and Muller et al. (1997) suggest that different component of volatility may exist at the intraday level. Bae et al. (2003) emphasize the importance of differentiating between volatility that arises from noise or liquidity trading and volatility that arises from information in the analysis of order placements. This chapter argues that if informed traders do use limit orders to exploit their information advantage, the limit order book slope should be informative not only about future volatility but also about the future permanent component of volatility. The second hypothesis regarding the informativeness of the limit order book slope about the future permanent component of volatility is formulated as follows:

H_2: The limit order book slope is negatively related to the future permanent component of price volatility.

The limit order book consists of orders submitted by buyers on the buy (demand) side and orders placed by sellers on the sell (supply) side. Prior literature has found that block purchases have a greater permanent price impact than block sales (see, for example, Kraus and Stoll, 1972; Holthausen et al., 1987, 1990; Burdett and O'Hara, 1987; Gemmill, 1996; Keim and Madhavan, 1996). The same result is also applied to institutional trades (Chan and Lakonishok, 1993, 1995; Saar, 2001). Similarly, Griffiths et al. (2000) provide evidence that aggressive buy orders on the Toronto Stock Exchange are more informative than aggressive sell orders. Ranaldo (2004) also documents that incoming sellers face a larger bid-ask spread than incoming buyers. Furthermore, buy orders have a higher probability of continuation than sell orders. Ranaldo (2004) attributes the finding of a higher spread and a lower autocorrelation for sell orders to the information advantage buyers have over sellers.

Based on the preceding discussion, this chapter hypothesizes that the information advantage of buyers over sellers is not only limited to aggressive orders but extends to non-aggressive (limit) orders. Therefore, the limit order book slope on the buy (demand) side should be more informative than the limit order book slope on the sell (supply) side. The third hypothesis is formulated as follows:

H_3: The limit order book slope of the demand (buy) side is more informative about the future permanent component of price volatility than the limit order book slope of the supply (sell) side.

The limit order book contains orders submitted by institutional and individual investors. It is therefore important to investigate whether the informativeness of the limit order book slope arises as a result of the liquidity provisions by institutional investors or individual investors. Analyzing a sample of NYSE stocks included in the TORQ database, Anand et al. (2005) document that institutional traders' limit orders outperform those of retail (individual) traders, even after controlling for stock and order characteristics. Utilizing the same dataset, Kaniel and Liu (2006) provide evidence that limit orders actually contain more information and thus outperform market orders. Furthermore, the relative informativeness of limit orders over market orders is greater for institutional orders than for individual orders. Based on the evidence presented in Anand et al. (2005) and Kaniel and Liu (2006) and on the findings in prior literature that institutional investors are better-informed investors, the following hypothesis regarding the informativeness of institutional limit orders and individual limit orders over the future permanent component of volatility is formulated:

H_4: The slope of the limit order book of institutional investors is more informative about the future permanent component of price volatility than the slope of the limit order book based on orders submitted by individual investors.

3.2.2 Anonymity and the Information Content of the Limit Order Book

Foucault et al. (2007) develop a theoretical model for limit order markets to explain the changing behavior of informed and uninformed traders after the removal of broker IDs. Foucault et al. (2007) argue that a transparent market, where broker IDs are displayed, fosters the front-running activities of uninformed investors. More specifically, uninformed investors infer information about future price movements from the orders submitted by informed traders. They try to front-run the informed traders to benefit from the information by setting more competitive quotes than those posted by the informed traders. In response, informed traders sometimes adopt "bluffing" strategies by posting non-aggressive orders and setting wider spreads than appropriate. An anonymous trading system eliminates the traders' ability to distinguish informed traders' orders from those of uninformed traders. Therefore, in an anonymous trading system, uninformed traders submit orders based on their belief about the identity of the traders with the orders in the limit order book. In this case, if the participation rate of informed traders is small (large), uninformed traders will be more (less) aggressive, and improve on the already posted orders more (less) often.

Empirical findings on the impact of removing broker IDs are provided by Comerton-Forde et al. (2005), Foucault et al. (2007) and Comerton-Forde and Tang (2008). Comerton-Forde et al. (2005), Foucault et al. (2007) and Comerton-Forde and Tang (2008) observe a reduction in the bid-ask spread following the move to anonymity in the Tokyo Stock Exchange, the Euronext Paris, and the ASX, respectively. An increase in the bid-ask spread is documented by Comerton-Forde et al. (2005) for the Korea Stock Exchange after it started disclosing broker ID information. Besides the bid-ask spread, Comerton-Forde and Tang (2008) find a reduction in adverse selection risk, trade execution costs, order exposure risk and order aggressiveness after the removal of broker IDs on the ASX. The results documented in

Chapter 2 of this thesis also show a reduction in order aggressiveness after the move to anonymity and this result applies for both institutional and individual investors. To the best of my knowledge, Foucault et al. (2007) is the only study that analyzes the impact of anonymity on the information content of the limit order book. They find the limit order book at the best quote, as reflected by the bid-ask spread, to be less informative about future volatility after the removal of broker IDs on Euronext Paris.

Drawing on the insights of Foucault et al. (2007), this chapter argues that if institutional investors are better informed than individual investors, in an anonymous trading system where the risk of front-running activities is reduced, institutional investors are more willing to submit informative limit orders. This will result in an increase in the informativeness of the slope of the overall limit order book and institutional limit orders. Since in the transparent market, the broker ID information on the ASX is disseminated only to the broker community, the move to anonymity does not significantly change individual investors' information environment, except for some very high net worth individuals. Therefore, there should be no significant changes in the informativeness of the individual slope about future volatility after the move to anonymity. Based on the above discussions, the hypotheses on the effect of anonymity on the information content of the limit order book are formulated as follows:

H_5: The move to anonymity results in an increase in the informativeness of the limit order book slope about the future permanent component of price volatility.

H_6: The move to anonymity has a larger impact on the informativeness of the institutional slope than the individual slope about the future permanent component of price volatility.

3.3 Data

3.3.1 Data Description

The information content of the limit order book is investigated based on a sample of the stocks making up the S&P/ASX 100 index for the period between 1 July 2005 and 30 June 2006. For each of these stocks, the proprietary Order Book Dataset, as described in Section 2.3, is used to reconstruct the state of the limit order book at the end of various intraday intervals. This chapter examines the informativeness of the limit order book based on a 30-minute interval. Since the ASX's staggered opening procedure takes up to 10 minutes to complete, the data for the first 10 minutes of each day are excluded from our sample to avoid any potential bias. Therefore, the time period examined in each trading day is from 10:10 to 16:00. The analysis of the information content of the limit order book is based on the state of the limit order book at 10:30, 11:00, 11:30, 12:00, 12:30, 13:00, 13:30, 14:00, 14:30, 15:00, 15:30, and 16:00 on every trading day. The sample is partitioned into large cap stocks and mid cap stocks. The large cap stocks are the constituent stocks of the S&P/ASX 50 index on 1 July 2005. The mid cap stocks are those included in the S&P/ASX 100 index but not in the S&P/ASX 50 index on 1 July 2005.[29] Finally, only seasoned stocks that have not been merged or acquired by other companies and the stocks for which data are available for the entire sample period are examined. The final sample includes 90 stocks, consisting of 47 large cap and 43 mid cap stocks.

The main difference between the stock selection criteria in this chapter and those in Chapter 2 is the exclusion of small cap stocks. In this chapter, the informativeness of the limit order book slope is analyzed based on intraday intervals with the number of trades and average

[29] These classification criteria for large cap and mid cap stocks are consistent with those of the ASX.

trade size in each interval as the controlled variables.[30] Therefore, the analysis in this chapter requires the use of liquid stocks, which have trading activity in almost all of the 30-minute intervals. This is the main reason why small cap stocks are excluded. Chapter 2 does not face this problem since the analysis there is 1) not a time series analysis and 2) based on order submissions, revisions, and cancellations and does not use information on order executions (transactions).

3.3.2 Return Series

Return series are constructed based on the mid-quote prices at the end of every 30-minute interval. Mid-quote prices are chosen instead of transacted prices because they reduce the measurement errors due to bid-ask bounce, which can result in substantial spurious volatility, as suggested by Roll (1984). The return for each interval is calculated as the difference of the natural logarithm of the mid-quote prices at the end of the current interval and those at the end of the previous interval. Similar to Foucault et al. (2007), overnight returns are excluded. Therefore, the returns for the first interval in each trading day are calculated as the difference of the natural logarithm of the mid-quote prices at the end of the interval and those at the beginning of the interval.

Andersen and Bollerslev (1997b), Martens (2001), Martens et al. (2002), and Andersen et al. (2003) argue that intraday patterns can severely corrupt traditional volatility models based on raw (unadjusted) high-frequency series. Therefore, this chapter follows the method of Andersen et al. (2003) in constructing seasonally adjusted intraday returns. First, the seasonal factors are obtained by averaging the individual squared returns in the various intraday intervals

[30] The choice of these control variables is consistent with Foucault et al. (2007).

$$s_i^2 = \frac{1}{T}\sum_{t=1}^{T} r_{it}^2 , \tag{3.1}$$

where r_{it} denotes the return for interval i on day t. The seasonally adjusted intraday returns ($\tilde{r}_{it}$) are then calculated as

$$\tilde{r}_{it} = \frac{r_{it}}{s_i}. \tag{3.2}$$

3.3.3 Slope of the Order Book

Following Naes and Skjeltorp (2006), the order book slope for firm i in interval t is measured as follows:

$$SLOPE_{i,t} = \frac{DE_{i,t} + SE_{i,t}}{2} , \tag{3.3}$$

where $DE_{i,t}$ and $SE_{i,t}$ represent the slopes of the bid (demand) side and ask (supply) sides respectively. The order book slope for the bid side for firm i in interval t is given as

$$DE_{i,t} = \frac{1}{N_B}\left\{\frac{v_1^B}{\left|p_1^B / p_0 - 1\right|} + \sum_{\tau=1}^{N_B-1}\frac{v_{\tau+1}^B / v_\tau^B - 1}{\left|p_{\tau+1}^B / p_\tau^B - 1\right|}\right\} \tag{3.4}$$

Similarly, the order book slope for the ask side can be given as

$$SE_{i,t} = \frac{1}{N_A}\left\{\frac{v_1^A}{p_1^A / p_0 - 1} + \sum_{\tau=1}^{N_A-1}\frac{v_{\tau+1}^A / v_\tau^A - 1}{p_{\tau+1}^A / p_\tau^A - 1}\right\}, \tag{3.5}$$

where N_B and N_A are the total number of bid and ask prices (tick levels) containing orders, respectively. τ denotes the tick levels, with $\tau = 0$ representing the best bid-ask mid-point and $\tau = 1$ representing the best ask (bid) quote with positive share volume. p_0 is the best bid-ask mid-point and v_τ^A and v_τ^B are the natural logarithm of the accumulated total share volume at the price level τ (p_τ) on the ask and bid side, respectively. In other words, v_τ^A (v_τ^B) is the natural logarithm of the total share volume supplied (demanded) at p_τ or lower (higher). At the end of each 30-minute interval, the 10 best bid and ask quotes are used together with the share volume at these quotes to calculate the order book slope for that particular interval. In addition, all undisclosed (hidden) orders are removed from the calculation of the limit order book slope.

3.4 Research Methodology

3.4.1 Predictive Power of the Order Book Slope

This chapter investigates the predictive power of the order book slope on future volatility and the effect on this predictive power of the move to anonymity. Since generalized autoregressive conditional heteroskedasticity (GARCH)-type models are widely used in studies that dealing with volatility modelling (Bollerslev et al., 1992), the analyses are based on estimating the following GARCH(1,1) model:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.6)$$

where r_t is the seasonally adjusted stock return at interval *t*, μ is a constant, ε_t are the serially uncorrelated errors (innovations) of stock returns with mean zero, σ_t^2 is the conditional variance of ε_t. $SLOPE_{t-1}$ is the limit order book slope at the end of interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the anonymous period (from 28 November 2005 onward), and zero otherwise. Consistent with Jones et al. (1994), the average trade size, ATS_{t-1}, and the total number of trades, NT_{t-1}, for the *(t-1)th* interval are included as control variables for price volatility.

In addition to the GARCH model, the predictive power of the limit order book slope is examined using Nelson's (1991) EGARCH model, which allows for the control for the "leverage effect", where a negative shock to financial time series is more likely to have a larger impact on volatility than a positive shock of the same magnitude. The EGARCH(1,1) model is specified as follows:

$r_t = \mu + r_{t-1} + \varepsilon_{t}$, $\qquad \varepsilon_t \mid \Omega_{t-1} \sim \text{i.i.d.}\ (0, \sigma_t^2)$

$$h_t = \omega + \beta\, h_{t-1} + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\ \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + (\delta_1 + \delta_2 D_{post})\ SLOPE_{t-1} + \varphi_1\ NT_{t-1}$$

$$+ \varphi_2\ ATS_{t-1}, \qquad (3.7)$$

where $h_t = \log(\sigma_t^2)$. The order book slope is expected to be informative about future volatility. Therefore, δ_1 is expected to be negative and significant in Equations (3.6) and (3.7). In both the GARCH and EGARCH models, an interaction term between the lagged value of the order book slope and the dummy variable D_{post} is included to analyze the effect of removing broker IDs on the information content of the limit order book slope. Consistent with Foucault et al. (2007), this thesis expects the removal of broker IDs on the ASX to have a significant impact on the informativeness of the limit order book slope. Thus, the majority of the coefficient estimates for δ_2 should be statistically significant. If δ_2 is positive (negative) and significant, the move to anonymity has resulted in a (an) decrease (increase) in the informativeness of the limit order book slope.

3.4.2 Order Book Slope and the Permanent Component of Volatility

Recent literature on volatility modelling argues for the existence of different volatility components at the intraday level. This phenomenon can be due to either heterogeneous information arrival processes, as suggested by Andersen and Bollerslev (1997a), or heterogeneous traders, as proposed by Muller et al. (1997). Since intraday volatility can contain different components, the component GARCH (CGARCH) model of Engle and Lee (1993) is also used to investigate the relation between the order book slope and the long-run component of volatility. Specifically, the conditional variance equation of the GARCH(1,1) model of Bollerslev (1986),

$$\sigma_t^2 = \varpi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{3.8}$$

can be expressed as

$$\sigma_t^2 = \overline{\varpi} + \alpha(\varepsilon_{t-1}^2 - \overline{\varpi}) + \beta(\sigma_{t-1}^2 - \overline{\varpi}) \ , \tag{3.9}$$

which shows a mean reversion to the constant $\overline{\varpi} = \varpi / (1\text{-}\alpha\text{-}\beta)$ for all time. Engle and Lee's (1993) CGARCH model allows a mean reversion to a varying level q_t as follows:

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \tag{3.10}$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2). \tag{3.11}$$

The conditional variance σ_t^2 is mean-reverting around a permanent component q_t, with the speed of mean-reversion determined by the parameters α and β. q_t is the time-varying long-run, permanent component of volatility and the speed of mean reversion for this permanent component of volatility is determined by ρ and ϕ. $\sigma_t^2 - q_t$ is the transitory component of the conditional variance. This chapter analyzes the predictive power of the order book slope on the permanent (long-run) component of future volatility by estimating the following CGARCH(1,1) model:

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) SLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}. \tag{3.12}$$

Similar to the model specified in Equations (3.6) and (3.7), δ_1 is expected to be negative and significant. A positive (negative) and significant estimate for δ_2 supports a decrease (increase) in the informativeness of the limit order book slope after the move to anonymity. In the current study, all of the GARCH, EGARCH, and CGARCH models are estimated using Student t-distribution to incorporate the potential leptokurtic distribution of the error term.

3.4.3 Information Content of the Limit Order Book Slope on the Demand and Supply Sides

The limit order book slope is calculated as the average of the limit order book slope on the demand and supply sides. This chapter further examines whether the slope on the demand side (buy slope, hereafter) is more or less informative than the slope on the supply side (sell slope, hereafter) about future volatility. The following CGARCH models are estimated for this analysis:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) BUYSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.13)$$

and

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) SELLSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.14)$$

where $BUYSLOPE_{t-1}$ and $SELLSLOPE_{t-1}$ are the slopes of the limit order book on the buy and sell sides, respectively at the end of period *t-1*. Consistent with Hypothesis 3, buy orders are expected to be more informative about the future permanent component of volatility than sell orders. Therefore, the slope of the limit order book on the buy (demand) side is expected to be more informative than that on the supply (sell) side. In other words, the number of negative and significant δ_1 in Equation (3.13) is expected to be larger than the number of negative and significant δ_1 in Equation (3.14).

3.4.4 Information Content of the Institutional and Individual Slopes

The limit order book contains orders submitted by institutional and individual investors. Prior literature suggests that institutional investors are better informed than individual investors.

Based on these findings, this chapter examines whether the informativeness of the limit order book slope comes from institutional or individual investors' limit orders. From the overall limit order book, two "smaller" limit order books are created: the institutional limit order book, which contains only institutional limit orders and the individual limit order book, which consists of only individual limit orders. The slopes of the institutional and individual limit order books are calculated using Equations (3.3), (3.4) and (3.5). The slope of the institutional limit order book is called the "Institutional slope" and the slope of the individual limit order book is referred to as the "Individual slope". The following CGARCH models are performed for analyzing the informativeness of both the Institutional slope and Individual slope:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) INSTSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.15)$$

and

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) INDISLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.16)$$

where $INSTSLOPE_{t-1}$ and $INDISLOPE_{t-1}$ are the Institutional and the Individual slope at the end of period $t-1$, respectively. Consistent with Hypothesis 4, the Institutional slope is expected to be more informative than the Individual slope. Therefore, the number of negative and significant δ_1 in Equation (3.15) should be larger than the number of negative and significant δ_1 in Equation (3.16). From Hypothesis 6, the move to anonymity is also expected to have a larger impact on the informativeness of institutional limit orders than for individual limit orders. For this reason, the number of significant coefficient estimates for δ_2 in Equation (3.15) should be larger than in Equation (3.16).

3.4.5 Information Content of the Limit Order Book at Different Levels

In the current chapter, the informativeness of the limit order book slope is analyzed based on the ten best quotes on the demand and supply side of the limit order book. Foucault et al. (2007) use the information contained in the best bid and ask quote (the bid-ask spread) in examining the informativeness of the limit order book about future volatility. Ahn et al. (2001) and Pascual and Veredas (2006) tackle the same problem utilizing the information contained in the limit order book, up to the five best quotes.

This chapter also examines the choice of 10 best limit order book levels against the use of best bid and ask quotes and the use of five best bid and ask quotes. Specifically, the bid-ask spread and the market depth at the end of each 30-minute interval are used as the proxy for the information contained in the best quotes of the order book. The following CGARCH models are estimated for this analysis:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SPREAD_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \quad (3.17)$$

and

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})DEPTH_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \quad (3.18)$$

where $SPREAD_{t-1}$ is the bid-ask spread at the end of interval *t-1*, which is calculated as the percentage of the difference between the best ask and bid quotes over the bid-ask mid-point. $DEPTH_{t-1}$ is the market depth at the end of interval *t-1*, which is calculated as the sum of the number of shares at the best bid and ask quotes of the order book. Following the suggestion of Cao et al. (2008, 2009), the limit order book beyond the best quotes is expected to have additional information over that contained in the best quotes. Therefore, the number of significant δ_l in Equations (3.17) and (3.18) is expected to be significantly lower than the number of significant δ_l in Equation (3.12).

In addition to estimating CGARCH models for the bid-ask spread and market depth separately, this chapter estimates the CGARCH models with both the lagged limit order book slope and lagged bid-ask spread or lagged market depth as explanatory variables for the permanent component of volatility. The following two CGARCH models are performed for this analysis:

$$r_t = \mu + r_{t-1} + \varepsilon_t ,$$

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) ,$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + (\delta_3 + \delta_4 D_{post})SPREAD_{t-1}$$

$$+ \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1} , \qquad (3.19)$$

and

$$r_t = \mu + r_{t-1} + \varepsilon_t ,$$

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) ,$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + (\delta_3 + \delta_4 D_{post})DEPTH_{t-1}$$

$$+ \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1} . \qquad (3.20)$$

The order book slope is expected to be more informative than the bid-ask spread and market depth about the future permanent component of volatility. Therefore, the number of significant δ_1 should be larger than the number of significant δ_3 in both Equations (3.19) and (3.20).

This chapter also compares the results obtained when using 10 best levels of the order book to calculate the order book slope to those obtained when only five best levels or the entire limit order book[31] is used in the calculation of the order book slope. The following CGARCH models are estimated for this examination:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE5BEST_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \tag{3.21}$$

and

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEALL_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \tag{3.22}$$

where $SLOPE5BEST_{t-1}$ is the order book slope, calculated from the five best levels of the order book, at the end of interval *t-1*. $SLOPEALL_{t-1}$ is the order book slope, calculated from all orders up to 100 levels of the order book, at the end of interval *t-1*. This chapter expects that limit orders from the sixth to 10th levels also contain information regarding future volatility so that the order book slope using the 10 best levels of the limit order book is more informative than the order book slope using the five best levels. However, the use of the entire order book to calculate order book slope will include some stale limit orders, which

[31] Consistent with Naes and Skjeltorp (2006), the entire order book is defined as the order book that contains all orders up to 100 ticks away from the best quotes.

may never be executed. Therefore, the order book slope calculated using the entire order book is expected to be less informative about future volatility than the order book slope calculated using the ten best levels of the order book. Overall, the number of negative and significant δ_I in Equations (3.21) and (3.22) is expected to be lower than the number of negative and significant δ_I in Equation (3.12).

3.5 Results and Discussion

3.5.1 Descriptive Statistics

Table 14 provides the summary statistics for the 90 stocks investigated in this chapter. The results are obtained by averaging across 30-minute interval for each stock and then averaging across stocks. Table 14 shows that large cap stocks are on average more than six times larger than mid cap stocks in term of market capitalization. The average order book slope of 19.9933 for large cap stocks is more than two times the average order book slope of 9.8139 for the mid cap stocks. This result implies that the order book slope is on average steeper in large cap than mid cap stocks. Therefore, the shares in the limit order book are distributed closer to the bid-ask mid-point for large cap stocks than for mid cap stocks. The order book slope on the sell side is also slightly larger than that on the buy side and the institutional slope is also higher than the individual slope. Consistent with Aitken, Almeida, Harris and McInish (2007), this finding implies that institutional limit orders are placed closer to the best quotes than individual limit orders. Large caps stocks are also traded more frequently than mid cap stocks, with the average number of trades in a 30-minute interval being 76, compared to 32 for mid cap stocks. In contrast, mid cap stocks have a higher average trade size of 3,984 shares, compared to 2,818 shares of large cap stocks. The bid-ask spread is also lower for large cap stocks but the depth at the best quote is lower for large cap stocks than for mid cap stocks.

