Institutional versus retail traders: A comparison of their order flow and impact on trading on the Australian Stock Exchange

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ABSTRACT

The objective of the thesis is to examine the trading behaviour and characteristics of retail and institutional traders on the Australian Stock Exchange. There are three aspects of these traders that are of particular interest to this study: (1) the information content of their trades, (2) their order placement strategies, and (3) the impact of their trading on share price volatility.

Trades made on the basis of private information such as those by institutional traders are found to be associated with larger permanent price changes while trades by uninformed traders such as retail traders are found to be associated with smaller changes. In addition, institutional trades are found to have smaller total price effect compared to retail trades suggesting retail traders incur higher market impact costs.

In order to profit from potentially short-lived information advantage, informed traders are expected to place more aggressive orders. The analysis of the order price aggressiveness showed institutions are more aggressive than other traders. In addition, retail traders are found to be less aware of the state of the market when placing aggressive orders. The analysis of the limit order book found significant differences between the contributions of institutional and retail traders to the depth of the limit-order book, with retail standing limit orders further from the market. This is consistent with the conjecture that uninformed traders such as retail traders have greater expected adverse selection costs.

The effect of trading by retail and institutional traders on price volatility are also investigated. There is some evidence that retail traders are more active and institutional traders are proportionally less active after periods of high volatility. Also, the effect of the order activity from different trader types on volatility differs depending on the measure of order activity used.

CHAPTER ONE
INTRODUCTION

"[T]he stock market is not a weighing machine, on which the value of each issue is recorded by an exact and impersonal mechanism – Rather – the market is a voting machine, whereon countless individuals register choices which are the product of reason and partly of emotion" (p.23, Graham and Dodd, 1934)

1.1 Background

The efficient markets hypothesis defined by Fama back in 1970 has been the central proposition of finance for over thirty years (Shleifer, 2000). A fundamental assumption of the efficient market hypothesis is that traders are "rational". Rational traders update their beliefs correctly when they receive new information and then make decisions given their beliefs so as to maximise their total profits or total utility (Barberis and Thaler, 2003).

The view that all traders are rational has proven to be a difficult underlying assumption in the face of an increasingly long list of phenomena which have found satisfactory explanation in behavioural finance. Stock market bubbles in Japan, Taiwan, and the US are some of the empirical patterns that have not been resolved using the traditional framework (Ritter, 2003). However, Stracca (2004) argues it is not a foregone conclusion that traditional finance based on utility maximisation and rationality will be replaced by the behavioural methodology.

One area that has attracted recent interest is the trading pattern of the individual investor, who appears to invest in a manner that is inconsistent with the rational paradigm. In the recent literature, the individual (also referred to as retail) investor has been found to be under-diversified (Benartzi and Thaler, 2001), loss averse (Odean, 1998a) and overconfident (Odean, 1999). Recent researchers have attributed the excessive trading to investor overconfidence, where traders are overconfident about the precision of their knowledge (Benos, 1998; Odean, 1998b). The models are supported by the observed high levels of trading activity in financial markets which cannot be explained by rational trading needs (Barber and Odean, 2000). Furthermore, retail investors have been found to be reluctant to realise losses, which is irrational given the benefits of tax relief associated with capital losses. This phenomenon was found not only in the US but also in Finland (Grinblatt and Keloharju, 2001) and somewhat in Australia (Brown et al., 2002).[1]

The Australian equity market experienced a substantial increase in trading volume during the 1990s and early 2000. The increase in volume results partly from an increase in the number of individual investors. A survey conducted by the Australian Stock Exchange (ASX) in 2000 found that the number of Australian retail investors, defined in the survey as individuals who invest either directly or indirectly in the share market, increased dramatically in the late 1990s (Australian Shareownership Study, 2000). According to a later survey (Australian Shareownership Study, 2003), the proportion of Australians who own shares directly or indirectly peaked at 54% in 2000.

A major factor contributing to the increase in the number of retail investors was the floatation of major institutions such as Telstra, Commonwealth Bank, Australian Stock Exchange and AMP. The privatisation of large government institutions raised the general public's awareness of financial markets as an investment vehicle instead of the traditional property market. The relatively smaller capital outlay when investing in shares compared to property also made investing in the financial markets more attractive to retail investors.

The increase was further fuelled by the declining costs of trading on the share market. As a result of competition between the Internet and discount brokers, commissions have been cut. The late 1990s saw the introduction of discount broker houses such as Commonwealth Securities (CommSec) and E*Trade, which provided a "Do-It-Yourself" approach to share investing in Australia. As a result, the minimum cost of trading decreased from $49.50 at the beginning of 2000 to as little as $15 in 2002 (Aylmer and Lekakis, 2000; Pretty, 2002).

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[1] The loss aversion is observable not only in the equity markets but also in futures markets (Heisler, 1994).

While boosting trading activity on the stock exchange, the increase in retail investor activity raised serious concerns for regulators and stock exchange operators. Hong and Kumar (2002) argue that individual investors are a dominant source of noise trading, given their lack of sophistication. While the ASX has welcomed the increase in retail volume, it cautioned that there is still a need to educate and provide information to retail investors to assist them in making informed decisions (Australian Shareownership Study, 2003). The study of the information content of retail orders will provide an insight into the “informativeness” of these traders and contribute to the behavioural studies on the irrationality of the individual trader.

There have also been suggestions that due to the lack of ability to become informed, retail traders cause larger fluctuations in share prices and influences the speed of price adjustment to new information (Greene and Smart, 1999). Hirshleifer, Myers, Myers and Teoh (2003), on the other hand, did not find individual investors to be the main source of the post-earnings announcement drift, a particularly puzzling anomaly. The study of the effects of retail trades on transaction price volatility provides additional evidence and contributes to the literature on the study of the price volatility and volume relation.

Unlike quote driven markets, limit order markets such as the ASX rely on limit orders as a major source of liquidity. This increases the importance of understanding the characteristics of the order placement strategies of different traders (Handa and Schwartz, 1996). Some theoretical models of the limit order book have described limit order placers as patient traders who use limit orders to minimise their market impact and transaction costs (see Handa and Schwartz, 1996). Others describe the factors that influence the bid-ask spread in a limit order book (Handa et al., 2003). It is unclear from the literature who provides liquidity, both at and away from the market, to a limit order market. An investigation of the impact of retail trades on liquidity will be of interest to the exchanges, regulators and academics.

1.2 Research questions

In the market microstructure literature, investors are often divided into two classes: informed and uninformed. Informed traders trade on the basis of private information about the price that is largely unknown to other traders at the time of the trade. Uninformed traders include liquidity traders who trade for liquidity reasons or to rebalance their asset portfolios (Admati and Pfleiderer, 1988) and noise traders who trade on noise as if it were information (Black, 1986). Large institutional investors are often seen as archetypal informed investors while retail investors are seen as uninformed (Keloharju and Torstila, 2002). The main aim of this thesis is to provide some insight into the question: Are retail traders uninformed when compared to institutional traders? To this end, three aspects of retail and institutional trades are examined: (1) the information content of their trades, (2) their order placement and (3) the impact of retail trading on share price volatility.

1.2.1 Information content of retail and institutional trades

Chapter Five is concerned with the short run price effect of transactions by retail and institutional traders. Trades made on the basis of private information are associated with a permanent price change while uninformed trading, such as noise trading, are argued to be associated with temporary price changes (Hasbrouck, 1991a). If institutional traders trade on the basis of private information, then their transactions will move price to the equilibrium, creating a permanent price movement. On the other hand, if retail traders are uninformed, their trades will be associated with temporary price movements. The analysis of price effects borrows from the block trade literature and the analysis of different order sizes (Walsh, 1997). The research question of interest here is the effect of trades by retail and institutional traders on transaction prices surrounding the trade.

1.2.2 Order placement strategies of retail and institutional traders

Chapter Six examines the trading strategy of retail and institutional traders. The joint decision faced by a trader when placing a buy or sell order is the price and size of the order (Harris and Hasbrouck, 1996). While size of the order used by informed traders has been the focus of many papers, the issue remains unresolved. Easley and O’Hara (1987) propose that informed traders are likely to place larger orders to maximise the profit from their short-lived information advantage. Others argue informed traders may spread their orders over time to camouflage their trading (Barclay and Warner, 1993; Kyle, 1985). The type of order used and price aggressiveness have been the focus of papers such as Handa et al. (2003) and Ranaldo (2004). In order to profit from potentially short-lived information advantage, informed traders are expected to place more aggressive orders. In their theoretical modelling of quote setting in a limit order book market, Handa et al. (2003) assume that informed traders use market orders while uninformed traders choose between market and limit orders. Keim and Madhavan (1995) refute the assumption that market orders are predominantly used by informed traders. Traders with technical and index trading strategies were found to place more aggressive orders (because they demand immediacy) when compared to value-motivated traders. While the study of order price aggressiveness does not necessarily indicate the trader is informed, it provides an insight into the strategies of retail and institutional traders and their demand for immediacy.

A related question with order aggressiveness is the provision of liquidity to a limit order market by the different trader types. Handa, Schwartz and Tiwari (1998) suggest, unlike in a quote driven market, liquidity in a limit order market is provided by investors whose primary objective is to implement a portfolio decision rather than selling immediacy to other traders. In a setting where transaction prices move solely due to information, trading via a limit order is costly because the trader who places the buy (sell) limit order has written a put (call) option to the market (Handa and Schwartz, 1996). However, if transaction prices move (temporarily) due to liquidity events, limit order traders can benefit from the mean-reversion in prices. The assumption that only uninformed traders place limit orders appears flawed as value-motivated traders can place limit orders to exploit temporary departures in transaction prices from the equilibrium (Bloomfield et al., 2005). One of the questions this thesis seeks to answer is, what is the role of the different trader types in the provision of liquidity? When limit orders are placed and remain on the schedule, what premium is charged by the different trader types to compensate for information driven price movements?

1.2.3 Impact of retail trading on share price volatility

Chapter Seven concerns the effect of trading by retail traders on price volatility. The empirical relation between price volatility and trading volume has been well documented. In his survey, Karpoff (1987) cites many studies that showed a positive relation between them. Bessembinder and Seguin (1993) suggest that the volatility-volume relation may depend on the type of trader. Studies such as Daigler and Wiley (1999) show the positive volatility-volume relation in futures markets is driven by "the general public", which includes individual speculators, managed funds and small hedgers. On the other hand, Sias (1996) find a positive contemporaneous relation between the level of institutional ownership and security return volatility after accounting for capitalisation. The analysis of the relation between retail volume and price volatility on the ASX adds to this literature.

1.3 Summary of findings

The identity of the trader is shown to be related to the price effect of the order in the heavily traded stocks. Orders placed by institutional traders are found to have relatively large permanent price effects, suggesting that these traders are informed. In contrast, orders placed by retail traders are associated with a smaller permanent price effect, which suggests retail traders are less informed. In studying the total price effect, institutional trades are associated with a smaller inventory cost and price-pressure effect. This reflects the lack of experience by retail traders in their order placement.

In the analysis of order placement strategies, institutional traders are found, on average, to place more aggressive orders. The retail traders also appear to be less aware of the state of the market when placing aggressive orders. The contributions of institutional and retail traders to the depth of the limit-order book are found to be significantly different, with retail standing limit orders being further from the market. The differences are larger at the beginning and end of the trading phase, when strategic traders are known to be more likely to trade.

There is evidence in the heavily traded stocks that volatility affects the mix of traders in the market. In particular, retail traders are more active after periods of high volatility. Conversely, institutional traders are less active after periods of high volatility. The effect of the order activity from different trader types on volatility differs depending on the measure of the order mix. A higher proportion of orders placed by retail traders reduces volatility and an increase in the proportion of order volume placed by retail traders increases volatility. It is possible that increases in retail volume are associated with larger retail traders who are not as informed about market conditions, so that their trades cause temporary price changes and larger share price variation.

An alternative explanation is given by the stealth trading hypothesis. When informed institutional traders attempt to camouflage their actions, they are more likely to transact in smaller order sizes. Thus a smaller proportion of order volume of institutional traders (also a larger proportion of order volume of retail traders) would be evidence of informed trading which is accompanied by higher volatility.

1.4 Structure of the thesis

The remainder of the thesis is organised as follows. Chapter Two discusses the research in the behavioural finance and market microstructure areas that is relevant, thus providing the basis on which the hypotheses are developed. These hypotheses are discussed in Chapter Three. Chapter Four describes the sample and provides a discussion of the market conditions and the online trading environment over the time period examined. The results are discussed in three separate chapters. Chapter Five presents the analysis of the information content of retail and institutional trades, Chapter Six presents the analysis of the order placement strategies and Chapter Seven presents the analysis of the impact of retail activity on share price volatility. The conclusions of the study, its limitations and a discussion of possible extensions of the research are contained in Chapter Eight.

CHAPTER TWO
PREVIOUS LITERATURE

2.1 Introduction

This thesis aims to provide insight into the question: How well-informed are retail traders? To answer this question, three aspects of retail and institutional trades are examined: (1) their order placement strategies, (2) the information content of their trades and (3) the impact of their trading on share price volatility. This chapter discusses the research in the behavioural finance and market microstructure areas that are relevant and provide the foundation on which hypotheses are developed.

Early theoretical models of financial markets argue that there should be no trade when rational expectations are assumed. For example, Milgrom and Stokey (1982) suggests that if the initial allocation of share holding is *ex ante* Pareto-optimal, the receipt of private information cannot create any incentive to trade. The argument is that if the initial allocation is Pareto-optimal, the only reason for any trader to participate in a trade is an "advantageous bet". Therefore, the willingness of the counterparty to trade suggests that they are in an unfavourable position which negates the assumption. The market microstructure literature has come a long way since then. The next section examines motives, in that literature, for trading. Many of the trader descriptions are highly stylised but nevertheless they provide an insight into how traders affect the market. The discussion of "noise" trading is particularly relevant to this thesis as individual investors are often identified with "noise" traders (Barber et al., 2004).

Section 2.3 discusses the research on individual investors. Aided by the availability of data, recent behavioural finance studies analyse the "mind set" of the individual trader. The research to date has focused on the motivation for individuals' trading and their portfolio management skills. Many of these studies are conducted at the portfolio level and evaluate the rationality of traders' portfolio choices and frequency of trading.

Section 2.4 examines recent research on the limit order market. The participants in an order driven market are vital to the well functioning of these markets. Stoll (1992) argues that continuous auction markets such as a limit order market will be illiquid unless professional traders post bids and asks in the system. The discussion includes the development of the modelling of the limit order book and the examination of order submission. These more recent studies are a vast improvement on previous papers that impose the theoretical framework of a dealer's market on a limit order book market.

The last section of my review addresses the relation between volume and volatility. Research on the volume and volatility relation has collectively identified trading based on public information (Jones et al., 1994a; Kim and Verrecchia, 1991), private information (Barclay et al., 1990) and noise (Black, 1986) as possible causes of share price volatility.

2.2 Motives for trading and impact on trade strategy

Stoll (1992) notes that the supply and demand of liquidity in a market depends on the motives of the traders. Traders are motivated by information or non-informational reasons. Even if there is an absence of new information, trading can occur due to the liquidity and speculative needs of investors (Karpoff, 1986). These speculative needs arise despite the absence of private information as opinion between investors can differ (Harris and Raviv, 1993). For example, the surge in trading activity after a public information announcement is likely to be due to disagreements among traders over the relationship between the announcement and the ultimate performance of the assets. This disagreement arises due to the way in which investors interpret information.

The theoretical market microstructure literature to date classifies the motives for trading into two main groups: (1) informational and (2) non-informational (see Admati and Pfleiderer, 1988; Kyle, 1985). Non-informational trading is often discussed synonymously with liquidity trading and noise trading. The following sections provide a brief overview of these motivations and discuss the implications for trading strategies.

2.2.1 Informational trading

Informed traders are those who possess some fundamental information about the true value of an asset that is both not readily available to other traders and has not been impounded into the share price. The source of information could be private or based on the analysis of publicly available information. There is a general assumption that these traders maximise their returns based on this information (Kyle, 1985). They do so by buying the asset when the price is below its fundamental value, profiting when the price adjusts to fundamental value. Conversely, they sell or short-sell when they believe price is above fundamental value. It is also assumed in the theoretical models that the advantage that the informed trader can gain from their information is transitory (Easley and O'Hara, 1987; Harris, 1998). This is because the information will eventually become common knowledge and price will change to reflect the information.

The assumption with regards to the speed at which the information is reflected in the price differs depending on the theoretical model examined. For example, Easley and O'Hara (1987) believe that in a competitive market with many informed traders information is impounded into share prices quickly. Each informed trader will ignore the effect of his trades on future trading opportunities and will maximise his expected profit, trade-by-trade. On the other hand, Kyle (1985) and Admati and Pfleiderer (1988) suggest that the private information is incorporated into prices gradually as traders camouflage their trades to prolong the period where they could profit on their private information. The assumptions are crucial to the implications with regards to order strategy such as size of order placed and type of order used by these traders. In reality, the traders' ability to trade on private information will be based on factors such as the quality of the information, their degree of risk aversion and their access to capital (Harris, 1998).

2.2.2 Non-informational trading

Uninformed trading, as opposed to informed trading, is by definition motivated by reasons other than information and encompasses liquidity trading and noise trading. Some researchers use "noise trading" and "liquidity trading" inter-changeably. For example, Kyle and Vila (1991) define noise trading as "uninformative trading for liquidity or life cycle motives" (p. 54). Liquidity trading arises from the need to smooth consumption over time. Harris (2003) refers to this as a mismatch of inter-temporal cash flow needs. If a trader faces a situation where his income is greater than expenses, the excess income could be invested in securities. Alternatively, if income is less than expenses, then the trader could sell securities he currently owns. Liquidity trading also arises from risk adjustment. For example, liquidity traders might trade to rebalance index portfolios, exchange risk by switching between stocks and bonds, or to reduce risk by using derivatives instruments in a hedging strategy.

Black (1986) defines noise trading as trading on noise as if it were information. In his basic model of financial markets, noise is contrasted with information whereby one rationally expects to profit from trading on information but not from noise. Noise traders as a group will lose money by trading most of the time, while informed traders as a group will make money. De Long et al. (1989) differentiate noise traders from rational traders by their misperception of "tomorrow's cum dividend price". The rational expectations theory suggests that traders do things only to maximise expected utility of wealth. Thus, noise traders are better off not trading. The question that arises is: why do people trade on noise? Black (1986) suggests they do so because they like it or because they believe they are trading on information.

The concept of irrationality and why people make seemingly irrational decisions has been studied in the psychology literature but not applied in the mainstream finance literature. A paper that has examined the irrational aspect of financial decision making is Kahneman and Tversky (1979). This paper critiques expected utility theory and develops an alternative model where the traders are averse to taking gambles that involve prospective gains but not those that involve avoiding losses. Such use of human behavioural biases to explain anomalies observed in financial markets has increased since the late 1990s. This is discussed further in Section 2.3.

Both liquidity trading and noise trading have been discussed in prior literature as important sources of liquidity in financial markets. In Admati and Pfleiderer's (1988) intraday model, informed traders trade when other liquidity traders are concentrated. The presence of liquidity traders provide opportunities for informed traders to "hide in the crowd" and earn profits, thus providing them with the incentive to collect information. Black (1986) proposes that noise trading is an important source of liquidity in financial markets. In a model with informed trading only, a trader with a special piece of information will know that other traders have their own information and thus will not be prepared to trade. On the other hand, noise traders are willing to trade as they erroneously believe they are trading on information. Thus, trading occurs more freely because noise traders provide opportunities for the informed traders to trade. Furthermore, traders may find it profitable to seek out costly information which they can trade on. Black (1986) argues that noise trading is essential to the existence of liquid markets as there would be very little trading in individual assets were it not for noise trading.

2.2.3 Motivation of trading and trading strategy

The literature on the motivation of trading and trading strategy has predominantly focused on the strategies of the informed trader. The seminal paper on the profit maximising behaviour of traders is Kyle (1985). In a closed form general equilibrium model, Kyle shows the evolution of the strategy of a single informed trader who has observed the full information price of an asset. Apart from the informed trader, Kyle identifies two other groups of traders – random noise traders who are uninformed and the market maker who is risk neutral. For the last two classes of traders, the asset value is normally distributed. Kyle's model shows that informed traders attempt to camouflage their trades by spreading them over time and hiding among the noise traders. The informed trader takes into account explicitly the effect his trading has on the price at one auction and the trading opportunities available at future auctions. He trades in such a way that his private information is incorporated into prices gradually and the private information is incorporated into prices by the end of trading in continuous auction equilibrium. As the informed trader is able to hide among the noise traders, the increase in trading by noise traders enables the informed trader to increase his profits.

To explain the concentrated trading patterns observed in financial markets, Admati and Pfleiderer (1988) develop a theoretical model in which traders determine when to trade. Their model comprises three types of trader: informed traders, liquidity traders and discretionary liquidity traders. Both informed and discretionary traders can decide when to trade, however the time when discretionary liquidity traders need to trade is determined exogenously. Admati and Pfleiderer show that in equilibrium, trading by discretionary liquidity traders is typically concentrated and their trading is relatively more concentrated in periods closer to the realisation of their demands. Informed traders trade more actively in periods when liquidity trading is more concentrated, to hide among the other traders and minimise their market impact.

Unlike the models discussed above, where the choice of the trade size is not addressed, Easley and O'Hara (1987) propose that informed traders' choice of trade size is influenced by the market width and the number of information-based trades. When the market is sufficiently wide or if there are fewer information-based trades, informed traders are likely to use larger orders. This is described in their paper as the separating equilibrium. Conversely, if the market is sufficiently illiquid or if there are many information-based trades, informed traders are likely to trade smaller quantities leading to the pooling equilibrium. Easley and O'Hara discuss the inclusion of transaction costs that decline with quantity as an additional factor that makes the separating equilibrium more likely. These transaction costs give the informed traders an additional incentive to purchase larger, rather than smaller quantities. Empirical studies that have provided support for Easley and O'Hara (1987) includes Hausman, Lo and MacKinley (1992) and Hasbrouck (1991a). They find that the larger the trade, the greater is the trade's impact on returns and volatility. Walsh (1998) provides Australian evidence that informed traders are perceived by other traders to use larger orders.

Barclay and Warner (1993) argue that the data from empirical studies has shown that insiders concentrate their trades in the medium size category. For example, Cornell and Sirri's (1992) case study shows that 78.2% of the insider trades are of medium size compared to only 38.4% of all trades in the same stock. Barclay and Warner also report that correspondence with Lisa Meulbroek reveals most trades in the sample used in her 1992 paper on insider trading (see Meulbroek, 1992) fall in the medium-size category.[2]

Uncertainty about the true value of the share, wealth limitations and constraints on borrowing and short selling are likely to reduce the trade size used by most traders other than large institutions. However, it seems unlikely informed traders would

[2] This was for those cases where data are available.

place only small orders as that would limit their profit potential. Taking into consideration the cost of placing an order and the time delay involved in spreading the trades, Barclay and Warner (1993) suggest that informed traders use medium size trades to profit from their private information. The stealth trading hypothesis states that if privately informed traders concentrate their trades in medium sizes, and if stock price movements are due mainly to private information, then most of a stock's cumulative price change will take place on medium-size trades. This hypothesis agrees with the theoretical models such as Kyle (1985) who argues profit-maximising informed investors attempt to camouflage their information by spreading trades over time.

Chakravarty (2001) finds that medium-size trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume. The result is consistent with the predictions of Barclay and Warner's (1993) stealth-trading hypothesis. In addition, Chakravarty finds the source of the disproportionately large cumulative price impact of medium-size trades is trades initiated by institutions. These findings appear to support anecdotal evidence that institutions are informed traders.

Barclay and Warner (1993) acknowledge in their discussion of the stealth trading hypothesis their failure to consider other aspects of stealth trading such as the choice between limit and market orders. It is not clear from the literature discussed whether informed traders are likely to submit market orders or limit orders. In Harris's (1998) analysis of the order submission strategies of stylised traders, he argues that if private information is material and will soon become public, informed traders will use market orders to trade quickly. Informed traders are assumed to be more impatient, presumed to demand more immediacy and will trade aggressively to utilise their informational advantage. However, they cannot be too anxious as they risk giving themselves away. The trader's choice between limit and market orders will be discussed further in Section 2.4.3.3.

2.3 Individual traders and rationality

Traditional finance models assume traders are rational and formulate their trading decision by maximising expected utility defined over their total wealth. Investors are assumed to evaluate each investment choice according to its impact on aggregate wealth. The high levels of trading volume on share markets have attracted the attention of researchers to the psychology of individual traders. The deviation of market prices from theoretical models such as the Capital Asset Pricing Model (CAPM) and research that has reversed earlier evidence favouring the Efficient Market Hypothesis (EMH) has stimulated the growth of the behavioural finance literature (De Bondt, 1998; Shleifer, 2000).

The behavioural finance literature relies on the concept of noise traders who are prone to judgement and decision making errors. These investors are commonly believed to be naïve and are used by some financial experts as contrarian indicators (De Bondt, 1998). The empirical research on individual traders has found support for the belief that individual traders are irrational. For example, Benartzi and Thaler (2001) observe that portfolios held by individual investors are under-diversified, while Odean (1999) believes individual investors are overconfident because they are found to trade excessively. De Bondt (1998) categorises the irrational behaviour into four anomalies: (1) investors' perception of the stochastic process of asset prices, (2) investors' perception of value, (3) the management of risk and return, and (4) trading practices. Using the broad categories set out by De Bondt, the theoretical and empirical studies on the characteristics of the individual trader are discussed in the following section.

2.3.1 Perception of price movement and value

The first of the anomalies is investors' perception of the future price movement. Using a survey of individual investors conducted by the American Association of Individual Investors, De Bondt (1993) finds that investors condition their forecast of future price movement on prior price movement. A rise in the market was found to increase the percentage of optimistic investors and decrease the number of pessimistic investors. The reverse is found when there is a fall in the market.

It is also believed that individual investors are unable to adequately value stocks using sophisticated valuation techniques even when information for valuation is made available. Information does not equate to informed traders as these investors may not have the adequate know-how (Brooker, 1998). Others have also suggested that the effort needed by retail investors to analyse the vast amount of information may not justify the potential benefits that may be achieved, thus they are not likely to be informed when they invest (Kingford-Smith and Williamson, 2004).

Studies on the post earnings announcement drift (PEAD) document that the market is slow to respond to earnings surprises and that the market discounts the news. Many studies consider this a major violation of the semi-strong form efficient market hypothesis (Fama, 1970). Ball (1978) surveys the literature that exhibited earnings-related anomalies and points to consistent evidence showing that there is a direct relationship between the PEAD and unexpected earnings. In his paper, he reviews 20 studies published up to 1977, 15 of which were company earnings announcements. The studies on a collective basis show very strong evidence of an anomaly.

The question of the cause of the PEAD has intrigued researchers ever since. In his review of literature on the PEAD, Brown (1997) concurs that the anomaly is not a result of inappropriate risk adjustment or of using the "wrong" earnings expectation model. The post-earnings announcement drift is also separate from the P/E effect, the size effect and the Value Line enigma. Ball (1992) provides two plausible explanations for the post-earnings announcement drift. The first is that it is not cost efficient for investors who are aware of this anomaly to arbitrage the profit opportunity. The second is that market participants fail to use earnings information efficiently, leaving exploitable abnormal profit opportunities.

More recent studies suggest the PEAD may be a result of the trading activity of individual investors. These studies are motivated by research that posits individual investors are less sophisticated than institutional investors and that they are unable to process the information available. Thus, the trading by individual investors is a major source of market inefficiencies (Grinblatt and Keloharju, 2000; Lee, 1992).

With the availability of data on trading by different trader types, two recent papers were able to examine the trading of individual investor as an explanation for the drift.

Hirshleifer et al. (2003) find that individual investor trading fails to subsume any of the power of extreme earnings surprises to predict future abnormal returns. However, individual traders trade "foolishly" in that their trades in the five days following the announcement are negative predictors of returns over the next six to nine months. Hirshleifer et al. (2003) suggest that individual investors may be the driving force behind some kind of market inefficiency but their trading appears to be unrelated to the PEAD. One major shortfall of the paper is that the data includes only those individuals who use a single major discount broker firm and the results may not be generalised to the entire market.

Another study, by Ahmed et al. (2003), conducted around the same time, examines trading by online traders around the release of an earnings announcement. Instead of studying the PEAD, Ahmed et al. (2003) use narrower windows around the earnings announcement to examine the change in the earnings response coefficient (ERC), trading volume reactions and the relation between trading volume and absolute price change. The evidence is consistent with their hypotheses; the increase in the proportion of online trading resulted in (1) higher earnings response coefficients, (2) an increase in trading volume reactions that are unrelated to price change, and (3) a decrease in the association between trading volume and absolute price change. The results provide support for their conjecture that online trading result in a decrease in the average precision of investor information prior to an earnings announcement, an increase in differential interpretation of the earnings signal and a decrease in differential precision prior to the announcement.

2.3.2 Management of risk and return

An important conclusion from modern portfolio theory is the need for diversification (Goetzmann and Kumar, 2005). The effect of diversification of a portfolio is higher returns at a lower level of risk. However, recent research has shown that many individual traders are not diversified. Benartzi and Thaler (2001) investigate how US individuals make their asset allocation decisions in their social security plans. Investors were found to follow the "1/*n*" diversification strategy naively and allocate 1/*n* of their savings to each of the *n* available investment options without regard for the options available. As a result, the proportion of funds invested in stocks depends on the proportion of stock funds in the plan. Similar findings on the lack of diversification were found when Goetzmann and Kumar (2002) examine the portfolios of 40,000 equity investment accounts from a large discount broker house. They find accounts are under-diversified and the least diversified are young and active investors, investors with low income and non-professional categories.

Other research shows that among the investors that do diversify, the diversification in their portfolio holdings is much less than recommended by the models (Barberis and Thaler, 2003). Investors tend have a "home bias", in that their portfolios are weighted strongly towards domestic equities (French and Poterba, 1991). The under-diversification is partly due to individual investors only actively following a few stocks. Merton (1987) points out that gathering information on stocks requires resources and investors conserve their resources by actively following only a few. As a result, investors tend to buy and sell those stocks that they actively follow. While investors are limited to selling stocks in their portfolio, they have a large choice of stocks to purchase. Barber and Odean (2005) find individual investors are net buyers of stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns. On the other hand, institutional investors do not display attention-based buying. Further support for the hypothesis that individual investors are irrational was provided when they find that buying stocks that have attracted attention do not generate superior returns.

2.3.3 Trading practices

Rational models of investing predict that there should be relatively little trading (Milgrom and Stokey, 1982). However, research shows that the volume of trading in financial markets is high and studies of individual traders show that these traders trade more often than expected for rational traders. For example, Barber and Odean (2000) observe that customers at a large discount broker between 1991 and 1996 turned their portfolio over approximately 75% annually. Those that trade often earn a return that is lower than the market return due to higher levels of trading and higher costs associated with frequent trading.

In a subsequent study on the trading of male and female day traders, Barber and Odean (2001) find men, who are identified in psychological research to be more confident, trade more frequently than women. Even though the stocks picked by men and women provided similar returns, the added cost of trading led the men to underperform compared to the women. Recent researchers have attributed the excessive trading to investor overconfidence where traders are overconfident about the precision of their knowledge (Benos, 1998; Odean, 1998b). Barber and Odean (2002) provide further support for the overconfidence argument by examining a sample of traders who switched from phone-based to online trading. Trading online is argued to increase overconfidence as traders believe they have better access to information and greater degree of control over their trading. The traders outperformed the market by two percent annually when using phone-based trading before the switch. Subsequent to the switch, these traders lagged the market by more than three percent. These traders also traded more frequently after the switch, increasing their total trading cost. Barber and Odean attribute the increase in trading to the increase in overconfidence.

Choi et al. (2002) believe that the self-selected nature of discount-broker customers used in Barber and Odean (2002) makes it difficult to draw inferences about the impact of new trading technologies on the "typical" investor. They examine the impact of the web on trading decisions of about 100,000 participants in two corporate 401(k) plans. As a comparison, they have a measure of trading activity for a set of large 401(k) plans that do not have a web channel. After 18 months, the web channels nearly doubled their daily trading frequency and increased daily turnover by more than 50 percent. However, they do not find evidence of “successful” trading via the web, consistent with the findings in Barber and Odean (2002).

Another trading practice by individual traders that has been extensively studied is the disposition effect whereby traders are reluctant to sell assets trading at a loss relative to the price at which they were purchased. Odean (1998a), using the trading accounts of investors at a large discount broker house, finds traders tend to sell the stocks that have appreciated in value too early but are reluctant to sell the stocks that have depreciated in value. The behaviour is irrational given the tax benefits of tax relief associated with capital losses. Furthermore, the stocks that the trader chose to sell were found to perform better than the stocks they held. The disposition phenomenon is present not only in the US but also in other countries such as Finland (Grinblatt and Keloharju, 2001) and to a degree in Australia (Brown et al., 2002).[3]

2.4 Research on the limit order book

This section examines the theoretical modelling of and empirical research on the limit order book. As the earlier theoretical market microstructure stems from the analysis of dealer markets, it is appropriate to start the review there.

2.4.1 Dealer type model and the limit order book

One of the first papers to examine the economics of transacting is Demsetz (1968). Demsetz uses a simple demand-supply framework to show there are two prices for an asset at equilibrium – a price for immediate sales and another for immediate purchases. While the model does not provide reasons why supply (or demand) of the asset at the equilibrium prices is not infinitely elastic, it suggests that immediacy has a price. The dealer making the market provides liquidity and subsequently earns the bid-ask spread. In this framework, Demsetz notes that the cost of transacting depends on synchronicity in the arrival of buyers and sellers. The spread between the bid and ask price decreases as the activity in the stocks increases, reflecting the lower cost to the dealer of bridging the time gap between buyers and sellers. The model developed by Demsetz provides a "beginning" for research on the bid-ask spread. Many of the concepts discussed by Demsetz appear frequently in subsequent research.

An important extension to the study of the spread is the inclusion of asymmetric information. Jack Treynor writing under the pseudonym of Walter Bagehot (1971) notes that the securities market can be viewed as a "conduit" through which money flows from uninformed traders (liquidity motivated) to informed traders (Stoll, 1999). Orders arrive sequentially at the market, and the market makers assess whether each order is informed or not. Since trading is more or less anonymous, the market makers have to build into the bid-ask spread a component to compensate

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[3] Brown et al. (2002) find the disposition effect is tempered by the effect of tax loss selling during June (the end of tax year for Australian individuals) for most investor classes except tax exempt government bodies and foreign investors.

them for the expected loss to informed traders. As informed traders continue to profit at the expense of the market maker, the bid-ask spread widens to impose a cost on the uninformed traders to compensate the market maker for the loss he incurs in making the market.

Following the line of thought by Bagehot (1971), Copeland and Galai (1983) develop a formal model that addresses the adverse selection problem from the viewpoint of the market maker. They show that the market maker maximises his net profit using the bid-ask spread where net profit results from the gains from trading with liquidity (uninformed) traders less the losses suffered from trading with informed traders. The bid-ask spread argument is developed using an option pricing framework. The market maker effectively writes a put option to the next trader at the bid and a call option to the next trader at the ask. The midpoint of the bid and ask prices is the price based on all current information. The strike prices that the market maker sets for the options maximises his profit. The expected profit, however, also depends on the arrival process of the orders, the probability of the next order being informed, and on the probability distribution of the asset price. Copeland and Galai (1983) note that the bid-ask spread increases when price volatility in the asset being traded increases, the asset price level increases, and trading volume decreases. The market maker also tends to acquire shares when prices fall and sell when they rise, and his inventory tends to increase just prior to a price declines and decrease prior to a price rise, which is consistent with the argument that the market maker loses to informed traders.

Earlier studies on limit order markets have drawn inferences for a limit order book from dealer models such as that of Copeland and Galai (1983). However, it is not clear if this is entirely appropriate. While limit order traders resemble the market maker in that they provide liquidity and immediacy to the market, the primary objective of limit order traders is to implement their investment decisions; provision of liquidity and selling of immediacy is likely to be secondary (Handa et al., 1998). It has been found that brokers in a limit order market, such as the ASX, “principal-trade” and help make the market in stocks even though they are not obliged to post two-sided quotes (Aitken and Swan, 1993). Nevertheless, the concept of “inventory cost” whereby market makers are compensated for maintaining a costly inventory may not apply as directly to a limit order driven market. Studies (Foucault, 1999;

Handa et al., 2003) on the limit order market have since provided more insight into what constitutes the bid-ask spread found in this type of market.

2.4.2 Modelling of the limit order book

The earlier literature on the modelling of the limit order book focuses on the trade-off between immediate execution of the market order and the better price (but uncertain execution) of the limit order. Cohen et al. (1981) develop a "gravitational pull" model to explain when a trader would submit a limit order as opposed to a market order. The trader's choice between a limit and market order strategy depends on the balancing of the relative costs of price improvement and execution risk associated with using a limit order vis-à-vis the use of a market order. As spreads narrow, the benefits of a better price associated with using a limit order decreases, causing more traders to place market orders. However, as more traders use market orders instead of limit orders, the spread is likely to widen and increase the attractiveness of the limit order.

Another earlier paper to consider the open limit order book is Glosten (1994). He analyses an "idealized electronic open limit order book" under fairly general conditions (Glosten, 1994, p.1127). One of the important assumptions of his model and also of subsequent models relates to the ability to trade on private information. As in Kyle (1985), Glosten (1994) assumes traders can submit orders of any quantity. However, the orders are not batched but arrive one at a time. In the limit order book market considered, competing individuals determine the terms of trade. The electronic limit order book is modelled as a publicly visible screen providing bids and offers, each specifying a price and a quantity. The source of bids and offers is a large population of risk neutral "patient traders". These liquidity suppliers are thought of as "patient" or "value" traders in that their only interest in trading is expected profit. Glosten suggests that it might be reasonable to think of this population as consisting of managers of reasonably large institutional and individual portfolios.

In the presence of adverse selection, the limit order book exhibits a positive bid-ask spread. The possibility of trading with an informed trader increases the probability of losses to the trader, who places an offer to sell at the lowest price or an offer to buy at the highest price. Market orders traded against the book pick off the limit orders at their limit prices. The market orders are presumed to be placed by risk averse traders after some rational optimisation process and possibly by informed traders. A limit buy (sell) order trader can expect to lose if the order executes upon the arrival of an informed trader with a valuation below (above) the limit price, and can expect to gain if the order executes upon the arrival of a liquidity trader. Traders will not choose to place a limit order unless the expected gain from transacting with a liquidity trader exceeds the expected loss from transacting with an informed trader. While Glosten's (1994) model provides the equilibrium price schedule in the open limit order book, it does so by assuming the existence of two distinct classes of trader: traders who place limit orders and those who place market orders. The analysis does not model the trader's choice to trade via limit order or market order.

In an extension of Glosten's analysis, Handa and Schwartz (1996) consider the choice faced by an investor who wishes to buy or sell a share of a risky asset. The investor can choose to trade via a market order and demand liquidity from the market or use a limit order and supply liquidity to the market. The choice depends critically on the probability of the limit order trading against an informed trader versus a liquidity trader. The model assumes that any transaction price change caused by the arrival of a liquidity trader is temporary and reversible while any change due to the arrival of an informed trader is permanent and irreversible. A limit order trader finds trading with an informed trader is undesirable but trading with a liquidity trader is desirable. In addition to the adverse selection problem, limit orders suffer from the risk of non-execution. If the limit order fails to trade, the trader has to decide whether to trade at the prevailing transaction price using a market order or forego trading. The act of not trading, obviously, has cost implications.

In comparing the performance of executed limit orders and market orders, Handa and Schwartz (1996) find that the differential limit order returns conditional upon execution are consistently positive and increase steadily for orders placed further behind the market. They suggest that limit orders are associated with higher returns because a sufficient proportion of limit order executions occur due to liquidity driven price changes and that prices tend to rebound over relatively short investment horizons. The question arises as to why we do not observe an abundance of limit orders. Handa and Schwartz (1996) argue that it is because of the positive cost of non-execution. Using market-adjusted returns, they find that differential limit order returns conditional on execution are positive and those conditional on non-execution are negative compared to market orders.[4] They suggest that an eager trader could find limit orders costly due to the non-execution and would choose to use market orders instead. However, a patient trader can avoid the cost of non-execution by simply not trading if the limit order does not execute.

While Handa and Schwartz (1996) analyse the rationale and profitability of limit order trading, they do not explicitly model the investor's decision to trade via a market or limit order. Foucault (1999) incorporates an investor's decision to trade via a limit order or market order, and develops a simple model in which the mix between limit and market orders can be characterised in equilibrium. Trading occurs in Foucault's model because of differences in valuation of the stock. It assumes that changes in the valuation of the stock are driven by public information and not by private information.

A limit order trader suffers from two risks: (1) execution risk and (2) the winner's curse. The probability that a limit order is not executed gives rise to execution risk. On the other hand, the winner's curse is associated with the order being "picked off" when the value of the stock changes and the limit order placed has not been amended to reflect the change in value. The bid-ask spread on the limit order book is determined by the trade-off between the two risks. The primary finding in Foucault's paper is that the volatility of the asset is a main determinant of the mix between limit and market orders. As volatility increases, the probability of being "picked off" before the limit order trader has a chance to amend his order increases; thus limit order traders ask for a larger compensation for providing liquidity. Limit order traders have to post higher ask prices and lower bid prices relative to their reservation prices in markets with higher volatility. Thus, market orders become less attractive and traders use more limit orders instead of market orders.

Handa, Schwartz and Tiwari (1998) use a model similar to Foucault (1999) to describe the limit order book. They suggest the "economics that drive the order-driven markets are intricate, and their viability is not obvious". Their model

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[4] Cho and Nelling (2000), in a subsequent paper, find that the probability of execution decreases as the limit order is placed further from the market.

describes two economic forces that drive trading: (1) a liquidity event and (2) an information event.[5] An information event is the advent of news that affects all investors' assessments of a security's share value while a liquidity event is unique to the individual investor. An example of the latter is a cash flow expenditure resulting in the investor's need to sell his shares.

Traders who submit limit orders always lose if only an information event occurs. Buy limit orders will execute only if bearish news occurs, while ask limit orders will execute only if the news is bullish. However, limit order traders profit from liquidity events where the arrival of liquidity-motivated sell (buy) market orders causes share prices to fall (rise) temporarily. After the liquidity event, prices tend to revert to their previous levels. As a result, buy (sell) limit order placers profit from the execution. The mean reversion of prices after liquidity events is associated with short-period price volatility. This accentuated short-period volatility offsets the cost of information events to limit order placers, enticing traders who are patient to place limit orders.

The order-driven market achieves a balance between limit and market order traders when the accentuated short-period volatility is just sufficient to compensate the marginal investor for placing a limit order. Conversely, the non-execution of limit orders makes it costly for impatient traders, inducing them to place market orders. Handa et al. (1998) suggest that unlike market makers the objective of limit order traders is to implement a portfolio decision. Limit order traders are not obliged to provide a two-sided market. The provision of liquidity and gaining the spread for providing immediacy is a secondary effect when placing a limit order.

In a subsequent paper, Handa, Schwartz and Tiwari (2003) extend Foucault (1999) by focusing on the bid-ask spread in a limit order market where the proportion of buyers and sellers is free to vary without restriction. In Foucault's model, the proportion of buyers and sellers is restricted to 0.5 although this restriction was relaxed in the special case considered. They also introduce adverse selection to the model by incorporating privately informed traders. The model assumes a single risky asset that trades in a continuous market environment where there are two groups of

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[5] See Section 2.2 for description of motives for trading.

traders in the market, one placing a high value to the asset and the other attaching a low value to the asset. A proportion of these investors is privately informed and assumed to trade using only market orders. The uninformed traders have a choice of market or limit orders.

The bid-ask spread derived in the model is a function of (1) the adverse selection cost, (2) the differences in valuation among groups of investors and (3) the proportion of investors in each of the groups. The difference in valuation causes the spread to exist even in the absence of asymmetric information. The spread is shown to widen with an increase in adverse selection costs or differences in valuation. The spread is widest when the proportion of investors in the two groups (with differences in valuation) is equal and minimised when the proportion is close to zero or one. Handa et al. (2003) suggest the results can be explained intuitively. The imbalance in the type of trader creates a competitive environment where traders on the crowded side compete with each other to gain priority. For example, traders place more aggressive buy limit orders if there are many buyers. The assumption here is that traders on the sell side do not shift their supply schedule. Handa et al. (2003) test their theory using CAC40 Index stocks from the Paris Bourse and find support for their model. The model was rejected at the 5% significance level for only 22% of the firms in the sample, which the authors argue is encouraging given the complexity of spread determination and the number of factors affecting spreads.

2.4.3 Order placement strategy

The volume of empirical research on a trader's order placement strategy has increased vastly over recent years due to the availability of the data and the realisation of the importance of the public trader to the functioning of an open limit order book market. The trader's order placement has two dimensions, price and size. Harris and Hasbrouck (1996) suggest it is likely that traders jointly determine order size and strategy. The papers reviewed in this section examine the price at which the orders are placed relative to the market quotes. Some papers examine the choice between limit and market order, while others examine the aggressiveness of the order. The earlier papers tend to focus on the former due to data limitations.

The theoretical models of the limit order book suggest that the choice between a limit and market order is at least partly driven by the expected profitability of providing liquidity and the cost of consuming it (Foucault et al., 2001; Handa and Schwartz, 1996; Harris and Hasbrouck, 1996; Hollifield et al., 2004; Hollifield et al., 2002). The choice between submitting a limit or market order involves a trade-off between the expected profit and the value of the free trading option. A trading option is created for the rest of market when a trader places a limit order (Copeland and Galai, 1983; Liu and Sawyer, 2003; Stoll, 1992). For example, a limit buy order is equivalent to writing a conditional free put option to the rest of the market. The value of the option depends on the probability of the arrival of adverse information. If bad news causes the price to fall, the limit buy order can be picked off at no cost to the seller. On the other hand, if price movements are caused by liquidity events, the expected profit is determined by the probability of execution and the difference between the order price and "true" price (Handa et al., 1998; Verhoeven et al., 2004). Consequently, the probability of execution is an important factor in the decision to place a market versus limit order. The larger the expected execution probability of a limit order, the shorter the expected waiting time and thus the smaller the expected adverse selection cost.

Harris and Hasbrouck (1996) analyse the performance of market and limit orders placed through SuperDOT of 144 randomly chosen stocks traded on NYSE from November 1990 to January 1991. They find the execution probabilities of limit orders are affected by the size and prices of the limit orders. Orders that are more aggressively priced and those of smaller sizes have higher probability of execution. While Harris and Hasbrouck have the bid-ask spread at the time of order entry, they did not analyse the impact of market conditions on the probability of execution. Cho and Nelling (2000) examine the probability of a limit order executing on the NYSE SuperDOT conditioned on the state of limit order book. Their results indicate the longer the limit order is outstanding, the less likely it is to be executed. Similar to Harris and Hasbrouck, they find the probability of execution is higher when the limit order price is closer to the prevailing quote and when the order is small. In addition, the probability of execution is higher when the spread is wide and when the limit order is placed in a period of high price volatility.

2.4.3.1 Order placement strategy conditioned on market liquidity

Many studies have examined the relation between order placement and market liquidity such as the bid-ask spread, market depth and previous order flow. Table 2.1 summarises the results of these studies and the following discussion reviews some of these studies in more detail.

Biais et al. (1995) examine the supply and demand for liquidity and also the "intertwined dynamics" of the order flow and order book in an order driven market such as the Paris Bourse. Using a dataset of 40 stocks in the CAC Index for 19 trading days, Biais et al. find investors' order strategies are influenced by the liquidity available from the market, where market liquidity is proxied by the bid-ask spread and the depth available at the best bid and ask prices. The flow of order placements was found to be concentrated at and inside the bid-ask quotes. A large proportion of these orders improve the best price, reflecting traders' attempts to undercut previous orders in order to compete in the supply of liquidity. The time interval between these price improvements is relatively small, which suggests that traders compete not only for price priority but also time priority.

In addition, Biais et al. find investors place more market orders when the spread is narrow whereas new orders within the quotes are more frequent when the spread is wide. Biais et al. suggest this reflects traders competing to supply liquidity when it is required but consuming liquidity when it is available. Order flow was also found to be affected by the depth of the market, with more orders being placed within the quotes when the order book is thick and the spread is wide. Biais et al. explain that this is due to the "price to probability of trade trade-off", between undercutting the best quote to obtain time priority and queuing up at the current quote.

Table 2.1 Order placement and market liquidity

Results of studies testing the relation between order placement and market liquidity such as bid-ask spread, market depth and previous order flow

Variables Examined	Relationship with Order Placement Strategy	Study	Market Examined
Spread	Market orders are more frequent when spread is tight while limit orders in the market are more frequent when spread is large.	Biais, Hillion and Spatt (1995)	Paris Bourse
		Al-Suhaibani and Kryzanowski (2000)	Saudi Stock Market
		Bae, Jang and Park (2003)	NYSE
	Positive relationship between spread and the number of limit orders. When spread widens, more orders are placed at the best bid and ask. Less limit orders are placed further away from the best bid and ask.	Chan (2000)	Stock Exchange of Hong Kong
	The wider the spread, the weaker the order aggressiveness.	Ranaldo (2004)	Swiss Stock Exchange
		Griffith, Smith, Turnbull and White (2000)	Toronto Stock Exchange
	A larger spread increases the number of limit orders placed (the study did not examine the mix of limit and market orders).	Chung, Van Ness and Van Ness (1999)	NYSE
Depth	Market orders are more frequent when depth at the quotes is large	Biais, Hillion and Spatt (1995)	Paris Bourse
		Al-Suhaibani and Kryzanowski (2000)	Saudi Stock Market
	Aggressive orders are observed when depth on the same side is larger.	Griffith, Smith, Turnbull and White (2000) Ranaldo (2004)	Toronto Stock Exchange Swiss Stock Exchange
	Passive orders are observed when depth on the opposing side is larger.	Griffith, Smith, Turnbull and White (2000)	Toronto Stock Exchange
		Ranaldo (2004)	Swiss Stock Exchange
Last order aggressive-ness	Aggressive orders are more likely after other aggressive orders.	Griffith, Smith, Turnbull and White (2000)	Toronto Stock Exchange
		Biais, Hillion and Spatt (1995)	Paris Bourse

For example, when the depth at the best ask quote is large, new limit sell orders placed at this price are unlikely to be traded due to the time priority. Traders would have an incentive to place sell orders within the spread to undercut the current best ask. From Table V in their paper, the effect of the depth does not seem to be as strong as that of spread.[6] In their analysis of order flow conditional on the previous order, Biais et al. find the probability of a given type of order or trade occurring is larger after this event has occurred than it would be unconditionally. For instance, it is more likely a large buy will be observed than any other order type if the previous order was a large buy. In addition, new orders within the quotes on the ask (bid) side and cancellations on the bid (ask) side are particularly frequent after large sales (purchases). Biais et al. suggest that large sales convey a negative signal about the value of the stock, encouraging others to sell and also buyers to retract their bids. On the other hand, large bids convey a positive signal, encouraging others to buy and sellers to withdraw their offers.

Al-Suhaibani and Kryznowski (2000) replicate a part of the study by Biais et al. (1995) on the Saudi Stock Market (SSM). Using 56 stocks listed on the SSM between 31 October 1996 and 14 January 1997, they investigate the probabilities of different types of order and trades given the previous state of the limit order book. They find that market orders occur more frequently when the spread is tight while limit orders occur within the spread more frequently when the spread is large. Limit orders within the spread occur more frequently when the depth at the quote is large while limit orders at the quotes are more frequent when depth is small. The results are consistent with those found by Biais et al. (1995) for the Paris Bourse.

Griffiths, Smith, Turnbull and White (2000) examine the costs and determinants of order aggressiveness using data from the Toronto Stock Exchange, which uses a centralised electronic order-matching system similar to the Paris Bourse and market makers like the NYSE. The paper extends previous work on limit versus market orders by classifying orders by aggressiveness using the six categories from Biais et al. (1995). One of the research questions in the paper is: What are the determinants of order aggressiveness? The five determinants examined using ordered probit analysis

[6] I was unable to verify the discussion by Biais et al. with the results in Table V possibly due to errors in the table. Each row in the table contains a probability vector that should add up to 100%. However, the first row of the table adds up to 91.9% suggesting there is a typographical error.

are: (1) aggressiveness of the previous order, (2) relative bid-ask spread immediately before the order, (3) depth at the best price on same side as the incoming order, (4) depth at best price on the opposing side as the incoming order, and (5) firm size.

Griffiths et al. (2000) find aggressive orders are more likely following other aggressive orders, which is consistent with the positive autocorrelation in order flow found in previous studies. Orders placed when the bid-ask spread is wide are less aggressive as the wide spread provides traders with an opportunity to place passive orders but still gain priority over the other limit orders. The wider bid-ask spread also imposes a larger cost on market orders, thus encouraging more limit order placements. More depth on the same side encourages more aggressive orders due to the order priority rules, while more depth on the opposing side reduces the need to place more aggressive orders. Griffiths et al. also find large firms' orders are less aggressive than orders of smaller firms. Private information is often assumed to be short-lived, thus informed traders are expected to place more aggressive orders to secure their profit. As information asymmetries in larger firms and the opportunities to profit in these firms are expected to be less than for smaller firms, less aggressive orders should be observed for larger firms.

2.4.3.2 Order strategy conditioned on price volatility

Studies have also extended the analysis to examine the impact of volatility on order placement strategies. Table 2.2 presents a summary of these studies and the following discusses some of the papers in detail.

Ahn, Bae and Chan (2001) extend the analysis of the role of limit order trading in liquidity provision in a pure order-driven market. Instead of the order book, they focus on the interaction between order-flow composition and price volatility. Their study is motivated by several theoretical papers (see Handa and Schwartz, 1996; Handa et al., 1998) that claim the choice of investors in placing a limit or market order is dependent on the investor's belief about the probability of his or her limit order executing against an informed or a liquidity trader. Investors are likely to place limit orders when price fluctuations are due to liquidity shocks, thus transitory volatility attracts limit orders more than market orders.

Table 2.2 Order flow and return volatility

Findings of the empirical studies testing the relationship between return volatility and order flow.

Variables Examined	Relationship with Order Placement Strategy	Study	Market Examined
Short term price volatility / Transient price volatility	Traders place more limit orders when stock price volatility is higher (the study did not examine the mix of limit and market orders).	Chung, Van Ness and Van Ness (1999)	NYSE
	Lagged return volatility is positively related to the total number of limit orders placed however it has no significant effect on the type (aggressiveness) of limit order placed.	Chan (2000)	Stock Exchange of Hong Kong
	The higher the volatility, the weaker the order aggressiveness.	Ranaldo (2004)	Swiss Stock Exchange
	Increases in upside (positive returns) volatility result in more limit sell orders instead of market sell orders. Increases in downside (negative returns) volatility result in more limit buy orders instead of market buy orders.	Ahn, Bae and Chan (2001)	Stock Exchange of Hong Kong
	The higher the transitory price volatility, the more likely will limit orders be placed relative to market orders.	Bae, Jang and Park (2003)	NYSE
	Did not find statistically significant relationship between volatility and submission of limit orders.	Bloomfield, O'Hara and Saar (2005)	Experiment-al market
Return	Lagged return is negatively (positively) related to total number of bid (ask) limit orders placed. However, number of orders placed at the best bid (ask) is positively (negatively) related to returns.	Chan (2000)	Stock Exchange of Hong Kong

The dataset used by Ahn et al. comprises 33 of the most actively traded stocks listed on the Hong Kong stock market between July 1996 and June 1997. First, they investigate the relation between transitory volatility and market depth. Ahn et al. find a rise in transitory volatility is followed by an increase in market depth, and a rise in market depth is followed by a decrease in transitory volatility. Their findings are consistent with the model discussed by Handa and Schwartz (1996) in which a lack of limit orders increases short term price fluctuations, thus making it more profitable for investors to place limit orders. The increase in limit orders provides liquidity to the market and subsequently dampens the volatility. Second, they examine how transitory volatility affects the mix of limit and market orders.