Table 14: Descriptive statistics of the order book slope and other variables

This table presents summary statistics of the order book slope and other variables, such as the bid-ask spread, the market depth, the number of trade, average trade size and market capitalization for 90 stocks investigated in this chapter. The sample period is between 1 July 2005 and 30 June 2006. The large cap stocks are the constituent stocks of the S&P/ASX 50 index at the beginning of the sample period (1-July-2005). The mid cap stocks are those included in the S&P/ASX 100 index but not in the S&P/ASX 50 index on 1-July-2005. "Market capitalization" is the market capitalization of firms in million. "Slope", "Slope5best" and "SlopeAll" are the limit order book slope based on the 10 best quotes, five best quotes and up to 100 best quotes, respectively. "Buyslope" and "Sellslope" are the slopes of the limit order book on the buy (demand) and sell (supply) sides, respectively. "Instslope" and "Indislope" are the slopes of the limit order book based on orders submitted by institutional and individual investors, respectively. "NT" and "ATS" are the number of trades and average trade size for each 30-minute interval, respectively. "Spread" is the bid-ask spread, measured as the percentage of the difference between the best ask and bid quotes over the bid-ask mid-point. "Depth" is the market depth at the best quote, which is calculated as the sum of the number of shares at the best bid and ask quotes. The results are obtained by averaging over all 30-minute intervals for each stocks and then averaging across stocks. This table presents the average for the whole sample and separately for large cap and mid cap stocks.

	All Firms	Large Cap	Mid Cap
Number of firms	90	47	43
Market capitalization	7,794.1282	13,142.5858	2,072.5254
Slope	15.1298	19.9933	9.8139
Slope5best	29.9454	39.6945	19.2893
SlopeAll	5.3277	6.1336	4.4468
Buyslope	15.0808	19.9532	9.7551
Sellslope	15.1788	20.0333	9.8727
Instslope	52.7599	65.4734	38.8637
Indislope	17.1012	22.7963	10.8763
NT	54.3351	75.2445	31.4806
ATS	3,374.9313	2,817.9092	3,983.7693
Spread	0.2146	0.1499	0.2853
Depth	110,999.4143	98,098.0327	125,100.9244

3.5.2 Predictive Power of the Order Book Slope

The predictive power of the order book slope on future volatility is examined based on the GARCH and EGARCH models as specified in Equations (3.6) and (3.7). The results of this investigation are given in Panels A and B of Table 15.

The results in Panel A of Table 15 provide strong support for the predictability of the limit order book slope on price volatility in the next 30-minute interval. Specifically, the coefficient estimate for the order book slope in the previous interval is negative and significant at the 5% (10%) level in 76.60% (87.23%) of large cap stocks and 81.40% (88.37%) of mid cap stocks. Similarly, utilizing EGARCH model, the coefficient estimates for δ_1 are negative and significant at the 5% (10%) level of significance in 65.96% (82.98%) of large cap stocks and 81.40% (88.37%) of mid cap stocks. The move to anonymity has resulted in significant changes in the informativeness of the limit order book slope in the majority of large and mid cap stocks, when using the GARCH model and in the majority of mid cap stocks when using the EGARCH model. The coefficient estimates for δ_2 are significant at the 5% (10%) level of significance in 48.93% (59.57%) of large cap stocks and 53.49% (65.11%) of mid cap stocks when the GARCH model is used and in 34.04% (40.42%) of large cap stocks and 48.84% (58.14%) of mid cap stocks when the EGARCH model is utilized.[32]

In addition, the limit order book slope tends to be more informative after the move to anonymity. Specifically, the coefficient estimates of δ_2 are positive and significant at the 5% level of significance in 14.89% (14.89%) of large cap stocks and 23.26% (16.28%) of mid cap stocks when using the GARCH (EGARCH) model. For these stocks, the move to

[32] These figures are obtained by summing the percentages of the positive and significant and negative and significant coefficient estimates for δ_2 in Table 15.

anonymity has resulted in a reduction of the informativeness of the order book slope. In contrast, δ_2 is negative and significant at the 5% level of significance in 34.04% (19.15%) of large cap stocks and 30.23% (32.56%) of mid cap stocks when the GARCH (EGARCH) model is used. This evidence suggests that, for these stocks, the order book slope is more informative in the anonymous market than in the transparent market.

Besides the GARCH and EGARCH models, the predictive power of the order book slope on the permanent component of volatility is investigated by utilizing the CGARCH model, as specified in Equation (3.12). The results of this examination are given in Panel C of Table 15. Similar to the results obtained when using the GARCH and EGARCH models, the coefficient estimates for the lagged order book slope are negative and significant at the 5% (10%) level in 80.85% (89.36%) of the large cap stocks and 88.37% (93.02%) of the mid cap stocks. This finding provides strong support for the predictive power of the order book slope on the future permanent component of volatility. Furthermore, consistent with the results obtained when using the GARCH and EGARCH models, the limit order book slope tends to be more informative after the move to anonymity, with stronger results observed for large cap stocks. All of the GARCH, EGARCH, and CGARCH models are also well-specified, as reflected by the insignificance of the majority of the Ljung-Box portmanteau tests for serial correlation in the squared residuals with 12 lags at the 5% level of significance.

Overall, the results presented in Table 15 support the first and second hypotheses. The findings are also consistent with Foucault et al.'s (2007) arguments that the limit order book is a channel for price volatility information. The predictive power of the limit order book on future price volatility is also consistent with the findings of the use of limit orders by informed traders, as highlighted in Bloomfield et al. (2005), Anand et al. (2005), and Kaniel and Liu (2006). The results in Table 15 indicate that the move to anonymity has a significant impact on the information content of the limit order book slope regarding future price volatility. Among the stocks that experience a significant impact of anonymity on the informativeness of the limit order book slope, the limit order book slope tends to become more informative for future volatility after the removal of broker IDs on the ASX. This finding is also stronger for large cap than for mid cap stocks.

Table 15: Predictive power of the order book slope

This table presents the results of investigating the predictive power of the order book slope on future volatility. The results are obtained from estimating of the following GARCH, EGARCH, and CGARCH models:

GARCH model:
$r_t = \mu + r_{t-1} + \varepsilon_t$,
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$$

EGARCH model:
$r_t = \mu + r_{t-1} + \varepsilon_t$,
$$h_t = \omega + \beta h_{t-1} + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$$

CGARCH model:
$r_t = \mu + r_{t-1} + \varepsilon_t$,
$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$
$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$$

where r_t is the seasonally adjusted return of the stock at the tth interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution; and $h_t = \log(\sigma_t^2)$. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time varying permanent (long-run) volatility. $SLOPE_{t-1}$, NT_{t-1} and ATS_{t-1} are, respectively, the order book slope, the total number of trades and the average trade size for interval $t-1$. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the GARCH, EGARCH, and CGARCH models. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The GARCH, EGARCH and CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A, B and C. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: GARCH model

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0252	0.0003	9.06	16.95
(5% level)	(76.60%), 0%	(34.04%), 14.89%		17.02%
(10% level)	(87.23%), 0%	(44.68%), 14.89%		21.28%
Mid Cap	-0.0431	-0.0007	9.25	15.68
(5% level)	(81.40%), 0%	(30.23%), 23.26%		16.28%
(10% level)	(88.37%), 0%	(34.88%), 30.23%		18.61%

Panel B: EGARCH model

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0383	0.0007	5.46	12.66
(5% level)	(65.96%), 0%	(19.15%), 14.89%		8.51%
(10% level)	(82.98%), 0%	(23.40%), 17.02%		10.64%
Mid Cap	-0.1205	-0.0029	3.69	15.09
(5% level)	(81.40%), 0%	(32.56%), 16.28%		16.28%
(10% level)	(88.37%), 0%	(37.21%), 20.93%		16.28%

Panel C: CGARCH model

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0262	8.98×10^{-5}	7.43	9.04
(5% level)	(80.85%), 0%	(27.66%), 17.02%		0%
(10% level)	(89.36%), 0%	(38.30%), 17.02%		4.26%
Mid Cap	-0.0421	0.0010	8.90	11.34
(5% level)	(88.37%), 0%	(34.88%), 34.88%		11.63%
(10% level)	(93.02%), 0%	(39.54%), 34.88%		16.28%

3.5.3 Predictive Power of the Demand and Supply Sides of the Order Book

Table 16 presents results of investigating the predictive power of the slope of the limit order book on the buy side (buy slope) and on the sell side (sell slope). The findings in Table 16 indicate that buy limit orders are more informative than sell limit orders about the future permanent component of volatility. The coefficient estimates for lagged buy slope are negative and significant at the 5% (10%) level of significance in 78.72% (91.49%) of large cap stocks and 86.05% (93.02%) of mid cap stocks. In contrast, the predictive power of the sell slope on the future permanent component of volatility is evident in only 63.82% of large cap stocks and 76.74% of mid cap stocks. These results are consistent with the argument presented in Hypothesis 3. The findings also support prior studies which document that aggressive buy orders are more likely to be motivated by information than aggressive sell orders. This chapter extends prior literature by demonstrating that the information advantage of buyers over sellers is not only evident in market orders, but also extends to the submissions of the less aggressive type of orders, limit orders.

The move to anonymity has larger impact on the informativeness of the buy slope than on that of the sell slope. The coefficient estimates for δ_2 for the slope of the order book on the buy (demand) side is significant at the 5% (10%) level of significance in 38.30% (51.06%) of large cap stocks and 53.49% (58.14%) of mid cap stocks. The impact of anonymity on the informativeness of the slope of the supply side is observed in only 31.91% of large cap stocks and 51.17% of mid cap stocks. In addition, the number of negative and significant δ_2 is also larger than the number of positive and significant δ_2 for both the buy and the sell slope and in both large cap and mid cap stocks. This finding suggests that among the stocks that experience significant changes in the informativeness of the buy and sell slopes, the buy and sell slopes tend to be more informative after the move to anonymity.

Table 16: Predictive power of the buy (demand) and sell (supply) side slopes

This table presents the results of investigating the predictive power of the slope of the order book on the demand (buy) and supply (sell) sides on future volatility. The results are obtained from estimating the following CGARCH models:

CGARCH model for the buy side:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) BUYSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

CGARCH model for the sell side:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) SELLSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

where r_t is the seasonally adjusted return of the stock at the *t*th interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $BUYSLOPE_{t-1}$, $SELLSLOPE_{t-1}$, NT_{t-1} and ATS_{t-1} are, respectively, the order book slope on the buy side, the order book slope on the sell side, the total number of trades and the average trade size for the interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A and B. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Buy side

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0221	0.0018	7.04	8.89
(5% level)	(78.72%), 0%	(25.53%), 12.77%		0%
(10% level)	(91.49%), 0%	(36.17%), 14.89%		0%
Mid Cap	-0.0333	0.0011	6.78	10.57
(5% level)	(86.05%), 0%	(27.91%), 25.58%		9.30%
(10% level)	(93.02%), 0%	(30.23%), 27.91%		11.63%

Panel B: Sell side

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0194	0.0010	5.72	8.79
(5% level)	(63.82%), 0%	(23.40%), 8.51%		0%
(10% level)	(68.08%), 0%	(27.66%), 10.64%		2.13%
Mid Cap	-0.0260	0.0015	6.65	13.03
(5% level)	(76.74%), 0%	(27.91%), 23.26%		0%
(10% level)	(79.07%), 0%	(27.91%), 25.58%		9.30%

3.5.4 Predictive Power of the Institutional and Individual Slopes

The results of examining the predictive power of the Institutional slope and Individual slope on the future permanent component of volatility are presented in Table 17. Table 17 shows that the lagged Institutional slope is informative about the future permanent component of volatility in 55.32% (70.21%) of the large cap stocks and 72.90% (79.07%) of the mid cap stocks at the 5% (10%) level of significance. Supportive evidence for the predictive power of the Individual slope on the future permanent component of volatility is found in only 27.66% of large cap stocks and 48.83% of mid cap stocks. Consistent with prior studies and Hypothesis 4, these results imply that institutional investors are more informed than individual investors and institutional limit orders do convey their information advantage over future volatility.

The move to anonymity has a larger impact on the informativeness of the Institutional slope than the Individual slope. The majority of the coefficient estimates for δ_2 for the Individual slope are not statistically significant at the 10% level of significance. For the investigation of the Institutional slope, δ_2 is negative and significant at the 5% (10%) level of significance in 36.17% (51.06%) of large cap stocks and 32.56% (34.88%) of mid cap stocks. Positive and significant estimates for δ_2 at the 5% (10%) level of significance are found in only 6.38% (12.77%) of large cap stocks and 25.58% (30.23%) of mid cap stocks. The CGARCH models for the Institutional slope and the Individual slope are also well-specified, as evident by the insignificance of the majority of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags.

Overall, the results presented in Panel C of Tables 15 and 17 support Hypothesis 5 and 6. The move to anonymity often results in an increase in the informativeness of the overall limit order book slope. Institutional limit orders are also more affected by this change than individual limit orders. After the move to anonymity, institutional investors are not only willing to submit more limit orders, as demonstrated in Chapter 2, but also more willing to incorporate their information advantage in their limit orders submissions. The increase in the informativeness of institutional investors after the move to anonymity also supports the theoretical model of Foucault et al. (2007). If anonymity reduces the incentive for better-informed investors to submit “bluffing” limit orders, their limit orders (their order book slope) should be more informative after the removal of broker IDs. For individual investors, since their information environment is largely unchanged after the move to anonymity, the removal of broker IDs has a minimal impact on the information content of their limit orders.

Table 17: Predictive power of the Institutional and Individual slopes

This table presents the results of investigating the predictive power on future volatility of the slope of the order book based on the orders submitted by institutional and individual investors. The results are obtained from estimating the following CGARCH models:

CGARCH model for the Institutional slope:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) INSTSLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

CGARCH model for the Individual slope:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post}) INDISLOPE_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

where r_t is the seasonally adjusted return of the stock at the *t*th interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $INSTSLOPE_{t-1}$, $INDISLOPE_{t-1}$, NT_{t-1} and ATS_{t-1} are, respectively, the order book slope based on institutional orders, the order book slope based on individual orders, the total number of trades and the average trade size for interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A and B. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Institutional slope

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0010	-8.30×10^{-5}	9.34	9.81
(5% level)	(55.32%), 0%	(36.17%), 6.38%		4.26%
(10% level)	(70.21%), 0%	(51.06%), 12.77%		6.38%
Mid Cap	-0.0015	0.0002	7.22	11.75
(5% level)	(72.09%), 0%	(32.56%), 25.58%		9.30%
(10% level)	(79.07%), 0%	(34.88%), 30.23%		16.28%

Panel B: Individual slope

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0084	0.0028	6.46	9.68
(5% level)	(27.66%), 0%	(12.77%), 8.51%		6.38%
(10% level)	(29.78%), 0%	(21.28%), 8.51%		6.38%
Mid Cap	-0.0185	0.0016	6.98	15.05
(5% level)	(48.83%), 0%	(11.63%), 20.93%		20.93%
(10% level)	(53.49%), 0%	(16.28%), 20.93%		23.26%

3.5.5 Predictive Power of the Limit Order Book at Different Levels

Table 18 presents the results of examining the predictive power of the bid-ask spread and market depth on the future permanent component of volatility. The bid-ask spread is informative about the future permanent component of volatility in 31.92% of large cap stocks and 37.21% of mid cap stocks. The predictive power of market depth is also observed in 27.66% of large cap stocks and 41.86% of mid cap stocks. Comparing these findings with those presented in Panel C of Table 15, it is concluded that the limit order book slope is more informative about future volatility than the bid-ask spread and market depth. The move to anonymity also has a little impact on the informativeness of the bid-ask spread and market depth, with the majority of the coefficient estimates for δ_2 are not statistically significant.[33]

Additional analysis on the informativeness of the order book slope and the bid-ask spread (market depth) is also performed by including both the lagged order book slope and the lagged bid-ask spread (lagged market depth) as explanatory variables in the CGARCH model. The result of this analysis is presented in Table 19.

Consistent with the results obtained in Table 18, the results of Table 19 indicate that the limit order book slope is more informative than the bid-ask spread and market depth about the future permanent component of volatility. The order book slope is informative about the future permanent component of volatility in 74.45% of large cap stocks and 79.07% of mid cap stocks. In contrast, the predictive power of the bid-ask spread is evident in only 12.77%

[33] Foucault et al. (2007) find a decline in the informativeness of the bid-ask spread after the move to anonymity on Euronext Paris. The difference between the finding in this chapter and those of Foucault et al. (2007) can due to the different way of measuring bid-ask spread. Foucault et al. (2007) calculate the bid-ask spread as either the equally-weighted or the time-weighted bid-ask spread over an interval. In this chapter, the bid-ask spread for each interval is calculated based on the best bid and ask quotes at the end of the interval. Since the limit order book slope is calculated based on the state of the limit order book at the end of every 30-minute interval, this chapter also calculate the bid-ask spread from the best bid and ask quotes at the end of the interval to facilitate the comparison of the informativeness of the bid-ask spread and the order book slope.

of the large cap stocks and 25.58% of the mid cap stocks. Similarly, when the lagged order book slope and lagged market depth are included as explanatory variables in the CGARCH model, the order book slope is informative about the future permanent component of volatility in 59.57% (76.75%) of large (mid) cap stocks. The lagged market depth contains information on future volatility in only 40.43% of large cap stocks and 55.81% of mid cap stocks. The move to anonymity also has a larger impact on the informativeness of the order book slope than on the informativeness of the bid-ask spread and market depth. This is evident from the larger number of significant coefficient estimates for δ_2 than for δ_4 in both Panels A and B of Table 19.

Overall, the results presented in Tables 18 and 19 highlight that the limit order book beyond the best quote as captured by the order book slope is more informative about the future permanent component of volatility than the limit order book at the best quotes, as captured by the bid-ask spread and the market depth. Consistent with Cao et al. (2008, 2009), this finding implies that the limit order book beyond the best quotes contains significant information on future volatility beyond that of the best quotes. The results in this chapter also support the recent trend toward opening up of the limit order book in equity and futures markets.[34]

[34] The NYSE introduced the OpenBook service on January 24, 2002, for all securities, which provides the aggregate limit order volume available in the NYSE Display Book system at each price point. The Korea Stock Exchange increased its limit order book disclosure from three to five best quotes on March 6, 2000 and from five to 10 best quotes on January 2, 2002. In January 2001, the Sydney Futures Exchange also increased its limit order book disclosure from depth at the best bid and ask prices to depth at the three best bid and ask prices. See Boehmer et al. (2005), Eom et al. (2007) and Bortoli et al. (2006) for more detailed discussion on these changes.

Table 18: Predictive power of the bid-ask spread and market depth

This table presents the results of investigating the predictive power of the bid-ask spread and market depth on future volatility. The results are obtained from estimating the following CGARCH models:

CGARCH model for the bid-ask spread:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SPREAD_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

CGARCH model for the market depth:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})DEPTH_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

where r_t is the seasonally adjusted return of the stock at the *t*th interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $SPREAD_{t-1}$ is the bid-ask spread, measured as the percentage of the difference between the best ask and bid quotes over the bid-ask mid-point, at the end of interval *t-1*. $DEPTH_{t-1}$ is the market depth, measured as the total number of shares at the best bid and ask quotes, at the end of interval *t-1*. NT_{t-1} and ATS_{t-1} are the total number of trades and the average trade size for interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A and B. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Bid-ask spread

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	0.5277	-0.0738	8.79	14.60
(5% level)	(0%), 31.92%	(10.64%), 2.13%		10.64%
(10% level)	(0%), 34.04%	(19.15%), 6.38%		14.89%
Mid Cap	0.3647	-0.0140	7.93	15.58
(5% level)	(0%), 37.21%	(20.93%), 18.61%		25.58%
(10% level)	(0%), 41.86%	(20.93%), 18.61%		30.23%

Panel B: Market depth

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-1.4×10^{-6}	-3.97×10^{-7}	12.11	29.54
(5% level)	(27.66%), 0%	(12.77%), 2.13%		36.17%
(10% level)	(27.66%), 0%	(12.77%), 4.25%		40.43%
Mid Cap	-1.62×10^{-6}	-6.88×10^{-7}	15.39	41.71
(5% level)	(41.86%), 0%	(9.30%), 6.98%		37.21%
(10% level)	(44.19%), 0%	(9.30%), 11.63%		39.53%

Table 19: Predictive power of the order book slope, controlling for bid-ask spread and market depth

This table presents the results of investigating the predictive power on the future volatility of the limit order book slope, controlling for the impact of the bid-ask spread and market depth. The results are obtained from estimating the following CGARCH models:

CGARCH model controlling for the impact of the bid-ask spread:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + (\delta_3 + \delta_4 D_{post})SPREAD_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

CGARCH model controlling for the impact of the market depth:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE_{t-1} + (\delta_3 + \delta_4 D_{post})DEPTH_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

where r_t is the seasonally adjusted return of the stock at the *t*th interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $SPREAD_{t-1}$ is the bid-ask spread, measured as the percentage of the difference between the best ask and bid quotes over the bid-ask mid-point, at the end of interval *t-1*. $DEPTH_{t-1}$ is the market depth, measured as the total number of shares at the best bid and ask quotes, at the end of interval *t-1*. $SLOPE_{t-1}$, NT_{t-1} and ATS_{t-1} are, respectively, the limit order book slope, the total number of trades and the average trade size for interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A and B. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Controlling for bid-ask spread

	δ_1	δ_2	δ_3	δ_4	DoF	$Q^2(12)$
Large Cap	-0.0278	-0.0028	-0.1382	0.0501	9.02	8.81
(5% level)	(74.45%), 0%	(25.53%), 8.51%	(0%), 12.77%	(10.64%), 8.51%		2.13%
(10% level)	(85.10%), 0%	(40.43%), 12.77%	(0%), 17.02%	(10.64%), 10.64%		4.26%
Mid Cap	-0.0515	-0.0039	0.2251	-0.0947	8.39	12.60
(5% level)	(79.07%), 0%	(30.23%), 20.93%	(0%), 25.58%	(23.26%), 2.32%		18.61%
(10% level)	(86.05%), 0%	(34.88%), 23.26%	(0%), 27.91%	(23.26%), 6.98%		18.61%

Panel B: Controlling for market depth

	δ_1	δ_2	δ_3	δ_4	DoF	$Q^2(12)$
Large Cap	-0.0166	0.0021	$-1.6\text{x}10^{-6}$	$3.21\text{x}10^{-7}$	12.38	16.08
(5% level)	(59.57%), 0%	(12.77%), 19.15%	(40.43%), 0%	(12.77%), 8.51%		23.40%
(10% level)	(82.98%), 0%	(25.53%), 21.28%	(42.55%), 0%	(17.02%), 17.02%		25.53%
Mid Cap	-0.0305	0.0015	$-2.1\text{x}10^{-6}$	$2.22\text{x}10^{-8}$	12.42	19.13
(5% level)	(76.75%), 0%	(13.95%), 13.95%	(55.81%), 0%	(23.26%), 11.63%		32.56%
(10% level)	(83.72%), 0%	(20.93%), 16.28%	(65.12%), 0%	(23.26%), 11.63%		37.21%

Table 20 reports the results of investigating the information content of the limit order book slope using the five best levels of the book and using all orders in the book, up to 100 ticks away from the best quotes. Table 20 shows significant predictive power of the limit order book slope on future volatility in the majority of large cap and mid cap stocks when using either the five best levels of the book or the entire order book. When using the five best levels of the order book (the entire order book) to calculate the order book slope, the order book slope is informative about the future permanent component of volatility in 63.83% (46.81%) of the large cap and 79.07% (62.79%) of the mid cap stocks. A comparison of the results obtained from Panel C of Table 15 and those reported in Table 20 reveals that the limit order book slope calculated using the 10 best levels in the limit order book is more informative than the limit order book slope calculated using the five best levels or up to 100 levels of the limit order book. This finding implies that the sixth to 10th best quotes of the limit order book contain additional information on volatility over that contained in the first five best quotes of the book. Including all orders in the order book, however, results in the inclusion of stale limit orders, which reduces the overall informativeness of the limit order book slope.