Ahn et al. (2001) distinguish volatility arising from the bid side vis-à-vis the ask side as they argue their impact on buy and sell order flow are different. They find that the lack of limit sell (buy) orders increases the upside (downside) volatility causing more traders to submit limit sell (buy) orders instead of market sell (buy) orders. The results are consistent with Biais et al. (1995), where traders enter and place limit orders to earn profits for their liquidity provision when the market is thin and consume liquidity when it is plentiful. An important contribution of Ahn et al. (2001) is recognising the need to distinguish between volatility arising from the bid side versus the ask side as well as depth changes on the bid side versus the ask side because they provide information on which side needs liquidity.

Instead of studying the choice between limit and market orders, Ranaldo (2004) was able to investigate the trading aggressiveness of the trader's order choices with (1) the thickness of the order book, (2) spread, and (3) volatility. Orders are categorised into five groups: (1) large market orders, (2) small market orders, (3) limit orders within the previous quotes, (4) limit orders at the previous quotes, or (5) withdrawals of an existing order. The dataset examined comprises 15 stocks quoted on the Swiss Stock Exchange over the sample period of March to April 1997. The stocks in the sample are relatively highly liquid and correspond to more than 94% of the total market value of the Swiss Market Index (SMI).

An ordered probit technique similar to Hausman et al. (1992) is used to deal with price discreteness. The independent variables are the depth on the buy and sell sides, the quotes spread and the order wait processing time. The order wait processing time is the average of the time elapsed between the last three subsequent order arrivals. Ranaldo (2004) notes that transient volatility is modelled separately due to statistical issues such as collinearity and omitted variables bias.

He finds evidence to support the hypothesis that a thick book strengthens order aggressiveness. The probability of a limit order placement decreases when the depth on the incoming trader's side of the book is large. He also finds the use of a market order increases when the volume of the limit orders on the incoming side of the book exceeds the volume of the limit orders on the opposite side. The order is less aggressive the greater the elapsed time between the previous and current order.

Bae, Jang and Park (2003) address a shortcoming with studies by Ahn et al. (2001) and Ranaldo (2004) in their use of the volatility measure. Foucault (1999) predicts in his model that price volatility is a main determinant of the mix between market and limit orders. When volatility increases, there is a greater risk of a limit order being picked off when a security's value changes. Thus, limit order traders seek greater compensation, by pricing less aggressive bid and ask orders. Subsequently, more traders find it better to submit limit orders (as opposed to market orders), as it is cheaper. Handa and Schwartz (1996) and Handa et al. (1998) show a rise in volatility due to information trading discourages the placement of limit orders because of the greater risk of being picked off by an informed trader. On the other hand, transitory volatility encourages limit orders as the gains from supplying liquidity exceed the losses from trading with informed traders.

Bae et al. (2003) decompose the variance of transaction prices of 144 NYSE-listed stocks over a three-month period from 1 November 1990 to 31 January 1991 into transitory and informational components using a Kalman filter. They find that the increase in the transitory component of volatility attracts limit-order submissions. However, an increase in informational volatility has little effect on the placement of limit orders. Bae et al. express surprise at the findings and suggest their measure of informational volatility may be inadequate or that adverse selection may be less important than researchers have been led to believe. Bae et al. (2003) also find that traders place more limit orders relative to market orders when (1) the spread is large, (2) the order size is large and (3) when there is little time left until the market closes. The results are closely related to studies such as Biais et al. (1995), Chung et al. (1999), Griffiths et al. (2000), Ahn et al. (2001) and Ranaldo (2004).

2.4.3.3 Order strategy conditioned on trader type

Literature looking at the strategies of different trader types in the limit order market is scarce (see Table 2.3 for a summary of some of these papers). This reflects "the difficulty of characterising how, when and what to trade when the market outcome attaching to individual strategies depends upon the collective strategies of all other market participants as well" (Bloomfield et al., 2005, p.169). Earlier papers on modelling the limit order book make their analyses tractable by imposing highly restrictive assumptions on the behaviour of informed traders or by ignoring such traders completely. For example, Cohen et al. (1981) completely ignore the role of informed traders in their analysis.

Other theoretical models in the literature assume that informed traders place only market orders. Glosten (1994) includes informed traders in his model of the order book but assumes these traders place only market orders. It is reasonable to assume that informed traders will use market orders if there is sufficient competition between informed market order users or the depreciation rate of private information is large enough. Liquidity traders are likely to be patient and willing to delay trading in the hope of finding another liquidity trader needing to take the opposite position.[7]

In their model of quote setting and formation in an order driven market, Handa, Schwartz and Tiwari (2003) assume the "short lived nature of the private information" implies informed traders use only market orders in their trading strategies. On the other hand, uninformed traders can choose between using market orders and limit orders. In their model, spread depends on the difference in valuations among investors, the proportion of investors with differing valuations and the adverse selection.[8] However, Handa et al. do not explicitly model the choice of limit and market orders for uninformed traders.

Harris (1998) examines the optimal dynamic order submission strategies for three stylised traders. The first is an uninformed liquidity trader who must fill an order by a deadline. The second is an informed trader who has a single piece of information that he wishes to profit from. The third is a value-motivated trader who also has information to profit from but the information is derived from on-going research into fundamental values. The type of information that the latter two traders have is distinguished to enable comparison of traders with different urgency. Harris

[7] This argument is possibly flawed as the second liquidity trader would have to use a market order for a trade to occur.

[8] For example, if the proportion of potential sellers to buyers is high, the best bid and ask prices will be set close to the price assessed by traders with the low valuation. Some potential buyers will place limit orders instead of market orders as the risk of execution is low. Conversely, some potential sellers will place limit orders because the benefits of trading low.

examines how these three trader types impact on demand and supply of immediacy through their use of limit and market orders.

Table 2.3 Order placement strategy and urgency to trade

Empirical studies on relationship the urgency to trade and order placement strategy.

Variables Examined	Relationship with Order Placement Strategy	Study	Market Examined
Time	More aggressive orders when the market just opens (the study compared the aggressiveness of limit orders placed and not the mix between limit and market orders).	Chan (2000)	Stock Exchange of Hong Kong
	Traders are more likely to place a limit order when there is more time left until the market closes.	Bae, Jang and Park (2003)	NYSE
	Use of market orders compared to limit order is more likely in the earlier part of the trading period. The trading strategies of the informed and liquidity trader diverge with time.	Bloomfield, O'Hara and Saar (2005)	Experiment-al market
Size	Larger orders are more likely to be limit orders.	Bae, Jang and Park (2003)	NYSE
Informed trader	Technical traders use market orders and value traders use limit and working orders. [9]	Keim and Madhavan (1995)	NYSE, Nasdaq and OTC
	Informed traders generally submit more limit orders than liquidity traders.	Bloomfield, O'Hara and Saar (2005)	Experiment-al market
	Informed traders use more limit orders in the later part of the trading day.	Bloomfield, O'Hara and Saar (2005)	Experiment-al market
		Anand, Chakravarty and Martell (2005)	NYSE
Liquidity trader	Index traders use market orders	Keim and Madhavan (1995)	NYSE, Nasdaq and OTC
	Liquidity traders use more market orders as the end of the trading period approaches.	Bloomfield, O'Hara and Saar (2005)	Experiment-al market

The liquidity trader's cash flow needs are determined exogenously. Nevertheless, the trader attempts to minimise his transaction costs by carefully choosing his trading

[9] Working orders are given to brokers to execute over a period of time to minimize price impact (Keim and Madhavan, 1995).

strategy. When the deadline to trade is distant and the market is illiquid, he chooses to place limit orders. However, the trader may need to increase the aggressiveness of the limit orders if the orders do not fill and the deadline draws nearer. If the orders do not execute by the deadline, the liquidity trader has to submit market orders to ensure execution.

The informed trader uses market orders to trade quickly if private information is material and if the information is likely to become common knowledge. Thus, he is likely to use market orders and trade as frequently as possible. However, trading repeatedly with market orders will cause prices to reflect the private information. If the market is liquid and deadlines are distant, an informed trader may submit limit orders to minimise his transaction costs and allow the trader to better hide his information. The use of limit orders involves execution risk and thus could be sub-optimal for the informed trader. If there are other informed traders, the orders from these traders are likely to cluster on the limit order book, signalling the presence of new information. Liquidity traders may be able to act strategically by deferring their trading until the competition among informed traders causes prices to adjust (Admati and Pfleiderer, 1988). This reduces the informed trader's opportunity to profit and, conversely, reduces the liquidity trader's loss.

The value-motivated trader, as described by Harris (1998), is essentially an informed trader. However, the information he receives is perpetual and allows him to estimate the security's value on a regular basis. Examples of value-motivated traders include market makers who estimate security values based on order flows. Value-motivated traders trade to profit from their flow of information and do so by trading repeatedly. Harris (1998) proposes that a value-motivated trader demands immediacy when he believes price is far from the underlying value as it will revert. On the other hand, the value-motivated trader places limit orders to profit from pricing errors other traders make. In doing so, value-motivated traders provide liquidity and resiliency to the market. These traders are also associated with providing the outside spread.

Hollifield, Miller, Sandås and Slive (2002) provide a model that examines the trader's choice of market versus limit order. The model differs from others such as that by Handa et al. (2003) in that any trader, informed or uninformed, can submit a limit order. A trader's willingness to pay for immediacy depends on his valuation of the stock. Traders with an extreme valuation lose more from failing to execute their order than traders with moderate valuations. Thus, these traders are more willing to pay for immediacy than traders with moderate valuations.

Using a sample from the Vancouver Stock Exchange, Hollifield et al. estimate the price of immediacy, the unobservable distribution of traders' valuations and the unobservable arrival rates of traders. The price of immediacy is computed by using the execution probabilities and picking off risks of alternative order submissions. They estimate the distribution of the traders' valuations and the arrival rates of the traders by combining the estimated price of immediacy with the traders' actual order submissions. The results provide support for their hypothesis that traders with higher valuations are more likely to submit market orders.

Kaniel and Liu (2006) use a simple Glosten and Milgrom (1985) type equilibrium model to investigate the decision of an informed trader on whether to use a limit or market order. Their model differs from others in the literature that assume that informed traders use market orders only, and also the literature that examines the limit order versus market order decision of uninformed traders. Kaniel and Liu (2006) demonstrate that if the probability of continuing to be informed is high, then informed traders are more likely to place limit orders than market orders. Their analysis highlights the fact that the expected horizon of the private information is critical in the choice between a market and a limit order. They argue the probability of the limit order being hit is greater when the expected horizon is longer, thus out-weighing the risk of uncertain execution.

The results from Kaniel and Liu are not surprising given the previous work by Keim and Madhavan (1995; 1997) on institutional order placement. Using the equity trades of 21 institutional traders, Keim and Madhavan (1995) examine the choice of order type and its relation to trading style. The institutional traders were classified into three broad categories: indexers, value traders and technical traders. Value-based strategies are based on the analysis of fundamental factors, technical strategies are based on market momentum and also "possibly" on fundamental factors and index strategies are based on the objective of mimicking the returns of a particular stock index. The four order types examined, in order of aggressiveness, are market orders, working orders, crossing orders and limit orders. Keim and Madhavan find the orders used by institutions are predominantly market orders (87% of the total number of orders). Liquidity motivated traders such as the indexers are likely to use market orders to minimise tracking error and technical traders are likely to use market orders as the value of their information decays rapidly. Value traders, on the other hand, access information whose value decays more slowly, thus are more likely to trade slowly. In a subsequent paper, Keim and Madhavan (1997) find the trades by value traders have lower price impact cost, a reflection of the order types these traders use. In a recent paper examining the price impact components of both active and index funds' trades using Australian funds that invest in Australian stocks, Frino et al. (2005) find similar results; that the trades by index funds have a higher price impact.

Bloomfield, O'Hara and Saar (2005) use an experimental asset market to investigate the evolution of liquidity in an electronic limit order market. They argue that previous studies fail to provide a clear indication on the issue of trading strategies vis-à-vis the use of market versus limit orders by both informed and uninformed traders. Focusing on how informed and liquidity traders differ in their provision and use of market liquidity and how the characteristics of the market affect these strategies, they also examine how the characteristics of the underlying asset affect the provision of liquidity.

They find that liquidity provision in the limit order market changes over the trading day with the variations being driven by the behaviour of informed traders. When trading begins, informed traders are more likely to use market orders due to the "rush" to profit from their private information. The market orders consume liquidity as they hit standing limit orders on the order book. As prices move toward the true value, the urgency to trade lessens and informed traders shift to submitting limit orders. Towards the end of the trading period, informed traders are on average trading with limit orders more often than liquidity traders. The converse is found for liquidity traders, where more limit orders are used at the beginning of trading but more market orders are used to meet their trading requirements as the end of the trading period approaches.

The finding that informed traders actively use limit orders contrasts with the common assumption in the theoretical literature that informed traders consume liquidity by using market orders. The results in Bloomfield et al. (2005) show that both trader types use limit orders and market orders, but informed traders use limit orders more often. The informed trader's choice between order types is also affected by the value of the information he possesses. When the value of the information is high, the trader is likely to place a market order to profit before the prices adjust. However, if the value of the information is low, he is more likely to participate as a dealer and earn a profit by supplying a limit order to the market.

Bloomfield et al. argue that information influences the market in important but different ways. Information allows informed traders to profit and cause prices to move to efficient levels; at the same time, it enables informed traders to provide liquidity to other traders in the market. Bloomfield et al. note that informed traders profit by taking on the role of a dealer when they realise that what they thought was private information is already reflected in price. Furthermore, informed traders ultimately have the advantage when supplying liquidity as they do not face the adverse selection risk confronting an uninformed liquidity trader. Their results are in contrast to earlier theoretical models, such as Glosten (1994) Handa et al. (2003), where informed traders demand liquidity by using market orders instead of providing liquidity by placing limit orders. The theoretical models, such as Harris (1998), also presume that the informed trader stops trading when his information is incorporated into price.

Anand, Chakravarty and Martell (2005) argue that the conclusions from Bloomfield et al. (2005) and from the earlier theoretical models are alternative hypotheses that can be tested empirically. They do so by using the TORQ dataset that comprises the audit trail of all orders and their execution details for 144 NYSE stocks over a three month period (November 1990 – January 1991). The orders are classified as "Individual" or "Institutions", corresponding to "uninformed" and "informed" traders respectively.

Anand et al. (2005) find institutional limit orders perform significantly better than the limit orders placed by individuals although this is limited to the more aggressive limit orders that are placed "at the market" or better.[10] Performance is measured in a number of ways. The first is the difference between the midpoint quote prevailing

[10] At the market orders are bid (ask) limit orders that have the same price as the best bid (ask) at the time of order submission.

five minutes after order submission and the midpoint quote at the time of submission. The second measure replaces the midpoint quote at the time of submission with the limit order price.

Anand et al. (2005) also find institutional medium sized market and marketable limit orders contribute a significantly higher proportion of the total price change in the first half of the day compared to the second half. This indicates the market and marketable limit orders are more likely to be informed in the first half than the second. The result is consistent with the prediction made by Bloomfield et al. that informed traders use market orders during the earlier parts of the trading period. The results are also consistent with Barclay and Warner (1993) in that informed traders are more likely to use medium sized orders.

In addition, Anand et al. (2005) find limit orders, both placed by institutional and individual traders, perform better in the first half than the second. Anand et al. claim this is consistent with informed traders turning to market making in the later part of the trading period. The conclusion is perhaps drawn prematurely as the evidence is not strong.

2.5 Information arrival, trading volume and prices

One of the most fundamental issues in financial market microstructure studies is the role of information in setting security prices. As the arrival of information is often unobservable, earlier studies use trading volume as a proxy for information. The underlying idea is that the release of information is likely to shift investor demand, resulting in trading (Brailsford, 1996). A survey of the theoretical and empirical results for trading volume and absolute value of security price change by Karpoff (1987) finds a positive correlation between the two variables. Further research has collectively identified trading based on public information (Jones et al., 1994a; Kim and Verrecchia, 1991), private information (Barclay et al., 1990) and noise (Black, 1986; De Long et al., 1990a) as possible causes of share price volatility.

Share price movements can be seen as the result of information flowing into the market and being incorporated into equilibrium prices. This relates to both public information and private information. Conversely, share price movements can be a reflection of noise trading or the inability or unwillingness of rational traders to counteract it (Danthine and Moresi, 1993). The noise trading effect could be “bad” as it leads to less efficient pricing. Chan and Fong (2000) suggest that while the empirical evidence on the relation between price volatility and volume is strong, it is still not clear what drives this relationship.

The theoretical work of Kyle (1985) and Admati and Pfleiderer (1988) provides a useful framework for examining the relationship between volatility and different types of trading. Kyle (1985) models a market with three types of trader: (1) informed traders who trade strategically to maximise profits from their private information, (2) random liquidity (or non-discretionary liquidity) traders whose orders arrive randomly, and (3) a specialist who has no private information but is able to observe and learn from the order flow. In Kyle’s model, private information is incorporated into price over time at a constant rate, with the price at the end of the trading period reflecting all private information. The variance of return over the entire trading period is a function of private information while the variance within a trading period is affected by the volume traded by the liquidity traders because the specialist is unable to distinguish between the trading of informed and liquidity traders. However, the noise is rational as the price established by the specialist through examining the order flow is an unbiased estimate of the true price conditional on his information set.

Admati and Pfleiderer (1988) extend Kyle’s model to include a class of trader called discretionary liquidity traders. They are similar to Kyle’s random liquidity traders in that they have no private information but different in that they have some discretion over the timing of their trades. Admati and Pfleiderer show that, in general, trades of both discretionary liquidity traders and informed traders will cluster around periods with high random liquidity trading. Discretionary liquidity traders prefer to trade with the random liquidity traders to minimise their losses and informed traders prefer to trade with liquidity traders to maximise their gains. This clustering of trades causes share price variance to be highest when trading is most active.

These models provide the theoretical foundation for studies on the relationship between volatility and the different types of trading. Different inferences can be drawn by examining volume and volatility. For example, an increase in volatility without an increase in volume would suggest an increase in trading on public information. On the other hand, an increase in volume and volatility without the increase in associated news releases would suggest increases in either trading on private information or noise trading.

2.5.1 Private information

A number of studies show that volatility is a product of private information that is revealed through trading (Barclay et al., 1990; French and Roll, 1986; Lockwood and Linn, 1990).

French and Roll (1986) examine how the variance of New York Stock Exchange (NYSE) returns was affected when the NYSE closed on 24 Wednesdays in 1968 to clear a paperwork backlog. Generally, equity returns are more volatile during exchange trading hours than during non-trading hours. French and Roll find mispricing causes approximately four to 12 percent of the daily variance. However, these errors are trivial compared to the difference between trading and non-trading variances. French and Roll conclude that the difference is caused by differences in the flow of information during trading and non-trading hours. The small return variance over the exchange holidays suggests that most of the information flow during trading hours is private.

Barclay, Litzenberger and Warner (1990) examine the volatility of equity returns on the Tokyo Stock Exchange (TSE). During their sample period, TSE had been open for half a normal trading day approximately three Saturdays per month, and closed on other Saturdays. Barclay et al. (1990) examine the variance of returns over weekends with and without Saturday trading, holding constant the normal flow of public information.

When the TSE was open for trading on a Saturday, the weekend variance was 112 percent higher than when the exchange was closed. While weekly volume also increased, the weekly variance was unaffected. This rejects the hypothesis that variance is generated by traders' overreaction which is directly related to trading hours, trading volume or both. The dissipation of the higher weekend variance is explained by the reduced variance for the weekdays immediately following Saturday trading. Since volume was not lower on the weekdays following Saturdays with trading, lower variance on these days cannot be explained by a reduction in irrational trading noise that is related to volume. The lower variance on the weekdays following Saturday trading is expected as privately informed traders accelerated some of their trades to Saturday.

Puffer (1991) tests whether the variance of stock returns in New York (Dow Jones Industrial Average) depends on the presence of Saturday trading in Tokyo. This paper is similar to Barclay et al. (1990) in that it uses a similar setup where an exchange does not trade on a particular day intermittently; that is TSE does not trade on all Saturdays. However, the paper involves testing the relationship between the Tokyo and New York stock markets. Puffer argues that if more private information is revealed through trading on both Saturday and Monday than on Monday alone when the market is closed on Saturday, then the ratio of returns on weekends with Saturday trading relative to weekends without Saturday trading will be greater than one.

Puffer finds the variance of Friday close to Monday open returns in Tokyo was more than 30 times greater when the Tokyo market was open on Saturday than when the Tokyo market was closed on Saturday. The New York market was also found to be three times more volatile when the Japanese market was open during the Saturday. Puffer argues that since the flow of public information is unrelated to Saturday trading, the increase in volatility in both markets is a function of private information revealed through trading in Tokyo.

2.5.2 Public information

The other stream of volume-volatility literature supports the conjecture that public information drives volatility on the market.

Jones, Kaul and Lipson (1994a) suggest that private information is a small (or negligible) fraction of the total flow of information and that it is largely public information that leads to trading. Jones et al. (1994a) use a new approach to analyse the effects of trading and the flow of public and private information on short-run volatility. They define non-trading as periods when exchanges and businesses are open but traders endogenously choose not to trade. Jones et al. find that a substantial degree of volatility occurs on NASDAQ without trading. If private information plays a dominant role in determining volatility, the bid-ask spreads on non-trading days should be smaller than spreads on trading days. This is based on the assumption that private information is impounded into share prices only when trading occurs. Conversely, if public information is the primary determinant of volatility, the adverse selection component of the spread should not only be small but also equal, on trading and non-trading days. They find that the difference between the average bid-ask spread on trading and non-trading days is economically insignificant, regardless of the cross-sectional characteristics of the firms in the sample. Re-examining the effect of closed exchanges on volatility, they find private information to be a small fraction of the total flow of information. Taken together, the results suggest that public information is the main determinant of short-term volatility.

Several theoretical papers have shown that unexpected public announcements will lead to trading (Foster and Viswanathan, 1993; Kim and Verrecchia, 1991). Foster and Viswanathan use a model to show the volume and volatility reactions to an announcement depend on the deviation of the information that is revealed from the investors' expectation. The model predicts that a higher absolute difference between the realised public information and the expectation (whether it is unexpectedly good or bad news) leads to greater price volatility and greater trading volume. Kim and Verrechia (1991) present a model where traders are diversely informed prior to the announcement and they react differently to the announcement, leading to trading in the market.

Harris and Raviv (1993) show that even without any private information, trading can occur due to differences in opinion. They develop a model of trading in speculative markets based on announcements of public information. Harris and Raviv focus on speculation being the major factor accounting for surges of trading activity after public information announcements. Disagreements among traders over the relationship between the announcement and the ultimate performance of the assets arise either because speculators have different private information or because they simply interpret the information differently. This gives rise to speculative trading. The model assumes two types of risk neutral speculative trader. The two types start with common prior beliefs about the return to a particular asset. However, they disagree on the extent to which the information announced is important. The "responsive" group increases their probability of a high return upon receipt of favourable information than those in the "unresponsive" group. The reverse occurs when unfavourable information is released. The model suggests that trading occurs when cumulative information switches from favourable to unfavourable, or vice versa. The main results are that absolute price changes are positively correlated with trading volume and volume is positively auto-correlated.

Grossman and Stiglitz (1980) allude to this relationship in their model. Specifically, they find the market to be thin when traders have homogenous beliefs. That is, when information is inexpensive, or when informed traders get sufficiently precise information, then equilibrium exists and the market price will reveal most of the informed traders' information. The model suggests a relationship between volume and volatility where volume increases when there is disequilibrium in price.

2.5.3 Noise trading

The effect of trading by different trader types can be examined in the framework of Friedman (1953) and Fama (1965). Rational arbitrageurs have correct beliefs and expectations and stabilise asset prices. Irrational speculators destabilise prices by, on average, buying when prices are high and selling when they are low. However, these irrational speculators are eliminated from the market due to the losses they make. Concurrently, rational arbitrageurs counter the deviation of prices from their fundamental values and stabilise them. Thus, the conclusion is that noise traders have no effect on asset price formation. Subsequent studies, such as Black (1986) and De Long et al. (1990a), question the validity of this conclusion and argue that noise trading can have a non-trivial impact on asset prices. De Long et al. cite empirical observations of overreaction of prices to news, price bubbles and autocorrelation of share prices as being consistent with their own model.

In Black's model of financial markets, noise is contrasted with information. Individuals who trade on information do so to make a profit while others who trade on noise think they are trading on information. Individuals without information also trade because they derive utility from the act of trading itself. Collectively, noise traders lose money by trading, while information traders make money. Black (1986) argues that noise trading is essential to the existence of liquid markets. If there is no noise trading, there will be very little trading in individual assets. A person with information or insights about individual firms will want to trade. However, if individuals trade only on information, no one will want to take the other side of the trade. Black argues that noise trading increases liquidity in the market.

While noise trading increases liquidity, a side effect is that it introduces noise into price and causes price to be less efficient. Black argues that as the true value of the security is not observable, the price of a stock reflects both information that informed traders trade on and the noise that noise traders trade on. As a result of noise trading, the variance of percentage price changes is greater than the variance of percentage value changes.

De Long et al. (1990a) argue that the "limit of arbitrage dedicated to noise traders' misperception" described in Friedman's (1953) argument may not hold. De Long et al. recognise that arbitrageurs are likely to be risk averse and myopic. Arbitrageurs essentially bet against noise traders when they take a position against the noise traders and bear the risk of holding a security (fundamental risk). As arbitrageurs are assumed to be risk averse, they would be discouraged from taking opposite positions. Furthermore, there are risks that noise traders' beliefs will not revert to their mean for a long time and might in fact cause prices to shift further from their fundamental values. De Long et al. argue that even in the absence of the fundamental risk, "noise trader risk" arises as noise traders causes prices to diverge from fundamental values. "Noise trader risk" acts as a further deterrent to arbitrageurs from trading against the noise traders.

De Long et al. (1989) discuss the impact of noise trading on prices and assess the welfare effects of such trading. The question of concern to the researchers is the effect of noise trading on the risk of investment. They note that a significant amount of volatility in stock prices cannot be explained by changes in the fundamental value of the stock. A possible explanation is that the volatility in stock prices is influenced by the proportion of noise trading. De Long et al. argue that noise trading can lead to adverse welfare effects, including mispricing and excess volatility as it reduces the capital stock. Ultimately, the welfare costs of noise trading may be borne by rational investors.

The effect of noise trading has been disputed. Danthine and Moresi (1993) model the effect of noise trading on price volatility and show that in a dynamic setting, noise trading affects the equilibrium price in two ways. Noise trading affects the net supply of the asset and thus prices adjust. Furthermore, noise trading affects the asset demand of rational traders. Prices are believed to convey information about the current and future activity of noise traders, thus affecting the expectations of future prices. Danthine and Moresi argue that the total effect of noise trading on the current price is ambiguous. Barber et al. (2004) propose two conditions are necessary for noise traders to have a cumulative effect on asset prices. First, there must be limits to the ability and willingness of informed traders to offset the pricing effects of noise traders. These limits include restrictions on and the cost of short-selling, and the availability of a perfect substitute for the stock. Second, the aggregate of trading by noise traders must be systematic. Barber et al find support for the second condition.

The empirical evidence on the effects of noise trading on stock prices is inconclusive. The empirical tests have sought to analyse how noise traders influence markets by using aggregate measures of investor sentiment. Many focus on the closed-end fund discount as a proxy for noise trader sentiment. Closed-end funds are found to be owned and traded primarily by individual investors. Lee, Shleifer and Thaler (1991) argue that closed-end fund discounts are a measure of the sentiment of individual investors. They find that the sentiment of these individual investors affects the prices of small stocks in similar ways as it affects the prices of closed-end funds. Both closed-end funds and small stocks tend to be held by individual investors and when small stocks perform well, the discount on closed-end funds is found to be narrower.

Sias, Starks and Tunic (2001) find, using 57 closed-end funds from July 1965 to December 1990, closed-end fund monthly returns are more volatile and exhibit greater mean reversion than the underlying asset returns. These results are consistent with the noise trader model, which suggests closed-end fund share returns are more volatile than the returns on the underlying assets and exhibit greater mean reversion because investor sentiment affects closed-end funds to a greater extent.

Brown (1999) tests the relationship between investor sentiment and closed-end fund volatility directly by using a sentiment measure compiled by the American Association of Individual Investors (AAII). A randomly selected group of the members of AAII was surveyed about stock market expectations. In particular, they were asked if they thought the stock market would be bullish or bearish or the same over the next six months. Brown finds unusual levels of individual investor sentiment are associated with greater volatility in closed-end fund returns.

Other empirical studies have found results suggesting volatility is not driven by noise traders or that noise traders are in fact not individual traders. Sias (1996) suggests an increase in institutional investor interest in stock may result in an increase in volatility due to trading frictions. These investors are likely to trade in larger volumes than individual investors and engage in program trading. Using yearly volatility measures estimated using weekly returns, Sias (1996) finds an increase in institutional holdings is associated with a subsequent increase in volatility. The results are consistent with the hypothesis that institutional holdings induce an increase in volatility.

Jackson (2003) analyses a comprehensive database containing 39 million retail investor trades from 47 Australian retail brokers. He finds that future weekly return volatility declines with an increase in the proportion of trading volume accounted for by individual investors. He argues that frictions such as “performance related mutual fund flows, herding due to career concerns, common investment strategies and style investing” can give rise to noise trader risk. Trueman (1988) suggests that uninformed investment managers trade even though they do not possess any private information because trading acts as a signal and increases investors’ assessment of the probability that the manager is privately informed.

2.6 Summary

Motivations to trade have been discussed since it is likely that they would affect a trader’s order placement strategies. Earlier studies debate the order size that informed traders are likely to use. Theoretical papers suggest informed traders are likely to use orders ranging from medium size (consistent with stealth trading) to large size (to maximise their profits). Empirical evidence indicates medium size orders placed by institutions are associated with abnormally large price changes relative to other order sizes. Few discuss the order placement strategy of an uninformed trader.

The notion that individual investors are uninformed was discussed, drawing from the behavioural finance literature. The general consensus is that individual investors, at the aggregate level, are irrational and are described synonymously with noise trading. Most studies test the irrational behaviour of individual investors on the portfolio level but on not the transaction level.

The operations of the limit order market were discussed, in particular the participants and their trading strategies. Papers discussed suggest a trader chooses between a limit and a market order depending on his motivation for trading and on the state of the market (e.g., available liquidity and bid-ask spread) when he submits his order. Studies on institutional trading have found evidence to suggest different brokers have differing abilities and impact on their choice of order type. The literature on limit order markets can be extended by examining the orders that originate from brokers that handle retail trades.

The last section discussed the impact of public information, private information and noise trading on return volatility. Noise trading affects share prices; however it is unlikely to be the case that all noise traders are individuals.

CHAPTER THREE
HYPOTHESES

3.1 Introduction

This chapter develops the hypotheses tested as part of my investigation into various aspects of trading by different trader types, i.e. institutional versus retail. The first (Chapter Five) examines the price effect of orders placed by the different trader types to provide an insight into the information content of their trades. The second (Chapter Six) investigates the differences in the order placement of different trader types and their role in the provision of liquidity to the market. The last (Chapter Seven) examines the contributions of order flow from different trader types to transaction price volatility.

Anecdotal evidence suggests that the growth in trading during the late 1990s and early 2000 had a substantial effect on the Australian stock market. Patrick (1999) reported that the boom in trading Internet and telecommunication stocks and the "explosion" of Internet day trading has made surveillance of the Australian Stock Exchange (ASX) much more difficult. The change in the composition of traders in the market place has attracted attention, with suggestions that the new breed of trader may have caused greater volatility because they are not as "savvy" as institutional traders. To illustrate, large unexplained share price movements prompted the ASX to refer 117 cases to the Australian Securities and Investment Commission (ASIC) for investigation in November 1999, almost 50% above the monthly average of 80.

The composition of the "retail trader" category is important in the development of the hypotheses. Financial planners in the US have advised clients to use online trading as a facility for trading using "play money" they can afford to lose (Opiela, 2000). While Opiela (2000) was cautious to state that not all clients who trade online are unsophisticated "punters", she suggests that the average client's level of understanding of economics is low. This is because online traders may have all the tools at their disposal but they may not know how to use them (Hurley, 2000).

Barber and Odean (1999b) find traders who switched from telephone trading to online trading not only traded more frequently and speculatively, they also traded less profitably. They suggest that lower trading costs, improved execution speed, and greater ease of access did not fully explain the observed behaviour. Instead, a probable explanation was the overconfidence of online traders, augmented by self-attribution bias, illusion of knowledge and illusion of control.[11] By studying the historical performance of traders with equity investment accounts with a large discount broker house, Goetzmann and Kumar (2002) conclude the vast majority of retail investors are under-diversified. In sum, the literature to date indicates clients of discount brokers are mostly uninformed and unsophisticated in their trading behaviour.

3.2 Price effect of retail and institutional orders

The increase in the number of retail traders and their uninformed nature are likely to be reflected in the price effect of their orders. The information content hypothesis is concerned with the price effect associated with orders (trades) submitted (executed) through retail brokers. The theoretical basis for inferring information content from prices is provided in both asymmetric information and inventory models. Many microstructure models decompose actual prices or quotes into a "true" or "efficient" price and a second "disturbance" component, which impounds various microstructure imperfections (Hasbrouck, 1991b). Temporary price changes occur due to inventory and order processing costs of suppliers of immediacy or liquidity. On the other hand, permanent price changes occur as a result of agents' beliefs about the private information content of the trade, whereby private information is essentially advance knowledge of public information. Prior research documenting and examining permanent versus temporary price effects includes the literature on block trading. It suggests trades by large informed traders have a permanent effect on

[11] Self attribution bias is when an individual ascribes their success to personal ability and failure to bad luck or the actions of others (Barber and Odean, 1999a, 1999b).

share prices due to the private information that is conveyed by the trade and subsequently incorporated in a new equilibrium price (Aitken and Frino, 1996a; Aitken et al., 1994; Ball and Finn, 1989; Chan and Lakonishok, 1993; Holthausen et al., 1987, 1990; Scholes, 1972; Walsh, 1997).

Previous studies have examined the relationship between information content and size of order (Barclay and Warner, 1993; Brown et al., 1999; Chakravarty, 2001; Easley and O'Hara, 1987; Walsh, 1997; Walsh, 1998). The study by Brown, Thomson and Walsh (1999) of trading on the Australian Stock Exchange finds that, compared to uninformed traders, informed traders on the ASX choose smaller orders. Chakravarty (2001) finds medium size trades move prices and are initiated by institutions. In their study of institutional trades, Lakonishok, Shleifer and Vishny (1992) find, even after controlling for the market capitalisation of the stock and the relative trade size, the dominant influence on the market impact of a trade is the identity of the money manager behind the trade. Extending the argument used by Lakonishok et al., I predict that the “type” of trader partly determines the price effect of the order because retail traders are less informed than institutional traders. Specifically, orders of retail traders that initiate trades are associated with smaller permanent price movements.

> H_1: *Compared to orders placed by institutional traders, orders placed by retail traders have smaller permanent price effects.*

Temporary price movements reflect inventory and order processing costs of suppliers of immediacy or liquidity. While the ASX is different from the US markets such as NYSE and NASDAQ, where market makers help provide liquidity when needed, Australian broker houses are found to act as de facto market makers.[12] Traders who need to trade large orders or to trade immediately would bear the “inventory” costs charged by these liquidity providers who have placed the limit orders. Institutional traders are likely to be more aware of market conditions and better able to manage their order placement. Other things equal, and in particular for a given order size,

[12] Previous studies of the Australian market show that brokers trade as market makers when they trade as principals and facilitate trading in an open limit order book (Aitken and Swan, 1993). Similarly, Chung and Brockman (2000) suggest in their analysis of trading on the Hong Kong Stock Exchange, de facto market makers provide liquidity in a pure limit order trading environment.

marketable orders placed by retail traders are likely to have a larger temporary price effect.

> *H_2:* *Compared to orders placed by institutional traders, orders placed by retail traders have larger temporary price effects.*

While it is argued here that retail traders are less aware of market conditions, this may not be true of all retail traders. Some retail traders are known to provide liquidity by placing market or marketable limit orders when they believe an opportunity exists. The temporary effect of their orders is not necessarily large. However, it is unlikely a sufficient number of retail traders would engage in substantial "day trading" activity for their impact on price to be significant.

3.3 Order aggressiveness

Biais et al. (1995) suggest a complex relationship exists between trader order strategy and a number of factors, including transmission of information to the market, the cost of trading and the nature of the liquidity available to the market. One of the most effective ways traders can maximise their portfolio return is through the management of their trading strategy. By optimising their trading strategy, traders can minimise their transaction costs compared to those who do not (Harris, 1998). When placing an order, a trader will need to choose between submitting a market or a limit order.[13] If the trader decides to submit a limit order, he will also have to decide the limit price. If the limit order does not execute, he will then need to choose between cancelling and amending the order.[14]

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[13] Market orders are instructions to buy (sell) a fixed quantity of shares at the best available price offered by the standing limit orders on the sell (buy) side of the market. Limit orders are instructions to buy (sell) at or up to the fixed quantity of shares at the limit order price set by the trader. An important difference in the two types of order is that a market order guarantees execution (assuming sufficient opposing limit orders exist) but does not provide price certainty (especially if market prices are changing quickly) while a limit order guarantees price certainty but does not guarantee execution. If no opposing orders exist, market orders cannot be placed. The ASX trading platform, for example, generates an error message when this occurs.

[14] Another decision the trader faces when submitting an order is the order size. Order size and order price are likely to be determined jointly (Harris and Hasbrouck, 1996).

A number of papers have examined the factors that influence the choice between a market and a limit order (Foucault, 1999; Lo and Sapp, 2003; Ranaldo, 2004; Verhoeven et al., 2004). While the study of the dichotomous choice of market versus limit order provides a good preliminary examination of trader strategy, it does not cover the full range of order strategy options available to a trader. The use of a market order involves accepting the best price on the opposing side, allowing the order to be executed immediately. In comparison, the use of a limit order is more involved as it requires the trader to set the price at which he is willing to trade. The limit order price could be in-the-market, at-the-market or behind-the-market.[15]

Harris and Hasbrouck (1996), one of the first papers to examine order placement strategy or aggressiveness of an order, define the latter as the extent to which it betters the existing quote. A number of subsequent papers (Griffiths et al., 2000; Hedvall et al., 1997; Ranaldo, 2004) have examined the concept of aggressiveness and its interaction with the state of the limit order book. Griffiths et al. (2000) categorise orders into six categories: (1) market orders; (2) marketable limit orders for quantities greater than the depth at the best opposing bid/ask; (3) marketable limit orders for quantities equal to the depth at the best opposing bid/ask; (4) limit orders that are in-the-market; (5) limit orders at-the-market; and (6) limit orders behind-the-market.

By definition, market orders consume liquidity while limit orders provide it. While the price of liquidity is the bid-ask spread, the use of limit orders does not come without a cost. Limit order traders face both the risks of non-execution and adverse selection. Harris (1998) suggests the strategy a trader selects reflects the trading problems they are attempting to solve. In the modelling of stylised trading strategies, Harris analyses three different types of traders, of which two are informed. The first informed trader has private information that may be short-lived. In his stylised model of trader strategy, Harris assumes the informed trader's informational advantage decays exponentially with time. As a result, the informed trader uses a market or a

[15] In-the-market orders have order price between the best bid and best ask. At-the-market orders have order price at the best available price on the same side as the order. For example, a bid (ask) order that is placed at-the-market has the same order price as the highest bid (lowest ask) on the schedule. Behind-the-market bid (ask) orders have order price less (more) than the best bid (ask) price available on the schedule.

more aggressively priced limit order to trade more quickly. However, if the bid-ask spread is wide and there is no time constraint on the informed trader, he is likely to submit a more passive limit order to minimise his transaction cost, or not trade at all. Harris also suggests another class of informed trader exists. They are the value motivated traders who receive private information that is long-lived and are likely to use working orders or limit orders that are placed behind-the-market. Limit orders allow them to trade discreetly and prolong their ability to trade profitably. The above discussion suggests that the study of order aggressiveness may not provide conclusive evidence on the informativeness of the different trader types as informed traders can use a mixture of order types depending on their beliefs about the longevity of their private information.

Keim and Madhavan (1995) examine the use of market and limit orders by institutional traders. They find a strong preference for market orders (90.1%) and that the choice of order type was asymmetrical across the different trading strategies. While 76.2% (77.6%) of the bid (ask) orders placed by value traders were market orders, traders adopting technical and index strategies used an even greater proportion (88-92%). The findings are supported by Campbell et al. (2004) who report that institutions on average demanded liquidity from other traders. It is debatable whether the traders following technical and index strategies examined by Keim and Madhavan should have been classified as informed. The placement of more aggressive orders may not be a reflection of whether a trader is informed so much as his desire to complete the trade, for whatever reason.

Given the findings from Keim and Madhavan (1995) and Campbell et al. (2004), we expect to find similar results in the Australian share market environment. Institutional traders are likely to demand immediacy due to the perceived short term nature of their private information about the underlying value, their “information” derived from technical analysis or their desire to track an index. Besides the demand for greater immediacy, the ability to monitor market conditions and react accordingly may result in the greater use of market orders (Dupont, 1998). Institutional traders are likely to monitor the market and place an order only when they judge the market to be favourable. This is akin to the “pre-considered” trader discussed in Harris

(2003).[16] The act of placing a limit order provides the market with the ability to trade, similar to granting the market a trading option (Copeland and Galai, 1983). Limit orders are also exposed to the possibility of being quote-matched (Aitken et al., 2001a; Harris, 1996).

Consider an institutional broker who has instructions from a client to buy at a price lower than the current best bid. If the broker submits the order to the trading system, the order would be classified as a passive order. The limit order runs the risk of being quote-matched by other traders placing another limit order at a price marginally higher. If the limit order is hit and share price increases, the quote-matcher will benefit from the price rise. However, if the price falls, the quote matcher may be able to limit his losses by selling to the institutional trader. Thus, the institutional broker may not submit the order immediately but would monitor the market and place the order only when the market moves towards the client's indicated price. Subsequently, the order would be classified as aggressive.

Due to the preference of institutional traders for immediacy and their ability to monitor the market, orders placed by these traders are likely to differ from those placed by retail traders. Hypothesis H_3 predicts that, ceteris paribus, orders placed by retail traders are less aggressive compared to those placed by institutional traders.

> H_3: *Orders from retail traders are less aggressive than orders from institutional traders.*

3.4 Liquidity premium

In contrast to the literature on the bid-ask spread in a dealer's market, the literature on the bid-ask spread in a pure order driven market is both sparse and recent. While some (see Aitken et al., 1996; Brockman and Chung, 1999) have tried to reconcile the bid-ask spread on the limit order book with the theoretical models developed for

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[16] Pre-considered traders know that they wish to trade but for various reasons will not reveal their wish to the public. They offer liquidity to the market only when a suitable trading opportunity arises (Harris, 2003, p 95).

a dealer's market, others (such as Cohen et al., 1981) have tried to explain the existence of the spread on a limit order book by attributing it to the transaction costs investors face in assessing information and monitoring the market. The adverse selection cost of trading with informed traders that has been discussed in the bid-ask spread models for a dealer's market, can also be used to explain the existence of the bid-ask spread on the limit order book (Glosten, 1994).

Traders can place two types of order in an order driven market: a market order or a limit order. Typically, an order that is not executed is kept on the limit order book until executed or cancelled. For a limit order to be executed, a market order must be placed by a trader who demands immediacy and is willing to accept the best bid or best offer. Thus, traders who submit limit orders provide liquidity to opposing traders by allowing them to trade when they wish. The demand for immediacy could arise from the trader's private information (real or perceived). Limit orders are exposed to adverse selection, which is often described as the winner's curse. It is important to note that traders in a limit order market are not obliged, like market makers, to provide liquidity. Handa, Schwartz and Tiwari (1998) suggest the primary objective of most investors is the implementation of a portfolio decision, not the provision of liquidity.

Handa et al. provide a simple yet intuitive model of the limit order book, suggesting "bid-ask spreads are a natural property of order-driven trading" (Handa et al., 1998, p.53). They describe the order driven market as an ecological system where different types of trader operate differently. In a market where transaction prices move solely in response to information, trading via a limit order is costly. This is because the trader who has placed a buy (sell) limit order has written a "free" put (call) option to the market as a whole. Another problem associated with the use of limit orders is the risk of non-execution. Limit orders are not traded if the market moves away from the order price.[17]

[17] Handa, Schwartz and Tiwari (1998) give an example. Consider an investor who wishes to buy shares of XYZ at $10 or better, and let that investor select between submitting a market order (that would execute, say, at $10) and submitting a limit order at $9.90. If news causes the share price to fall below $9.90, assuming the trader has submitted a limit buy order, the option will be exercised and the individual can lose from trading with a more informed investor. Alternatively, if news causes the price to rise, the individual might miss the investment opportunity.

Handa and Schwartz (1996) show accentuated volatility due to liquidity (non-informational) events is required to compensate limit order traders whereas the possible non-execution or delayed execution of limit orders induces eager traders to submit market orders. The bid-ask spread on the limit order book is thus a function of adverse selection and probability of non-execution. Institutional traders are likely to place higher costs on non-execution due to the resources they invest in arriving at their trading strategy. Also, retail traders are relatively less informed and their standing limit orders are likely to be "picked off" by more informed traders; thus retail traders have a greater expected adverse selection risk. The combination of these factors affects the pricing of the limit orders that remain on the schedule.

> *H_4:* *Standing ask (bid) limit orders placed by retail traders are further away from the best ask (bid) compared to those placed by institutional traders.*

3.5 Interaction of orders placed by retail brokers with transient volatility

The effect of trading on volatility has been the focus of many previous studies, both empirical and theoretical. The theoretical models fall into two groups: competitive and strategic. In a competitive model with asymmetric information, the size of trade is positively related to the quality of the information possessed by informed traders (Easley and O'Hara, 1987; Holthausen and Verrecchia, 1990). In a strategic model, asymmetric information also leads to trading, but a monopolistic informed trader may camouflage his trading activity by making several small-sized trades rather than one large trade (Barclay and Warner, 1993; Kyle, 1985). This weakens the positive relation between the size of the transaction and the informed trader's information.

However, Holden and Subrahmanyam (1992) show that, in a more realistic strategic model with multiple informed traders, the distinction between strategic and competitive models is blurred. In both models the trade size or trading volume of the informed agents' trading increases with the quality of their information, resulting in a positive relation between volume and absolute price change. Subsequently, Jones et al. (1994b) find empirically that the number of transactions, rather than the volume, is more closely associated with volatility. Their results suggest that it is the "occurrence of the transactions per se" and not the size of the trades that generates volatility.

Chan and Fong argue that it may be "premature to conclude that the size of trades has no information content beyond that contained in the number of trades" (Chan and Fong, 2000, p.249). They suggest that if informed traders are to stealth trade by using medium sized orders as suggested by Barclay and Warner (1993), the volatility-trade size relation would not be detected using average trade size, as shown by Jones et al. (1994b). The literature on the volume-volatility relation suggests informed traders drive the volatility. That is, an increase in volume "per se" would not generate volatility but an increase in the number of informed traders would.

Recent papers on the volume-volatility relation have focused on the role of uninformed traders. Greene and Smart (1999) liken the trading by uninformed investors or "liquidity traders" to noise trading, where traders in fact have no private information to exploit. A large number of studies have emphasised the significance of noise traders in financial markets. Black (1986), for example, argues "noise" makes trading in financial markets possible as it is an important source of liquidity. Greene and Smart find that market liquidity increased modestly and the adverse selection component of the spread decreased significantly in response to noise trading stimulated by *The Wall Street Journal*'s "Investment Dartboard" column. Others have argued noise traders may be a source of risk that derives from their positive feedback trading behaviour (De Long et al., 1990b). In their analysis of SOES (Small Order Execution System) bandits, Battalio et al. (1997) find day traders who bought in "up-trending" and sold in "down-trending" markets exaggerated price movements, causing higher volatility in the short run.

Retail traders (also known as individual traders) are often described synonymously with noise traders. Hong and Kumar (2002) argue that, due to their relative lack of sophistication, small individual investors are likely to be a dominant source of noise trading in the market. Retail traders are predicted to be overconfident and uninformed and to engage in momentum trading. As a result, their trading causes volatility in the market, which leads to hypothesis H_5.

H_5: *Periods with a greater proportion of orders from retail traders exhibit higher stock price volatility.*

A number of factors may mitigate this effect. First, institutional traders may also engage in "noise" trading (Sias, 1996). For example, institutional traders could be more susceptible to herding behaviour than individual retail traders because of the close knit nature of the institutional investor community and the importance of benchmarking performance relative to other institutional traders. Thus, their herding behaviour may exacerbate price movements and increase volatility. A second argument arises from the clustering of informed trading with liquidity trades. Dupont (1998) argues that the equilibrium price is more volatile and less informative when there are more rational traders such as institutional traders. He suggests rational traders hide behind the noise created by liquidity traders and thereby keep more of the noise in the market in equilibrium than naïve traders, such as individual investors, would.

3.6 Summary

This chapter developed five hypotheses to be tested as part of my investigation into the role of different trader types. I hypothesise that institutional traders on the whole, are likely to be more informed and that their marketable orders would have larger permanent price effects than orders placed by retail traders (H_1). On the other hand, retail traders are less experienced in order placement and their orders would have a larger temporary price effect (H_2). Orders placed by institutional traders are expected to be more aggressive (H_3) and the standing limit orders placed by retail traders are predicted to be further away from the market to compensate them for the adverse selection cost of providing liquidity (H_4). The liquidity premiums charged by institutional and retail traders are likely to be different due to the information asymmetry that exists. The final hypothesis deals with the relationship between order volume and volatility. Due to a greater proportion of noise trading, other things being equal, orders from retail traders are predicted to be associated with greater volatility in transaction prices (H_5).

CHAPTER FOUR
DATA

4.1 Introduction

This chapter outlines the data set used in this thesis and the investment environment over the period 1999 to 2001. It has three sections: the first discusses the sample period and the subset of stocks selected for analysis, the second section discusses the use of order and trade information and the third discusses the classification of orders using broker house information.

4.2 Data period and sample

Trade and order data for all stocks traded on the Australian Stock Exchange (ASX) from January 1999 to December 2001 are used to provide an overview of changes in market activity on the exchange. Detailed analyses and tests of hypothesises are deferred to Chapter Five. Due to constraints on the ability to process the vast amount of data generated each day, detailed analysis is performed on a selected number of companies over the year 2001. The sample is selected from the first and last deciles of the top 200 ASX stocks ranked by trading volume (measured by dollar value of all on-market trades). The Securities Industry Research Centre of Asia-Pacific (SIRCA) provided the trade and order flow data used in the analysis.[18] The stocks selected are listed in

Table 4.1; Panel A lists the stocks that are heavily traded and Panel B those that are lightly traded.

In order to avoid statistical issues associated with "thin trading", four stocks that did not trade on more than 25% of the trading days are eliminated from the sample. Both Decile 1 (heavily traded) and Decile 10 (lightly traded) comprise 18 stocks

[18] See Appendix A for details of information available from trade and order records.

respectively. Order and trade data for the period January to December 2001 inclusive is used in the analysis.

Table 4.1 Trading statistics of sample stocks

Trading statistics of stocks in Decile 1 (heavily traded stocks) and Decile 10 (lightly traded stocks) selected for analysis.

	Percentage of days with one or more trades (%)	Total trading volume for the year ($'000,000)	Total trading volume for the year ('000,000)	Average daily trading volume per company ($'000)	Average Last Trade Price ($)
Panel A: Heavily Traded Stocks					
BHP	100	25,245	1,882	99,781	14.99
TLS	100	25,058	4,354	99,043	5.81
NAB	100	22,525	739	89,032	30.73
NCP	100	16,355	1,005	64,643	16.36
CBA	100	16,106	541	63,662	29.90
ANZ	100	12,444	785	49,187	15.82
WBC	100	10,902	786	43,091	13.91
RIO	100	9,693	289	38,312	33.64
AMP	100	8,199	423	32,407	19.36
WMC	100	8,175	948	32,313	8.65
BIL	100	7,309	414	28,890	32.39
WPL	100	6,544	465	25,866	14.12
WOW	100	5,858	585	23,153	10.04
QAN	100	4,861	1,443	19,289	3.37
CML	95	3,882	551	16,109	7.04
LLC	100	3,691	283	14,589	12.81
MAY	98	3,322	510	13,343	6.42
CSR	100	3,246	531	12,828	6.10
Panel B: Lightly Traded Stocks					
KIM	100	105	166	415	0.57
IFM	100	104	60	413	1.72
OML	100	103	87	405	1.14
GNS	100	101	25	401	3.93
PLM	77	100	14	512	5.38
RIC	100	96	117	381	0.81
TIM	100	93	156	368	0.91
GWT	100	90	40	357	2.26
MYO	100	90	100	357	0.97
VRL	100	90	54	356	1.66
ARG	100	89	24	351	3.72
VNA	100	88	295	351	0.15
NUF	100	88	30	349	2.96
HRP	87	87	57	398	1.47
SLX	100	87	24	345	3.65
AQP	100	86	10	342	8.19
MXO	100	86	345	339	0.22
CPH	100	84	195	332	0.44

As expected, the stocks in Panel A, on average, have higher trading volume (dollar value) than those in Panel B. However, this is not the case when trading volume is measured by the number of shares traded. For instance, trading volumes for VNA and MXO (in Decile 1) are higher than RIO and LLC (in Decile 10). This is due to the low denomination of VNA and MXO ($0.15 and $0.22 on average, respectively). The heavily traded stocks (Decile 10) account for 59% of the total trade value of $328 billion in 2001 and 16% of the total number of shares traded (103 billion).

Although the majority of the lightly traded stocks (Decile 10) do not contribute substantially to aggregate market activity (1% of total trades by value and 2% by number of shares), the stocks are representative of most of the stocks listed on the exchange in that relatively little trading activity occurs in them. The inclusion of these stocks in the analysis will provide a comparison of the differences, if any, between the strategies of institutional and retail traders and their impact on the more actively traded and less actively traded stocks. Four of the stocks in the sample did not trade on all days in the period examined due to suspensions and delisting.[19]

4.3 Use of order and trade data

The Stock Exchange Automated Trading System (SEATS) used by the ASX is an electronic limit order book, equally transparent to all market participants. All existing limit orders on every stock are visible to traders before they submit their new orders. The display of the limit orders is also known as the bid-ask schedule. It separates the orders into bids and asks, ranking them by price and time priority. The limit orders on the bid-ask schedule show the price and the quantity that are available for trading. The order book is not entirely transparent because traders can opt to hide part or all of the quantity if the order is for $200,000 or more (*SEATS Reference Manual*, 2002).[20] When traders submit their orders, they must specify the quantity and the price. Orders can be classified based on the order's price in relation to the best bid and ask on the bid-ask schedule. Orders are classified as market orders when the order price equals or betters the current best opposing price. These orders execute

[19] The two stocks, PLM and HRP, were delisted on 29 November 2001 and 24 December 2001 respectively. CML traded under a different code (CMLDA) for two weeks because of changes in the entitlement of the shareholders.
[20] The disclosure threshold initially was $10,000. It was increased to $25,000 on 24 October 1994 and further increased to $100,000 on 16 October 1996 (Aitken et al., 2001b). On 25 June 2001, the threshold was increased to the current requirement of $200,000 (ASX Participant Circular 229/01, 2001).

immediately if the price submitted is sufficiently high and there are enough shares offered on the opposing side to satisfy the order. If not, the order is part completed and the incomplete portion remains on the order book at the submitted price. If the price of the submitted bid (ask) order is lower (higher) than the current best ask (bid), it is known as a limit order and it does not execute immediately. The submission of limit orders does not consume liquidity but increases the depth of the bid-ask schedule. Conversely, the submission of market orders consumes liquidity and decreases the depth of the bid-ask schedule.

The brief discussion of the trading process above shows that trades are a result of the order submission process. When a market order arrives, it is executed against the limit orders on the schedule. A larger order may not be executed against a single order but a number of smaller orders, thus triggering several smaller trades. Analysis in Chapter Six shows that each market or marketable limit order results in approximately 1.4 trades. In sum, when studying the submission strategy of traders, it is clear that I should analyse order flow and not just trades.