Table 20: Predictive power of the order book slope based on five levels and up to 100 levels of the order book

This table presents the results of investigating the predictive power of the limit order book slope, calculated based on the five best levels of the order book, or based on all orders in the order book up to 100 ticks away from the best quotes (up to 100 levels). The following CGARCH models are estimated

CGARCH model for the order book slope calculated from the best five levels of the order book

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE5BEST_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

CGARCH model for the order book slope calculated from all orders up to 100 levels of the order book

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEALL_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$,

where r_t is the seasonally adjusted return of the stock at the tth interval. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $SLOPE5BEST_{t-1}$ is the order book slope, calculated from the five best levels of the order book, at the end of interval $t-1$. $SLOPEALL_{t-1}$ is the order book slope, calculated from all orders up to 100 levels of the order book, at the end of interval $t-1$. NT_{t-1} and ATS_{t-1} are the total number of trades and the average trade size for interval $t-1$. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panel A and B. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Using five levels of the order book

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0129	0.0003	5.59	8.78
(5% level)	(63.83%), 0%	(23.40%), 10.64%		0%
(10% level)	(74.47%), 0%	(29.78%), 10.64%		0%
Mid Cap	-0.0289	0.0011	6.10	11.13
(5% level)	(79.07%), 0%	(23.26%), 25.58%		9.30%
(10% level)	(83.72%), 0%	(25.58%), 25.58%		11.63%

Panel B: Using all orders, up to 100 levels of the order book

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0391	0.0080	9.17	12.24
(5% level)	(46.81%), 0%	(34.04%), 12.77%		6.38%
(10% level)	(53.19%), 0%	(44.68%), 14.89%		8.51%
Mid Cap	-0.0377	0.0045	7.74	14.89
(5% level)	(62.79%), 0%	(27.91%), 25.58%		13.95%
(10% level)	(72.09%), 0%	(34.88%), 30.23%		18.61%

3.5.6 Robustness Tests

This section provides additional robustness tests for the results regarding the informativeness of the limit order book slope about future volatility. The first robustness test involves the use of an alternative measure of the order book slope. Specifically, the Kalay et al.'s (2004) measure of the limit order book slope is used to investigate the information content of the limit order book slope. The Kalay et al.'s (2004) measure of the order book on the supply side is measured as follows:

$$SEKSW_{i,t} = \frac{1}{N_A}\left\{\sum_{\tau=0}^{N_A}\frac{(V_{\tau+1}^A - V_\tau^A)/NOSH_{i,t}}{p_{\tau+1}^A / p_\tau^A - 1}\right\}, \tag{3.23}$$

where $SEKSW_{i,t}$ is the Kalay et al.'s (2004) measure of the slope on the supply side of the order book for firm i in interval t. $NOSH_{i,t}$ is the number of shares outstanding for firm i in interval t. V_τ^A is the total share volume at the ask price level τ (p_τ^A). N_A is the total number of bid prices (tick levels) containing orders. The order book on the buy side is calculated in a similar manner. The overall limit order book slope is then calculated as the average of the slope on the buy (demand) and sell (supply) sides. The 10 best bid and ask quotes together with the share volume at these quotes are used in the order book slope calculation. The following CGARCH model is estimated for the first robustness test:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEKSW_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \tag{3.24}$$

where $SLOPEKSW_{t-1}$ is the Kalay et al.'s (2004) measure of the order book slope at the end of interval $t-1$.

The second robustness test involves including hidden orders when calculating the order book slope. The following is the CGARCH model for this analysis:

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEHIDDEN_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.25)$$

where $SLOPEHIDDEN_{t-1}$ is the order book slope calculated when hidden orders are included at the end of interval *t-1*.

Finally, the informativeness of the order book slope is investigated based on a one-hour interval instead of a 30-minute interval. The following CGARCH model is estimated for this analysis:

$r_{1hour,\,t} = \mu + r_{1hour,\,t-1} + \varepsilon_t$,

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE1HOUR_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}, \qquad (3.26)$$

where $r_{1hour,t}$ is the seasonally adjusted return of the stock in the *t*th one-hour interval and $SLOPE1HOUR_t$ is the order book slope calculated at the end of the *t*th one-hour interval. The results of the three robustness tests are given in Table 21.

Consistent with the results obtained in Panel C of Table 15, the results for the first and second robustness tests, as documented in Panels A and B of Table 21, provide strong support for the informativeness of the limit order book slope about the future permanent component of volatility. The coefficient estimates for the lagged order book slope in Panels A and B of Table 21 are negative and significant for the majority of stocks under investigation. In addition, the move to anonymity also has a significant impact on the informativeness of the order book slope, with the order book slope tending to become more rather than less informative after the removal of broker IDs on the ASX.

Panel C of Table 21 reports the results obtained when a one-hour frequency is used instead of a 30-minute frequency. Support for the informativeness of the limit order book slope about the future permanent component of volatility is still observed in the majority of large cap and mid cap stocks. Using a one-hour frequency instead of a 30-minute frequency, however, results in a decline in the informativeness of the limit order book slope. For large cap stocks, the number of negative and significant coefficient estimates for the lagged order book slope has declined from 80.85% with the 30-minute frequency, as in Panel C of Table 15, to 51.06% with the one-hour frequency. Similarly, the limit order book slope is informative about the future permanent component of volatility in 88.37% of the mid cap stocks when using the 30-minute frequency; but this figure drops to 55.82% when the one-hour frequency is used instead.

Overall, the results of different robustness tests indicate that the findings for the informativeness of the limit order book slope about the future permanent component of volatility are robust to different measures of the order book slope, the inclusion of hidden orders in the slope calculation, and the use of different interval frequencies. The informativeness of the limit order book slope is also stronger when using a 30-minute interval compared to one-hour interval.

Table 21: Robustness tests on the predictive power of the order book slope

This table presents the results of the three robustness tests on the predictive power of the limit order book slope. The first robustness test uses a different measurement of the limit order book slope, based on the Kalay et al. (2004), to investigate the informativeness of the limit order book slope about the future permanent component of volatility. The second robustness test uses the Naes and Skjeltorp's (2006) measure of the order book slope and includes hidden (undisclosed) orders in the calculation of the limit order book slope. The third robustness test investigates the predictive power of the limit order book slope using a one-hour frequency. The following CGARCH models are estimated for these three robustness tests

Robustness test 1: Using Kalay et al.'s (2004) measure of the limit order book slope

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEKSW_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

Robustness test 2: Using Naes and Skjeltorp's (2006) measure of the limit order book slope and including hidden orders in the limit order book slope calculation

$r_t = \mu + r_{t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPEHIDDEN_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

Robustness test 3: Using Naes and Skjeltorp's (2006) measure of the limit order book slope and a one-hour frequency

$r_{1hour,t} = \mu + r_{1hour,t-1} + \varepsilon_t$,

$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1})$,

$q_t = \varpi + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\delta_1 + \delta_2 D_{post})SLOPE1HOUR_{t-1} + \varphi_1 NT_{t-1} + \varphi_2 ATS_{t-1}$

where r_t is the seasonally adjusted return of the stock at the *t*th interval, calculated using a 30-minute frequency. $r_{1hour,t}$ is the seasonally adjusted return of the stock at the *t*th interval, calculated using a one-hour frequency. σ_t^2 is the conditional variance of the error term process ε_t, which follows a Student's t-distribution. $\sigma_t^2 - q_t$ is the transitory volatility component and q_t is the time-varying permanent (long-run) volatility. $SLOPEKSW_{t-1}$ is the order book slope, calculated based on the methodology of Kalay et al. (2004), at the end of interval *t-1*. $SLOPEHIDDEN_{t-1}$ is the order book slope, calculated from normal and hidden (undisclosed) orders, at the end of interval *t-1*. $SLOPE1HOUR_{t-1}$ is the order book slope, calculated using one-hour frequency, at the end of interval *t-1*. NT_{t-1} and ATS_{t-1} are the total number of trades and the average trade size for interval *t-1*. D_{post} is a dummy variable that takes on the value of one for the period from 28 November 2005 onward and zero otherwise. "DoF" is the average Degree of Freedom for the CGARCH model. $Q^2(12)$ is the average of the Ljung-Box portmanteau test statistics for serial correlation in the squared residuals with 12 lags. The CGARCH models are estimated using the quasi-maximum likelihood method, as described by Bollerslev and Wooldridge (1992). The mean estimates of the coefficients are reported in Panels A, B and C. The percentages inside the parentheses indicate the numbers of estimates that are negative and significant, whereas the percentages outside the parentheses indicate the numbers of estimates that are positive and significant. "(5% level)" and "(10% level)" show significance at the 5% and 10% level of significance, respectively.

Panel A: Robustness test 1

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-4.3430	-0.3012	6.43	9.15
(5% level)	(74.47%), 0%	(17.02%), 12.77%		0%
(10% level)	(89.36%), 0%	(29.79%), 19.15%		0%
Mid Cap	-3.7808	-0.0012	5.71	10.46
(5% level)	(86.05%), 0%	(23.26%), 20.93%		9.30%
(10% level)	(90.70%), 0%	(25.58%), 23.26%		13.95%

Panel B: Robustness test 2

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0275	0.0005	12.43	10.10
(5% level)	(85.10%), 0%	(21.28%), 17.02%		6.38%
(10% level)	(93.62%), 0%	(29.79%), 19.15%		10.64%
Mid Cap	-0.0421	0.0027	12.83	13.47
(5% level)	(88.37%), 0%	(27.91%), 23.26%		18.61%
(10% level)	(93.02%), 0%	(32.56%), 27.91%		25.58%

Panel C: Robustness test 3

	δ_1	δ_2	DoF	$Q^2(12)$
Large Cap	-0.0117	-0.0007	6.03	10.50
(5% level)	(51.06%), 0%	(17.02%), 6.38%		8.51%
(10% level)	(59.57%), 0%	(27.66%), 8.51%		8.51%
Mid Cap	-0.0386	-0.0013	6.99	10.31
(5% level)	(55.82%), 0%	(16.28%), 11.63%		11.63%
(10% level)	(69.77%), 0%	(30.23%), 13.95%		11.63%

3.6 Conclusions

This chapter examines the information content of the order book slope in explaining future price volatility on the ASX. This chapter also investigates whether the relation between the order book slope and future price volatility is affected by the removal of broker IDs on the ASX. Analyzing the stocks included in the S&P/ASX 100 index for the period between 1 July 2005 and 30 June 2006, this chapter finds that the order book slope is informative in explaining the future price volatility of the majority of stocks under investigation. The predictive power of the order book slope is present in both the overall volatility and the permanent component of volatility. These findings support the importance of limit orders in the order submission strategies of informed investors and the notion that the limit order book is a channel for volatility information. The slope of the order book on the buy side is also more informative than the slope of the limit order book on the sell side about the future permanent component of volatility. In addition, institutional limit orders are more informative than individual limit orders about the future permanent component of volatility. This finding implies that the informativeness of the limit order book derives mainly from limit orders submitted by institutional investors. This chapter also documents that the limit order book beyond the best quotes contains significant information on future volatility over that contained in the best quotes of the limit order book. The five best quotes of the limit order book are less informative about future volatility than the 10 best quotes of the order book. However, using all orders in the order book up to 100 ticks away from the best quotes does not yield better prediction of future volatility than utilizing information contained in the 10 best quotes of the order book.

The removal of broker IDs on the ASX has a significant impact on the predictive power of the limit order book slope in both large cap and mid cap stocks. Moreover, significant change in the informativeness of the order book slope is observed for institutional limit orders, whereas anonymity has a minimal impact on individual limit orders. For the stocks that experience significant changes in the informativeness of the order book slope, the order book slope tends to become more informative after the move to anonymity. This finding implies that the move to anonymity has reduced the risk of front-running activities and better-informed investors are more willing submit and expose their limit orders in the limit order book. Overall, the results in this chapter support the ASX's decision to stop disclosing broker identity information in the central limit order book.

Chapter 4: Volume-Volatility Relation

4.1 Introduction

4.1.1 Purpose and Motivation

The purpose of this chapter is to investigate the relation between trading volume and stock price volatility for the constituent stocks included in the S&P/ASX 100 index. Three research questions related to the volume-volatility relation are addressed in this chapter. First, which of the two components of trading volume, the number of trades or the average trade size, has a greater impact on volatility? Second, what is the impact on volatility of the trading activity of different types of traders? More specifically, does institutional trading or individual trading have a larger impact on volatility? Finally, does order imbalance or net order flow play an important role in explaining the volume-volatility relation, as suggested by Chan and Fong (2000), or do the number of trades and average trade size have a significant role beyond that of order imbalance in explaining volatility?

Investigating the volume-volatility relation has been a topical area of research interest for a long time and prior empirical studies often observe a positive relation between these two variables.[35] Karpoff (1987), in his review paper, outlines several reasons why the price-volume relation is important. First, this relation provides evidence on issues such as the rate of information flow to the market, how information is disseminated in markets, and the extent to which market prices convey information. The answers to these issues offer insights into the structure of financial markets. Second, the relation is important for event studies that use a combination of price and volume data from which to draw inferences. Thirdly, the price-

[35] Karpoff (1987) provides a review of the early work. For more recent empirical studies on the volume-volatility relation, see, among other, Lamoureux and Lastrapes (1990), Gallant et al. (1992), Bessembinder and Seguin (1992, 1993), Jones et al. (1994), Andersen (1996), Daigler and Wiley (1999), Chan and Fong (2000), Huang and Masulis (2003), Kalev et al. (2004), Chan and Fong (2006) and Naes and Skjeltorp (2006).

volume relation is also critical to the debate over the empirical distribution of speculative prices.

4.1.2 Main Findings

This chapter documents a positive relation between trading volume and volatility for the majority of the constituent stocks of the S&P/ASX 100 index over the period between 3 January 2005 and 30 June 2006. Consistent with Jones et al. (1994), this chapter finds the number of trades plays a more significant role in the volume-volatility relation than the average trade size. When the number of trades is decomposed into number of trades of different size, the medium-sized trades often possess the largest impact on volatility. This finding is consistent with Chan and Fong (2000) and the "stealth trading hypothesis" of Barclay and Warner (1993).

This chapter also shows that the trading activities of institutional and individual investors are positively related to volatility. Individual trading, however, has a larger effect on volatility than institutional trading. Since institutions are potentially a better-informed class of investors than individuals, this finding is consistent with the theoretical model of Shalen (1993), which predicts that the volume-volatility relation is driven by the trading activity of the less-informed group of investors, who possess greater dispersion of belief.

Finally, similar to Chan and Fong (2006), this chapter documents a positive relation between absolute order imbalance and volatility. However, the significance and the explanatory power of absolute order imbalance on volatility are less than those of other variables, such as the number of trades. Following Chan and Fong (2000), the role of order imbalance in the volume-volatility relation is also examined by analyzing the volume-volatility relation before and after controlling for the impact of daily order imbalance on daily returns. The results indicate minimal change to the volume-volatility relation after the return impact of daily order imbalance is taken into consideration. Therefore, in contrast to Chan and Fong (2000), on the ASX, a limit order book market, the order imbalance is not the main factor behind the volume-volatility relation. Other variables, such as the number of trades and size of trade, contain significant volatility information, beyond that of order imbalance.

4.1.3 Chapter Outline

The rest of the chapter is organized as follows. Section 4.2 provides the review of the related literature on volume-volatility relation and the hypotheses to be tested in the current chapter. Section 4.3 describes the data utilized and Section 4.4 discusses the methodology used in empirical work. Section 4.5 provides results and discussions while Section 4.6 concludes the chapter.

4.2 Literature Review and Hypotheses Development

4.2.1 The Volume-Volatility Relation

There are various theoretical models that provide an explanation for the relation between volume and volatility. Models, such as the Mixture of Distribution Hypothesis (MDH) of Clark (1973) and the Sequential Arrival of Information Hypothesis (SAIH) of Copeland (1976) use information as the driving force behind the volume-volatility relation. Microstructure theories attribute the volume-volatility relation to the competitive or strategic trading of traders with different levels of information or opinions.

According to the MDH of Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986), and Andersen (1996), volatility and volume are driven by the same underlying latent news arrival or information flow variable. The arrival of information generates price movements, with unexpected "good news" resulting in price increases and "bad news" resulting in price decreases. The arrival of new information is also accompanied by above-average trading activity in the market as the market adjusts to a new equilibrium to reflect the new information. Thus, the MDH predicts a positive relation between volume and volatility.

Copeland (1976, 1977), Morse (1981), Jennings et al. (1981) and Jennings and Barry (1983) develop and extend the SAIH, in which new information is disseminated sequentially to different traders. In the SAIH, information is disseminated sequentially rather than simultaneously to all traders. Trading occurs after each trader receives the information but traders that are not yet informed cannot infer the content of the information from the trading of informed traders. Traders react to the information sequentially such that a series of intermediate equilibria exist. Once all traders have reacted to the information signal, a final equilibrium is reached. Consequentially, the sequential arrival of new information to the market generates both trading volume and price movements. The sequential reaction to information in the SAIH also suggests that lagged values of volatility may have the ability to predict current trading volume, and vice versa. Hence, the SAIH is consistent with both a contemporaneous and a lead-lag relation between volume and volatility.

Besides the MDH and SAIH, the volume-volatility relation can also be explained by various microstructure models, which can be divided into two classes, competitive and strategic models. In competitive models, agents are differentiated based on their information or belief (see, for example, Pfleiderer, 1984; Grundy and McNichols, 1989; Holthausen and Verrecchia, 1990; Kim and Verrecchia, 1991; Shalen, 1993; Harris and Raviv, 1993; Wang, 1994).[36] These models suggest that the over-response of uninformed investors to an observed increase in trading activity generates a positive volume-volatility relation. For example, in Shalen's (1993) model, information asymmetry exists among traders but uninformed traders' differences of opinions are the key factor affecting the volume-volatility relation. Shalen (1993) argues that excess volatility and volume are associated with uninformed traders' differences of opinions because uninformed traders cannot differentiate informed from uninformed trading and thus respond to all types of trades in the order flow. Therefore, uninformed traders can overreact to changes in liquidity demand and increase both trading volume and price volatility above what would be expected in equilibrium. Thus, the volume-volatility relation is influenced more by the trading activity of uninformed traders.

The strategic models also allow for information asymmetry among investors, but assume that a single informed investor, or a small group of informed investors, trades strategically by making several small-sized trades (see, for example, Kyle, 1985; Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Holden and Subrahmanyam, 1992).[37] In strategic models, a positive volume-volatility relation arises due to the strategic trading of informed and uninformed investors. For example, Admati and Pfleiderer (1988) present a theoretical model with informed traders; nondiscretionary liquidity traders, who must trade a particular number of shares at a particular time; and discretionary liquidity traders, who also possess liquidity demand but can be strategic in choosing the timing of their trade. Admati and Pfleiderer (1988) show that trading is concentrated in some particular periods during the trading day and the variability of price changes is higher during periods of concentrated

[36] Harris and Raviv (1993) show that the positive volume-volatility relation can also arise from the differences of traders' opinions regarding the common, public information.
[37] Holden and Subrahmanyam (1992) show that the distinction between strategic and competitive models is blurred in the case of multiple informed traders who act noncooperatively.

trading. Therefore, transactions and price movements are bunched in time, implying a positive relation between volume and volatility.

Empirical studies often find a positive relation between volume and volatility. Karpoff (1987) reviews early work on the volume-volatility relation. For more recent empirical evidence on the volume-volatility relation in the equity market see, among others, Harris (1987), Smirlock and Starks (1988), Schwert (1989), Lamoureux and Lastrapes (1990), Gallant et al. (1992), Jones et al. (1994), Andersen (1996), Chan and Fong (2000), Wu and Xu (2000), Chen et al. (2001), Gopinath and Krishnamurti (2001), Huang and Masulis (2003), Darrat et al. (2003), Chan and Fong (2006), Naes and Skjeltorp (2006) and Darrat et al. (2007).[38] Brailsford (1996) and Kalev et al. (2004) also observe a positive relation between trading volume and volatility for the stocks traded on the ASX.

Based on the theoretical prediction of the MDH, SAIH and various microstructure models, as well as the extensive empirical literature regarding the positive volume-volatility relation, the first hypothesis is formulated as follows[39]

H_1: Trading volume is positively related to volatility.

4.2.2 Number of Trades, Average Trade Size and Volatility

The role of trade size and the number of trades on volatility is supported in several theoretical models, which can generally be divided into two groups: competitive and strategic models (Jones et al., 1994). In competitive models with asymmetric information, such as those of

[38] The positive volume-volatility relation is also observed in other markets, such as the derivatives market (see, among others, Bessembinder and Seguin, 1992, 1993; Daigler and Wiley, 1999; Luu and Martens, 2003; Chen and Daigler, 2008; Chen et al., 2008), the foreign exchange market (see, among others, Goodhart and Figliuoli, 1991; Bollerslev and Domowitz, 1993; Hartmann, 1999; Galati, 2000; Bjonnes et al., 2003), and the bond market (see, among others, Kalimipalli and Warga, 2002; Downing and Zhang, 2004; Dungey et al., 2008).

[39] All the hypotheses in this chapter are stated in alternative form.

Pfleiderer (1984), Grundy and McNichols (1989), Holthausen and Verrecchia (1990), and Kim and Verrecchia (1991), informed traders prefer to trade large amounts at any given price. Therefore, trade size reveals the information of informed traders and thus possesses information about prices. Consequently, Pfleiderer (1984) and Kim and Verrecchia (1991) explicitly show that absolute price change (volatility) is positively related to volume, where volume is measured by trade size. In strategic models such as in Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990), a monopolist informed trader can attempt to camouflage his or her trading activity by splitting one large order into several orders of smaller sizes. This strategic behaviour attenuates the impact of trade size on volatility and implies that the number of trades can contain significant information on prices. The role of the number of trades in the determination of asset prices is also highlighted by Easley and O'Hara (1992). In their model, the authors show that the total number of trades is informative about price changes because both trades and the "lack of trades" are informative to the market maker.

Empirical findings generally support the dominant role of the number of trades in the volume-volatility relation. Jones et al. (1994) document that for NASDAQ stocks, the positive relation between volume and volatility reflects the positive relation between volatility and the number of trades. The average trade size has no information content beyond the number of trades. Consistent with Jones et al. (1994), Gopinath and Krishnamurti (2001) and Huang and Masulis (2003) find the number of trades to have a more significant impact on volatility than average trade size on the NASDAQ and the London Stock Exchange, respectively. Investigating a sample of NASDAQ and NYSE stocks, Chan and Fong (2000) also conclude that the volume-volatility relation is driven mainly by the number of trades. When considering the impact of the number of trades of different sizes, however, Chan and

Fong (2000) observe that the impact of medium-sized trades on volatility is larger than that of small-sized and large-sized trades. This finding reconfirms the role of trade size beyond that of the number of trades in the volume-volatility relation. This finding is also consistent with the evidence of the "stealth-trading" hypothesis of Barclay and Warner (1993) and Chakravarty (2001), in which medium-sized trades account for the majority proportion of cumulative stock price change.

Using realized volatility to measure daily volatility, Chan and Fong (2006) reemphasize the dominant role of the number of trades over trade size in explaining the volume-volatility relation. The authors document that the average trade size does not add significantly more explanatory power to realized volatility than the number of trades. More recent findings on the impact of the number of trades and average trade size on volatility are documented in Song et al. (2005), Tai et al. (2006), and Ciner and Sackley (2007). In those studies, the number of trades is found to have a more important role than average trade size in explaining volatility on the Shanghai Stock Exchange, the Taiwan over-the-counter market, and the Taiwan Stock Exchange, respectively.

Consistent with Jones et al. (1994), this chapter expects the number of trades to have a more significant impact on volatility than average trade size. In addition, based on the evidence presented in Chan and Fong (2000) and the prediction of the "stealth-trading" hypothesis of Barclay and Warner (1993) and Chakravarty (2001), this chapter also expects that medium-sized trades is more important than large and small trades in affecting volatility. The hypotheses on the impact of the number of trades and average trade size on volatility are formulated as follows:

H_{2a}: The number of trades has a more significant impact on volatility than average trade size.

H_{2b}: The number of trades in the medium size category possesses a more significant impact on volatility than the number of trades in either the large or small size categories.

4.2.3 Trader Types and Volatility

Gabaix et al. (2006) present a theoretical model in which excess stock market volatility is due to trades by large institutional investors. This implies a positive relation between institutional trading and volatility. Empirical studies, however, provide mixed evidence on this issue. Consistent with Gabaix et al. (2006), Sias (1996) and Dennis and Strickland (2002) observe a positive relation between institutional trading and volatility. In contrast, Reiley and Wachowicz (1979), Bohl and Brzeszczynski (2006), and Bohl et al. (2008) document a negative relation between institutional trading and volatility while Lee and Ward (1980) document that institutional trading has little or no impact on volatility. In a comprehensive study of institutional trading in the stocks of 43 countries, Chiyachantana et al. (2006) conclude that institutional trading does not destabilize markets by increasing volatility. It should be noted that the previously mentioned studies often investigate the relation between institutional trading and volatility based on either institutional ownership data (Sias, 1996; Dennis and Strickland, 2002; Bohl and Brzeszczynski, 2006; Bohl et al., 2008) or the trading of a subset of institutions in the whole market (Reiley and Wachowicz, 1979; Lee and Ward, 1980; Chiyachantana et al., 2006). Using a complete record of institutional trading on the Shanghai Stock Exchange, Li and Wang (2008) document a negative relation between institutional trading and volatility.

The noise traders framework of Black (1986), De Long et al. (1990), and Campbell and Kyle (1993) provide a theoretical background for the impact of uninformed investors trading on volatility. Harris and Raviv (1993) and Shalen (1993) highlight the importance of differences of opinion as the key factor behind the volume-volatility relation. Since informed traders have relatively homogeneous beliefs, the volume-volatility relation is attributed to the trading activity of uninformed investors (Shalen, 1993; Daigler and Wiley, 1999).

The notion that uninformed traders increase volatility is also consistent with the noise traders framework of Black (1986), De Long et al. (1990), and Campbell and Kyle (1993). In these models, the presence of noise (uninformed) traders and limits of arbitrage result in excessively high volatility. Thus, changes in noise traders' demand for stocks increase volatility. In the current literature, individual investors are often believed to have psychological biases and are viewed as noise traders, who trade for reasons other than fundamental information (Kaniel et al., 2008; Foucault et al., 2008).[40] Therefore, individual trading should have a positive impact on volatility (Foucault et al., 2008).

Current empirical literature often finds a positive relation between individual trading and volatility. Kyrolainen (2008) and Bae et al. (2008) shows a positive relation between individual trading and volatility on the Helsinki Stock Exchange and the Tokyo Stock Exchange, respectively. Kaniel et al. (2008) find that volatility increases prior to intense individual trading. Andrade et al. (2008) observe that stocks with volatile trading imbalance, as measured by changes in shares held in margin accounts of individuals, have more volatile returns. Foucault et al. (2008) document that after a reform in the French stock market that made short selling more expensive for individual investors relative to institutions, the

[40] Barber et al. (2009) and Hvidkjaer (2008) show that stocks heavily purchased by individual investors underperform those heavily sold by individuals. Grinblatt and Keloharju (2000) and Frazzini and Lamont (2008) document that individual investors systematically lose out money to institutional investors.

volatility of stocks affected by this reform declines relative to the volatility of other stocks. This finding suggests a positive relation between individual trading and volatility.

Prior studies also address the role of trading by different types of traders in the volume-volatility relation. Bessembinder and Seguin (1993) suggest that the volatility-volume relation in financial markets may depend on the type of trader. Daigler and Wiley (1999) analyze the volume-volatility relation for five financial futures contracts on the Chicago Board of Trade, where trading volume is decomposed into four components: the trading volume of scalpers, the trading volume of clearing member's house account, the trading volume of other floor traders, and the trading volume of the general public. The authors find that the volume-volatility relation is driven by the volume of the general public who are distant from the trading floor and are thus less informed and possess greater dispersion of beliefs. In contrast, the trading of clearing members and floor traders, who have timely access to order flow information, often decreases volatility. Consistent with Daigler and Wiley (1999), Wang (2002a, 2002b) and Kartsaklas (2008) highlight that volatility is more influenced by the trading activity of the less informed group of investors on the International Monetary Market, the S&P 500 index futures market, and the KOSPI 200 index futures market, respectively.

Based on the preceding discussion, this chapter hypothesizes that both institutional and individual trading have a positive impact on volatility. Moreover, since individual investors are potentially less informed than institutional investors, they may possess larger dispersion of belief.[41] Therefore, following Shalen's (1993) prediction, this chapter argues that volatility is more affected by individual trading activity than institutional trading activity. The third hypothesis is formulated as follows:

H_3: Institutional and individual equity trading are positively related to stock price volatility with a stronger relation observed for individual trading.

4.2.4 Order Imbalance and the Volume-Volatility Relation

Kyle (1985) and Admati and Pfleiderer (1988) present a theoretical background for the role of order imbalance in the volume-volatility relation. In the strategic models of Kyle (1985) and Admati and Pfleiderer (1988), market makers cannot distinguish whether the order is submitted by an informed or an uninformed (liquidity) investor. Market makers will infer informed traders' information by observing the order imbalance or net order flow and revise their quotation accordingly. They will revise their prices upward (downward) when there are excess buy (sell) orders. Therefore, price volatility is induced by order imbalance and order imbalance should play an important role in the volume-volatility relation (Chan and Fong, 2000).

To the best of my knowledge, Chan and Fong (2000) are the first to address the impact of order imbalance on the volume-volatility relation. Investigating a sample of NYSE and NASDAQ stocks in the last six months of 1993, the authors document that after controlling for the effect of order imbalance on return, the volume-volatility relation becomes much weaker. This finding suggests that order imbalance plays a major role in explaining the volume-volatility relation. Examining a sample of stocks traded on the NYSE between April

[41] The greater differences of opinions of individual investors compared to institutional investors can also be observed from the results presented in Table 14 in Chapter 3. In Table 14, the Institutional slope is more than three times larger than the Individual slope. Since a larger limit order book slope reflects a smaller difference of opinions (Naes and Skjeltorp, 2006), this result implies a greater difference of opinion among individual investors than among institutional investors.

and June 1995, Wu and Xu (2000) show that order imbalance has a strong explanatory power on volatility, over and above that of the number of trades and average trade size. In contrast, utilizing the sum of intraday squared returns (realized volatility) to measure daily volatility for Dow Jones Industrial Average (DJIA) index stocks between 1993 and 2000, Chan and Fong (2006) find that order imbalance does not add significant additional explanatory power to realized volatility beyond that of the number of trades. Chen et al. (2008) provide support for Chan and Fong's (2000) results in futures market and find that for the E-Mini S&P 500 index futures, trading imbalance is more important than the number of trades or trading volume in explaining volatility.

This chapter investigates the role of order imbalance on the volume-volatility relation for stocks traded on the ASX, a limit order book market. Consistent with prior theoretical and empirical studies, this chapter argues that order imbalance plays a significant role in the volume-volatility relation. However, since the ASX is an order-driven market with no market makers, this chapter expects the role of order imbalance on the ASX to be less prominent than on specialists and dealers markets such as the NYSE and NASDAQ. In other words, similar to Chan and Fong (2006), it is expected that other factors, such as the number of trades and size of trade possess significant volatility information beyond that of order imbalance. The hypotheses on the role of order imbalance in the volume-volatility relation are formulated as follows:

H_{4a}: *Order imbalance plays a significant role in the volume-volatility relation.*

H_{4b}: *The number of trades and size of trade possess significant roles, beyond that of order imbalance, in the volume-volatility relation.*

4.3 Data

This chapter investigates the volume-volatility relation for the constituent stocks of the S&P/ASX 100 index on 3 January 2005. The sample period is from 3 January 2005 to 30 June 2006. Two different datasets are collected, the Order Book Dataset and the Market Depth Dataset. These two datasets are similar to those utilized in Chapter 2 to examine institutional and individual investors' order aggressiveness. The Order Book Dataset contains information on all order executions together with the unique identification of the orders that are matched in these transactions. Therefore, apart from the normal price and volume information, this dataset also provides details when one large order is executed against several smaller orders. This can be seen when several transactions occur at the same time and from one initiated order. This chapter presents the evidence regarding the volume-volatility relation when the number of trades and average trade size are calculated without considering the multiple executions from one large order. In addition, the results for the volume-volatility relation are also documented with several smaller transactions initiated by one large order grouped together. These two ways of measuring the number of trades and average trade size are referred to as "Disaggregate Measurement" and "Aggregate Measurement", respectively.

The Market Depth Dataset provides information on the best 10 bid and ask quotes in the limit order book. Based on the information of the best bid and ask quotes, various volatility measures are calculated. The use of bid-ask mid-point instead of transaction prices to calculate volatility is motivated by Roll (1984), where returns calculated from transaction prices are influenced by the bid-ask bounce, which results in spurious volatility in returns.[42]

[42] Kaul and Nimalendran (1990) provide evidence that even for the average NASDAQ firm, the bid-ask bounce could account for 30% of the daily return variance, and for small firm this proportion is in excess of 50%.

Since the ASX's staggered opening procedure takes up to 10 minutes to complete, the data for the first 10 minutes of each day are excluded to avoid any potential bias. In addition, the volume-volatility relation is analyzed based only on normal transactions executed during the continuous trading session, such that all crossing trades, off-market trades, and after hour trades are also excluded. Therefore, trading volume, the number of trades, average trade size, and order imbalance are calculated based on normal transactions executed between 10:10 and 16:00. Similarly, the bid-ask mid-points between 10:10 and 16:00 are used to calculate various volatility measures.

The sample stocks are divided into large capitalization (large cap) stocks and medium capitalization (mid cap) stocks. The large cap stocks are the constituent stocks of the S&P/ASX 50 index on 3 January 2005, and the mid cap stocks are those included in the S&P/ASX 100 index but not in the S&P/ASX 50 index on 3 January 2005.[43] Finally, only seasoned stocks that have not been merged or acquired by other companies and stocks for which data are available for the entire sample period are examined. The final sample consists of 88 stocks, with 46 large cap and 42 mid cap stocks.

Similar to Chapter 3, this chapter considers only large cap and mid cap stocks in the investigation of the volume-volatility relation. Besides measuring volatility based on the absolute residuals of the regression of daily returns on lagged daily returns and day-of-the-week dummy variables as in Jones et al. (1994), this chapter also uses realized volatility (Andersen and Bollerslev, 1998; Andersen et al., 2001; Andersen et al., 2003), which is the sum of intraday squared returns, to measure daily volatility. Moreover, the volume-volatility relation is analyzed based on daily intervals as well as intraday intervals (30-minute and one-

[43] These classification criteria for large cap and mid cap stocks are consistent with those of the ASX.

hour intervals). Therefore, only large cap and mid cap stocks are included in the sample to ensure that there are trading activities in the majority of the intraday intervals.

4.4 Research Methodology

4.4.1 Volume, Number of Trades, Average Trade Size, and Volatility

Consistent with Jones et al. (1994), the volume-volatility relation is examined based on a two-stage regression procedure. In the first stage, building on Schwert (1990), the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it} \ , \qquad (4.1)$$

where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables, which are used to capture differences in mean returns (see, for example, French, 1980; Keim and Stambaugh, 1984). The lagged daily returns (R_{it-j}) are used to control for serial dependence in daily returns. The daily return is calculated as the difference between the natural logarithm of the daily closing and daily opening bid-ask mid-point.

In the second stage, the volume-volatility relation is analyzed by estimating the following regressions:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i V_{it} + \eta_{it} \ , \qquad (4.2)$$

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i NT_{it} + \eta_{it} \ , \qquad (4.3)$$

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i ATS_{it} + \eta_{it} \ , \qquad (4.4)$$

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1} NT_{it} + \beta_{i2} ATS_{it} + \eta_{it}, \qquad (4.5)$$

where V_{it} is the trading volume, in terms of number of shares traded, for stock i on day t. NT_{it} and ATS_{it} is the number of trades and average trade size for stock i on day t, respectively. The lagged values of $|\hat{\varepsilon}_{it}|$ are used to control for persistence in volatility. Consistent with Jones et al. (1994), the "trading-gap" dummy variable MON_t, which equals one for Mondays and zero otherwise, is included to control for the opening of market on Mondays after the weekend trading break. Equations (4.2), (4.3), (4.4) and (4.5) are consistent with the sets of equations in Jones et al. (1994) and Chan and Fong (2006). This study also includes TUE_t, which is a dummy variable for Tuesday to control for the impact of the U.S. markets' Monday opening on the ASX. The regressions in Equations (4.2), (4.3), (4.4) and (4.5) are estimated for every stock under investigation. Results for all time series regressions in this chapter are obtained using the Newey-West (1987) heteroskedasticity consistent covariance procedure.

Consistent with Hypothesis 1, volume is expected to be positively related to volatility, so that the coefficient β_i in Equation (4.2) is expected to be positive and significant. The comparison of the results obtained from Equations (4.3) and (4.4) highlights whether the volume-volatility relation as in Equation (4.2) is a result of the relation between the number of trades and volatility, as in Equation (4.3), or the relation between average trade size and volatility, as in Equation (4.4). From Hypothesis 2a, the number of positive and significant β_i in Equation (4.3) is expected to be larger than the number of positive and significant β_i in Equation (4.4). The regression in Equation (4.5) provides a direct comparison of the significance of the number of trades and average trade size in the volume-volatility relation. In this chapter, number of trades is expected to be more significant in explaining volatility than average trade size. Therefore, in Equation (4.5), the number of positive and significant β_{i1} is expected to be larger than the number of positive and significant β_{i2}.

In order to investigate the potential role of the size of trades beyond that of the number of trades, following Chan and Fong (2000), Equation (4.3) is modified by replacing the daily number of trades with the daily number of trades in the five different trade size categories. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000.[44] Compared to prior studies, such as Barclay and Warner (1993) and Chakravarty (2001), Category 1 represents small-sized trades; Categories 2, 3 and 4 represent medium-sized trades, while Category 5 consists of the large-sized trades. The regression model is specified as follows:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\left|\hat{\varepsilon}_{it-j}\right| + \sum_{h=1}^{5}\beta_{h,i}NT_{h,it} + \eta_{it}\ , \quad (4.6)$$

The role of the size of trades, beyond that of the number of trades in the volume-volatility relation is reflected by the differences in the magnitudes and significance of the five coefficient estimates $\beta_{h,i}$ in Equation (4.6). In contrast, if trade size does not matter, the volatility impact of the number of trades should be the same across the five trade size categories and there should be no difference among the magnitudes and significance of the five coefficient estimates for $\beta_{h,i}$.

4.4.2 Institutional Trading, Individual Trading, and Volatility

This chapter examines the impact of institutional and individual trading on volatility based on the following regressions:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1Inst}InstNT_{it}$$
$$+\beta_{i2Inst}InstATS_{it} + \eta_{it}, \quad (4.7)$$

[44] This classification scheme is consistent with that applied by Barclay and Warner (1993) for stocks traded on the NYSE. Walsh (1998) investigates three alternative proxies to approximate the trade size classes on the ASX and shows that the distribution of these trade sizes is indeed consistent with the classifications employed by Barclay and Warner (1993) and in this chapter.

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1Indi}IndiNT_{it}$$
$$+\beta_{i2Indi}IndiATS_{it} + \eta_{it}, \tag{4.8}$$

where $|\hat{\varepsilon}_{it}|$ is the absolute residual estimated from Equation (4.1). $InstNT_{it}$ and $InstATS_{it}$ are the number of institution-initiated transactions and their average trade size, respectively. Similarly, $IndiNT_{it}$ and $IndiATS_{it}$ are the number of individual-initiated transactions and their average trade size, respectively. From Hypothesis 2a, the number of trades is expected to have a more significant impact on volatility than average trade size. Therefore, the number of positive and significant $\beta_{i1Inst}(\beta_{i1Indi})$ is expected to be greater than the number of positive and significant β_{i2Inst} (β_{i2Indi}). Moreover, from Hypothesis 3, individual trading is expected to have a greater effect on volatility than institutional trading. Thus, the number of positive and significant β_{i1Indi} and β_{i2Indi} is expected to be greater than the number of positive and significant β_{i1Inst} and β_{i2Inst}. The impacts of individual trading and institutional trading on volatility are also compared based on the following regression:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1}InstNT_{it}$$
$$+\beta_{i2}InstATS_{it} + \beta_{i3}IndiNT_{it} + \beta_{i4}IndiATS_{it} + \eta_{it}, \tag{4.9}$$

Consistent with Hypothesis 3, the number of positive and significant β_{i3} and β_{i4} is expected to be larger than the number of positive and significant β_{i1} and β_{i2}.

4.4.3 Order Imbalance and the Volume-Volatility Relation

Finally, this chapter examines the role of order imbalance in explaining the volume-volatility relation. Order imbalance is defined as the difference between the number of buyer-initiated transactions and the number of seller-initiated transactions over a trading day. Following Chan and Fong (2000), Equation (4.1) is modified to include order imbalance as one of the regressors. The regression model is specified as follows:

$$R_{it} = \sum_{k=1}^{5}\hat{\alpha}_{ik}D_{kt} + \sum_{j=1}^{12}\hat{\beta}_{ij}R_{it-j} + \delta_i OIB_{it} + \hat{\varepsilon}_{it}, \tag{4.10}$$

where OIB_{it} is the order imbalance for firm i on day t. This regression is motivated by trade indicator models, such as that of Huang and Stoll (1997), where price movements are caused by the net initiated order flow. Since Equation (4.10) takes into consideration the impact of order imbalance on returns, Chan and Fong (2000) suggest the use of the absolute residual estimated from Equation (4.10) as the proxy for volatility when analyzing the volume-volatility relation, as in Equation (4.3). If the daily order imbalance plays a vital role in the volume-volatility relation, as suggested by Chan and Fong (2000), the volume-volatility relation should be much weaker after controlling for the impact of order imbalance on daily returns. In other words, the volume-volatility relation revealed by using the absolute value of the residuals, estimated from Equation (4.10) should be weaker than the volume-volatility relation revealed by using the absolute value of the residuals, estimated from Equation (4.1).