4.4 Classification of retail and institutional trades or orders

Previous studies have used order size and trade size as proxies for institutional trading (Aitken and Frino, 1996a; Kraus and Stoll, 1972; LaPlante and Muscarella, 1997; Madhavan and Cheng, 1997; Walsh, 1997). A common method involves labelling orders above some cut-off size as institutional, and those below a lower cut-off as retail or individual. However, using trade size as a proxy for trader identity is flawed as it assumes that all institutional/informed traders use large orders and that their orders result in large trades. Lee and Radhakrishna (2000) evaluate several alternative cut-off rules by applying them to the TORQ dataset, which comprises trades with complete identification of market participants. While they find that cut-offs of $20,000 for institutional and $2,500 for individuals are most effective at accurately classifying trades, it is not clear that these results apply more generally as the TORQ dataset contains only a small sample of the stocks traded on the NYSE (Campbell et al., 2004).

Furthermore, large orders submitted by institutional traders may not result in large trades as orders are often traded against other traders who have submitted smaller orders. Studies have also shown that institutional traders split their orders to "stealth trade", thus rendering invalid the assumption that large trades are from informed traders (Barclay and Warner, 1993; Chakravarty, 2001). Recent work by Campbell et al. (2004) develops a new method for inferring high-frequency institutional trading by using a transaction database (TAQ) and an institutional holdings database (Spectrum). They claim that the cut-off functions they have developed are better than the absolute cut-off used in Lee and Radhakrishna (2000). However, they concede that the mapping of order to trader types using order size remains problematic due to the incentive for institutions to conceal their activity and the overlap between the trade sizes that may be used by wealthy individuals.

In this thesis, broker houses are used as the proxy for inferring the type of trader for each order and trade. This relies on the assumption that particular traders are attracted to or utilise certain types of broker and vice versa. The assumption is justified in that institutional brokers are less likely to want to service retail traders due to their smaller net worth. Conversely, retail traders will not seek out institutional style brokers because of the higher commissions they charge. This classification is by no means without its shortfalls, one being that some brokers are known to deal with both wealthy retail and smaller institutional traders. Robustness checks are made to verify that the results are not unduly influenced by the classification method.

4.4.1 Clustering analysis

Using the off-market activity of broker houses, I classify brokers into two main groups: (1) institutional and (2) others. Off-market trading is the diversion of order flow from the primary market and arises from a variety of sources (Fong et al., 2001). On the NYSE, for instance, order flow is diverted to crossing systems such as POSIT or the "upstairs" market, where block trades are arranged by negotiation and after-hours trading takes place. In this case, brokers or proprietary systems operate to match trades after the primary market has closed. Fong et al. (2001) conclude that cross-sectional institutional interest is positively related to off-market trading. They show that larger stocks that generally attract institutional interest have a higher proportion of their trading executed off-market.

Clustering analysis can be used to categorise the broker houses based on the off-market trade value and frequency. Off-market trades are trades that are not matched by SEATS. Orders received other than between 10:00am and 4:05pm are not automatically matched by SEATS. Orders placed during the pre-opening between 7.30am and approximately 10:00am are batched for the single price opening. Between 4:05pm and 7:00pm, brokers must contact the priority buyer or seller and request to trade manually. If a trade is executed, it must be reported to the market at first opportunity. Orders received after 7.00pm and before 7.30am the next day may be executed off-market at prices mutually agreed between parties. The resulting trades must be reported to the market (through SEATS) by 9.45am before the next available regular trading session (ASX, 2004). During normal trading hours, only "block specials" and "portfolio specials" can be traded off-market. "Block specials" are trades in one security for more than $2 million in value. "Portfolio specials" are trades in multiple securities order with aggregate value of more than $5 million comprising single security trades with value above $200,000.[21] Off-market trades do not, by construction, bias the clustering to differentiate between brokers that trade large parcels versus those that trade smaller parcels. After SEATS closes for regular trading (i.e., after 4:00pm) both large block and smaller trades may be transacted off-market.

The initial classification is based on two factors: (1) the broker house's share of the total off-market trade dollar volume for the entire market, and (2) the broker house's share of the total off-market trade frequency for the entire market. First, the ACECLUS procedure in SAS is used to transform the data such that the resulting within-cluster covariance matrix is spherical. The procedure obtains approximate estimates of the pooled within-cluster covariance matrix and then computes canonical variables to be used in cluster analysis. The clustering analysis was performed using the Ward's minimum-variance method. The statistics used in determining the clusters are presented in Table 4.2. The cubic clustering criterion values (CCC) are all positive, suggesting that all clusters presented in Table 4.2 are

[21] See Appendix C for a more detailed discussion of off-market trades.

either a “potential” cluster (value between 0 and 2) or a “good” cluster (value greater than 2). The pseudo F (PSF) statistic peaks when observations are clustered in three groups. From the PST2 column, possible clustering levels occur at 14 clusters, 11 clusters, seven clusters, five clusters and four clusters.

Table 4.2 Clustering analysis using canonical variables

The results are derived from (1) the broker house’s share of the total off-market dollar volume of trades for the entire market, and (2) the broker house’s share of the total off-market trade frequency for the entire market. Columns 2-5 contain the squared multiple correlations (R^2), pseudo F (*PSF*), t^2 (*PST2*) statistics and cubic clustering criterion (CCC).

Number of Clusters	R^2	*PSF*	*PST2*	*CCC*
15	1.00	4106.25	39.07	26.66
14	1.00	2953.40	0.00	23.62
13	1.00	2243.68	117.77	21.10
12	1.00	1623.32	2.23	18.09
11	0.99	1272.78	0.00	15.86
10	0.99	1094.74	52.28	14.51
9	0.99	988.96	40.09	13.63
8	0.99	913.15	16.41	12.95
7	0.98	770.61	5.17	11.35
6	0.97	599.44	109.75	8.89
5	0.96	471.23	0.00	6.44
4	0.93	358.29	3.49	2.50
3	0.89	361.16	18.44	2.68
2	0.74	254.04	14.79	0.94
1	0.00	0.00	254.04	0.00

The squared multiple correlations, R^2, show that two clusters account for almost three quarters of the variance (about 74%). In other words, only two clusters are necessary to explain approximately three-quarters of the variance. The first cluster comprises broker houses with relatively higher trading conducted off-market, while the second cluster comprises broker houses with relatively lower off-market trading. The orders from the first group of broker houses are assigned “institutional orders”. Of the second group of broker houses with relatively less off-market activity, orders from brokers with Automated Client Order Processing (ACOP) are identified and placed into the second category – “retail traders”. The orders from the remaining brokers are placed into the third category – “others”. Due to the constraint on information with regards to the ACOP information, the clustering analysis is conducted using off-market trading data for November 2001; the qualitative data was available only for that month. Using the November 2001 data resulted in 11 brokers being placed in the institutional group, ten in the retail group and 69 in “others”. As a robustness check, the clustering analysis was performed using data from December

2001; the broker groups were similar. The list of brokers and their group classifications are presented in the Table B.1 in Appendix B.[22]

4.4.2 Alternative categorisation method

The method of classifying the brokers described above has its shortcomings. One is that brokers who offer online trading facilities and who attract retail traders may not have ACOP. An alternative classification of brokers as "retail" is the use of the larger non-advisory internet brokers as a proxy for retail brokers. The financial press reported that the largest four internet brokers in Australia in 2002 were CommSec, E*Trade, Westpac and TD Waterhouse (Pretty, 2002). With a customer base of around 105,000 Westpac was the third-largest online broker in Australia behind CommSec (712,300) and E*Trade (110,000) (Lekakis, 2002). Consolidation of the market in 2003 (after my sample period) saw the sale of TD Waterhouse by it parent company, Toronto Dominion Bank, to CommSec in May 2003 (Kavanagh, 2004). Chapter Five examines the implications of including only the four internet brokers as retail brokers and reclassifying the other brokers previously classified as retail to the "others" category.

4.5 Changes in order flow and trades

The period January 1999 to December 2001 coincided with the active growth of the online broker industry and the rapid uptake of security investment by retail investors in Australia. The following section examines the growth in the online broker industry proxy by retail activity and provides a background to subsequent chapters.

[22] The Australian Stock Exchange published a Participant's Directory in 2001 that lists the broker firms and the type of clients that the brokers nominated that they deal with. The brokers listed as "Institutional" and "Retail" for this study is a smaller (and more restrictive) subset of the ASX published list.

4.5.1 Background on the growth of online trading

The introduction of Internet share trading started in the United States as early as 1994 with K. Aufhauser & Co. Inc. being the first broker firm to offer Internet trading via its WealthWEB (Claude-Gaudillat, 2002). Prior to this, other companies like E*Trade (America) had been providing online trading services through America Online and CompuServe since 1992. But these online services were available via the Internet. In Australia, CommSec became the first broker house to offer Internet share trading, in March 1997. Low execution fees and access to real-time information has attracted many to online trading. It is commonly believed that with the right software and an Internet stockbroker, an investor can arm himself with almost as much information as a professional trader. In addition, investors can place their orders to trade from virtually anywhere in the world. The increase in competition between Internet brokers saw the costs of transactions online plummet. The average commission per online trade in the US fell from $72.68 in 1994 to $53.44 in 1999 and $15.75 in 2000 (Claude-Gaudillat, 2002). Some US internet stockbrokers were even found to provide free trades (Trombly, 2000). Similar scenarios have been seen in Australia. Some of these strategies were (obviously) not viable as consolidation of the market occurred shortly thereafter, with some of the Internet brokers being taken over (this occurred in Australia in 2003).

4.5.2 Trading activity from January 1999 to December 2001

Figure 4.1 shows aggregate trading volume, aggregate value and aggregate number of trades on ASX on a monthly basis over the period January 1999 to December 2001. There was a general increase in trading prior to the April 2000 technology stock "crash". Figure 4.1 shows the number of trades and number of shares traded peaked in March 2000. Subsequent to April 2000, trading volume and trade frequency returned to their levels observed prior to January 2000. However, the gradual increase in the value of shares traded did continue. Taken together, they suggest either a shift in the average trader type or in trading strategy. September 2001 saw the terrorist bombing of the Twin Towers in the city of New York, USA. However, it does not appear to have impacted greatly on trading volume or frequency on the ASX.

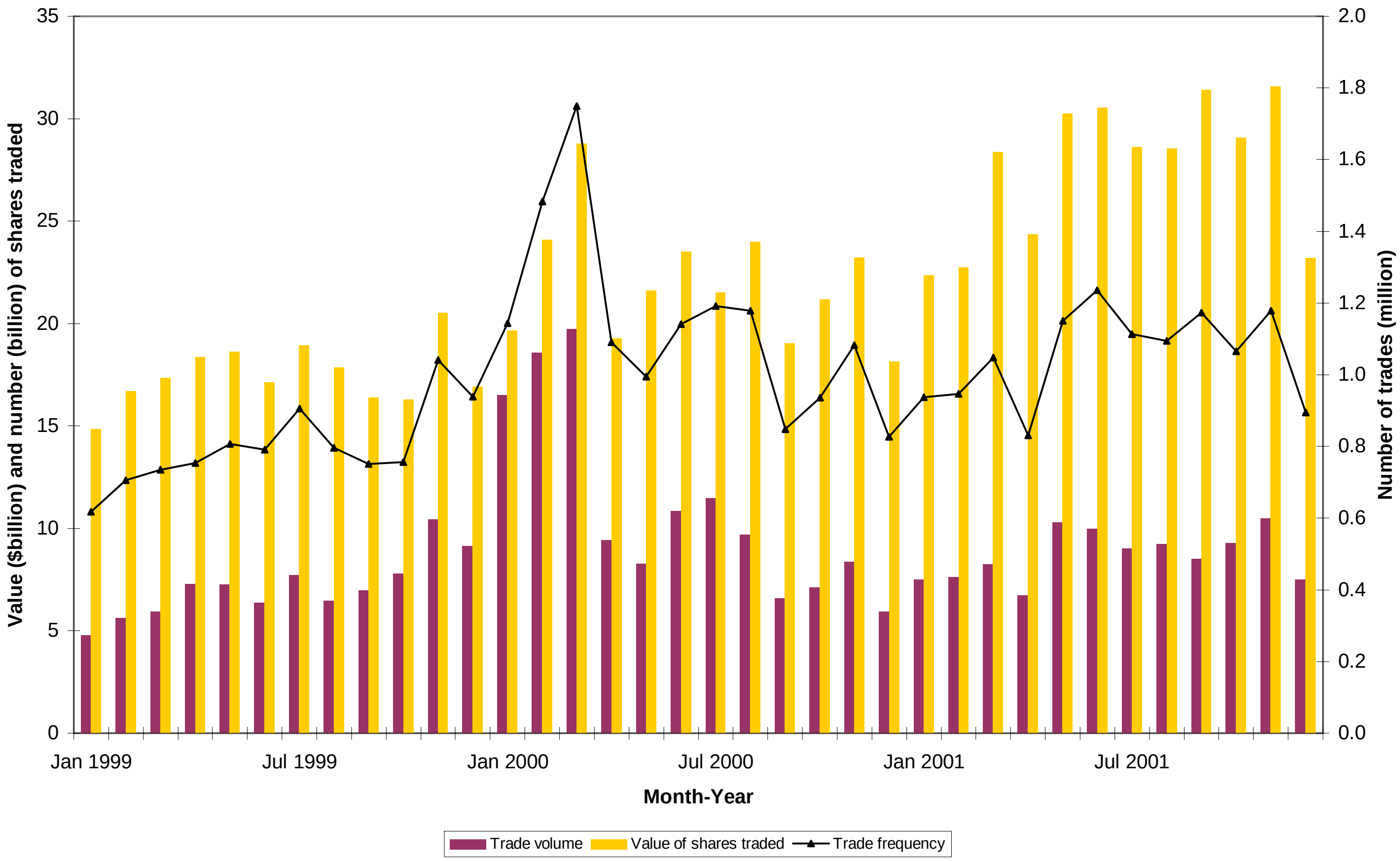

Figure 4.1 Aggregate trading volume, aggregate value and aggregate number of trades on the ASX on a monthly basis from January 1998 to December 2001.

Figure 4.2 plots the average dollar value trade size over the same period. Average trade size decreased prior to April 2000 and increased after it. Two possible interpretations of what may be occurring prior to the April 2000 technology crash are: (1) the shares that were more frequently traded during the run up to April 2000 were those of lower value, and (2) retail traders were entering the share market prior to the crash, having been attracted to the market by discount brokers offering low cost trading opportunities (Sykes, 1999).

The time series pattern in the average number of shares per trade over the three year period is noticeably different from that of average trade size measured in terms of dollar value. There was a gradual increase in the average number of shares per trade, with a sharp peak in January 2000, followed by a decrease over the next five months, after which trading returned to about its level prior to the increase. While there was a sharp decline in the average number of shares per trade over those five months, the average trade size measured by dollar value remained relatively stable. This pattern is likely a function of the increase in share prices during the boom and investors still preferring to place orders of similar value.[23]

As discussed in Wee (1996), the broker fee is an important determinant of how small the average dollar value of each order would be. A small order may not be enough to justify the broker fee involved. Thus the broker fee helps establish a floor to the dollar value of a typical order. Further analysis of the order submission strategy provides additional insight. After April 2000, there was a general increase in the average dollar value of trades while the average number of shares per trade remained stable. This is likely to be due to a shift away from lower priced stocks, thus giving further support to my interpretation of Figure 4.1.

[23] The market index (All Ordinaries Price Index) increased by 16.1% between January 1999 and December 2001 and 10.5% between May 2000 and December 2001

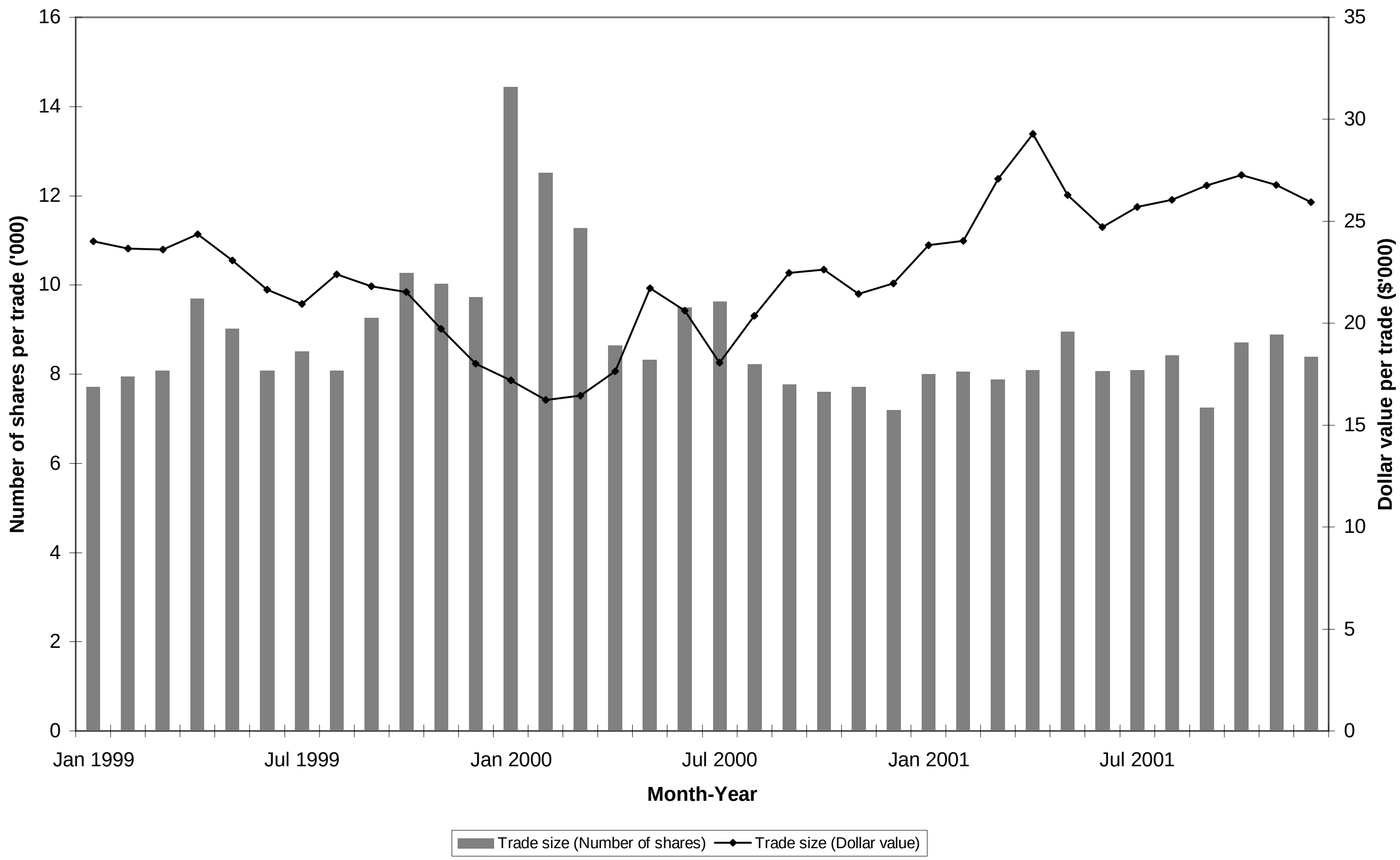

Figure 4.2 Average number of shares per trade and average trade value on a monthly basis from January 1999 to December 2001.

4.5.3 Order submission from January 1999 to December 2001

The aggregate number and volume of orders placed are graphed in Figure 4.3 for institutional and retail traders. The time series of order volume and frequency for both types of trader are similar to those of trading volume and frequency. The number and volume of orders placed were generally lower for retail traders compared to institutional investors. However, during the boom from January to April 2000, both the volume and the number of orders placed were greater for retail investors. The percentage increases in the volume and number of orders for retail traders were greater than the increases for institutional traders. For example, the order volume from retail traders increased by 202% compared to an increase of 167% for institutional traders over the period December 1999 to March 2000.

The average order size of institutional and retail traders graphed in Figure 4.4 provides some interesting results. While retail traders placed smaller orders in terms of their dollar value, the number of shares in each order was comparable to that of institutional orders, except from January to March 2000. This suggests that the type of share traded by the two types of trader is substantially different and that activity from retail traders is found mainly in stocks with smaller denominations. This observation is supported by the results in Table 4.3. During the period April 1999 to March 2000, 25.61% of the order volume was placed by institutional traders and 24.26% by retail traders. Over that same period, approximately 75% of the order volume from retail traders was in stocks with denomination $0.50 or less, while institutional traders placed 21% of their order volume in similarly priced stocks.

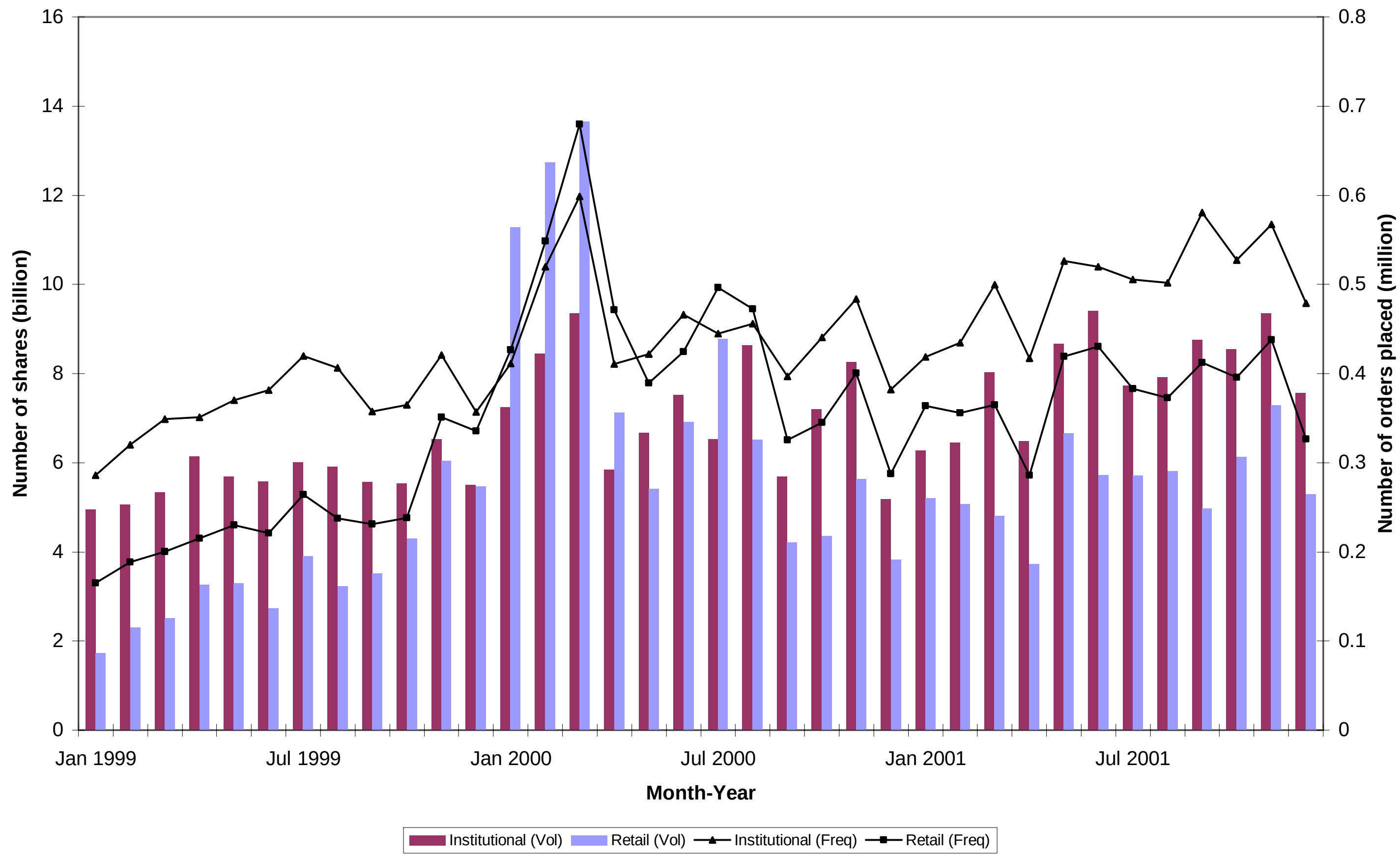

Figure 4.3 Aggregate number of shares and aggregate number of orders submitted by institutional and retail traders on a monthly basis from January 1999 to December 2001.

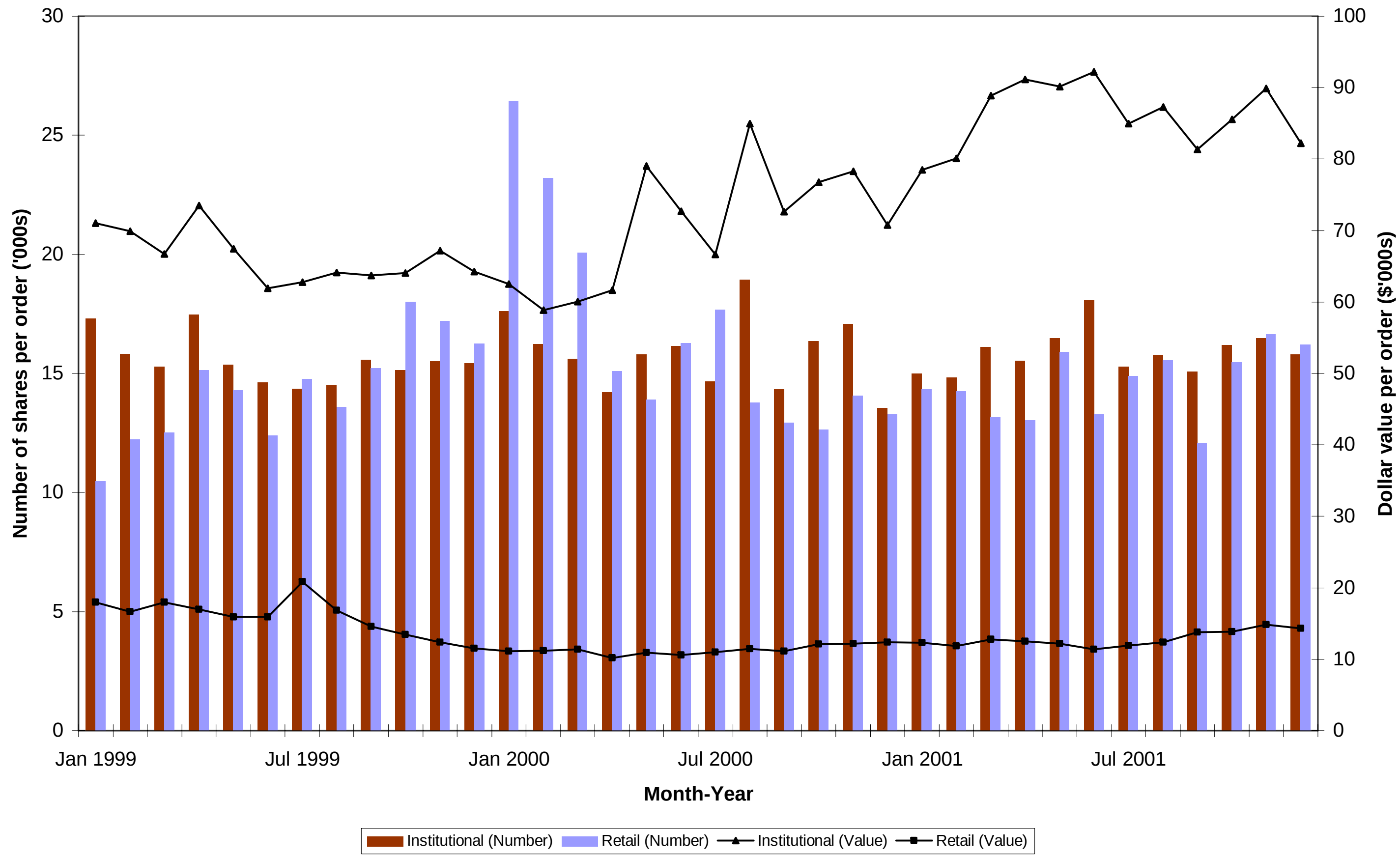

Figure 4.4 Average number of shares per order and average dollar value per order measured on a monthly basis for institutional and retail traders from January 1999 to December 2001.

Table 4.3 Stock price, trader type and order volume

Breakdown of order volume placed by different classes of trader according to the order price in the two sub-periods April 1999 to March 2000 and May 2000 to April 2001 inclusive.

	Institutional (%)	Retail (%)	Others (%)	Total (%)
		Apr 1999-Mar 2000		
$\$0.00 < p \leq \$0.50$	5.41	18.43	36.67	60.51
$\$0.50 < p \leq \$1.00$	2.48	2.17	4.44	9.08
$\$1.00 < p \leq \$5.00$	11.23	2.99	6.78	20.99
$p > \$5.00$	6.49	0.68	2.25	9.42
	25.61	24.26	50.13	100.00
		May 2000-Apr 2001		
$\$0.00 < p \leq \$0.50$	3.78	18.05	26.48	48.31
$\$0.50 < p \leq \$1.00$	3.87	2.81	4.64	11.32
$\$1.00 < p \leq \$5.00$	15.34	3.82	7.96	27.11
$p > \$5.00$	9.74	0.78	2.73	13.25
	32.74	25.45	41.81	100.00

These findings are consistent with prior research on institutional trading in the US. For example, Falkenstein (1996) found mutual funds tend to avoid small firms and low priced stocks. Using a dataset covering a longer time period, Gompers and Metrick (2001) found institutional investors differ from other investors in their stock selection. Institutional investors prefer larger, more liquid stocks and this demand was stable over the sample period (1980-1996). This preference for larger stocks could be due to the higher transaction costs (such as percentage bid-ask spread) associated with lower priced stocks (McInish and Wood, 1992).

Research generally focuses on larger, more liquid stocks partly due to problems associated with analysing infrequently traded stocks and also because institutions trade mainly in the larger stocks. The activity of retail traders in these larger, more liquid stocks may be relatively small and their effect insignificant. This provides further justification for our sample selection criteria discussed in Section 4.2.

As explained previously, as a robustness check, only the top four online broker houses were classified as retail traders. Figure 4.3 and Figure 4.4 were reproduced with the new classification. As expected with the lower number of broker houses in the retail traders category, a lower number and volume of orders appears to have been placed by retail traders (Figure 4.5). In addition, the average number of shares in each retail order and their average value are smaller in Figure 4.6 than the corresponding numbers in Figure 4.4. The use of the first classification method could have included some larger traders and possibly institutional traders. This could bias the results against finding a significant difference between the two groups. The analysis should be done with this in mind.

To support the above observations from the graphs, Table 4.4 compares the average order value, volume, frequency and size for ASX stocks over two sub-periods (1) April 1999 to March 2000 and (2) May 2000 to March 2001. The order flow data is further analysed by using the sub groupings: (1) institutional and (2) retail traders. Results in Table 4.4 (Panel A) show that the number of shares transacted increased over the period April 1999 to April 2001 for the entire market and also for institutional traders. However, the same was not true for retail traders, since the number of shares transacted by retail traders decreased.

As shown in Figure 4.3, the order volume from retail traders peaked during the months prior to the April 2000 crash. The change in order volume measured by dollar value (Table 4.4 Panel B) is not consistent with the change measured by the number of shares, for institutional traders. The average daily value of shares transacted decreased significantly. It suggests that institutional traders are trading more shares and might have been picking up the technology stocks that declined in value due to the technology crash. Table 4.4 Panel C shows that the frequency of orders placed increased significantly over the two sub-periods for all groupings. The average number of shares per order decreased for the market as a whole and for retail traders. There was no significant change in average order size (measured by the number of shares) for institutional traders. The average order size (in terms of dollar value of shares) increased for the market as a whole and for the sub-group of institutional traders but decreased for the sub-group of retail traders. Table 4.4 generally supports the observations from the graphs.

Table 4.4 Comparison of order flow across time

Tests for changes in the average daily volume, frequency, size and value of orders placed by institutional and retail traders over the period April 1999 to April 2001.

	Period	N	Mean	*t*-statistic	25% quartile	75% quartile
Panel A: Average daily order volume (number of shares transacted) (million)						
All	4/99-3/00	254	1,250		1,075	1,415
	5/00-4/01	253	1,630	(10.730)***	1,338	1,813
Institutional	4/99-3/00	254	305		249	354
	5/00-4/01	253	328	(2.460)**	272	357
Retail	4/99-3/00	254	289		150	375
	5/00-4/01	253	255	(-2.520)**	206	280
Panel B: Average daily value of shares transacted ($million)						
All	4/99-3/00	254	2,030		1,717	2,333
	5/00-4/01	253	2,420	(7.850)***	2,076	2,657
Institutional	4/99-3/00	254	1,190		750	1,510
	5/00-4/01	253	1,000	(-4.460)***	854	1,065
Retail	4/99-3/00	254	212		159	236
	5/00-4/01	253	209	(-0.430)	180	230
Panel C: Average daily number of orders						
All	4/99-3/00	254	59,847		46,095	72,653
	5/00-4/01	253	62,938	(2.280)**	57,494	67,284
Institutional	4/99-3/00	254	19,520		17,093	22,272
	5/00-4/01	253	20,793	(3.640)***	18,408	22,545
Retail	4/99-3/00	254	15,665		10,606	20,514
	5/00-4/01	253	17,835	(4.460)***	15,845	19,278
Panel D: Average order size (number of shares)						
All	4/99-3/00	15,200,000	19,899		1,170	15,000
	5/00-4/01	15,900,000	15,900	(-42.000)***	1,000	10,000
Institutional	4/99-3/00	4,960,000	15,622		1,300	11,000
	5/00-4/01	5,260,000	15,756	(0.670)	1,152	10,000
Retail	4/99-3/00	3,980,000	18,444		1,000	10,000
	5/00-4/01	4,510,000	14,281	(-69.550)***	1,000	10,000
Panel E: Average order size (dollar value)						
All	4/99-3/00	15,200,000	33,931		3,903	26,800
	5/00-4/01	15,900,000	38,446	(13.850)***	3,268	26,400
Institutional	4/99-3/00	4,960,000	63,810		6,000	69,000
	5/00-4/01	5,260,000	78,537	(20.180)***	5,700	79,488
Retail	4/99-3/00	3,980,000	13,513		2,900	11,813
	5/00-4/01	4,510,000	11,705	(-5.750)***	2,450	10,500

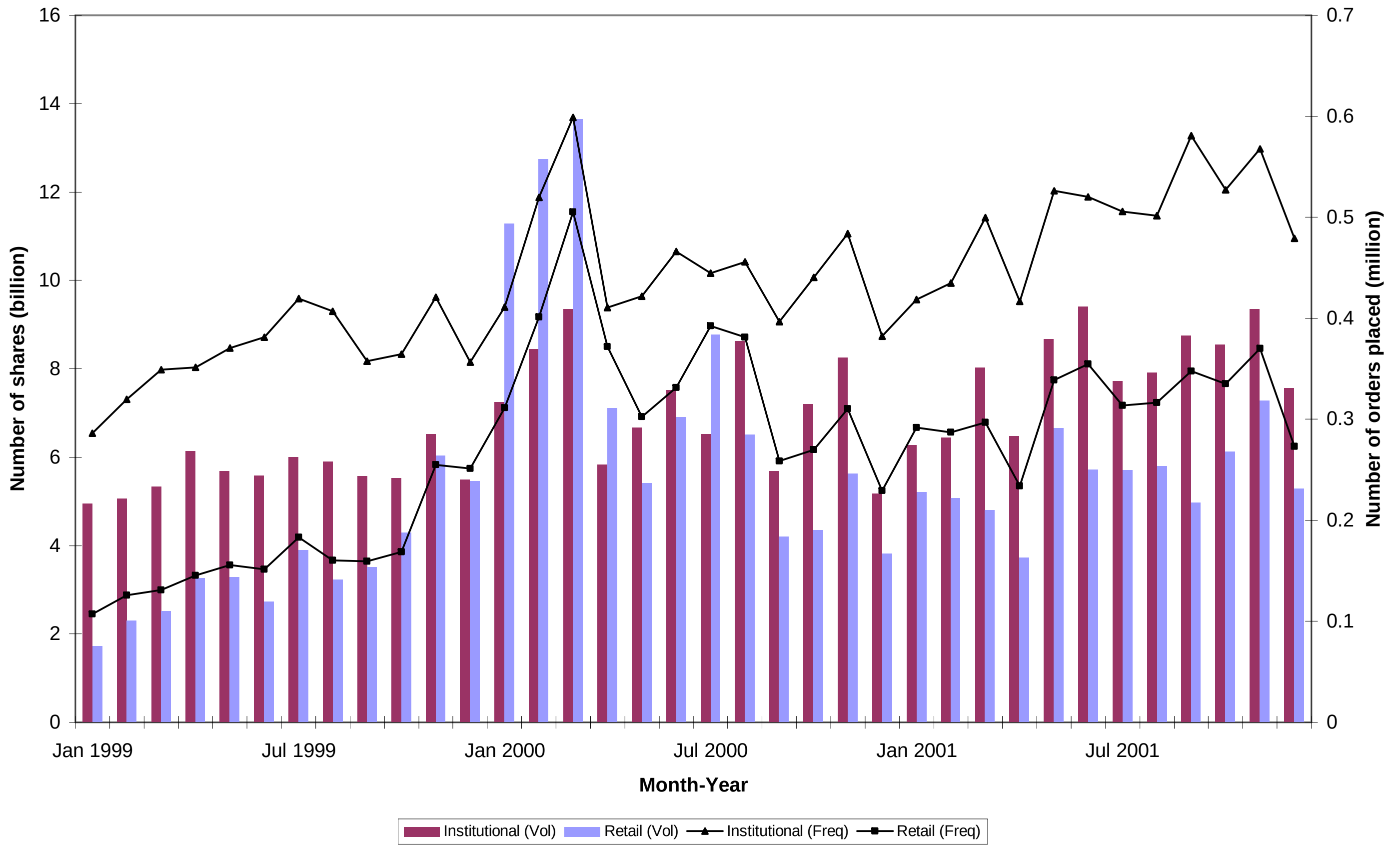

Figure 4.5 Monthly order volume and order frequency from January 1999 to December 2001 using an alternative classification. The retail category comprises only the top four online broker houses.

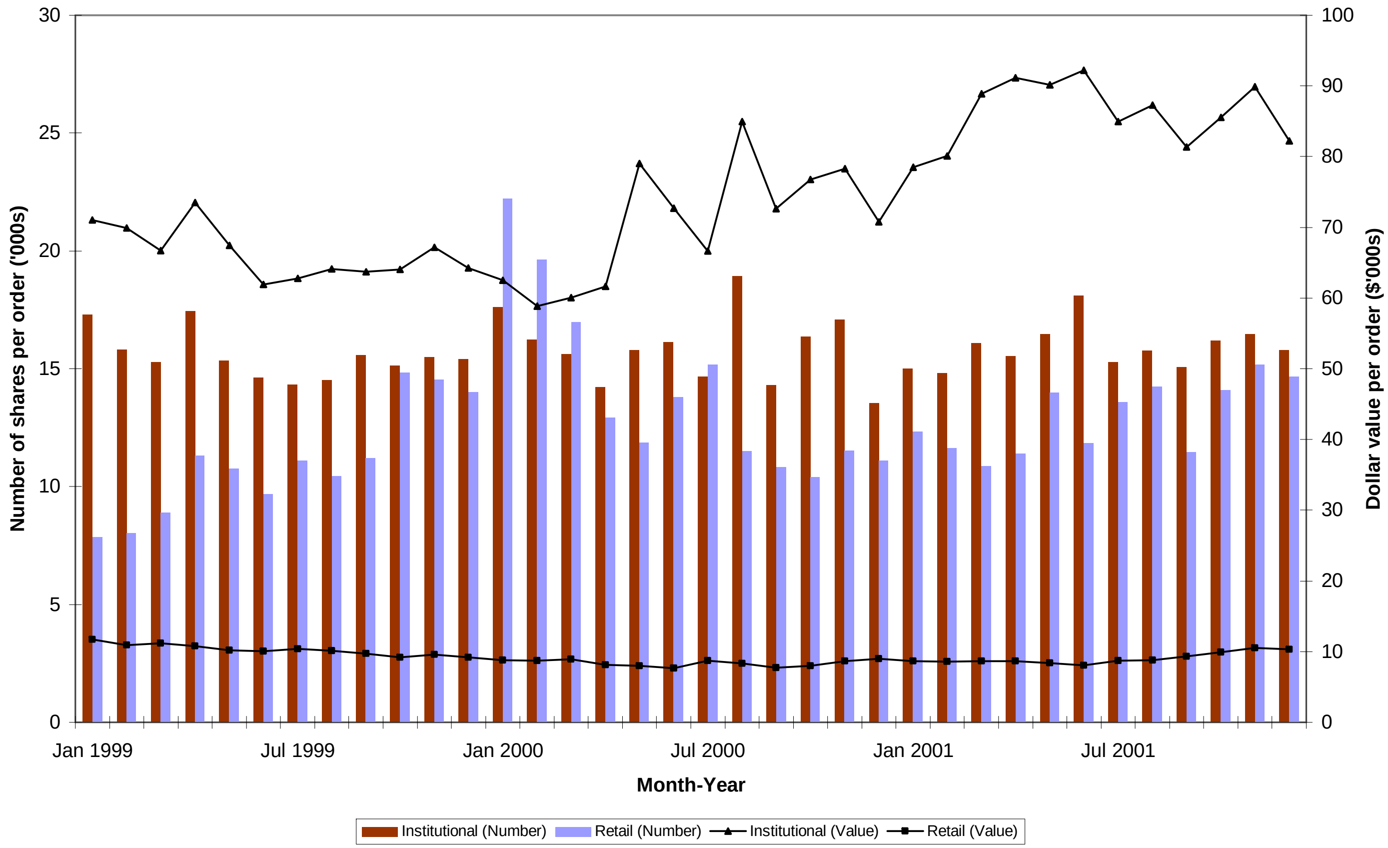

Figure 4.6 Monthly average order size measured by number of shares per order and dollar value per order from January 1999 to December 2001 using an alternative classification. The retail category comprises only the top four online broker houses.

4.6 Summary

This chapter discusses the data used in the analysis of retail versus institutional trading. It also discusses the clustering procedure used to classify brokers into the two trader groups and the problems associated with it. A general description of the market conditions over the three year period, 1999 to 2001, was presented to provide background for the analysis and discussion that follows.

The composition of participants on the Australian financial market changed over the three years examined. Prior to the technology crash of April 2000, there is an increase in order flow from retail traders. The graphs in this chapter show order volume (number of shares) from retail traders exceeded institutional traders during the months prior to the crash. No large fluctuations in order volume or order frequency are observed in 2001, suggesting that the changes in the composition in the market may have stabilised. The months prior to the April 2000 crash also saw large changes in the average order size of retail traders. Again, it stabilises in 2001.

Important results to note include significant differences in the order size of the different trader types and differences in their activity levels in shares with different denominations.

CHAPTER FIVE
INFORMATION CONTENT OF TRADER IDENTITY

5.1 Introduction

Madhavan (2000) suggests the identity of the broker submitting an order may provide valuable information about the source and motivation for the trade. An important issue in the financial microstructure literature is the information content of trades, which is the nature of any information that can be inferred from trading activity. Prior literature has shown that features of the trading process may reveal information to market participants. For instance, Easley and O'Hara (1987) suggest trade size provides information because private information about the security's true value is correlated with trade size. This chapter examines the price impact by trader type and provides preliminary evidence on the information content of trader identity.

Easley and O'Hara (1992) model the way traders learn from both trades and the lack of trades. Empirically, there is no clear consensus about what drives the relation between trades and prices: trade size or the occurrence of trades per se. Jones et al. (1994b) find the occurrence of trades themselves contains relevant information for pricing securities. However, Chan and Fong (2000) argue the finding in Jones et al. is flawed and trade size does contain information. Their failure to show a significant relationship between trade size and price impact is because the relationship is not linear as predicted in the earlier market microstructure models. The stealth trading hypothesis (Barclay and Warner, 1993), for example, suggests the relationship may be convex. The literature to date has implied trade size is an unsatisfactory indicator of information risk and that traders learn from other aspects of the trading process (Pascual et al., 2004).

There is an extensive literature on the effect of trades or orders placed by different traders on share price using the size of order placed as a proxy for trader type. More recently, researchers have used the "size" of the investor himself as a proxy for the identity of the trader (e.g., Ekholm and Pasternack, 2002). The ideal research setting would involve the use of the identity of the trader such as the information available from the Australian Clearing House Electronic Sub-register System (CHESS). However, the CHESS records allow only the tracking of shareholders' daily aggregate holdings on each account and do not allow the identification of the trader behind each separate transaction (Da Silva Rosa et al., 2003). This study extends the research by using an alternative way of identifying the type of trader, namely the identity of the broker who enters the order on SEATS.

Informed traders profit from trading if prices are not at full-information levels. The price effect of the order reveals the knowledge of the trader who submitted the order. A number of theoretical papers predict traders with private information will choose a different order size in contrast to an uninformed trader. Easley and O'Hara (1987) argue informed traders would trade large blocks due to the decline in per share transaction cost and their aversion to uncertain price movements. On the other hand, Seppi (1990) finds the costs of trading blocks are too great for informed traders. As a result, they are more likely to submit smaller orders. Empirical work by Hasbrouck (1991) and Hiemstra and Jones (1994), among others, find price-change and order size are non-linearly related. More recent research by Chakravarty (2001) shows that medium-size trades initiated by institutional traders are associated with a disproportionately large cumulative price impact. These findings corroborate the stealth trading hypothesis loosely formulated by Barclay and Warner (1993). The research to date indicates that trade size may not be a reliable proxy for "informativeness".

This chapter investigates the relationship between a broker's identity and the price effect of their orders. Specifically, it investigates whether the broker's identity provides information content, which is measured using the price impact of the trades. The analysis will allow the evaluation of hypotheses H_1 and H_2. Hypothesis H_1 predicts orders placed by retail traders have a smaller permanent price effect when compared to orders placed by institutional traders; and hypothesis H_2 predicts orders placed by retail traders have a larger temporary price effect when compared to orders placed by institutional traders.

5.2 Method

The literature on block trading suggests ways to infer the information content of trades. If a sale of securities indicates that the seller possesses private information, the market price of the share will fall to reflect the expected value of the information. Scholes (1972) uses this concept to formulate his information hypothesis. Under that hypothesis, the downward price adjustment to the price of a stock when a large block is sold in the market is the expected value of information contained in the large-block sale. The adjustment is permanent and is not a temporary inducement to other parties to buy, as the alternative price-pressure hypothesis suggests. Also, the effect is not necessarily reduced to just the price change that occurs contemporaneously with the trade or order, but may be associated with a price effect that precedes or follows the trade or order. The block trade literature suggests that the price effect of different size blocks can be decomposed into temporary and permanent price effects. The following subsections describe the method used in this thesis to examine the temporary and permanent effects of trades and orders placed by different traders.

5.2.1 Analysis of the permanent price effect of orders by institutional and retail traders

The method used in the study of block trades is extended to examine the price effect of market and marketable limit orders placed by retail and institutional traders. The prices examined here are the aggregated traded prices of the market and marketable limit orders.

The total price effect of an order is defined as the price change from the price some known number of orders (*j*) before the order of interest, P_{t-j}, until the order is executed at, P_t. The total price change due to an order is $\left(P_t - P_{t-j}\right)$. The permanent price change due to an order is defined as the change in price from order $\left(t-j\right)$ to order $\left(t+k\right)$; that is until '*k*' transactions after the order of interest has taken place.

Hence the permanent price change due to an order is $\left(P_{t+k} - P_{t-j}\right)$. The permanent price effect corresponds to the supposed information content of the order. The greater the information contained in the order, the larger its permanent price effect.

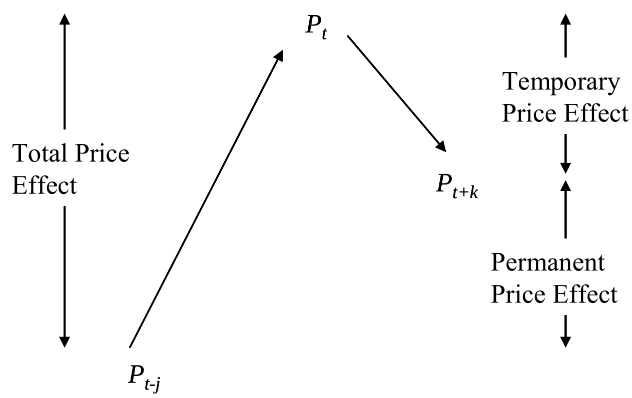

Figure 5.1 Decomposition of the total price effect of a buy order traded at P_t into the temporary and permanent price effect.

Kyle (1985) views market depth as the size of the order flow innovation that is required to make the price move; thus the total price effect is a proxy for the depth of the market. An order will have a larger total price effect if the market is not as deep. The permanent price effect corresponds to the supposed information content of the order. The greater the information content, the larger the permanent price effect. The temporary component corresponds to the inventory costs of traders who provide the liquidity to absorb the order. It is unclear how that would apply in the Australian setting because, unlike the NYSE for example, where market makers are required to facilitate liquidity, the ASX operates a relatively transparent limit order book, where liquidity is provided by the public limit order traders. Walsh argues the temporary effect should "correspond directly to the trade-off between inventory costs and informational benefits that the trader on the other side of the trade pays or receives" (Walsh, 1997, p. 51).

The choice of *j* and *k* is arbitrary. While it is argued that prices in an efficient market adjust to new information quickly, all investors may not be able to react immediately to new information, in reality. Hillmer and Yu (1979) study a small sample of US firms and find prices adjust to new information in public announcements rapidly but the speed of adjustment depends on the size of the firm. In his study of information content of different order sizes, Walsh (1997) uses two sets of values for *j* and *k*, namely *k*=*j*=1 and *k*=*j*=5 as a robustness check. This study adopts a similar procedure. The transactions immediately before (P_{t-1}) and after (P_{t+1}) the trade in question, and also the fifth trade before (P_{t-5}) and after (P_{t+5}) the trade in question, are used to calculate the price effects.

5.2.2 Calculation of order price

Marketable limit orders placed do not necessarily trade at their nominated prices. They can trade at prices that are more favourable, resulting in a "true" buy (ask) order price that is lower (higher) than the nominated price. In a market with volatile prices, traders can place marketable limit orders to safeguard themselves from uncertain execution prices and at the same time ensure execution. For example, a marketable limit sell order will specify the lowest sale price acceptable to the seller and trade against all available bids above the sell price.

To calculate the permanent and temporary price effects, the order's average traded price is computed as the volume weighted traded price for the order. Any part of an order that is not traded is excluded from the calculation. That is,

$$\text{Order average traded price} = \frac{\sum_{i=1}^{n} TP_i \times Vol_i}{\sum_{i=1}^{n} Vol_i}$$

where TP_i and Vol_i are the price and volume, respectively, of each trade *i* executed as a result of the order.

5.2.3 Measure of order size

In analysing the price effect of an order, there is a need to control for the size ($Size_t$) of the orders being placed because prior studies have shown that the price effect is related to size (Walsh, 1997). While many studies have examined trade or order size, there is no standard measure of size itself and a number of variations have been used in the past. The simplest measures are the number and dollar value of shares in the order. However, these measures are not suitable for the purposes of measuring price effects because the number of shares and the dollar value of shares that can be readily absorbed by the market differ for each stock. Even when considering the same stock, market conditions may change over time, thereby affecting the market's price reaction to a particular order size. Thus, order size should be measured relative to the local trading volume when considering price impact.

Two measures of size are used in this thesis, PMEAN and DTOTAL. They are defined as follows:

PMEAN – the number of shares in order *i* expressed as a proportion of the average daily number of shares of the stock traded over the sample period:

$$\frac{Q_{i,t}}{\frac{1}{n}\left(\sum_{t=1}^{n} TQ_t\right)}$$

where $Q_{i,t}$ is the quantity of order, *i,* made during day *t* and TQ_t is the total quantity of shares traded during day *t*.

DTOTAL – the number of shares expressed as a proportion of the total number of shares in that stock that are traded on the day of the trade of interest:

$$\frac{Q_{i,t}}{TQ_t}$$

5.2.4 Regression analysis of the permanent price effect on trader identity

The relationship between price effect and order size has been documented in earlier research (Walsh, 1997). I examine the impact of adding the identity of the trader to the price effect and order size relationship. A simple model is used to analyse the permanent effect on price (PPE_t) of order size ($Size_t$) and the identity of the trader:

$$PPE_t = \sum_{j=1}^{5}\left(\alpha_j Size_{j,t} + \alpha_{j+5} Size_{j,t} \times DumIns_t + \alpha_{j+10} Size_{j,t} \times DumRet_t\right) + \alpha_{16} DumAggr_t$$
$$+\alpha_{17} Depth_t^{Opp} + \alpha_{18} \Delta Depth_t^{Opp} + \varepsilon_t$$

where

$Size_{j,t}$	=	a dummy variable equal to one if order size is in quintile j and zero otherwise (ranges from j=1, smallest, to j=5, largest order),
$DumIns_t$	=	a dummy variable equal to one for orders placed through institutional brokers,
$DumRet_t$	=	a dummy variable equal to one for orders placed through retail brokers,
$DumAggr_t$	=	a dummy variable equal to one for orders that have buy (ask) order price greater (less) than the best sell (buy) order price (i.e., market buy (sell) orders that walk up (down) the book) ,
$Depth_t^{Opp}$	=	the standardised depth on the opposing side of the order prior to the order being placed,[24]
$\Delta Depth_t^{Opp}$	=	the difference between the depth on the opposite side at transaction time, t-5, and transaction time, t-1.

The above model does not contain an intercept term because there are five size dummy variables (one for each size quintile). It is important to note that the placement of orders by rational traders is likely to be conditioned on their anticipation of any impact on price (Griffiths et al., 2000). Where the price impact is expected to be large, rational traders are likely to reduce the size of their order or avoid placing orders altogether. Thus the findings here are conditional on the orders being placed.

[24] Depth is standardised using the stock's depth on the same side over the period examined (Chan et al., 1995). For example, we standardised bid depth by firstly calculating the mean and standard deviation of the depth on the bid side for the period examined. Each depth measure is standardised by subtracting the mean and dividing the result by the standard deviation.

Wagner and Edwards (1993) suggest order size, market depth, trade urgency and broker skill all affect the price impact of an order. A number of explanatory variables are included in the model to isolate the information effect of trader identity. The first set of variables is the order size. As the relationship between size and price effect may not be linear, the specification above allows us to compare the information content of orders of different size directly from the regression coefficients (Chan and Fong, 2000). Suppose orders in a medium size category (e.g., j=3) are more likely to be information motivated; then the coefficient α_3 is expected to be the highest among the coefficients α_1 to α_5.

Studies that have examined trade or order size have typically used three (Barclay and Warner, 1993) or five (Chan and Fong, 2000) groupings. For this thesis, the choice of the number of groups for classifying order size is affected by the distribution of order size by trader type. While choosing a larger number of groups allows a finer analysis of the relation between order size and price effect, the number of groups is constrained by retail traders placing relatively few larger orders. For instance, initial analysis using ten groups revealed no retail orders in the largest order size decile. I settled on five.

The interaction variables $Size_{j,t} \times DumIns_t$ and $Size_{j,t} \times DumRet_t$ are included to allow the sensitivity of price to order size to vary by trader type. Traders are likely to vary their order size conditional on the information they have. While the relationship between size and price impact is expected to vary in a similar direction across different trader type, the magnitude of the coefficient may not be the same. Keloharju and Torstila (2002) suggest that when an individual investor and an institutional investor place orders of similar size, the individual investor is likely to be risking a much large proportion of his wealth. Thus, the individual investor can be expected to be more informed when placing a similarly large order compared to an institutional trader.