Since price impact may vary across trade of different sizes, the order imbalance for each of the five different trade sizes discussed previously are also calculated. The role of the order imbalance of the different trade size categories in the volume-volatility relation is then examined in a similar manner to that of daily order imbalance. Specifically, Equation (4.1) is modified to include the order imbalance of five different trade size categories as one of the regressors. The regression is specified as follows:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \sum_{h=1}^{5} \delta_{h,i} OIB_{h,it} + \hat{\varepsilon}_{it} \, , \tag{4.11}$$

where $OIB_{h,it}$ is the order imbalance for trade size category h for firm i on day t. The absolute residual estimated from Equation (4.11) is then used as the dependent variable for the regression model in Equation (4.6). Comparison of the relation between the number of trades of different size categories and volatility obtained when using the absolute residual estimated from Equation (4.11) with that obtained when using the absolute residual estimated from

Equation (4.1) illustrates the importance of daily order imbalance in the volume-volatility relation.

As specified in Hypothesis 4b, this chapter expects number of trades and size of trade to possess significant roles, beyond that of order imbalance in the volume-volatility relation. Therefore, little change to the volume-volatility relation is expected after controlling for the return impact of daily order imbalance, as in Equations (4.10) and (4.11).

Chan and Fong (2006) argue that the methodology presented in Chan and Fong (2000) for investigating the role of order imbalance in the volume-volatility relation does not directly analyze the impact of order imbalance on volatility. They suggest an alternative approach where volatility is regressed on the absolute value of order imbalance. The regression model is specified below:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \delta_i ABSOIB_{it} + \eta_{it} \,, \qquad (4.12)$$

where $ABSOIB_{it}$ is the absolute value of order imbalance for firm i on day t. Consistent with Chan and Fong (2006), comparing the results obtained in Equation (4.12) with those in Equation (4.3) provides insights into the question of whether the volume-volatility relation is driven mainly by order imbalance, as suggested by Chan and Fong (2000), or whether the number of trades plays an additional role beyond that of order imbalance in explaining the volatility-volume relation.

This chapter also extends Chan and Fong's (2006) analysis by examining the effect on volatility of order imbalance in different size categories. Specifically, the following regression is estimated:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \sum_{h=1}^{5} \delta_{h,i} ABSOIB_{h,it} + \eta_{it}, \qquad (4.13)$$

where $OIB_{h,it}$ is the order imbalance for trade size category h for firm i on day t. The results obtained from Equation (4.13) are then compared with those of Equation (4.6) to highlight whether the order imbalance of different trade size categories is more important than the number of trades of different trade size categories in explaining volatility.

Consistent with Hypothesis 4b, this chapter expects that in a limit order book market, order imbalance is not the key factor behind the volume-volatility relation. Therefore, the number of positive and significant δ_i in Equation (4.12) is expected to be less than the number of positive and significant β_i in Equation (4.3). Similarly, the number of positive and significant $\delta_{h,i}$ in Equation (4.13) is expected to be less than the number of positive and significant $\beta_{h,i}$ in Equation (4.6).

4.5 Results and Discussions

4.5.1 Descriptive Statistics

Panel A of Table 22 presents the descriptive statistics for the different daily volatility measures utilized in this chapter, namely, the absolute residuals of Equation (4.1) and realized volatility. The volatility statistics in Panel A indicate that the distribution of all volatility measures is non-normal and rightly-skewed. Consistent with prior literature,[45] the natural logarithm of realized volatility is closer to a normal distribution than realized volatility. Therefore, in this chapter, the natural logarithm of realized volatility will be used instead of realized volatility when performing regressions. Finally, the mean statistics of all volatility measures are higher in mid cap than in large cap stocks. This observation indicates that mid cap stocks are more volatile than large cap stocks during the sample period.

[45] See, for example, Andersen et al. (2001) and Andersen et al. (2003).

The descriptive statistics of various trading activity variables are documented in Panel B of Table 22. The results in this panel show that large cap stocks are more liquid than mid cap stocks, as reflected by the higher average daily number of trades for large cap stocks. In contrast, the daily average trade size of mid cap stocks is larger than that of large cap stocks. During the sample period, individual investors are more active than institutional investors; they initiate an average of 505 (201) trades per day in large cap (mid cap) stocks, compared to an average of 406 (172) trades initiated by institutions in large cap (mid cap) stocks. In other words, individuals initiate, on average, around 55.43% of trades in large cap stocks and 53.84% of trades in mid cap stocks. This finding is consistent with D'Aloisio's (2005) observation that the trading activities of individuals account for about 51% of the market turnover as measured by the number of transactions. Individual investors, however, on average, trade in smaller size than institutional investors in both large and mid cap stocks.

Different ways of measuring the number of trades and average trade size have a significant impact on the value of these two variables. Specifically, when the possibility that one large order is executed against several smaller orders and results in several transactions is taken into consideration, the average value for the daily number of trades declines from 911 (373) to 561 (235) in large (mid) cap stocks. On the contrary, the average trade size increases from 3,152 (4,529) to 5,085 (6,936) shares in large (mid) cap stocks. These two findings illustrate that ignoring the possibility of one large order being executed against several smaller orders can result in significantly different measurements of the number of trades and average trade size. Therefore, in this chapter, all the results are presented for both cases, where the possibility for one large order to be executed against several smaller orders is ignored and where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together.

In large cap and mid cap stocks, trades with sizes greater than 1,000 shares and less than or equal to 5,000 shares are the most common, except in large cap stocks when Disaggregate Measurement is used. On the other hand, in both large cap and mid cap stocks, trades with sizes greater than 5,000 shares and less than or equal to 9,999 shares are the least common. Finally, the average daily order imbalance is negative when using Disaggregate Measurement and positive when Aggregate Measurement is utilized. This finding indicates that the number of large sell orders that are executed against several smaller orders in the limit order book is higher than the number of large buy orders. This inflates the number of seller-initiated transactions and results in a negative order imbalance based on Disaggregate Measurement. When several transactions initiated by one larger order are grouped together, buyer-initiated transactions are actually more common than seller-initiated transactions during the sample period.

Table 22: Descriptive statistics of volatility and trading activity measures

This table presents the descriptive statistics of the volatility and trading activity measures used in this chapter. In total, this chapter examines a sample of 88 stocks of the S&P/ASX 100 index, consisting of 46 large cap stocks and 42 mid cap stocks, for the period between 3 January 2005 and 30 June 2006. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. $|\hat{\varepsilon}_{it}|$ is the absolute residual of the regression of daily returns on 12 lagged daily returns and day-of-the-week dummy variables. The daily return is calculated as the difference between the natural logarithms of the daily closing and the daily opening bid-ask mid-point. *RV* is realized volatility, which is calculated as the sum of intraday squared five-minute interval returns. The return for each five-minute interval is calculated as the difference between the natural logarithms of the closing bid-ask mid-point at the end and at the opening of the interval. *rv* is the natural logarithm of daily realized volatility. *NT* and *ATS* are the daily number of trades and daily average trade size, respectively. *InstNT* (*IndiNT*) and *InstATS* (*IndiATS*) are the number of institution-initiated (individual-initiated) transactions and their average trade size, respectively. NT_1 is the daily number of trades with the size less than or equal to 500 shares. NT_2 is the daily number of trades with the size greater than 500 shares and less than or equal to 1,000 shares. NT_3 is the daily number of trades with the size greater than 1,000 shares and less than or equal to 5,000 shares. NT_4 is the daily number of trades with the size greater than 5,000 shares and less than or equal to 9,999 shares. NT_5 is the daily number of trades with a size of at least 10,000 shares. *OIB* is the daily order imbalance, measured as the difference between the daily number of buyer-initiated transactions and the daily number of seller-initiated transactions. *ABSOIB* is the absolute value of daily order imbalance. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. *Mean*, *Median*, *Std Dev*, *Skewness* and *Kurtosis* denote the mean, median, standard deviation, skewness and kurtosis statistics, respectively. The volatility and trading activity statistics are obtained by averaging across all days for each stock. The mean, median, standard deviation, skewness and kurtosis statistics are then calculated across 46 large cap stocks and 42 mid cap stocks.

Panel A: Volatility statistics

	Large Cap				Mid Cap			
	Mean	Std Dev	Skewness	Kurtosis	Mean	Std Dev	Skewness	Kurtosis
$\lvert\hat{\varepsilon}_{it}\rvert$	0.0104	0.0297	9.4830	151.3796	0.0166	0.0417	8.2707	115.2875
RV	0.0328	0.1522	6.6113	61.9216	0.0687	0.2346	3.7569	16.8004
rv	-8.9493	1.6490	4.0172	26.4158	-8.0350	2.2901	2.9317	11.9848

Panel B: Trading activity statistics

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
NT	911.0423	839.8696	561.5481	523.1087	373.6745	335.1071	235.1584	213.3095
ATS	3,152.7305	2,991.9887	5,085.1122	4,820.8280	4,529.3963	4,094.9419	6,936.3168	6,251.5250
InstNT	406.0297	375.2826	239.1659	225.1413	172.4797	155.1905	109.5335	100.4643
InstATS	3,522.2757	3,296.7142	6,190.0521	5,662.4411	4,761.1839	3,996.4565	7,835.0742	6,303.2823
IndiNT	505.0126	458.5652	322.3822	292.7065	201.1949	173.4881	125.6249	108.6429
IndiATS	2,894.6712	2,749.0672	4,568.2195	4,321.2386	4,504.1816	4,094.3335	6,960.7354	6,257.3351
NT_1	355.6493	315.3804	160.4632	143.8913	119.9326	104.9762	57.8771	50.5357
NT_2	156.8538	143.4891	91.1554	83.3261	58.7773	51.3214	34.9303	29.9643
NT_3	291.8271	269.0000	205.9536	190.1630	131.7371	114.9286	87.5972	77.6429
NT_4	51.2676	46.8913	44.1450	40.6957	27.4499	23.0357	19.9876	17.2857
NT_5	55.4446	48.2500	59.8309	53.2935	35.7825	28.9167	34.7698	28.6310
OIB	-1.3212	-6.5543	15.7610	7.9674	-3.9194	-5.1667	2.2521	-0.0595
ABSOIB	108.2921	84.2826	82.0278	62.7391	65.2167	49.6905	48.4192	36.3571

4.5.2 The Volume-Volatility Relation

Table 23 presents the results of investigating the relations between trading volume, number of trades, average trade size and volatility. Consistent with prior literature, the results from Panel A of Table 23 indicate a positive relation between trading volume and volatility for the majority of the large cap and mid cap stocks. The results are stronger for large cap stocks than for mid cap stocks. The coefficients for trading volume are also smaller for large firms, suggesting that more liquid stocks are able to impound information with a smaller price impact than less liquid stocks (Glosten and Harris, 1988).

The results for the number of trades, reported in Panel B of Table 23, are consistent with the results obtained for volume. The number of trades is positively related to volatility in both large cap and mid cap stocks, with stronger results observed in large cap stocks. A comparison of the results presented in Panels B and C indicates that the number of trades plays a more significant role than average trade size in the volume-volatility relation. The number of positive and significant coefficients for the number of trades is much higher than the number of positive and significant coefficients for the average trade size in both large cap and mid cap stocks. A similar finding is observed in Panel D when volatility is regressed on both average trade size and the number of trades. The addition of average trade size to the regression of volatility on the number of trades also results in minimal improvement in the adjusted R^2, with the adjusted R^2 increases from 0.0813 (0.1049) in Panel B to 0.0904 (0.1100) in Panel D for large (mid) cap stocks. This finding is consistent with Chan and Fong (2006), who observe a minimal increase in the adjusted R^2 when average trade size is included to the regression of volatility on the number of trades. Table 23 also presents the results of the likelihood ratio test for the significance of the average trade size variable by comparing the log-likelihood measure obtained when volatility is regressed on the number of trades, as in Equation (4.3), and the log likelihood measure obtained when volatility is regressed on the number of trades and average trade size, as in Equation (4.5). The likelihood ratio test statistics are insignificant for the majority of large cap and mid cap stocks. This finding implies that for most stocks, the inclusion of average trade size to the regression of volatility on the number of trades does not improve the overall goodness-of-fit of the regression model. Table 23 also reports results regarding the effect of the number of trades and average trade size on volatility when multiple trades arising from the submission of one large market order are grouped together. The use of Aggregate Measurement increases the significance of the average trade size variable on volatility, as indicated in Panel C of Table 23. In general, however, the results obtained when using Aggregate Measurement are qualitatively similar to those obtained when Disaggregate Measurement is used in performing regressions.[46]

Overall, consistent with Jones et al. (1994), the results presented in Table 23 indicate that there is a positive relation between trading volume and volatility and that the number of trades is more important than average trade size in explaining volatility. These results are robust to different ways of measuring the number of trades and average trade size. The results are also consistent with the arguments presented in strategic microstructure models such as Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990), where the number of trades can reflects information on prices as a monopolist informed traders can disguise their trading activities by splitting one large orders into several smaller orders.

[46] Note that trading volume is the same regardless of whether "Disaggregate Measurement" or "Aggregate Measurement" is used when performing regressions. Therefore, in Panel A of Table 23, only the results using "Disaggregate Measurement" are reported.

Table 23: Volume, number of trades, average trade size and volatility

This table presents the results of investigating the relation between trading volume, the number of trades, average trade size and volatility for the stocks included in the S&P/ASX 100 index on 3 January 2005. In total, the study examines a sample of 88 stocks, consisting of 46 large cap stocks and 42 mid cap stocks, for the period between 3 January 2005 and 30 June 2006. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on a two-stage regression method. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:
$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it}$,
where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables. The daily return is calculated as the difference of the natural logarithms of the daily closing and opening bid-ask mid-points. In the second stage, the relation between trading volume, the number of trades, average trade size and volatility is examined based on the following set of regressions:
$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i V_{it} + \eta_{it}$;
$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i NT_{it} + \eta_{it}$;
$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_i ATS_{it} + \eta_{it}$;
$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1} NT_{it} + \beta_{i2} ATS_{it} + \eta_{it}$,
where V_{it} is the trading volume, in terms of number of shares traded, for stock i on day t. NT_{it} and ATS_{it} are the number of trades and average trade size for stock i on day t, respectively. MON_t and TUE_t are the dummy variable for Monday and Tuesday, respectively. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. The mean and median number of observations are 351 and 352, respectively. "Coefficient" and "Adj R^2" are the average of coefficient estimates and adjusted R^2 across 46 large cap and 42 mid cap stocks. "LR" refers to the average likelihood ratio test statistics, which equal twice the difference between the log likelihood value of the models estimated in Panels D and the model estimated in Panel B. The likelihood ratio test statistics follow a $\chi^2(1) = 3.84$ at 5% significance level. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Trading volume								
V_{it}	2.93×10^{-9}	0.0773			9.23×10^{-9}	0.0984		
	(0%), 60.87%				(2.38%), 45.24%			

Panel B: Number of trades								
NT_{it}	8.78×10^{-6}	0.0813	1.65×10^{-5}	0.0851	3.59×10^{-6}	0.1049	1.26×10^{-6}	0.1023
	(0%), 63.04%		(0%), 58.70%		(9.52%), 42.86%		(7.14%), 45.24%	
Panel C: Average trade size								
ATS_{it}	1.43×10^{-6}	0.0435	9.36×10^{-7}	0.0458	2.06×10^{-6}	0.0710	1.85×10^{-6}	0.0739
	(2.17%), 17.39%		(2.17%), 26.09%		(4.76%), 19.05%		(4.76%), 26.19%	
Panel D: Number of trades and average trade Size								
NT_{it}	8.97×10^{-6}	0.0904	1.65×10^{-5}	0.0923	4.69×10^{-6}	0.1100	1.60×10^{-6}	0.1082
	(0%), 60.87%		(0%), 58.70%		(9.52%), 45.24%		(7.14%), 47.62%	
ATS_{it}	1.84×10^{-6}		8.47×10^{-7}		2.14×10^{-6}		1.40×10^{-6}	
	(2.17%), 15.22%		(0%), 10.87%		(0%), 14.29%		(12.38%), 11.91%	
LR	3.6614		2.8498		2.0771		2.3582	
	30.43%		13.04%		14.29%		16.67%	

Chan and Fong (2000) suggest that trades of different size categories may have different impacts on volatility and thus trade size contains additional information on volatility beyond that of number of trades. Following Chan and Fong (2000), the impact of the number of trades of different size categories on volatility is examined by regressing volatility on the number of trades of different size categories, as in Equation (4.6). The results of this investigation are given in Table 24.

Similar to the findings of Chan and Fong (2000), the results presented in Table 24 show that the number of trades in different size categories have different impact on price volatility. Specifically, the total percentage of positive and significant coefficient estimates for the number of trades in the medium size category (Categories 2, 3 and 4) is at least three times larger than that for the small and large size categories (Categories 1 and 5, respectively). The number of trades in Category 3 (trades with size greater than 1,000 shares and less than or equal to 5,000 shares) generally possesses the most information on volatility. Increases in the number of positive and significant coefficient estimates for the number of trades and adjusted R^2 are observed when using Aggregate Measurement in performing regressions. The number of trades in Category 3 still has the most significant impact on volatility in mid cap stocks. In large cap stocks, besides the number of trades in Category 3, the number of trades in Category 4 also plays an important role in explaining volatility. The hypothesis of equal the coefficient estimates for the number of trades in different trade size categories is also rejected in the large number of stocks under investigation, especially when Aggregate Measurement is utilized.

A comparison of the results obtained in Panel B of Table 23 and Table 24 also implies that replacing the number of trades with the number of trades in different trade size categories results in an improvement in the explanatory power of the regression model. For Disaggregate Measurement, the average adjusted R^2 for large (mid) cap stocks when the number of trades is used is 0.0813 (0.1049), which increases to 0.1047 (0.1309) when the number of trades in the five trade size categories are used. Similarly, for Aggregate Measurement, the average adjusted R^2 for large (mid) cap stocks when the number of trades is used is 0.0851 (0.1023), which increases to 0.1133 (0.1322) when the number of trades in the five categories are used. In both cases, the improvement in the explanatory power is at least 24.78%.

Overall, this study documents that the number of trades in different trade size categories have different impacts on volatility and it is generally the number of trades in the medium size category that has the most significant impact on volatility. The result that trades of different sizes have different volatility impacts may also explain Jones et al.'s (1994) findings and the finding in Table 23 that the number of trades is more important than average trade size in explaining volatility. Averaging the size of trades over a time interval can smoothes the underlying variability of the trade size variable, thereby lowering its information content and significance (Huang and Masulis, 2003). The finding that the volatility impact of medium-sized trades is higher than that of large and small trades is also consistent with Hypothesis 2b and the "stealth-trading" hypothesis of Barclay and Warner (1993), where medium-sized trades normally account for the majority of the proportion of cumulative stock price change. Consistent with Chan and Fong (2000), the results presented in Table 24 imply that size of trade has a significant role, beyond that of the number of trades, in the volume-volatility relation.

Table 24: Impact of number of trades in different size categories on volatility

This table presents the results of investigating the relation between the number of trades of different size categories and volatility for the stocks included in the S&P/ ASX 100 index on 3 January 2005. In total, the study examines a sample of 88 stocks, consisting of 46 large cap stocks and 42 mid cap stocks, for the period between 3 January 2005 and 30 June 2006. Large cap stocks are those included in the ASX/S&P50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ ASX 100 index, but not in the S&P/ ASX 50 index on 3 January 2005. Results are obtained based on a two-stage regression method. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it}$,

where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables. The daily return is calculated as the difference of the natural logarithms of the daily closing and opening bid-ask mid-points. In the second stage, the relation between the number of trades of different size categories on volatility is examined based on the following regression:

$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \sum_{k=1}^{5} \beta_{h,i} NT_{h,it} + \eta_{it}$,

where $NT_{h,it}$ is the number of trades in size category h for stock i on day t. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000. MON_t and TUE_t are the dummy variables for Monday and Tuesday, respectively. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. The mean and median number of observations are 351 and 352, respectively. "Coefficient" and "Adj R^2" are the average of coefficient estimates and the adjusted R^2 across 46 large cap stocks and 42 mid cap stocks, respectively. "F-stat" refers to the average test statistics of the hypothesis that the impact of the number of trades on volatility is equal across different trade size categories. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

	Large Cap Stocks				**Mid Cap Stocks**			
	Disaggregate Measurement		**Aggregate Measurement**		**Disaggregate Measurement**		**Aggregate Measurement**	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
$NT_{1,it}$	5.08×10^{-6}	0.1047	8.02×10^{-6}	0.1133	-2.26×10^{-5}	0.1309	-2.78×10^{-5}	0.1322
	(2.17%), 4.35%		(0%), 8.70%		(4.76%), 0%		(9.52%), 2.38%	
$NT_{2,it}$	1.03×10^{-5}		5.19×10^{-6}		-3.23×10^{-5}		-2.32×10^{-5}	
	(4.35%), 8.70%		(13.04%), 6.52%		(4.76%), 7.14%		(7.14%), 4.75%	

$NT_{3,it}$	3.32×10^{-6}	2.43×10^{-6}	6.53×10^{-5}	3.18×10^{-5}
	(0%), 28.26%	(0%), 26.09%	(7.14%), 38.10%	(4.76%), 33.33%
$NT_{4,it}$	4.05×10^{-5}	8.40×10^{-5}	-3.91×10^{-4}	8.42×10^{-4}
	(0%), 8.70%	(0%), 28.26%	(7.14%), 11.90%	(2.38%), 19.05%
$NT_{5,it}$	1.62×10^{-4}	6.63×10^{-5}	-6.41×10^{-4}	-5.47×10^{-4}
	(0%), 8.70%	(2.17%), 15.22%	(7.14%), 7.14%	(9.52%), 19.05%
F-stat	1.8245	2.2409	2.1223	2.7327
	30.43%	45.65%	42.86%	54.76%

4.5.3 Impact of Institutional and Individual Trading on Volatility

Table 25 presents the findings of the analysis of the impact of institutional and individual trading on volatility. Consistent with the results obtained in Table 23, the results presented in Panels A and B of Table 25 indicate that institutional and individual investors' number of trades and average trade size are positively related to volatility. Comparison of the percentages of positive and significant coefficient estimates in Panels A and B suggests that the number of trades plays a more important role in affecting volatility for individual investors than for institutional investors. In contrast, the institutional average trade size appears to have a more important role in explaining volatility than individual average trade size. Consistent with Jones et al. (1994), the daily number of trades is more important than the daily average trade size in affecting volatility, especially for individual investors. These results are robust to the use of either Disaggregate Measurement or Aggregate Measurement when performing regressions. Finally, the adjusted R^2 in Panel B is higher than that in Panel A, implying that individual trading has a greater explanatory power on volatility than institutional trading.

Panel C of Table 25 presents evidence of the impact on volatility of the number of trades and average trade size of institutional and individual investors. Consistent with Hypothesis 3, the trading activity of individual investors is more important than that of institutional investors in affecting volatility. This is evident from the higher number of positive and significant coefficient estimates for the number of trades and average trade size of individual investors than that of institutional investors. Panel C also documents the result of the likelihood ratio test for the significance of the number of trades and average trade size variables of institutional investors. This is achieved by comparing the log-likelihood measure obtained when volatility is regressed on the number of trades and average trade size of individual investors, as in Equation (4.8) and that obtained when volatility is regressed on the number of trades and average trade size of both institutional and individual investors, as in Equation (4.9). The likelihood ratio test rejects the null hypothesis of insignificant institutional number of trades and average trade size variable in 26.09% (26.09%) of large cap stocks and 26.19% (23.81%) of mid cap stocks when using Disaggregated Measurement (Aggregate Measurement) in performing regressions. This finding implies that the inclusion of the institutional number of trades and average trade size to the regression of volatility on individual number of trades and average trade size does not result in a significant improvement in the overall goodness-of-fit of the regression model.

Overall, the empirical evidence in Table 25 suggests that the trading activities of both institutions and individuals are positively related to volatility. A positive relation between institutional trading and volatility is consistent with the prediction of Gabaix et al. (2006), whereas a positive relation between individual trading and volatility is consistent with Shalen (1993) and the noise trader framework of Black (1986), De Long et al. (1990), and Campbell and Kyle (1993). This chapter also documents that individual trading is more important than institutional trading in affecting volatility. This finding supports the theoretical models of Harris and Raviv (1993) and Shalen (1993), where groups with more disagreement cause stronger volume-volatility relations. Since institutions are potentially a better-informed class of investors than individuals, their opinions are more homogeneous than those of individuals. The less-informed group of investors, with a wider dispersion of beliefs, tends to exaggerate price movements, which results in greater price volatility (Daigler and Wiley, 1999). This explains why individual trading has a larger impact on volatility than institutional trading.

Table 25: Institutional trading, individual trading and volatility

This table presents the results of investigating the relation between institutional and individual investors' number of trades, average trade size and volatility for the stocks included in the S&P/ASX 100 index on 3 January 2005. In total, the study examines a sample of 88 stocks, consisting of 46 large cap stocks and 42 mid cap stocks, for the period between 3 January 2005 and 30 June 2006. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on a two-stage regression method. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it} \ ,$$

where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables. The daily return is calculated as the difference of the natural logarithms of the daily closing and opening bid-ask mid-points. In the second stage, the relation between institutional and individual investors' number of trades, average trade size and volatility is examined based on the following regressions:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1Inst} InstNT_{it} + \beta_{i2Inst} InstATS_{it} + \eta_{it},$$

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1Indi} IndiNT_{it} + \beta_{i2Indi} IndiATS_{it} + \eta_{it},$$

where $InstNT_{it}$ ($IndiNT_{it}$) and $InstATS_{it}$ ($IndiATS_{it}$) are the number of institution-initiated (individual-initiated) transactions and their average trade size for stock i on day t, respectively. MON_t and TUE_t are the dummy variables for Monday and Tuesday, respectively. The impact of institutional and individual trading on volatility is jointly examined in the following regression:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1} InstNT_{it} + \beta_{i2} InstATS_{it} + \beta_{i3} IndiNT_{it} + \beta_{i4} IndiATS_{it} + \eta_{it}$$

"Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. The mean and median number of observations are 351 and 352, respectively. "Coefficient" and "Adj R^2" are the average of coefficient estimates and adjusted R^2 across 46 large cap stocks and 42 mid cap stocks, respectively. "LR" refers to the average likelihood ratio test statistics, which equals twice the difference between the log-likelihood value of the model estimated in Panel C and that estimated in Panel B. The likelihood ratio test statistics follow a $\chi^2(2) = 5.99$ at the 5% significance level. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

	Large Cap Stocks				Mid Cap Stocks			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Institutional investors								
$InstNT_{it}$	1.10×10^{-5}	0.0766	1.77×10^{-5}	0.0790	1.44×10^{-5}	0.0930	1.69×10^{-5}	0.0924
	(0%), 54.35%		(0%), 47.83%		(7.14%), 47.62%		(4.76%), 30.95%	
$InstATS_{it}$	1.93×10^{-6}		9.93×10^{-7}		1.28×10^{-6}		9.44×10^{-7}	
	(0%), 30.43%		(0%), 21.74%		(2.38%), 23.81%		(2.38%), 21.43%	
Panel B: Individual investors								
$IndiNT_{it}$	1.76×10^{-5}	0.0858	3.06×10^{-5}	0.0860	4.98×10^{-6}	0.1102	1.80×10^{-5}	0.1070
	(0%), 63.04%		(0%), 56.52%		(2.38%), 47.62%		(2.38%), 52.38%	
$IndiATS_{it}$	8.73×10^{-7}		1.92×10^{-7}		1.29×10^{-6}		1.03×10^{-6}	
	(2.17%), 23.91%		(0%), 13.04%		(11.91%), 7.14%		(2.38%), 9.52%	
Panel C: Institutional and individual investors								
$InstNT_{it}$	2.35×10^{-6}	0.0993	6.12×10^{-6}	0.1012	3.01×10^{-6}	0.1209	4.76×10^{-6}	0.1173
	(0%), 28.27%		(0%), 32.61%		(9.52%), 19.04%		(9.52%), 11.91%	
$InstATS_{it}$	2.36×10^{-6}		9.23×10^{-7}		8.93×10^{-7}		3.18×10^{-7}	
	(4.35%), 2.17%		(4.35%), 4.35%		(2.38%), 7.14%		(4.76%), 4.76%	
$IndiNT_{it}$	1.70×10^{-5}		2.71×10^{-5}		1.61×10^{-5}		2.63×10^{-5}	
	(0%), 54.34%		(0%), 45.65%		(0%), 50.00%		(2.38%), 42.86%	
$IndiATS_{it}$	-1.17×10^{-6}		-4.86×10^{-7}		3.30×10^{-7}		7.13×10^{-7}	
	(2.17%), 17.39%		(0%), 13.04%		(9.52%), 4.76%		(4.76%), 4.76%	
LR	4.7473		4.5151		4.3815		4.2735	
	26.09%		26.09%		26.19%		23.81%	

4.5.4 The Role of Order Imbalance in the Volume-Volatility Relation

This section provides evidence regarding the role of daily order imbalance in the volume-volatility relation on the ASX. The analysis is based on Chan and Fong's (2000) methodology, where the volume-volatility relation is examined after controlling for the return impact of daily order imbalance, and Chan and Fong's (2006) methodology, where volatility is directly regressed on the absolute value of daily order imbalance. The results obtained after applying Chan and Fong's (2000) methodology are presented in Panels A and B of Table 26, while Panels C and D document the results obtained after using Chan and Fong's (2006) methodology.

The findings in Panels A and B of Table 26 indicate little change in the significance of the number of trades and the number of trades in different size categories after controlling for the effect of order imbalance on returns. Specifically, a comparison of the findings in Panel B of Table 23 and in Panel A of Table 26 shows minimal changes in the average adjusted R^2 and the number of positive and significant coefficient estimates for the number of trades. The results obtained in Panel B of Table 26 are also qualitatively similar to those in Table 24. The average adjusted R^2 decreases when Aggregate Measurement is used, with a maximum decline of 9.97% (from 0.1133 to 0.1020) for large cap stocks. This is much smaller than the declines in R^2 of 55.25% and 60.37% documented in Chan and Fong (2000) for the NYSE and NASDAQ, respectively.

The results in Panel C suggest a positive relation between the absolute value of daily order imbalance and volatility. The relation is statistically significant at the 5% level for 47.83% (19.56%) of large cap stocks and 38.09% (21.43%) of mid cap stocks when Disaggregate Measurement (Aggregate Measurement) is used. In addition, the results documented in Panel

D show that the absolute value of daily order imbalance of transactions of size of at least 10,000 shares has the most significant impact on volatility. Replacing the absolute value of daily order imbalance with the absolute value of daily order imbalance in different trade size categories also results in an improvement in the adjusted R^2. This finding is consistent with the finding on the number of trades, as highlighted in Table 24, and implies that both the number of trades and size of trades play significant roles in the volume-volatility relation. More importantly, the adjusted R^2 observed in Panel C of Table 26 is smaller than that observed in Panel B of Table 23. Similarly, the adjusted R^2 obtained in Panel D of Table 26 is smaller than that obtained in Table 24. In other words, replacing the number of trades (number of trades of five different trade size categories) by the absolute daily order imbalance (absolute daily order imbalance of five different trade size categories) does not result in improvements in adjusted R^2. This evidence is consistent with the empirical results of Chan and Fong (2006) for NYSE stocks. These findings suggest that although daily order imbalance does play a role in explaining volatility, its explanatory power on volatility is smaller than that of the daily number of trades.

Overall, the results in Table 26 indicate that order imbalance has a significant impact on the volatility of the top 100 stocks on the ASX, an order-driven market. The role of order imbalance in the volume-volatility relation, however, is weaker on the ASX, than that documented on the NYSE and NASDAQ.[47] Therefore, consistent with Chan and Fong (2006), it is concluded that order imbalance does not supplant the number of trades in explaining volatility. In other words, the number of trades contains additional information on volatility, beyond that of daily order imbalance.

[47] Using a longer and more recent period than that of Chan and Fong (2000), Chan and Fong (2006) find that order imbalance does not add significantly more explanatory power to volatility beyond the number of trades.

Table 26: Order imbalance and the volume-volatility relation

This table presents the results of investigating the role of order imbalance in the volume-volatility relation for the stocks included in the S&P/ASX 100 index on 3 January 2005. In total, the study examines a sample of 88 stocks, consisting of 46 large cap stocks and 42 mid cap stocks, for the period between 3 January 2005 and 30 June 2006. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on the methodologies of Chan and Fong (2000) and Chan and Fong (2006).

In Chan and Fong (2000), the role of order imbalance in the volume-volatility relation is examined based on a two-stage regression method. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \delta_i OIB_{it} + \hat{\varepsilon}_{it} ,$$

where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables. OIB_{it} is the order imbalance for stock i on day t, which is calculated as the difference between the number of buyer-initiated transactions and the number of seller-initiated transactions. The daily return is calculated as the difference of the natural logarithms of the daily closing and opening bid-ask mid-points. In the second stage, the relation between the number of trades and volatility is examined based on the following regressions:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} |\hat{\varepsilon}_{it-j}| + \beta_i NT_{it} + \eta_{it} ,$$

where NT_{it} is the number of trades for stock i on day t. MON_t and TUE_t are the dummy variables for Monday and Tuesday, respectively.

In Chan and Fong (2006), the role of order imbalance in the volume-volatility relation is examined by regressing volatility measure on the absolute value of the daily order imbalance. A two-stage regression method is utilized. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it}$$

In the second stage, the volatility measure is regressed on the absolute value of the daily order imbalance ($ABSOIB_{it}$) as in the following regression:

$$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} |\hat{\varepsilon}_{it-j}| + \delta_i ABSOIB_{it} + \eta_{it}$$

The role of order imbalance of the different trade size categories in the volume-volatility relation is examined in a similar way by replacing the daily order imbalance and the absolute value of daily order imbalance with the order imbalance of five trade size categories and the absolute value of order imbalance of five trade size categories. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. The mean and median number of observations are 351 and 352, respectively. "Coefficient" and "Adj R^2" are the average of coefficient estimates and adjusted R^2 across 46 large cap stocks and 42 mid cap stocks, respectively. "F-stat" refers to the average test statistics of the hypothesis that the impact on volatility of the number of trades and the absolute order imbalance are equal across different trade size categories. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

	Large Cap Stocks				Mid Cap Stocks			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Chan and Fong (2000) – order imbalance								
NT_{it}	8.67×10^{-6}	0.0865	1.74×10^{-5}	0.0879	2.20×10^{-6}	0.1052	5.16×10^{-6}	0.1061
	(0%), 65.22%		(0%), 60.87%		(7.14%), 42.86%		(4.76%), 47.62%	
Panel B: Chan and Fong (2000) – order imbalance of different size categories								
$NT_{1,it}$	9.50×10^{-6}	0.1018	1.10×10^{-5}	0.1020	-1.43×10^{-5}	0.1197	-1.28×10^{-5}	0.1198
	(2.17%), 10.87%		(2.17%), 13.04%		(11.91%), 2.38%		(9.52%), 4.76%	
$NT_{2,it}$	6.10×10^{-6}		1.42×10^{-5}		-2.83×10^{-5}		-2.21×10^{-5}	
	(2.17%), 8.70%		(6.52%), 2.17%		(4.76%), 9.52%		(7.14%), 9.52%	
$NT_{3,it}$	1.66×10^{-6}		1.90×10^{-5}		6.34×10^{-5}		3.86×10^{-5}	
	(0%), 21.74%		(0%), 21.74%		(7.14%), 26.19%		(2.38%), 26.19%	
$NT_{4,it}$	3.72×10^{-5}		6.08×10^{-5}		-3.69×10^{-4}		8.23×10^{-4}	
	(0%), 2.17%		(0%), 10.87%		(4.76%), 7.14%		(4.76%), 14.29%	
$NT_{5,it}$	1.75×10^{-4}		8.88×10^{-5}		-8.96×10^{-4}		-7.88×10^{-4}	
	(4.34%), 8.70%		(2.17%), 15.22%		(2.38%), 9.52%		(4.76%), 19.05%	
F-stat	1.4155		1.6893		1.8809		2.2391	
	19.57%		30.43%		33.33%		45.24%	
Panel C: Chan and Fong (2006) – absolute order imbalance								
$ABSOIB_{it}$	1.97×10^{-5}	0.0572	6.72×10^{-6}	0.0452	1.61×10^{-5}	0.0833	9.81×10^{-6}	0.0740
	(2.17%), 47.83%		(2.17%), 19.56%		(4.76%), 38.09%		(4.76%), 21.43%	
Panel D: Chan and Fong (2006) – absolute order imbalance of different size categories								
$ABSOIB_{1,it}$	3.30×10^{-5}	0.0915	-3.39×10^{-5}	0.0891	-2.14×10^{-5}	0.1116	4.02×10^{-5}	0.1015
	(2.17%), 17.39%		(13.04%), 2.17%		(7.14%), 7.14%		(9.52%), 2.38%	
$ABSOIB_{2,it}$	2.16×10^{-6}		5.50×10^{-5}		5.15×10^{-5}		-7.83×10^{-5}	
	(2.17%), 17.39%		(4.35%), 13.04%		(4.76%), 11.91%		(4.76%), 2.38%	

$ABSOIB_{3,it}$	2.51×10^{-5}	3.02×10^{-5}	3.95×10^{-5}	6.13×10^{-5}
	(0%), 23.92%	(2.17%), 10.87%	(0%), 35.71%	(4.76%), 16.67%
$ABSOIB_{4,it}$	3.78×10^{-5}	3.95×10^{-5}	-1.45×10^{-5}	4.00×10^{-6}
	(2.17%), 8.70%	(0%), 13.04%	(4.76%), 21.43%	(4.76%), 14.29%
$ABSOIB_{5,it}$	3.57×10^{-4}	2.49×10^{-4}	3.78×10^{-4}	5.25×10^{-4}
	(0%), 36.96%	(0%), 41.30%	(2.38%), 28.57%	(4.76%), 35.71%
F-stat	2.0059	2.7766	2.7309	2.3850
	41.30%	47.83%	42.86%	47.62%

4.5.5 Robustness Tests

This section provides various robustness tests for the impact on volatility of the number of trades, trade size, individual trading, institutional trading, and order imbalance. The first robustness test involves using an alternative proxy for volatility besides the absolute residuals obtained after estimating Equation (4.1). Andersen and Bollerslev (1998), Andersen et al. (2001) and Andersen et al. (2003) suggest the use of realized volatility, which is calculated as the sum of intraday squared returns, as a measure of volatility. The rationale for using realized volatility is that the utilization of daily data in calculating volatility cannot capture intraday price fluctuations, which can be substantial. In contrast, realized volatility, which is calculated using intraday returns, provides a better, more robust estimate of actual price volatility.[48]

In this chapter, realized volatility is calculated as the sum of intraday squared five-minute interval returns, with the first interval being from 10:10 to 10:15. The use of five-minute intervals in calculating daily realized volatility is consistent with previous empirical research (see, among others, Andersen and Bollerslev, 1998; Andersen et al., 2001 and Andersen et al., 2003). In addition, Taylor (2004) further argues that the five-minute frequency is deemed to be sufficiently low enough to avoid stale prices and high enough to avoid loss of information. In their investigation of the volume-volatility relation for DJIA stocks, Chan and Fong (2006) also calculate realized volatility as the sum of intraday squared returns sampled at five-minute intervals. Intraday returns for each interval are calculated as the difference between the natural logarithms of the interval's closing and opening bid-ask mid-points. For the first robustness test, the impact on volatility of the number of trades and average trade

[48] Andersen and Bollerslev (1998) document that utilizing the sum of five-minute returns to measure daily volatility for the two exchange rates DM-$ and ¥-$ produces measurement errors from the latent volatility of 0.004 and 0.003, respectively. In contrast, when measuring daily volatility with daily returns, the measurement errors from the latent volatility increase to 1.138 and 0.842, respectively.

size, the number of trades in different size categories, institutional and individual trading, and absolute order imbalance is examined, with volatility measured by realized volatility. Thus, Equations (4.5), (4.6), (4.9), and (4.12) are re-estimated, with $|\hat{\varepsilon}_{it}|$ replaced by realized volatility. The results of the first robustness test are given in Table 27.

The results in Panel A of Table 27 indicate that the number of trades is more important than average trade size in explaining volatility. When the number of trades is decomposed into the number of trades in five different size categories, as in Panel B, the number of trades in the medium size category often possesses the most significant impact on volatility. From Panel C, both institutional trading and individual trading are found to have a positive relation with volatility, with the stronger relation observed for individual trading. Finally, the findings in Panel D support a positive relation between the absolute value of order imbalance and volatility. The number of significant coefficient estimates and the adjusted R^2 for the absolute order imbalance in Panel D is, however, less than those of the number of trades and average trade size in Panel A. This finding indicates that although order imbalance has an important role in the volume-volatility relation, its importance does not supplant the role of the number of trades and size of trade. These results are consistent regardless of whether Disaggregate Measurement or Aggregate Measurement is used when performing regressions. The results documented in Table 27 are also qualitatively similar to those obtained in Panel C of Table 23, Tables 24 and 25, and Panel C of Table 26, when the absolute residuals of Equation (4.1) are used to measure volatility. Therefore, it is concluded that the findings on the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance are robust to different measures of volatility.