Another explanatory variable is the aggressiveness of the order, $DumAggr_t$. The orders examined here comprise market and marketable limit orders. While they are all more aggressive compared to limit orders, they are, within the group, differentiable from each other. Buy (sell) orders that have a nominated price greater (less) than the sell (buy) side are more aggressive than the buy (sell) orders that have a price equal to the opposing side. More aggressive orders are likely to have a greater price impact as they convey more information and are likely to cause a change in the best opposing price. For example, buy orders with price greater than the best sell can "walk up" the order book if there is insufficient depth at the best sell to complete the order. Depth on the opposing side to the order, $Depth_t^{Opp}$, will affect the price impact of the order. The lack of depth on the opposing side will result in a larger price impact. As the stock variable can incorporate stale orders, the change in depth, $\Delta Depth_t^{Opp}$, is also included. It provides a more current indication of how the market is moving.

The model is analysed for both bid and ask orders and also for stocks in the first and last deciles. Griffiths et al. (2000) suggest aggressive buys are more likely to be motivated by information than aggressive sells. Purchases and sales are examined separately due to the possible asymmetry in the relationship between order size, trader identity and price effect. To obtain the same signed coefficients for the independent variables, $-PE_t$ is used for the ask orders. Two measures of the permanent (total) price effect are used in the regressions: $PPE1_t$ and $PPE2_t$ ($TPE1_t$ and $TPE2_t$). These provide evidence on the effect of the durations examined, j and k. The computation of $PPE1_t$ and $TPE1_t$ uses one lead (j=1) and one lag (k=1) while the computation of $PPE2_t$ and $TPE2_t$ uses five leads (j=5) and five lags (k=5).

5.3 Data

The dataset comprises 18 fully paid ordinary shares selected from the top and 18 from the bottom deciles of the 200 securities most traded on the ASX.[25] The list of securities and their summary statistics were presented in Chapter Four. The data includes all market or marketable limit orders placed during normal trading hours, i.e. between 10 a.m. and 4 p.m. The period analysed is January 2001 to December 2001. Investigation of outliers in the data set provided interesting insights into the order placement errors made by traders. For example, the maximum difference

[25] Activity is measured using the dollar trading value of the security for the year 2001.

between the bid order price and traded price was \$739.53. It resulted from an order being placed at \$747.00 and executed at \$7.47. Clearly, this is an error of the SEATS terminal operator.[26] Not surprisingly, the maximum for the ask orders is not as large as for the bid orders as the entry error can only be as large as the share price.

The transaction records are analysed for outliers and erroneous data. By imposing a filter of $(0.5 \times \text{Trade Price}) < \text{Order price} < (1.5 \times \text{Trade Price})$, 115 of the ask orders and 44 of the bid orders were eliminated. However, the filter does not change the weighted mean number of trades executed from the order placed, suggesting the outliers were small orders. Removing the 159 cases has a trivial impact on the sample size, given the number of observations in the dataset: removing outliers reduces the number of observations from 2,677,710 to 2,677,551. The data set was further reduced by 5,167 transactions where the market conditions could not be determined due to the absence of orders on the opposite side of the market. The final sample therefore comprises 2,672,384 orders.

5.3.1 Summary statistics

Table 5.1 presents summary statistics for the marketable limit and market orders examined (henceforth collectively known as marketable orders) and the market conditions at the time the orders were placed. There are 1,315,894 sell and 1,356,483 buy orders that resulted in the execution of trades. About half were placed by institutional traders and 18% by retail traders. Consistent with the previous discussion, orders placed by retail traders are smaller than those placed by institutional and other traders. This is independent of whether order size is measured by number of shares per order or dollar value per order. Using both *PMEAN* and *DTOTAL*, orders placed by retail traders are smaller than those by institutional and other traders.

Table 5.1 shows the difference between the order price and volume-weighted traded price. On average, marketable ask (bid) orders are traded at 0.341 (0.358) cents

[26] The trade was not reversed perhaps due to the price it traded at. The trade was for 500 shares and executed at the best ask price of \$7.47. If the stock had been illiquid, the amount of losses would have been much larger.

higher (lower) than the offer (bid) price of the order. In comparison with institutional and other traders, retail traders are more aggressive with their order placement where 27.8% (30.4%) of ask (bid) orders placed by retail traders have prices that are lower (higher) than the best bid (ask) at the time the order is placed compared to 3.7% (3.6%) for institutional traders. As a result, ask orders placed by retail traders are traded at 1.49 cents above the offer price stated on the order while bid orders are traded at 1.66 cents lower than the bid price stated.

The reason why retail traders offer (bid) at a lower (higher) price than that which the market is currently willing to accept can be explained by the following. Retail traders may be averse to the use of market orders for fear of price uncertainty. Price uncertainty can arise because of the delay in routing the order through to SEATS. The delay could be due to reasons such as Internet traffic and brokers not offering straight through processing (Synnott, 2002, p. 6). As such, retail traders who are impatient to trade but at the same time want a certain price will place aggressive marketable limit orders. The strategy of placing more aggressive orders does not necessarily disadvantage retail traders as their orders are small in size and are not likely to "walk up or down" far on the schedule when there is inadequate depth at the best opposite price. The delay in routing orders from the online brokers to SEATS is less common as most of the larger online brokers have straight through processing.

Table 5.1 shows marketable orders are larger than the standing limit order on the schedule with the highest priority. On average, each marketable ask (bid) order results in 1.41 (1.37) trades being executed.[27] The number of trades against a marketable order placed by a retail trader is smaller than for that placed by an institutional trader. On average 1.54 trades are executed when a marketable ask order is placed by an institutional trader compared to 1.21 when placed by a retail trader. This is consistent with the discussion in Chapter Four, that the orders of retail traders are generally smaller than institutional traders.[28]

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[27] The largest number of trades that resulted from a single order being placed is 450. This was for a large block sale of Telstra (1,000,000) shares at $5.00.
[28] The number of trades executed when a market order or marketable limit order arrives will nevertheless depend on the depth and size of orders available on the schedule on the opposing side.

Table 5.1 Descriptive statistics for marketable limit and market orders examined

The table presents descriptive statistics for all marketable limit and market orders placed on the ASX during the year 2001. Panel A presents the statistics for ask orders and Panel B for buy orders. The second column shows the number of order placed by the different trader types. The third column expresses the number as a percentage of the total number of orders analysed. Average order size is expressed in terms of number of shares (#Order Size), dollar value ($Order Size), as a proportion of the average daily number of shares traded over the sample period for the company (PMEAN) and as a proportion of the total number of shares in that company that are traded on the day of the trade of interest (DTOTAL). Price Imp is the price improvement between order price and volume-weighted trade price; for bid orders it is calculated as the order price less the volume-weighted traded price and for ask orders it is calculated as the volume-weighted traded price less the order price (in cents). #Trades is the number of trades executed as a result of the market or marketable limit order. Depth on Opposite Side shows the standardised depth (#shares) on the opposing side of the order placed. The last column shows the percentage of ask (bid) orders that are placed with order price lower (greater) than the best order on the opposing side.

Trader Type	Number of Orders	Percentage of total orders placed (%)	#Order Size	$Order Size	PMEAN	DTOTAL	Price Imp. (¢)	#Trades	Depth on Opposite Side	Percentage of orders placed that are aggressively priced (%)
					Panel A: Ask Orders					
Institutional	629,929	24	8,308	94,400	0.004	0.003	0.069	1.540	-0.003	3.7
Others	451,258	17	4,470	42,690	0.003	0.004	0.123	1.334	-0.005	5.0
Retail	234,713	9	2,455	16,613	0.002	0.002	1.491	1.206	0.018	27.8
All	1,315,900	49	5,948	62,793	0.003	0.003	0.341	1.409	0.000	8.5
					Panel B: Bid Orders					
Institutional	684,541	26	8,772	100,434	0.004	0.004	0.063	1.475	-0.057	3.6
Others	439,516	16	4,504	43,372	0.003	0.003	0.127	1.307	0.041	5.6
Retail	232,427	9	2,569	17,792	0.002	0.002	1.663	1.186	0.088	30.4
All	1,356,484	51	6,327	67,785	0.003	0.003	0.358	1.371	0.000	8.8

5.3.2 Sequence of trades

Table 5.2 shows the sequence of marketable orders placed by different trader types. The previous literature has shown that the probability of a given type of order occurring is larger after this event has just occurred than it would be unconditionally (Biais et al., 1995). Biais et al. label this the "diagonal effect" and propose three alternative hypotheses for this phenomenon: (1) strategic order splitting, (2) traders imitating each other and (3) traders reacting similarly but successively to the same events.

From Panel A, the conditional relative frequency of an institutional sell order after an institutional sell order, $P(Type_t = Ins \cap Sell \mid Type_{t-1} = Ins \cap Sell)$, is greater than the unconditional relative frequency of observing an institutional order, $P(Type_t = Ins \cap Sell)$. This is the same for other types of order. The data is further partitioned into three periods of the day: (1) 10:00a.m.-12:00p.m., (2) 12:00p.m.-2:00p.m. and (3) 2:00p.m.-4:00p.m. As shown in Panels B, C and D of Table 5.2, the conditional relative frequency of an order after an order of the same type is higher than the unconditional relative frequency of observing an order of that type, irrespective of the time of day.

Table 5.3 shows that when an order is conditioned on the same side as the previous order, the percentage of cases where the two successive orders are at the same price is 76%. The unconditional frequency percentage is 63%. The results in Table 5.2 and 5.3 suggest that the probability of observing the same side, trader type and traded price in the second of two consecutive orders is higher than the unconditional probability of observing two consecutive orders at the same price. The computation of the permanent price effect may be overstated and the temporary price effect may be understated for some orders if this is not taken into consideration. Robustness checks will be conducted to accommodate this possibility, whereby orders from the same trader type are amalgamated.

Table 5.2 Frequency of events at transaction time *t* conditional upon the previous event type at transaction time *t-1*

The table presents the frequency of events conditional upon the previous event type and the relative frequencies are in parentheses. The events are either bid or ask orders placed by the three trader types. Each row corresponds to a given event at transaction time *t*-1. Each column corresponds to a given event at transaction time *t*. Each row can be thought of as a probability vector that adds up to 1. To facilitate interpretation, events with percent frequency greater than the unconditional percent frequency are in bold face type. Panel A shows the frequency using all stocks across the whole trading day. Panel B shows the frequency in the morning (between 10am and 12pm). Panel C shows the frequency in the early afternoon (between 12pm and 2pm) and Panel D shows the frequency in the late afternoon (between 2 and 4pm).

Panel A: Orders placed between 10am and 4pm

		Ask			Bid			
t-1		Institutional	Others	Retail	Institutional	Others	Retail	Total
Ask	Institutional	**179,686 (0.29)**	91,396 (0.15)	44,686 (0.07)	**175,056 (0.28)**	93,307 (0.15)	43,918 (0.07)	628,049
	Others	99,339 (0.22)	**109,491 (0.24)**	**50,041 (0.11)**	95,602 (0.21)	61,391 (0.14)	33,640 (0.07)	449,504
	Retail	49,353 (0.21)	**51,728 (0.22)**	**39,401 (0.17)**	42,286 (0.18)	31,749 (0.14)	19,486 (0.08)	234,003
Bid	Institutional	**174,454 (0.26)**	103,070 (0.15)	47,135 (0.07)	**213,781 (0.31)**	96,480 (0.14)	47,723 (0.07)	682,643
	Others	86,318 (0.20)	61,777 (0.14)	33,291 (0.08)	103,471 (0.24)	**104,455 (0.24)**	**48,592 (0.11)**	437,904
	Retail	38,924 (0.17)	31,982 (0.14)	19,385 (0.08)	52,480 (0.23)	**50,483 (0.22)**	**38,440 (0.17)**	231,694
Unconditional		628,074 (0.24)	449,444 (0.17)	233,939 (0.09)	682,676 (0.26)	437,865 (0.16)	231,799 (0.09)	2,663,797

Panel B: Orders placed between 10am and 12pm

		Ask			Bid			
t-1		Institutional	Others	Retail	Institutional	Others	Retail	Total
Ask	Institutional	70,803 (0.28)	37,664 (0.15)	17,859 (0.07)	68,233 (0.27)	40,490 (0.16)	18,470 (0.07)	253,519
	Others	40,881 (0.22)	44,955 (0.24)	19,668 (0.11)	38,783 (0.21)	26,615 (0.14)	14,249 (0.08)	185,151
	Retail	20,001 (0.22)	20,456 (0.22)	14,698 (0.16)	16,513 (0.18)	13,070 (0.14)	7,702 (0.08)	92,440
Bid	Institutional	67,854 (0.25)	41,825 (0.16)	18,811 (0.07)	80,901 (0.30)	40,630 (0.15)	19,621 (0.07)	269,642
	Others	37,374 (0.20)	26,900 (0.14)	13,968 (0.07)	43,272 (0.23)	45,387 (0.24)	20,589 (0.11)	187,490
	Retail	16,488 (0.17)	13,338 (0.14)	7,577 (0.08)	21,751 (0.23)	21,302 (0.22)	15,394 (0.16)	95,850
Unconditional		253,401 (0.23)	185,138 (0.17)	92,581 (0.09)	269,453 (0.25)	187,494 (0.17)	96,025 (0.09)	1,084,092

Panel C: Orders placed between 12pm and 2pm								
		Ask			Bid			
t-1		Institutional	Others	Retail	Institutional	Others	Retail	Total
Ask	Institutional	**25,196 (0.26)**	15,941 (0.16)	9,670 (0.10)	**22,790 (0.23)**	14,679 (0.15)	8,993 (0.09)	97,269
	Others	16,746 (0.18)	**24,848 (0.27)**	**14,090 (0.15)**	15,491 (0.17)	12,883 (0.14)	8,588 (0.09)	92,646
	Retail	10,453 (0.17)	**14,403 (0.24)**	**13,091 (0.21)**	8,606 (0.14)	8,330 (0.14)	6,103 (0.10)	60,986
Bid	Institutional	**22,825 (0.22)**	16,330 (0.16)	9,505 (0.09)	**29,583 (0.28)**	16,251 (0.16)	9,943 (0.10)	104,437
	Others	13,930 (0.16)	13,062 (0.15)	8,594 (0.10)	17,072 (0.19)	**22,993 (0.26)**	**12,864 (0.15)**	88,515
	Retail	7,809 (0.13)	8,152 (0.14)	6,250 (0.11)	10,721 (0.18)	**13,372 (0.23)**	**12,070 (0.21)**	58,374
Unconditional		96,959 (0.19)	92,736 (0.18)	61,200 (0.12)	104,263 (0.21)	88,508 (0.18)	58,561 (0.12)	502,227
Panel D: Orders placed between 2pm and 4pm								
		Ask			Bid			
t-1		Institutional	Others	Retail	Institutional	Others	Retail	Total
Ask	Institutional	**83,687 (0.30)**	37,791 (0.14)	17,157 (0.06)	**84,033 (0.30)**	38,138 (0.14)	16,455 (0.06)	277,261
	Others	41,712 (0.24)	**39,688 (0.23)**	**16,283 (0.09)**	41,328 (0.24)	21,893 (0.13)	10,803 (0.06)	171,707
	Retail	18,899 (0.23)	**16,869 (0.21)**	**11,612 (0.14)**	17,167 (0.21)	10,349 (0.13)	5,681 (0.07)	80,577
Bid	Institutional	**83,775 (0.27)**	44,915 (0.15)	18,819 (0.06)	**103,297 (0.33)**	39,599 (0.13)	18,159 (0.06)	308,564
	Others	35,014 (0.22)	21,815 (0.13)	10,729 (0.07)	43,127 (0.27)	**36,075 (0.22)**	**15,139 (0.09)**	161,899
	Retail	14,627 (0.19)	10,492 (0.14)	5,558 (0.07)	20,008 (0.26)	**15,809 (0.20)**	**10,976 (0.14)**	77,470
Unconditional		277,714 (0.26)	171,570 (0.16)	80,158 (0.07)	308,960 (0.29)	161,863 (0.15)	77,213 (0.07)	1,077,478

Table 5.3 Frequency of orders traded at a price equal to or different from the price of the previous order

The table presents the frequency of orders traded at a price (Price_t) equal to or different from the price of the previous order (Price_{t-1}). t denotes the observed order and t-1 denotes the order traded prior to the observed order. Side_t indicate if the observed order is on the buy or sell side. Type_t indicates the trader type that has submitted the order.

Side_{t-1}	Side_t	$\text{Type}_{t-1}=\text{Type}_t$	$\text{Price}_t<\text{Price}_{t-1}$		$\text{Price}_t=\text{Price}_{t-1}$		$\text{Price}_t>\text{Price}_{t-1}$		Total
Bid	Ask	No	189,722	(0.56)	142,158	(0.42)	8,840	(0.03)	340,720
Bid	Ask	Yes	104,454	(0.41)	141,760	(0.55)	9,402	(0.04)	255,616
Bid	Bid	No	20,393	(0.05)	301,855	(0.76)	76,981	(0.19)	399,229
Bid	Bid	Yes	14,218	(0.04)	271,090	(0.76)	71,368	(0.20)	356,676
Ask	Ask	No	73,824	(0.19)	293,577	(0.76)	19,142	(0.05)	386,543
Ask	Ask	Yes	66,478	(0.20)	249,409	(0.76)	12,691	(0.04)	328,578
Ask	Bid	No	8,948	(0.03)	143,536	(0.42)	188,018	(0.55)	340,502
Ask	Bid	Yes	10,012	(0.04)	143,780	(0.56)	102,141	(0.40)	255,933
Unconditional			488,049	(0.18)	1687,165	(0.63)	488,583	(0.18)	2,663,797

5.4 Results

All marketable orders for the 36 companies submitted during the year 2001 are ranked according to order size and categorised into two sets of quintiles. In the first set, orders are categorised according to the volume of the order as a proportion of the average daily volume for the stock for the entire period (*PMEAN*); in the second, they are categorised by the volume of the order as a proportion of the total volume for the stock on the day the order is placed (*DTOTAL*). The results are presented separately for the companies in the top and bottom deciles, that is, 18 of the most heavily traded stocks and 18 of the least traded stocks.

5.4.1 Simple analysis of permanent price effect of orders and trader identity

5.4.1.1 Heavily traded stocks (*k*=*j*=*1*)

Both Figure 5.2 (*DTOTAL*) and Figure 5.3 (*PMEAN*) show (1) a positive relationship between size of order and the permanent price effect, and (2) a negative relationship between size of order and the temporary price effect for stocks in decile 1.[29] There is no clear directional relationship between order size and total price effect. The relationships are similar for institutional and retail traders. These results are consistent with Walsh (1997).

The permanent price effect increases with order size because of the information it conveys. Contrary to the inventory hypothesis, the temporary price effect decreases with order size. Walsh (1997) argues that this has little meaning as a negative relationship between temporary price effect and size suggests either liquidity providers require compensation for smaller orders or the price pressure effect decreases with order size. He suggests neither of these two explanations is likely. Instead, it is plausible that market depth is equal for all order sizes leading to the same price effect, regardless of order size. The temporary price effect is no more than the price reversal that takes place after the information content of the order has been incorporated into price.

An issue of concern in this thesis is the effect of differences between retail and institutional traders. The permanent price effects of bid and ask orders placed by institutional traders are on average larger than those placed by retail traders. On the other hand, the total price effect of orders placed by institutional traders is smaller than for those placed by retail traders, indicating that the price reversal experienced by institutional traders is less than for retail traders. Although it was suggested earlier that market depth is the same for all order sizes, it differs across orders placed by different trader types. The figures provide evidence that trades by retail traders convey less information (H_1) and that institutional traders are more aware of market conditions and time their orders better (H_2). The patterns are consistent across the two measures of order size, *DTOTAL* (Figure 5.2) and *PMEAN* (Figure 5.3).

[29] By definition, temporary price effect is equal to total price effect minus permanent price effect.

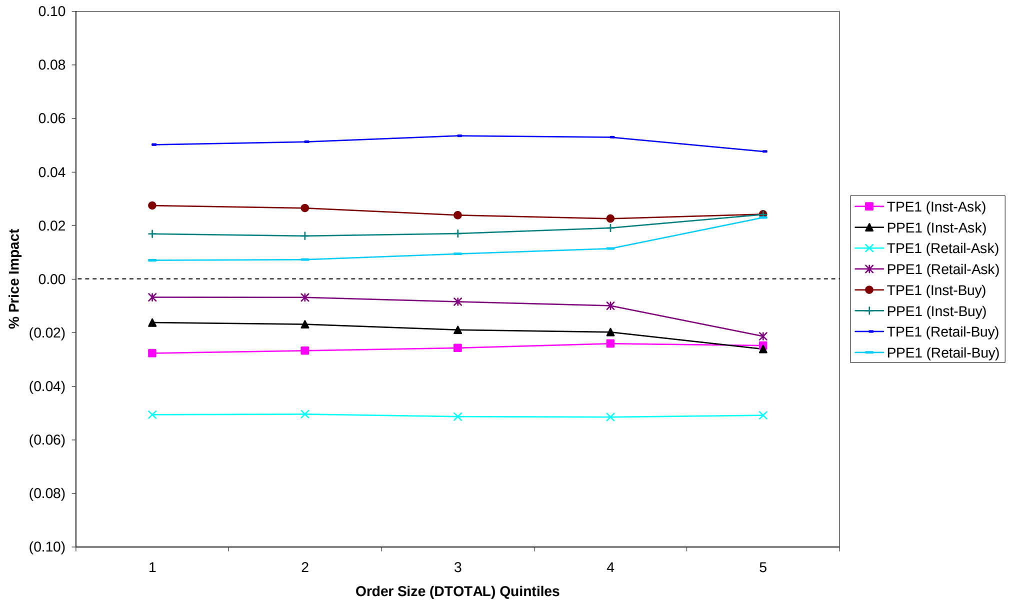


Figure 5.2 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 1 (i.e., heavily traded stocks). Orders are ranked and grouped into quintiles based on DTOTAL (order size as a percentage of the number of shares traded on the day) where Quintile 1 comprises the smallest orders. Price effect is computed using k=j=1.

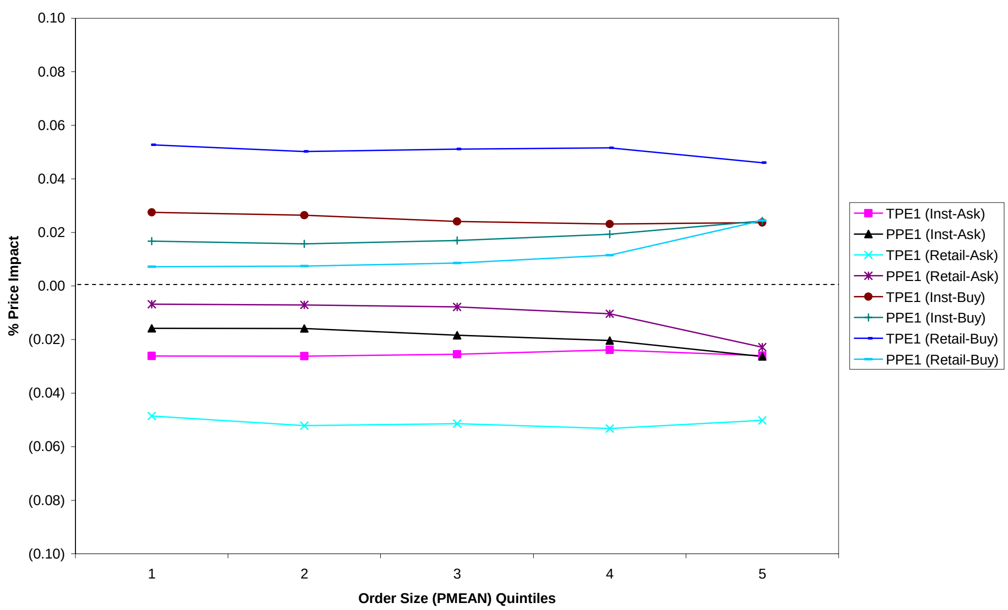


Figure 5.3 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 1 (i.e., heavily traded stocks). Orders are ranked and grouped into deciles based on PMEAN (order size as a percentage of average daily number of shares traded over the sample period for the company) where Quintile 1 comprises the smallest orders. Price effect is computed using k=j=1.

5.4.1.2 Lightly traded stocks (*k*=*j*=*1*)

Figure 5.4 and 5.5 show a positive relationship between size of order and the permanent price effect for stocks in decile 10, which comprises the smaller stocks in the sample. The effect of trading on the share prices of the smaller stocks is greater than for the larger stocks.[30] This could be due to their lower liquidity, indicated by lower depth and less trading activity. Similar to the results for the heavily traded stocks, there is no visually obvious evidence that the temporary price effect is related to order size. However, the permanent price effect of orders placed by institutional traders is smaller than for orders placed by retail traders. Contrary to hypothesis H_1, more information is conveyed by retail trades compared to institutional trades.

Consistent with the results for larger stocks, the temporary price effect of orders placed by institutional traders is smaller than for orders placed by retail traders. This supports hypothesis H_4, that institutional traders incur smaller transaction costs as they are likely to be more efficient in their order placement. The use of the different measures of order size, *DTOTAL* and *PMEAN*, produces similar findings. While trades by retail traders convey more information compared to institutional trades, their orders are associated with a lower temporary price effect.

5.4.2 Price effect where *k*=*j*=*5*

The relationship between the price effect, order size and trader type where k=j=5 is qualitatively similar to that found where k=j=1. The permanent price effect is positively related to order size for (1) bids and offers, (2) institutional and retail traders and (3) both proxies for order size. Also, there is no obvious relationship between the total price effect and order size. The graphs are presented in Appendix D (see Figures D.1 to D.4).

[30] Note the differences in the scale of the y-axis for the figures for stocks in the first and last deciles.

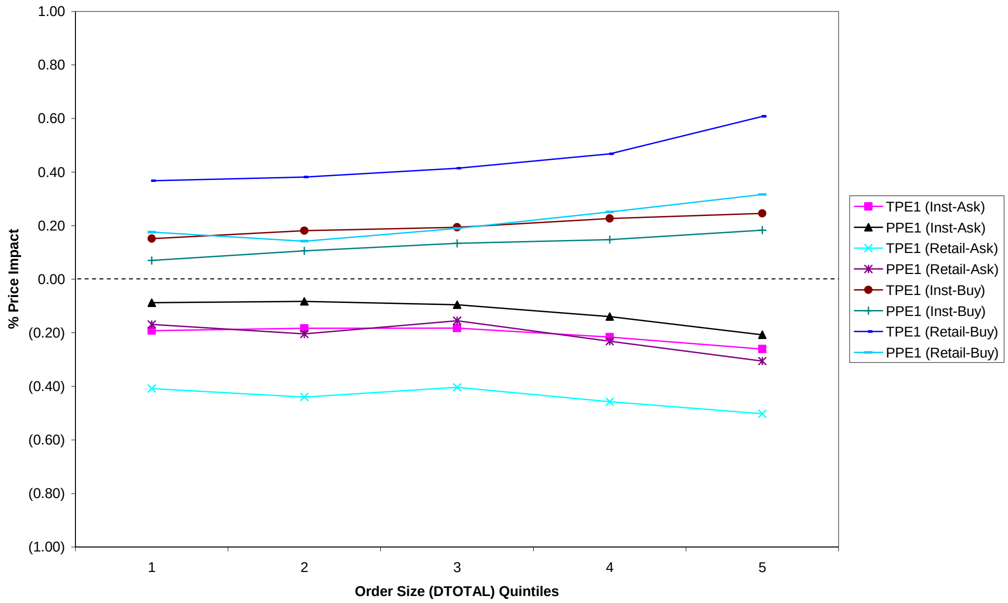


Figure 5.4 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 10 (i.e., lightly traded stocks). Orders are ranked and grouped into deciles based on DTOTAL (order size as a percentage of the number of shares traded on the day) where Quintile 1 comprises the smallest orders. Price effect is computed using k=j=1.