Table 27: Volume-volatility relation, with volatility measured by realized volatility

This table presents the results of investigating the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance, with volatility measured by realized volatility. The sample includes 88 stocks (46 large cap stocks and 42 mid cap stocks) of the S&P/ASX 100 index on 3 January 2005. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on the following set of regressions:

$$rv_{it} = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\, rv_{it-j} + \beta_{i1}NT_{it} + \beta_{i2}ATS_{it} + \eta_{it},$$

$$rv_{it} = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\, rv_{it-j} + \sum_{h=1}^{5}\beta_{h,i}NT_{h,it} + \eta_{it},$$

$$rv_{it} = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\, rv_{it-j} + \beta_{i1}InstNT_{it} + \beta_{i2}InstATS_{it} + \beta_{i3}IndiNT_{it} + \beta_{i4}IndiATS_{it} + \eta_{it},$$

$$rv_{it} = \varphi_{i0} + \varphi_{i1}MON_t + \varphi_{i2}TUE_t + \sum_{j=1}^{12}\gamma_{ij}\, rv_{it-j} + \delta_i ABSOIB_{it} + \eta_{it},$$

where rv_{it} is the natural logarithm of realized volatility for stock i on day t. Realized volatility is calculated as the sum of intraday squared returns. Intraday squared returns are calculated for each five-minute interval, with the return for each interval calculated as the difference between the natural logarithms of the interval's closing and opening bid-ask mid-points. NT_{it} and ATS_{it} are the number of trades and average trade size for stock i on day t, respectively. $NT_{h,it}$ is the number of trades in size category h for stock i on day t. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000. $InstNT_{it}$ and $IndiNT_{it}$ are the number of institution-initiated transactions and individual-initiated transactions for stock i on day t, respectively. $InstATS_{it}$ and $IndiATS_{it}$ are the average size of institution-initiated transactions and individual-initiated transactions, respectively. $ABSOIB_{it}$ is the absolute value of the daily order imbalance (the difference between the number of buyer-initiated transactions and the number of seller-initiated transactions) for stock i on day t. MON_t and TUE_t are the dummy variables for Monday and Tuesday, respectively. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. The mean and median number of observations are 351 and 352, respectively. "Coefficient" and "Adj R^2" are the average of coefficient estimates and adjusted R^2 across 46 large cap and 42 mid cap stocks. "F-stat" refers to the average test statistics of the hypothesis that the impact of the number of trades on volatility is equal across different trade size categories. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

	Large Cap				Mid Cap			
	Disaggregate Measurement		**Aggregate Measurement**		**Disaggregate Measurement**		**Aggregate Measurement**	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Number of trades and average trade size								
NT_{it}	5.32×10^{-4}	0.1271	9.63×10^{-4}	0.1312	2.92×10^{-4}	0.1241	8.66×10^{-4}	0.1245
	(2.17%), 60.87%		(2.17%), 56.52%		(2.38%), 40.48%		(0%), 42.86%	
ATS_{it}	-1.57×10^{-5}		-4.75×10^{-5}		-8.42×10^{-5}		-6.31×10^{-5}	
	(13.04%), 10.87%		(23.91%), 8.70%		(16.67%), 2.38%		(23.81%), 2.38%	
Panel B: Number of trades in different size categories								
$NT_{1,it}$	2.47×10^{-4}	0.1371	3.14×10^{-4}		8.82×10^{-6}	0.1315	5.26×10^{-4}	0.1322
	(0%), 17.39%		(8.70%), 23.91%		(7.14%), 9.52%		(4.76%), 7.14%	
$NT_{2,it}$	4.79×10^{-5}		-7.17×10^{-4}		4.68×10^{-4}		1.55×10^{-3}	
	(4.35%), 4.35%		(10.87%), 6.52%		(7.14%), 16.67%		(4.76%), 9.52%	
$NT_{3,it}$	1.18×10^{-3}		1.29×10^{-3}		1.63×10^{-3}		1.91×10^{-3}	
	(2.17%), 28.26%		(2.17%), 28.26%		(2.38%), 14.29%		(4.76%), 19.05%	
$NT_{4,it}$	1.77×10^{-3}		4.04×10^{-3}		-7.41×10^{-3}		0.0171	
	(2.17%), 8.70%		(0%), 19.57%		(2.38%), 2.38%		(0%), 9.52%	
$NT_{5,it}$	-9.44×10^{-4}		-1.21×10^{-3}		-0.0309		-0.0384	
	(19.57%), 4.35%		(17.39%), 10.87%		(14.29%), 2.38%		(19.05%), 2.38%	
F-stat	2.0843		2.6383		1.4903		1.4670	
	32.61%		47.83%		21.43%		21.43%	
Panel C: Institutional and individual trading								
$InstNT_{it}$	5.10×10^{-4}	0.1327	0.0010		4.76×10^{-4}	0.1314	7.28×10^{-4}	0.1318
	(0%), 30.43%		(0%), 30.43%		(2.38%), 7.14%		(0%), 9.52%	
$InstATS_{it}$	-2.27×10^{-5}		-3.62×10^{-5}		-7.69×10^{-5}		-4.69×10^{-5}	
	(13.04%), 4.35%		(23.91%), 4.35%		(19.05%), 2.38%		(14.29%), 2.38%	
$IndiNT_{it}$	7.19×10^{-4}		0.0013		6.75×10^{-4}		0.0012	
	(4.35%), 36.96%		(4.35%), 41.30%		(2.38%), 23.81%		(0%), 28.57%	
$IndiATS_{it}$	1.09×10^{-5}		-1.06×10^{-5}		-1.78×10^{-5}		-2.95×10^{-5}	
	(6.52%), 6.52%		(6.52%), 6.52%		(14.29%), 7.14%		(11.91%), 9.52%	
Panel D: Absolute order imbalance								
$ABSOIB_{it}$	7.57×10^{-4}	0.1038	5.62×10^{-4}	0.1033	1.27×10^{-3}	0.1167	1.26×10^{-3}	0.1162
	(2.17%), 21.74%		(2.17%), 23.91%		(0%), 11.91%		(0%), 19.05%	

The second robustness test assesses the issue of whether time aggregation of individual trades into daily sums and averages has any impact on the information content of the number of trades, average trade size, institutional and individual trading activity, and order imbalance. Huang and Masulis (2003) argue that this issue is particularly important for average trade size, where the use of a daily frequency can smooth out the underlying variability of the trade size variable, thereby lowering its information content and significance. In order to address this issue, Equations (4.5), (4.6), (4.9), and (4.12) are re-estimated using 30-minute and one-hour intervals. Price volatility for firm *i* in interval *t* is calculated as the absolute value of the difference between the natural logarithms of the bid-ask mid-point at the end and at the beginning of interval *t*. The set of the estimated regressions are specified as follows:

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \beta_{i1}NT_{it} + \beta_{i2}ATS_{it} + \eta_{it}, \tag{4.14}$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \sum_{h=1}^{5}\beta_{h,i}\,NT_{h,it} + \eta_{it}, \tag{4.15}$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \beta_{i1}InstNT_{it}$$
$$+\beta_{i2}InstATS_{it} + \beta_{i3}IndiNT_{it} + \beta_{i4}IndiATS_{it} + \eta_{it} \tag{4.16}$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \delta_i ABSOIB_{it} + \eta_{it}, \tag{4.17}$$

where *n* is the number of lags, which is chosen based on the Akaike information criteria (AIC). The number of lags for one-hour and 30-minute analyses is 4 and 6, respectively. $FIRST_{it}$ and $LAST_{it}$ are the dummy variables for the first and last interval of the trading day, respectively. These two dummy variables are included to control for the intraday pattern of volatility, as highlighted in Wood et al. (1985), Admati and Pfleiderer (1988), and Brock and Kleidon (1992).

Table 28 presents the results of the second robustness test. The analysis is based on the use of 30-minute and one-hour intervals instead of daily intervals, as in Tables 23, 24, 25 and 26. Consistent with the results obtained in Panel B of Table 23, the results in Panel A of Table 28 show that the number of trades is more important than average trade size in explaining volatility. In addition, similar to the findings of Table 24, the evidence presented in Panel B shows that the number of trades of different size categories generally possess different impacts on volatility, with the medium-sized trades often having the most significant impact. The results in Panel C of Table 28 imply that the trading activities of institutional and individual investors are positively related to volatility. Moreover, the total number of positive and significant coefficient estimates for individual investors' number of trades and average trade size is also larger than that for institutional investors'. Therefore, consistent with the results in Table 25, it is concluded that the trading activity of individual investors has a more significant role in the volume-volatility relation than the trading activity of institutional investors. Finally, the findings in Panel D of Table 28 show a positive relation between the absolute value of order imbalance and volatility. The number of positive and significant coefficient estimates for the absolute order imbalance, however, is much smaller than that for the number of trades and average trade size in Panel A. Thus, similar to the findings of Table 26, order imbalance is not the key factor behind the volume-volatility relation. Overall, the results in Table 28 indicate that the findings on the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance are robust to the use of different time intervals.

Table 28: Intraday analysis of the volume-volatility relation

This table presents the results of investigating the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance, based on 30-minute and one-hour intervals. The sample includes 88 stocks (46 large cap stocks and 42 mid cap stocks) of the S&P/ASX 100 index on 3 January 2005. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on the following set of regressions:

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \beta_{i1}NT_{it} + \beta_{i2}ATS_{it} + \eta_{it},$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \sum_{h=1}^{5}\beta_{h,i}NT_{h,it_{i1}} + \eta_{it},$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \beta_{i1}InstNT_{it} + \beta_{i2}InstATS_{it} + \beta_{i3}IndiNT_{it} + \beta_{i4}IndiATS_{it} + \eta_{it},$$

$$VOLA_{it} = \varphi_{i0} + \varphi_{i1}FIRST_t + \varphi_{i2}LAST_t + \sum_{j=1}^{n}\gamma_{ij}\,VOLA_{it-j} + \delta_i ABSOIB_{it} + \eta_{it},$$

where the volatility for stock i in interval t ($VOLA_{it}$) is measured by the absolute value of the interval return, which is calculated as the difference between the natural logarithms of the interval's closing and opening bid-ask mid-points. NT_{it} and ATS_{it} are the number of trades and average trade size for stock i on day t, respectively. $NT_{h,it}$ is the number of trades in size category h for stock i in interval t. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000. $InstNT_{it}$ and $IndiNT_{it}$ are the number of institution-initiated transactions and individual-initiated transactions for stock i in interval t, respectively. $InstATS_{it}$ and $IndiATS_{it}$ are the average size of the institution-initiated transactions and individual-initiated transactions for stock i in interval t, respectively. $ABSOIB_{it}$ is the absolute value of the daily order imbalance (the difference between the number of buyer-initiated transactions and the number of seller-initiated transactions) for stock i in interval t. The number of lags, n, is chosen based on the Akaike Information Criteria (AIC). The number of lags for one-hour and 30-minute analyses is 4 and 6, respectively $FIRST_t$ and $LAST_t$ are the dummy variables for the first and last intervals of the trading day, respectively. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. "Coefficient" and "Adj R^2" are the average of coefficient estimates and adjusted R^2 across 46 large cap and 42 mid cap stocks. "F-stat" refers to the average test statistics of the hypothesis that the impact of the number of trades on volatility is equal across different trade size categories. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

Results when using 30-minute intervals

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Number of trades and average trade size								
NT_{it}	0.0063	0.0047	0.0111	0.0048	0.0137	0.0054	0.0192	0.0059
	(0%), 58.70%		(0%), 52.17%		(2.38%), 71.43%		(2.38%), 64.29%	
ATS_{it}	6.10×10^{-5}		6.18×10^{-6}		-4.07×10^{-5}		-2.64×10^{-5}	
	(6.52%), 19.57%		(8.70%), 17.39%		(7.14%), 19.05%		(9.52%), 23.81%	
Panel B: Number of trades in different size categories								
$NT_{1,it}$	-0.0034	0.0057	0.0022	0.0055	-0.0029	0.0063	-0.0019	0.0058
	(15.22%), 2.17%		(6.52%), 4.35%		(19.05%), 7.14%		(23.81%), 7.14%	
$NT_{2,it}$	0.0087		0.0131		0.0103		0.0219	
	(2.17%), 6.52%		(2.17%), 8.70%		(4.76%), 11.91%		(2.38%), 11.91%	
$NT_{3,it}$	0.0199		0.0211		0.0077		0.0236	
	(2.17%), 19.57%		(2.17%), 17.39%		(4.76%), 7.14%		(0%), 26.19%	
$NT_{4,it}$	0.0074		0.0186		0.0267		0.0227	
	(2.17%), 4.35%		(4.35%), 8.70%		(0%), 16.67%		(0%), 4.76%	
$NT_{5,it}$	-0.0358		-0.0085		-0.0013		-0.0257	
	(21.74%), 4.35%		(8.70%), 15.22%		(26.19%), 19.05%		(21.43%), 23.81%	
F-stat	1.5598		1.4512		2.5260		2.0900	
	32.61%		26.09%		59.52%		52.38%	
Panel C: Institutional and individual trading								
$InstNT_{it}$	0.0041	0.0051	0.0064	0.0051	0.0119	0.0061	0.0185	0.0071
	(2.17%), 6.52%		(0%), 8.70%		(0%), 23.81%		(0%), 21.43%	
$InstATS_{it}$	3.69×10^{-5}		-3.25×10^{-6}		-4.88×10^{-5}		-3.58×10^{-5}	
	(2.17%), 10.87%		(6.52%), 6.52%		(7.14%), 11.91%		(9.52%), 16.67%	
$IndiNT_{it}$	0.0087		0.0154		0.0149		0.0188	
	(2.17%), 39.13%		(0%), 43.48%		(2.38%), 33.33%		(2.38%), 28.57%	
$IndiATS_{it}$	1.57×10^{-5}		7.83×10^{-7}		1.42×10^{-5}		8.62×10^{-6}	
	(6.52%), 4.35%		(0%), 6.52%		(9.52%), 11.91%		(9.52%), 23.81%	
Panel D: Absolute order imbalance								
$ABSOIB_{it}$	0.0078	0.0038	0.0058	0.0037	0.0161	0.0043	0.0125	0.0038
	(0%), 17.39%		(0%), 13.04%		(4.76%), 42.86%		(2.38%), 30.95%	

Results when using one-hour intervals

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Number of trades & average trade size								
NT_{it}	0.0075	0.1089	0.0136	0.1092	0.0114	0.0935	0.0186	0.0941
	(0%), 65.22%		(0%), 69.57%		(0%), 52.38%		(0%), 57.14%	
ATS_{it}	2.96×10^{-4}		1.16×10^{-4}		-1.12×10^{-6}		-4.16×10^{-5}	
	(4.35%), 26.09%		(6.52%), 19.57%		(7.14%), 16.67%		(7.14%), 21.43%	
Panel B: Number of trades in different size categories								
$NT_{1,it}$	-2.20×10^{-4}	0.1103	0.0092	0.1106	-0.0032	0.0947	0.0021	0.0944
	(13.04%), 4.35%		(8.70%), 8.70%		(19.05%), 4.76%		(19.05%), 7.14%	
$NT_{2,it}$	0.0144		0.0196		-0.0014		0.0049	
	(4.35%), 15.22%		(4.35%), 13.04%		(4.76%), 7.14%		(7.14%), 9.52%	
$NT_{3,it}$	0.0133		0.0131		0.0091		0.0223	
	(0%), 13.04%		(0%), 19.57%		(7.14%), 7.14%		(2.38%), 19.05%	
$NT_{4,it}$	0.0040		0.0293		0.0277		3.94×10^{-4}	
	(2.17%), 4.35%		(2.17%), 13.04%		(2.38%), 11.91%		(0%), 9.52%	
$NT_{5,it}$	-0.0091		0.0047		0.2202		0.0499	
	(13.04%), 4.35%		(6.52%), 6.52%		(11.91%), 11.91%		(7.14%), 7.14%	
F-stat	1.3724		1.4244		1.8077		1.5860	
	23.91%		23.91%		35.71%		40.48%	
Panel C: Institutional and individual trading								
$InstNT_{it}$	0.0066	0.1095	0.0126	0.1097	0.0108	0.0944	0.0217	0.0954
	(0%), 15.22%		(0%), 19.57%		(0%), 19.05%		(0%), 16.67%	
$InstATS_{it}$	1.47×10^{-4}		4.33×10^{-5}		-1.22×10^{-4}		-1.02×10^{-4}	
	(2.17%), 8.70%		(2.17%), 6.52%		(7.14%), 9.52%		(9.52%), 11.91%	
$IndiNT_{it}$	0.0087		0.0153		0.0124		0.0169	
	(0%), 23.91%		(2.17%), 26.09%		(0%), 28.57%		(0%), 23.81%	
$IndiATS_{it}$	1.42×10^{-4}		5.34×10^{-5}		1.73×10^{-4}		9.44×10^{-5}	
	(2.17%), 10.87%		(2.17%), 8.70%		(4.76%), 21.43%		(2.38%), 16.67%	
Panel D: Absolute order imbalance								
$ABSOIB_{it}$	0.0082	0.1068	0.0062	0.1067	0.0139	0.0919	0.0138	0.0916
	(0%), 13.04%		(2.17%), 8.70%		(0%), 26.19%		(4.76%), 14.29%	

The final robustness test analyzes the effect of the move to anonymity on the ASX on the results regarding the impact of the number of trades and average trade size, institutional and individual trading, and order imbalance on volatility. For this robustness test, the overall sample period is partitioned into two subsamples: the transparent market sample (from 3 January 2005 to 25 November 2005) and the anonymous market sample (from 28 November 2005 to 30 June 2006). Equations (4.5), (4.6), (4.9), and (4.12) are then re-estimated for the transparent and anonymous markets and a comparison of the results will indicate the effect of anonymity on the volume-volatility relation. Table 29 presents results of this robustness test.

From Panel A of Table 29, the number of trades has a more significant role in the volume-volatility relation than the average trade size in both the transparent and anonymous markets. The results in Panel B of Table 29 also indicate that medium-sized trades have a more significant impact on volatility than large and small trades. Among the five trade size categories, the number of trades in Category 3 often has the most significant impact on volatility. Consistent with the results for the overall sample, as presented in Table 25, the findings in Panel C of Table 29 highlight that in both transparent and anonymous markets, volatility is more affected by individual trading than institutional trading. Finally, the results in Panel D show a positive relation between absolute order imbalance and volatility. In both transparent and anonymous markets, however, the significance and explanatory power of the absolute order imbalance on volatility are less than that of the number of trades and average trade size, as documented in Panel A. Therefore, in both the transparent and anonymous markets, order imbalance is not the key factor behind the volume-volatility relation. Overall, it is concluded that the findings regarding the effect on volatility of the number of trades and average trade size, institutional and individual trading, and order imbalance are consistent in both the transparent and anonymous markets.

Table 29: Anonymity and the volume-volatility relation

This table presents the results of investigating the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance, in the transparent market (from 3 January 2005 to 25 November 2005) and anonymous market (from 28 November 2005 to 30 June 2006). The sample includes 88 stocks (46 large cap stocks and 42 mid cap stocks) of the S&P/ASX 100 index on 3 January 2005. Large cap stocks are those included in the S&P/ASX 50 index on 3 January 2005. Mid cap stocks are those included in the S&P/ASX 100 index, but not in the S&P/ASX 50 index on 3 January 2005. Results are obtained based on a two-stage regression method. In the first stage, the daily price volatility for each stock is estimated from the absolute residuals of the following regression model:

$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it}$,

where R_{it} is the return of stock i on day t and D_{kt} are the day-of-the-week dummy variables. The daily return is calculated as the difference of the natural logarithms of the daily closing and opening bid-ask mid-points. In the second stage, the impact on volatility of the number of trades, average trade size, institutional and individual trading, and order imbalance is investigated based on the following regressions:

$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1} NT_{it} + \beta_{i2} ATS_{it} + \eta_{it},$

$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \sum_{h=1}^{5} \beta_{h,i} NT_{h,it} + \eta_{it},$

$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \beta_{i1} InstNT_{it} + \beta_{i2} InstATS_{it} + \beta_{i3} IndiNT_{it} + \beta_{i4} IndiATS_{it} + \eta_{it},$

$|\hat{\varepsilon}_{it}| = \varphi_{i0} + \varphi_{i1} MON_t + \varphi_{i2} TUE_t + \sum_{j=1}^{12} \gamma_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \delta_i ABSOIB_{it} + \eta_{it},$

where NT_{it} and ATS_{it} are the number of trades and average trade size for stock i on day t, respectively. $NT_{h,it}$ is the number of trades in size category h for stock i in interval t. The trade belongs to Category 1 if the number of shares executed is less than or equal to 500. The trade belongs to Category 2 if the number of shares executed is greater than 500 and less than or equal to 1,000. The trade belongs to Category 3 if the number of shares executed is greater than 1,000 and less than or equal to 5,000. The trade belongs to Category 4 if the number of shares executed is greater than 5,000 and less than or equal to 9,999. The trade belongs to Category 5 if the number of shares executed is at least 10,000. $InstNT_{it}$ and $IndiNT_{it}$ are the number of institution-initiated transactions and individual-initiated transactions for stock i in interval t, respectively. $InstATS_{it}$ and $IndiATS_{it}$ are the average size of the institution-initiated transactions and individual-initiated transactions for stock i in interval t, respectively. $ABSOIB_{it}$ is the absolute value of the daily order imbalance (the difference between the number of buyer-initiated transactions and the number of seller-initiated transactions) for stock i in interval t. "Disaggregate Measurement" refers to the situation where the number of trades and average trade size are calculated in a way that ignores the possibility of one large order being executed against several smaller orders and thus, creating several transactions. "Aggregate Measurement" refers to the situation where the number of trades and average trade size are calculated with several transactions arising from one large order executed against several smaller orders, grouped together. The regressions are performed separately for each of the 88 stocks under investigation and separately for the transparent and anonymous market. The results are obtained with the Newey-West (1987) heteroskedasticity consistent covariance procedure. "Coefficient" and "Adj R^2" is the average of the coefficient estimates and adjusted R^2 across 46 large cap and 42 mid cap stocks. "F-stat" refers to the average test statistics of the hypothesis that the impact on volatility of the number of trades is equal across different trade size categories. The percentages inside the parentheses indicate the number of estimates that are negative and significant at the 5% level of significance, whereas the percentages outside the parentheses indicate the number of estimates that are positive and significant at the 5% level of significance.

Transparent Markets

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Number of trades and average trade size								
NT_{it}	1.01×10^{-5}	0.1290	1.42×10^{-5}	0.1258	1.35×10^{-5}	0.1480	1.99×10^{-5}	0.1454
	(0%), 69.57%		(0%), 58.70%		(2.38%), 45.24%		(4.35%), 45.24%	
ATS_{it}	1.28×10^{-6}		8.91×10^{-7}		-1.48×10^{-6}		-5.89×10^{-7}	
	(2.17%), 13.04%		(0%), 13.04%		(4.35%), 4.35%		(2.38%), 7.14%	
Panel B: Number of trades in different size categories								
$NT_{1,it}$	-1.81×10^{-6}	0.1471	-1.19×10^{-5}	0.1515	5.44×10^{-5}	0.1705	6.74×10^{-5}	0.1709
	(0%), 10.87%		(2.17%), 6.52%		(4.35%), 9.52%		(4.35%), 9.52%	
$NT_{2,it}$	1.71×10^{-5}		-1.35×10^{-5}		-7.53×10^{-5}		-5.13×10^{-5}	
	(0%), 4.35%		(6.52%), 2.17%		(2.38%), 9.52%		(2.38%), 7.14%	
$NT_{3,it}$	7.20×10^{-6}		6.13×10^{-6}		1.13×10^{-5}		3.72×10^{-6}	
	(0%), 26.09%		(0%), 21.74%		(0%), 28.57%		(2.38%), 21.43%	
$NT_{4,it}$	4.57×10^{-5}		1.28×10^{-4}		-4.45×10^{-4}		-2.76×10^{-4}	
	(0%), 10.87%		(0%), 19.57%		(11.91%), 9.52%		(7.14%), 16.67%	
$NT_{5,it}$	2.69×10^{-4}		9.34×10^{-5}		7.05×10^{-5}		1.50×10^{-5}	
	(2.17%), 6.52%		(0%), 15.22%		(11.91%), 7.14%		(11.91%), 11.91%	
F-stat	1.1905		1.6785		1.7034		1.9839	
	15.22%		30.43%		30.95%		35.71%	
Panel C: Institutional and individual trading								
$InstNT_{it}$	7.40×10^{-6}	0.1395	1.31×10^{-5}	0.1368	2.59×10^{-6}	0.1612	2.12×10^{-6}	0.1594
	(0%), 36.96%		(2.17%), 30.43%		(4.35%), 9.52%		(2.38%), 9.52%	
$InstATS_{it}$	2.48×10^{-6}		1.13×10^{-6}		1.96×10^{-7}		-3.93×10^{-7}	
	(2.17%), 2.17%		(4.35%), 4.35%		(2.38%), 9.52%		(7.14%), 7.14%	
$IndiNT_{it}$	1.69×10^{-5}		2.21×10^{-5}		2.61×10^{-6}		9.19×10^{-6}	
	(2.17%), 47.83%		(0%), 43.48%		(0%), 47.62%		(2.38%), 42.86%	
$IndiATS_{it}$	-2.39×10^{-6}		-7.95×10^{-7}		-3.05×10^{-6}		-1.14×10^{-6}	
	(4.35%), 6.52%		(2.17%), 6.52%		(11.91%), 2.38%		(9.52%), 2.38%	
Panel D: Absolute order imbalance								
$ABSOIB_{it}$	2.46×10^{-5}	0.0855	3.87×10^{-6}	0.0686	1.15×10^{-5}	0.1134	7.42×10^{-6}	0.1016
	(0%), 50.00%		(2.17%), 30.43%		(0%), 42.86%		(0%), 23.81%	

Anonymous Market

	Large Cap				Mid Cap			
	Disaggregate Measurement		Aggregate Measurement		Disaggregate Measurement		Aggregate Measurement	
	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2	Coefficient	Adj R^2
Panel A: Number of trades and average trade size								
NT_{it}	1.35×10^{-5}	0.1925	2.55×10^{-5}	0.1966	1.39×10^{-5}	0.2032	2.61×10^{-5}	0.2009
	(0%), 73.91%		(0%), 60.87%		(0%), 64.29%		(0%), 59.52%	
ATS_{it}	2.30×10^{-7}		-4.62×10^{-7}		9.71×10^{-6}		6.51×10^{-6}	
	(0%), 10.87%		(0%), 13.04%		(0%), 19.05%		(0%), 26.19%	
Panel B: Number of trades in different size categories								
$NT_{1,it}$	1.19×10^{-5}	0.2296	1.55×10^{-5}	0.2356	-2.75×10^{-6}	0.2406	2.32×10^{-6}	0.2447
	(0%), 10.87%		(4.35%), 13.04%		(2.38%), 0%		(4.35%), 0%	
$NT_{2,it}$	1.37×10^{-5}		5.78×10^{-5}		-5.49×10^{-5}		-4.97×10^{-5}	
	(2.17%), 10.87%		(6.52%), 6.52%		(0%), 9.52%		(9.52%), 2.38%	
$NT_{3,it}$	6.68×10^{-6}		1.13×10^{-6}		2.55×10^{-4}		1.09×10^{-4}	
	(2.17%), 32.61%		(0%), 30.43%		(2.38%), 26.19%		(0%), 33.33%	
$NT_{4,it}$	3.43×10^{-5}		7.94×10^{-5}		-1.41×10^{-3}		2.47×10^{-3}	
	(8.70%), 4.35%		(10.87%), 10.87%		(0%), 11.91%		(0%), 4.35%	
$NT_{5,it}$	1.07×10^{-4}		6.35×10^{-6}		-6.48×10^{-4}		2.87×10^{-4}	
	(2.17%), 17.39%		(4.35%), 17.39%		(2.38%), 7.14%		(4.35%), 28.57%	
F-stat	2.1688		2.1700		1.8954		2.0424	
	23.91%		41.30%		28.57%		35.71%	
Panel C: Institutional and individual trading								
$InstNT_{it}$	4.42×10^{-6}	0.2109	8.18×10^{-6}	0.2146	7.56×10^{-6}	0.2204	1.79×10^{-5}	0.2171
	(0%), 28.26%		(0%), 28.26%		(2.38%), 19.05%		(0%), 14.29%	
$InstATS_{it}$	9.40×10^{-7}		-9.22×10^{-8}		5.56×10^{-6}		3.23×10^{-6}	
	(4.35%), 0%		(2.17%), 4.35%		(2.38%), 14.29%		(2.38%), 16.67%	
$IndiNT_{it}$	2.86×10^{-5}		4.53×10^{-5}		1.93×10^{-5}		2.96×10^{-5}	
	(0%), 34.78%		(0%), 39.13%		(0%), 47.62%		(0%), 45.24%	
$IndiATS_{it}$	-8.01×10^{-7}		-4.46×10^{-7}		3.97×10^{-6}		3.14×10^{-6}	
	(2.17%), 10.87%		(2.17%), 13.04%		(4.35%), 4.35%		(2.38%), 9.52%	
Panel D: Absolute order imbalance								
$ABSOIB_{it}$	2.31×10^{-5}	0.1453	1.49×10^{-5}	0.1297	2.44×10^{-5}	0.1453	3.35×10^{-5}	0.1371
	(0%), 39.13%		(2.17%), 23.91%		(0%), 28.57%		(4.35%), 11.91%	

4.6 Conclusions

This chapter examines the role of the number of trades and average trade size, institutional and individual investors' trading activity, and order imbalance in the volume-volatility relation. Investigating the constituent stocks of the S&P/ASX 100 index for the period between 3 January 2005 and 30 June 2006, this chapter provides supportive evidence for a positive relation between trading volume and volatility for the majority of stocks under investigation. In addition, consistent with the findings of Jones et al. (1994), when daily trading volume is decomposed into the daily number of trades and daily average trade size, the daily number of trades is found to be more important in explaining volatility. When the daily number of trades is further divided into the daily number of trades in five different size categories, the number of trades in the medium size category often has the most significant impact on volatility. These findings indicate that although the daily number of trades is generally more important than the daily average trade size in affecting volatility, the size of trade also possesses significant information, beyond that of the number of trades, in the volume-volatility relation. Therefore, it is concluded that both the number of trades and the size of trade play a significant role in the volume-volatility relation.

Using a complete dataset of all institutional and individual trading in the central limit order book, this chapter also provides empirical support for a positive relation between institutional and individual investors' trading activity and volatility. Moreover, this chapter documents that individual trading is more important than institutional trading in affecting volatility. Since institutions are potentially the better-informed class of investors than individuals, they should have a more uniform opinion than individuals.[49] Therefore, the finding that individual trading has a larger impact on volatility than institutional trading is consistent with the "Difference of Opinion" models of Shalen (1993), where stronger volume-volatility relations are caused by the trading activity of the less informed groups of investors, who possess greater dispersion of belief.

Consistent with Chan and Fong (2006), this chapter supports a positive relation between absolute order imbalance and volatility. The significance and the explanatory power of order imbalance on volatility are, however, less than those of number of trades. Furthermore, little change is observed for the volume-volatility relation after the impact of order imbalance on daily returns is taken into consideration. Thus, it is concluded that on the ASX, a limit order book market, the volume-volatility relation is not driven mainly by order imbalance. In other words, other variables, such as the daily number of trades and size of trade, contain significant information on volatility, beyond that of daily order imbalance.

[49] Szewczyk et al. (1992), Alangar et al. (1999), Dennis and Weston (2001), Chakravarty (2001) and Anand et al. (2005) provide empirical evidence that institutional investors are better informed than individual investors. The evidence that individuals possess greater differences of opinion than institutions is also highlighted in Table 14 in Chapter 3.

Chapter 5: Conclusions

5.1 Overview and Conclusions

This thesis presents three empirical essays on various issues related to the demand and supply of liquidity of institutional and individual investors on the ASX. This chapter presents a summary of the main findings and directions for future research.

The first empirical essay, presented in Chapter 2, investigates the decision of institutional and individual investors to demand liquidity (submit market orders) and supply liquidity (place limit orders) based on the concept of order aggressiveness. The overall results provide support for a positive (negative) relation between order aggressiveness and the same-side (opposite-side) market depth. Investors' order aggressiveness is also negatively related to the bid-ask spread. Institutions and individuals (institutions) tend to be less (more) aggressive when volatility increases in mid (large) cap stocks. This chapter also highlights that institutional investors are more aggressive during the first trading hour, whereas individual investors are less aggressive early in the day and increase their order aggressiveness as the end of the trading day approaches. In addition, institutional investors are more aggressive when submitting large orders in large and mid cap stocks whereas individual investors are less aggressive when submitting large orders. Institutional and individual investors are also more aggressive in their selling activities than in their buying activities in mid cap and small cap stocks. Finally, both institutional and individual investors become less aggressive in their order submissions following the removal of broker IDs on the ASX, with stronger results observed for individual investors. This finding implies that following the move to anonymity, both institutional and individual investors are more willing to supply liquidity and display their orders in the central limit order book.

The second essay, presented in Chapter 3, analyzes the supply side of liquidity and examines the information content of the limit order book. More specifically, this chapter investigates the informativeness of the limit order book slope about future volatility and the impact of anonymity on the order book slope informativeness. This chapter documents supportive evidence for the informativeness of the order book slope about future price volatility. This finding is consistent with the notion that informed traders use limit orders in their order submission strategies, as suggested by Chakravarty and Holden (1995), Wald and Horrigan (2005) and Kaniel and Liu (2006). This chapter also finds the slope of the limit order book on the demand (buy) side to be more informative than that on the supply (sell) side. In addition, institutional limit orders are more informative than individual limit orders about the future permanent component of volatility. Finally, institutional limit orders become more informative about future volatility after the move to anonymity, while a minimal impact is observed for the informativeness of individual limit orders. This finding implies that the removal of broker IDs on the ASX has made the better-informed investors more willing to submit and expose their informative limit orders in the limit order book. Overall, the empirical results in Chapters 2 and 3 support the ASX's decision to stop disclosing broker identity information in the central limit order book.

The third essay, presented in Chapter 4, examines the demand side of liquidity and focuses on the roles of the number of trades, average trade size, institutional and individual trading, and order imbalance in the volume-volatility relation. This chapter provides evidence supporting a positive relation between trading volume and volatility. Consistent with Jones et al. (1994), the daily number of trades is more important than the daily average trade size in explaining volatility. When the daily number of trades is further divided into the daily number of trades in five different trade size categories, the number of trades in the medium size category often has the most significant impact on volatility. Both institutional trading and individual trading are positively related to volatility, with individual trading having a more significant impact on volatility than institutional trading. Since institutions are potentially a better-informed class of investors than individuals, this finding is consistent with the "Difference of Opinion" models of Shalen (1993), where stronger volume-volatility relation is caused by the trading activity of the less-informed groups of investors, who possess greater dispersion of belief. Finally, this chapter addresses the role of order imbalance in the volume-volatility relation. The findings indicate that, in contrast to the evidence for the NYSE and NASDAQ stocks as presented in Chan and Fong (2000), on the ASX — a limit order book market — order imbalance is not the main driving factor for the volume-volatility relation.

5.2 Directions for Future Research

This thesis addresses issues related to the demand and supply of liquidity of institutional and individual investors on the ASX. There are other related issues that are beyond the scope of the current study and are therefore not addressed in this thesis. First, this thesis focuses exclusively on the order submissions of institutional and individual investors in the continuous trading session after the market has already opened. An important issue therefore is to investigate the order submissions of institutions and individuals during the preopening period. Since the preopening period is also a period in which price discovery takes place (see, for example, Biais et al., 1999; Cao et al., 2000), the analysis of investors' order submissions in this period will provide insights into the price discovery process as well as evidence regarding issues such as market manipulation and signalling.[50] The analysis can also allow for the joint decision of order type and order size, as in Lo and Saap (2005) and Bessembinder et al. (2008). Modification of the econometric models to allow for the fact that

[50] See, among others, Cao et al. (2000), Davies (2003), and Kuk et al. (2008) for empirical evidence on market manipulations and signalling in the preopening period.

investors can only place an order within the best quotes (Category 4 aggressiveness orders) when the spread is greater than one tick will also be beneficial.

Second, the results presented in Chapter 3 highlight the importance of limit orders in the order submission strategies of informed investors. A more direct comparison of the informativeness of limit and market orders in a similar spirit to that of Kaniel and Liu (2006) will provide important implications to the question of what types of orders informed traders use. The analysis can be performed in various intraday intervals or across days of the week to conform to the predictions regarding the different behaviors of informed traders in those periods (see, for example, Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Bloomfield et al., 2005). The analysis of the informativeness of limit versus market orders can also be performed in periods around important corporate announcements, such as earnings announcements. Since these announcements are more likely to convey price-sensitive information, this analysis will provide insights into the order submission strategies of informed traders in periods with high information asymmetry.

Third, the results in Chapter 4 suggest that individual trading has a more significant impact on volatility than institutional trading. If individuals are the noise traders, as often classified in the literature (see, for example, Foucault et al., 2008; Barber et al., 2009) this finding implies that noise traders increase volatility, as predicted by Black (1986) and De Long et al. (1990). A direction for future research, therefore, is to examine the relation between noise trading and price volatility. Prior studies have investigated this issue but often rely on the use of a sentiment index as a proxy for noise trading (see, for example, Verma and Verma, 2007; Kurov, 2008). Since a sentiment index often is available on a weekly or monthly basis, its use limits the ability of prior studies to investigate the relation between noise trading and volatility in daily frequency. Berkman and Koch (2008) have recently proposed a measure of noise trading based on the dispersion of daily net initiated order flow across brokers. This opens an avenue for the daily analysis of the relation between noise trading and volatility.[51] The analysis can also be performed for the market before and after the move to anonymity to highlight the effect of a reduction in market transparency on the impact of noise trading on volatility and returns.

Finally, it is important to analyze the dynamics and the interaction between the demand and supply of liquidity of institutional and individual investors. This analysis has important implications to issues related to market resiliency. Kyle (1985, p. 1316) defines resiliency as "the speed with which prices recover from a random, uninformative shocks". Therefore, resiliency provides a time dimension of liquidity, as opposed to the price dimension (bid-ask spread) and the quantity dimension (market depth) of liquidity. Research on resiliency is particularly important for limit order book markets without any market makers, such as the ASX. In a dealership market, market makers have an obligation to assure liquidity and price continuity under all circumstances. In contrast, in a limit order book market, liquidity is provided solely by the submission of limit orders. Because of this feature, in a limit order book market, liquidity can vary over time and may even be absent at certain periods (Degryse et al., 2005). Resiliency is therefore a very important measure of the functionality of limit order markets. Moreover, since the presence of market makers is often cited as an advantage of dealership markets, resiliency plays an important role in determining the competitiveness of limit order book markets in comparison to dealership markets.

[51] Using Berkman and Koch's (2008) proxy, Podolski-Boczar et al. (2009) find that noise trading increases volatility on the ASX.

Despite extensive research on bid-ask spread and market depth, empirical studies on resiliency are relatively sparse.[52] One of the difficulties in analyzing resiliency is the requirement for the market shock to be uninformative. Future studies, however, can arguably apply a broader definition of resiliency, motivated by Foucault et al. (2005), and define resiliency as the time it takes for the market to recover to its original state (in terms of prices, depth and spreads) from a shock that increases the bid-ask spread. This approach follows closely the requirement of uninformative shock, since if the shock is informative, it is likely to move the market and the market is unlikely to bounce back to its original state before the shock. Analysis of the demand and supply of liquidity of institutional and individual investors after the submissions of an aggressive order that increases the bid-ask spread[53] can therefore provide evidence regarding how institutions and individuals react to such shocks and which investors provide liquidity to help restore the market to its original, pre-shock level.

[52] For prior empirical studies on resiliency, see, among others, Coppejans et al. (2004), Gomber et al. (2004), Degryse et al. (2005), Large (2007), and Kempf et al. (2008).

[53] Degryse et al. (2005) adopt the same research approach in their analysis of the resiliency of the stocks traded on the Paris Bourse.

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Appendices

Appendix 1: Robustness tests on the impact of volatility on order aggressiveness

This table presents robustness checks for the results of the effect of volatility on order aggressiveness. The effect of volatility on order aggressiveness is examined with volatility as the only explanatory variable. The effect of volatility on order aggressiveness is also analyzed with volatility as one of the explanatory variables, but volatility is measured as the standard deviation of the 10 or 30 most recent mid-quote returns multiplied by 100, rather than the standard deviation of the 20 most recent mid-quote returns, as in the Table 3. The following ordered probit models are estimated for institutional and individual orders: $Z_i = \beta_1 Vola_i + \varepsilon_i$; $Z_i = \beta_1 Depth_{same,i} + \beta_2 Depth_{opposite,i} + \beta_3 Spread_i + \beta_4 Vola10_i + \beta_5 FirstInt_i + \beta_6 Size_i + \beta_7 Direction_i + \beta_8 Anonymous_i + \varepsilon_i$, and $Z_i = \beta_1 Depth_{same,i} + \beta_2 Depth_{opposite,i} + \beta_3 Spread_i + \beta_4 Vola30_i + \beta_5 FirstInt_i + \beta_6 Size_i + \beta_7 Direction_i + \beta_8 Anonymous_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $Depth_{same,i}$ ($Depth_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. $Spread_i$ is the relative bid-ask spread at the time of order submission. $FirstInt_i$ is the dummy variable for the first trading hour of the trading day. $Direction_i$ and $Anonymous_i$ is the dummy variable for sell orders and for orders submitted from 28 November 2005 onwards, respectively. $Size_i$ is the natural logarithm of the number of shares in the particular order. $Vola_i$ is defined as the standard deviation of the 20 most recent mid-quote returns multiplied by 100. $Vola10_i$ is defined as the standard deviation of the 10 most recent mid-quote returns multiplied by 100. $Vola30_i$ is defined as the standard deviation of the 30 most recent mid-quote returns multiplied by 100. "Coeff" refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at the 5% level. For brevity reason, only the results for volatility are reported.

Panel A: Institutional orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
$Vola_i$	-1.4841	23.33%	70.00%	0.0941	40.00%	33.33%	0.0493	30.00%	23.33%
$Vola10_i$	-0.1138	30.00%	53.33%	0.3003	53.33%	20.00%	0.1149	40.00%	10.00%
$Vola30_i$	-0.8049	26.67%	66.67%	0.1149	46.67%	33.33%	0.0239	36.67%	20.00%

Panel B: Individual orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
$Vola_i$	-0.2144	33.33%	43.33%	0.0391	46.67%	26.67%	-0.1683	10.00%	53.33%
$Vola10_i$	-0.7039	26.67%	36.67%	0.0409	43.33%	26.67%	-0.1404	13.33%	53.33%
$Vola30_i$	-0.8826	33.33%	40.00%	0.0297	46.67%	20.00%	-0.0931	13.33%	43.33%

Appendix 2: Determinants of institutional and individual order aggressiveness – using the remaining time to market close

This table presents the results of investigating the determinants of institutional and individual investors' order aggressiveness. The following ordered probit model is estimated for institutional and individual orders: $Z_i = \beta_1 \, Depth_{same,i} + \beta_2 \, Depth_{opposite,i} + \beta_3 \, Spread_i + \beta_4 \, Volatility_i + \beta_5 \, TTC_i + \beta_6 \, Size_i + \beta_7 \, Direction_i + \beta_8 \, Anonymous_i + \varepsilon_i$, where Z_i is the latent order aggressiveness, $Depth_{same,i}$ ($Depth_{opposite,i}$) is the natural logarithm of the same-side (opposite-side) market depth, in terms of number of shares, at the time of order submission. $Spread_i$ is the relative bid-ask spread at the time of order submission. $Volatility_i$ is defined as the standard deviation of the most recent 20 mid-quote returns times 100. TTC_i is the remaining time (in hours) until market closing time. $Direction_i$ and $Anonymous_i$ are the dummy variables for sell orders and orders submitted from 28 November 2005 onward, respectively. $Size_i$ is the natural logarithm of the number of shares in the particular order. 'Coeff' refers to the average of the estimated coefficients. % t-stat > 1.96 (% t-stat < -1.96) refers to the percentage of coefficients that are positive (negative) and significant at 5% level.

Panel A: Institutional orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
$Depth_{same}$	-0.0775	0 %	96.67 %	-0.0628	13.33 %	73.33 %	-0.0676	16.67 %	66.67 %
$Depth_{opposite}$	0.1056	96.67 %	0 %	0.1195	90.00 %	6.67 %	0.0420	46.67 %	13.33 %
Spread	0.5271	83.33 %	6.67 %	0.1534	66.67 %	6.67 %	0.1379	86.67 %	3.33 %
Volatility	-0.6721	33.33 %	66.67 %	0.0446	46.67 %	26.67 %	-0.0543	13.33 %	26.67 %
TTC	-0.0063	13.33 %	70.00 %	-0.0008	20.00 %	40.00 %	-0.0017	23.33 %	40.00 %
Size	-0.1206	3.33 %	96.67 %	-0.0415	6.67 %	93.33 %	0.0384	63.33 %	30.00 %
Direction	-0.0035	40.00 %	40.00 %	-0.0066	26.67 %	50.00 %	-0.0311	30.00 %	46.67 %
Anonymous	0.0326	63.33 %	16.67 %	0.0327	50.00 %	30.00 %	0.0161	53.33 %	20.00 %

Panel B: Individual orders

	Large Cap Stocks			Mid Cap Stocks			Small Cap Stocks		
	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96	Coeff	% t-stat > 1.96	% t-stat < -1.96
$Depth_{same}$	-0.0786	0 %	93.33 %	-0.0774	6.67 %	70.00 %	-0.1100	3.33 %	83.33 %
$Depth_{opposite}$	0.0673	86.67 %	3.33 %	0.0648	80.00 %	10.00 %	0.0751	53.33 %	6.67 %
Spread	0.9791	93.33 %	3.33 %	0.0452	46.67 %	33.33 %	-0.0485	16.67 %	50.00 %
Volatility	-0.8590	33.33 %	33.33 %	0.0167	46.67 %	16.67 %	-0.0945	13.33 %	43.33 %
TTC	0.0233	100.00 %	0 %	0.0168	86.67 %	3.33 %	0.0189	93.33 %	0 %
Size	0.0263	60.00 %	30.00 %	0.0468	73.33 %	16.67 %	0.0407	73.33 %	13.33 %
Direction	0.0035	53.33 %	26.67 %	0.0005	40.00 %	43.33 %	-0.0469	20.00 %	53.33 %
Anonymous	0.0939	90.00 %	3.33 %	0.2049	96.67 %	3.33 %	0.2786	93.33 %	6.67 %