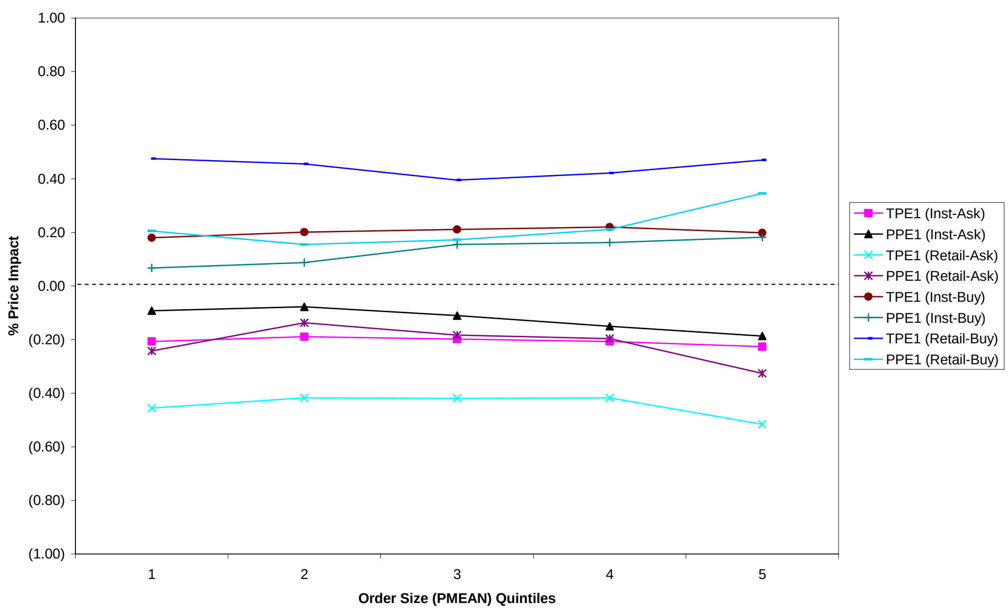


Figure 5.5 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 10 (i.e., lightly traded stocks). Orders are ranked and grouped into deciles based on PMEAN (order size as a percentage of average daily number of shares traded over the sample period for the company) where Quintile 1 comprises the smallest orders. Price effect is computed using k=j=1.

5.4.3 Regression analysis of permanent price effect of orders

For each stock, the four measures of price effect (TPE1, TPE2, PPE1 and PPE2) are regressed against the two sets of order size measures (*PMEAN* and *DTOTAL*) and trader type dummy variables (*DumRet* and *DumInst*). The models are generated separately for buy and sell orders. The results presented are the averages of the separate regressions performed for each stock.

5.4.3.1 Heavily traded stocks (*k*=*j*=1)

From Table 5.4 we observe that the expected positive relationship between the permanent price effect and order size holds for 17 of the 18 heavily traded stocks regardless of the measure of order size. Panel A shows the results using $PMEAN$ as the measure of order size. There is a general increase in the permanent price effect with an increase in order size. The interaction variable, $DumRet * PMEAN$, has negative coefficients. The negative relation is significant for 13 of the 18 stocks for $DumRet * PMEAN1$. This provides some support for H_3, which predicts retail orders have a smaller permanent price effect because they convey less information. The less significant negative coefficients for $DumRet * PMEAN3$ to $DumRet * PMEAN5$ show larger orders placed by retail traders convey similar information to other orders placed in the market. The negative coefficient for the interaction variable, $DumIns * PMEAN5$, suggests larger orders from institutional traders are not information-based but are liquidity motivated.

The variables *DumAggr, Depth_opp* and *Depth_opp_D* have the predicted signs. More aggressive orders have a higher permanent price effect but the coefficients are significant (at 5% level) only for four of the stocks examined for bid orders ($\bar{\alpha}_{16}$=0.003) and 12 of the stocks examined for ask orders ($\bar{\alpha}_{16}$=0.006). The depth variables show that the price impact depends on the depth on the opposing side to the order. Large depth or recent increases in depth on the opposing side lessen an order's price impact.

Panel B shows the results using *DTOTAL* as the measure of order size. The results are similar to those for *PMEAN*. For instance, order size is positively related to the permanent price effect. The interaction variables, *DumRet*DTOTAL*, are negative but significant only for the smallest two quintiles of order size, *DumRet*DTOTAL1* and *DumRet*DTOTAL2*, for more than eight of the 18 stocks examined.

5.4.3.2 Lightly traded stocks (*k*=*j*=1)

The regressions estimated for lightly traded stocks and are presented in Table 5.5. The relation between order size and permanent price effect is present. However, its statistical significance is lower than for the heavily traded stocks. The negative relation between the interaction variable, *DumRet*PMEAN*, and the permanent price effect found previously is not found here. The positive relation between the interaction variable, *DumIns*PMEAN*, and permanent price effect is also absent. Panel B shows the results using *DTOTAL* as the measure of order size are similar.

5.4.3.3 Price effect where *k*=*j*=5

The models are regenerated using *k*=*j*=5 to calculate the permanent price effect. The general positive relation between size and permanent price effect is found for most of the heavily traded stocks (at least 15 of the 18): see Table 5.6. The relations between the interaction variables, *DumIns*PMEAN*, *DumRet*PMEAN*, *DumIns*DTOTAL* and *DumRet*DTOTAL*, are also consistent with those found using narrower windows, *k*=*j*=1. The coefficients of the variables are, however, less statistically significant. For example, *DumRet*PMEAN1* is significantly negative (at the 5% level) for 5 of the 18 stocks and *DumRet*DTOTAL1* is significantly negative (at the 5% level) for 3 of the 18 stocks examined.

The corresponding results for lightly traded stocks using the wider windows *k*=*j*=5 are shown in Table 5.7. They are broadly similar to those found using narrower windows. For instance, order size and price effects tend to be positively related. However, they are less significant statistically than for the heavily traded stocks. The negative price effect previously found for the interaction variable, *DumRet*PMEAN*, is not evident, neither is a positive effect for the interaction variable, *DumIns*PMEAN*.

Table 5.4 Regressions of permanent price effect (PPE1) on order size (PMEAN & DTOTAL) for the heavily traded stocks

The dependent variable is the permanent price effect, PPE1, calculated using the volume weighted trade price of the order traded prior to the order examined and the order traded after the order examined, i.e., *j*=*k*=1. The independent variables are the order size (*PMEAN* or *DTOTAL*), dummy variables for orders placed by institutional traders (*DumIns*) and by retail traders (*DumRet*), order aggressiveness (*DumAggr*), depth on the opposite side (*Depth_opp*), and the change in depth on the opposite side (*Depth_opp_Δ*). The regression models are generated for ask and bid orders of each stock separately. The coefficients presented are the means in the 18 regressions, the number of positive and significant coefficients (at the 5% level) and the number of negative and significant coefficients (at the 5% level). The mean of the *t*-statistic for each variable is also shown.

	Panel A: Size of order measured using PMEAN								*Panel B: Size of order measured using DTOTAL*							
	Bids				Asks				Bids				Asks			
	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of –ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat
SIZE1	0.015	17	0	8.94	0.015	17	0	8.39	0.015	17	0	8.64	0.015	17	0	8.45
SIZE2	0.014	18	0	8.89	0.013	17	0	7.54	0.014	18	0	8.65	0.013	18	0	7.68
SIZE3	0.016	17	0	9.56	0.015	18	0	9.25	0.016	18	0	9.17	0.015	18	0	8.87
SIZE4	0.020	18	0	9.82	0.020	18	0	11.41	0.019	18	0	10.06	0.019	18	0	10.64
SIZE5	0.032	18	0	12.38	0.030	18	0	13.30	0.032	18	0	12.91	0.031	18	0	14.57
DumIns*SIZE1	0.003	5	0	1.12	0.001	6	3	1.20	0.004	5	0	1.47	0.002	7	1	1.54
DumIns*SIZE2	0.003	6	0	1.66	0.003	6	0	1.77	0.003	6	0	1.66	0.004	9	1	2.32
DumIns*SIZE3	0.002	5	1	1.53	0.004	9	1	2.24	0.003	6	0	1.62	0.005	9	0	2.38
DumIns*SIZE4	0.001	5	2	0.78	0.002	7	0	1.26	0.001	4	0	0.89	0.002	7	2	1.33
DumIns*SIZE5	-0.006	0	10	-1.62	-0.002	2	2	-0.25	-0.007	0	8	-1.75	-0.003	2	4	-0.79
DumRet*SIZE1	-0.007	0	13	-2.54	-0.008	1	13	-2.99	-0.006	0	10	-2.32	-0.008	1	12	-2.85
DumRet*SIZE2	-0.005	0	9	-1.79	-0.006	1	8	-1.87	-0.006	0	10	-1.92	-0.006	0	9	-1.92
DumRet*SIZE3	-0.005	0	7	-1.35	-0.005	0	9	-1.75	-0.004	0	5	-1.36	-0.005	0	7	-1.73
DumRet*SIZE4	-0.006	0	5	-1.26	-0.005	0	5	-1.47	-0.007	0	4	-1.26	-0.007	0	9	-1.70
DumRet*SIZE5	-0.006	0	3	-0.97	-0.007	0	4	-1.11	-0.009	0	8	-1.42	-0.009	0	6	-1.50
DumAggr	0.003	4	0	1.28	0.006	12	1	2.65	0.003	3	0	1.26	0.006	12	0	2.71
Depth_opp	-0.003	0	16	-6.71	-0.003	0	15	-5.54	-0.003	0	16	-6.01	-0.002	0	12	-4.64
Depth_opp_Δ	-0.079	0	17	-8.23	-0.071	0	17	-8.41	-0.079	0	17	-8.28	-0.072	0	17	-8.44
Adjusted R^2	0.034				0.036				0.034				0.036			

Table 5.5 Regressions of permanent price effect (PPE1) on order size (PMEAN & DTOTAL) for the lightly traded stocks

The dependent variable is the permanent price effect, PPE1, calculated using the volume weighted trade price of the order traded prior to the order examined and the order traded after the order examined, i.e., *j*=*k*=1. The independent variables are the order size (*PMEAN* or *DTOTAL*), dummy variables for orders placed by institutional traders (*DumIns*) and by retail traders (*DumRet*), order aggressiveness (*DumAggr*), depth on the opposite side (*Depth_opp*), and the change in depth on the opposite side (*Depth_opp_D*). The regression models are generated for ask and bid orders of each stock separately. The coefficients presented are the means in the 18 regressions, the number of positive and significant coefficients (at the 5% level) and the number of negative and significant coefficients (at the 5% level). The mean of the *t*-statistic for each variable is also shown.

	Panel A: Size of order measured using PMEAN								*Panel B: Size of order measured using DTOTAL*							
	Bids				Asks				Bids				Asks			
	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat
SIZE1	0.087	7	0	1.67	0.117	9	0	1.98	0.086	11	0	2.15	0.130	10	0	2.57
SIZE2	0.107	10	0	2.10	0.135	12	0	2.54	0.107	9	0	2.49	0.121	10	0	2.63
SIZE3	0.149	13	0	2.94	0.175	13	0	3.32	0.167	14	0	3.13	0.175	12	0	3.09
SIZE4	0.197	17	0	4.16	0.199	16	0	3.44	0.173	15	0	3.33	0.219	13	0	3.74
SIZE5	0.244	17	0	5.45	0.275	15	0	5.39	0.291	16	0	4.94	0.262	14	0	4.51
DumIns*SIZE1	0.009	1	0	0.12	0.017	0	1	-0.02	-0.024	1	0	-0.08	-0.020	0	1	-0.22
DumIns*SIZE2	-0.052	1	1	-0.36	-0.053	0	4	-0.78	-0.010	0	0	-0.01	0.023	0	1	-0.27
DumIns*SIZE3	0.021	0	0	0.10	-0.056	0	2	-0.74	-0.003	0	2	0.00	-0.036	0	3	-0.75
DumIns*SIZE4	-0.060	2	2	-0.27	-0.054	1	2	-0.27	0.018	0	0	0.01	-0.093	0	3	-0.66
DumIns*SIZE5	-0.053	0	3	-0.62	-0.053	0	2	-0.74	-0.119	0	4	-0.82	-0.061	0	2	-0.72
DumRet*SIZE1	0.029	3	2	0.35	0.071	2	1	0.59	0.027	2	0	0.37	-0.002	0	1	-0.03
DumRet*SIZE2	0.043	2	0	0.31	-0.033	0	2	-0.46	0.008	0	1	-0.04	0.041	2	0	0.20
DumRet*SIZE3	-0.047	1	1	-0.36	-0.059	0	2	-0.56	0.007	0	0	0.20	-0.065	0	1	-0.47
DumRet*SIZE4	-0.002	1	0	-0.38	-0.087	0	0	-0.54	0.055	1	0	0.32	-0.039	0	2	-0.69
DumRet*SIZE5	-0.057	0	2	-0.55	-0.050	1	2	-0.66	-0.100	0	4	-0.77	-0.042	1	2	1.48
DumAggr	0.103	3	0	0.98	0.125	7	0	1.68	0.104	4	0	1.08	0.121	5	0	1.61
Depth_opp	-0.031	0	10	-2.01	-0.045	0	11	-2.33	-0.031	0	10	-1.89	-0.033	0	6	-1.56
Depth_opp_D	-0.447	0	10	-2.13	-0.274	0	10	-2.17	-0.473	0	10	-2.17	-0.280	0	9	-2.18
Adjusted R^2	0.042				0.051				0.037				0.051			

Table 5.6 Regressions of permanent price effect (PPE2) on order size (PMEAN & DTOTAL) for the heavily traded stocks

The dependent variable is the permanent price effect, PPE2, calculated using the volume weighted trade price of the fifth order traded prior to the order examined and the fifth order traded after the order being examined, i.e., j=k=5. The independent variables are the order size (*PMEAN* or *DTOTAL*), dummy variables for orders placed by institutional traders (*DumIns*) and by retail traders (*DumRet*), order aggressiveness (*DumAggr*), depth on the opposite side (*Depth_opp*), and the change in depth on the opposite side (*Depth_opp_D*). The regression models are generated for ask and bid orders of each stock separately. The coefficients presented are the means in the 18 regressions, the number of positive and significant coefficients (at the 5% level) and the number of negative and significant coefficients (at the 5% level). The mean of the *t*-statistic for each variable is also shown.

	Panel A: Size of order measured using PMEAN								*Panel B: Size of order measured using DTOTAL*							
	Bids				Asks				Bids				Asks			
	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of –ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat
SIZE1	0.017	16	0	5.13	0.014	14	0	3.90	0.017	16	0	4.78	0.015	14	0	4.05
SIZE2	0.017	15	0	4.97	0.013	14	0	3.66	0.020	17	0	5.65	0.013	13	0	3.55
SIZE3	0.023	17	0	6.23	0.018	17	0	5.06	0.021	16	0	5.88	0.018	17	0	5.09
SIZE4	0.030	17	0	7.52	0.026	17	0	6.57	0.029	18	0	7.62	0.024	17	0	6.36
SIZE5	0.052	18	0	10.74	0.047	18	0	10.53	0.050	18	0	10.81	0.047	18	0	10.71
DumIns*SIZE1	0.005	4	2	1.06	0.005	9	0	1.39	0.005	6	0	1.04	0.007	7	0	1.60
DumIns*SIZE2	0.004	3	0	1.04	0.005	6	0	1.35	0.003	4	0	0.75	0.007	8	0	1.81
DumIns*SIZE3	0.000	3	1	0.33	0.004	5	0	1.29	0.004	5	0	0.93	0.005	5	0	1.24
DumIns*SIZE4	0.001	3	1	0.48	0.004	6	0	1.27	0.002	5	2	0.65	0.006	8	0	1.60
DumIns*SIZE5	-0.007	1	5	-0.90	0.002	4	1	0.49	-0.006	2	4	-0.73	0.000	3	1	0.25
DumRet*SIZE1	-0.004	1	5	-0.83	-0.007	1	6	-1.02	-0.004	1	3	-0.75	-0.006	1	7	-0.91
DumRet*SIZE2	-0.006	0	3	-0.67	-0.001	2	2	-0.20	-0.008	0	4	-0.98	-0.002	3	2	-0.27
DumRet*SIZE3	-0.006	0	4	-0.78	-0.005	1	2	-0.66	-0.004	1	6	-0.60	-0.006	1	2	-0.80
DumRet*SIZE4	-0.006	1	3	-0.42	-0.008	1	4	-0.81	-0.008	0	5	-0.70	-0.008	1	5	-0.97
DumRet*SIZE5	-0.011	0	5	-1.05	-0.015	0	2	-1.35	-0.018	0	5	-1.53	-0.019	0	8	-1.70
DumAggr	-0.015	1	13	-4.07	-0.011	0	11	-3.08	-0.015	0	13	-4.10	-0.010	0	10	-3.00
Depth_opp	-0.011	0	17	-10.82	-0.010	0	18	-10.15	-0.010	0	17	-9.84	-0.009	0	18	-9.22
Depth_opp_D	-0.628	0	18	-21.47	-0.593	0	17	-24.21	-0.629	0	18	-21.49	-0.594	0	17	-24.24
Adjusted R^2	0.043				0.048				0.043				0.048			

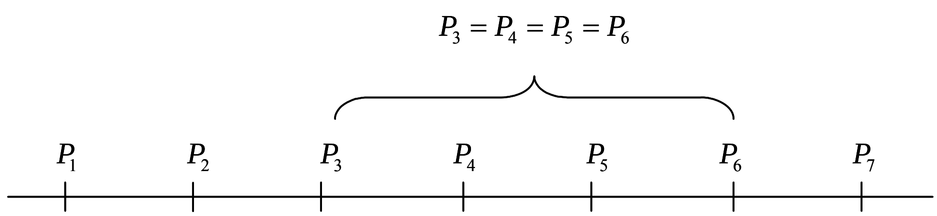
Table 5.7 Regressions of permanent price effect (PPE2) on order size (PMEAN & DTOTAL) for the lightly traded stocks

The dependent variable is the permanent price effect, PPE1, calculated using the volume weighted trade price of the fifth order traded prior to the order examined and the fifth order traded after the order examined, i.e., *j*=*k*=5. The independent variables are the order size (*PMEAN* or *DTOTAL*), dummy variables for orders placed by institutional traders (*DumIns*) and by retail traders (*DumRet*), order aggressiveness (*DumAggr*), depth on the opposite side (*Depth_opp*), and the change in depth on the opposite side (*Depth_opp_D*). The regression models are generated for ask and bid orders of each stock separately. The coefficients presented are the means in the 18 regressions, the number of positive and significant coefficients (at the 5% level) and the number of negative and significant coefficients (at the 5% level). The mean of the *t*-statistic for each variable is also shown.

	Panel A: Size of order measured using PMEAN								*Panel B: Size of order measured using DTOTAL*							
	Bids				Asks				Bids				Asks			
	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat	Av. coeff. value	No. of +ve coeff	No. of -ve coeff	Mean *t*-stat
SIZE1	0.145	6	1	1.40	0.137	6	1	1.53	0.157	10	0	2.18	0.249	8	0	2.11
SIZE2	0.199	11	0	1.95	0.186	6	0	1.87	0.212	10	0	2.45	0.170	9	0	1.99
SIZE3	0.336	15	0	3.11	0.273	12	0	2.53	0.342	13	0	3.38	0.184	8	0	2.08
SIZE4	0.279	13	0	3.08	0.182	10	1	2.54	0.230	12	1	2.87	0.279	12	0	2.85
SIZE5	0.440	14	0	5.21	0.420	13	0	4.50	0.549	16	0	4.11	0.414	12	0	3.87
DumIns*SIZE1	-0.079	2	1	-0.06	0.024	1	2	0.02	-0.047	1	2	-0.15	-0.097	0	4	-0.33
DumIns*SIZE2	-0.131	0	2	-0.51	0.033	2	2	-0.06	-0.086	0	1	-0.28	0.019	0	1	-0.04
DumIns*SIZE3	-0.242	0	2	-0.62	-0.122	0	0	-0.50	-0.139	0	0	-0.54	-0.043	0	1	-0.33
DumIns*SIZE4	-0.061	2	0	-0.10	0.009	0	1	-0.04	-0.013	0	0	-0.16	-0.059	0	1	-0.50
DumIns*SIZE5	-0.051	0	2	-0.28	-0.139	0	2	-0.67	-0.102	1	4	-0.34	-0.112	0	2	-0.34
DumRet*SIZE1	0.086	1	1	0.36	0.057	1	0	0.35	0.093	2	0	0.57	-0.006	0	0	0.19
DumRet*SIZE2	0.027	1	0	0.08	0.185	3	0	0.36	0.012	0	0	0.03	0.133	1	0	0.42
DumRet*SIZE3	-0.155	0	3	-0.81	0.007	0	0	-0.11	-0.051	1	2	-0.43	0.081	0	0	0.24
DumRet*SIZE4	0.041	1	0	0.06	0.066	1	0	0.11	0.117	1	1	0.37	-0.071	0	0	-0.49
DumRet*SIZE5	-0.030	1	0	0.02	-0.001	0	0	-0.26	-0.138	0	2	-0.48	0.023	1	2	3.14
DumAggr	-0.092	0	2	-0.62	0.007	1	2	-0.14	-0.008	1	2	-0.39	0.016	1	2	-0.09
Depth_opp	-0.106	0	13	-3.62	-0.122	0	16	-4.28	-0.106	0	13	-3.47	-0.097	0	15	-3.52
Depth_opp_D	-3.509	0	16	-8.28	-2.371	0	15	-6.67	-3.569	0	16	-8.34	-2.357	1	15	-6.58
Adjusted R2	0.059				0.065				0.060				0.066			

5.5 Robustness testing - successive orders from the same trader type

As discussed in Section 5.3.2, successive orders placed by the same trader type and traded at the same price can bias the permanent price effect measures. Consider the following timeline (Figure 5.6), with seven transactions executed at prices P_1 to P_7, with P_3, P_4, P_5 and P_6 being the same amount.



$$PPE1 = (P_3 - P_1)/P_1$$

Figure 5.6 Timeline of trades where the third, fourth, fifth and sixth trades are transacted at the same price.

Assume that P_3, P_4, P_5 and P_6 are from the same trader type and are on the same side. The $PPE1$ for transactions 4 and 5 will be zero as the transaction prices are the same for transactions 3 to 6. Assuming the trades are executed for information reasons, the method used in the earlier results will understate the price effect. To overcome this difficulty, the temporary price effect ($TPE1$ and $TPE2$) and the permanent price effect ($PPE1$ and $PPE2$) are recomputed using the average price of successive orders if they are from the same trader type and same side of the market. In the above example, the price series used is thus re-computed as in Figure 5.7

$$PPE1 = (P_A - P_1)/P_1 \quad \text{where } P_A = (P_3 + P_4 + P_5 + P_6)/4$$

Figure 5.7 Timeline of trades where the trades transacted at the same transaction price are amalgamated.

Table 5.8 shows the temporary and permanent price effects of orders after making the above-mentioned adjustments. The results are consistent with the previous discussion. Panel A shows the results for the heavily traded stocks (Decile 1) where the permanent price effect (both *PPE*1 and *PPE*2) for retail trades is less than for institutional trades for both bid and ask orders examined. This provides evidence that retail trades convey less information than the other trade types, giving further support for hypothesis H_1. The total price effect is greater for retail trades, resulting in a greater temporary price effect. This is again consistent with the previous results and hypothesis H_2. The larger temporary price movements suggest retail trades are placed in inferior market positions.

Panel B shows the results for lightly traded stocks (Decile 10). The results are again consistent with the previous analysis. Contrary to hypothesis H_1, retail trades convey more information than institutional trades while the temporary price effect of retail trades is larger than for institutional trades.

Table 5.8 Price effect of orders where successive orders on the same side and of the same broker type are amalgamated

Side	Type	N	*TPE1*	*TPE2*	*PPE1*	*PPE2*
		Panel A: Heavily Traded Stocks				
Ask	Institutional	437,169	0.031	0.024	0.019	0.019
	Others	320,618	0.049	0.041	0.013	0.011
	Retail	182,247	0.060	0.053	0.008	0.004
Bid	Institutional	459,620	0.031	0.027	0.018	0.020
	Others	313,413	0.050	0.043	0.015	0.015
	Retail	180,004	0.060	0.053	0.009	0.005
		Panel B: Lightly Traded Stocks				
Ask	Institutional	13,074	0.298	0.352	0.141	0.208
	Others	21,149	0.452	0.435	0.201	0.255
	Retail	13,065	0.544	0.627	0.221	0.329
Bid	Institutional	11,140	0.265	0.259	0.134	0.159
	Others	21,648	0.434	0.416	0.197	0.287
	Retail	13,983	0.551	0.537	0.216	0.297

5.6 Summary

The results from this chapter show that the identity of the trader is related to the price effect of the order. However, the expected relationship between trader identity and price effect is evident only in the most heavily traded stocks. In these stocks, orders placed by institutional traders have larger permanent price effects and this relationship remains, after controlling for order size. Based on the information hypothesis, I conclude that institutional traders are better informed. In contrast, orders placed by retail traders are associated with a smaller permanent price effect, which lends support for the hypothesis that retail traders are less informed (H_1). Institutional trades are associated with a smaller total price effect when compared to retail trades, suggesting that the inventory cost or price-pressure effect is smaller for institutional traders. This provides support for hypothesis (H_2), that retail traders are less experienced in their order placement and incur higher transaction costs when executing their trades.

CHAPTER SIX
PROVISION OF LIQUIDITY AND ORDER PLACEMENT

"I'm concerned about the great influx of new and relatively inexperienced investors who may be so seduced by the ease and speed of internet trading that they may be trading in a way that does not match their specific goals and risk tolerances." (Levitt, 1999)

6.1 Introduction

Share markets are generally grouped into two types: (1) quote driven and (2) order driven. A market is quote driven if dealers announce the prices at which other market participants can trade. Examples of such markets include National Association of Securities Dealers Automated Quotations (NASDAQ) in the United States and the Stock Exchange Automated Quotation System (SEAQ) in London. A market is classified as order driven if investors (or brokers acting as principals), by placing limit orders, establish the prices at which other participants can buy and sell. Examples of order driven markets include the Tokyo Stock Exchange, Paris Bourse and the Australian Stock Exchange (ASX). Some exchanges are a hybrid of the two and rely, at least partially, upon limit orders for the provision of liquidity. An example of this is the New York Stock Exchange (NYSE). Traders can place limit orders while the specialist is obliged to supply liquidity when the need arises.

The frequent use of order driven markets and the reliance of these markets on limit orders as a major source of liquidity makes it useful to understand the placement strategies of different traders. It was discussed in Chapter Five that traders who trade through different brokers can be classified into three types: (1) institutional traders, (2) retail traders and (3) others. Using this classification, the statistics presented in Chapter Four showed that the level of trading by retail traders has increased substantially over the period examined. Furthermore, the contrast between the change in trade frequency and trading volume confirms our intuition that institutional traders and retail traders differ in the size of their orders. While the frequency of trades by retail traders has increased substantially over the period examined, aggregate trading volume has not increased by the same proportion. Given the growth of the prominence of retail trading, there is an interesting question: Does order placement strategy differ by trader type?

Several theoretical studies have addressed the mix of limit and market orders in an order driven market (Foucault, 1999; Foucault et al., 2001; Parlour, 1998). Parlour (1998) developed a one-tick model where the trader's choice between a limit and market order depends on the state of the limit order book, in particular the depth available at the best bid and ask. Parlour's model assumes each trader chooses his order by evaluating its execution probability and how the order would affect the order placement of other traders who follow. Foucault (1999) analyses a model in which limit order traders face the risk of non execution and are exposed to their risk of the order being executed at a loss when the limit order becomes mispriced. He finds the volatility of the asset to be a major determinant of the mix between market and limit orders. As (information based) volatility increases, limit order traders have a greater tendency to price their orders further from the market to compensate themselves for the higher probability of being picked off by informed traders. This results in higher execution costs for market order traders thus decreasing the proportion of market orders used. Foucault et al. (2001) model the limit order book as a market for liquidity provision and consumption. Their model comprises discretionary liquidity traders who trade off the cost of waiting against the cost of obtaining immediacy. They show tick size, cost of time and the proportion of patient traders determine the market equilibrium.

Other empirical papers have examined the choice of limit versus market orders (Ahn et al., 2001; Al-Suhaibani and Kryzanowski, 2001; Harris and Hasbrouck, 1996; Ranaldo, 2004; Verhoeven et al., 2004). Verhoeven et al. (2004) examine the mix of limit and market orders in two liquid stocks traded on the ASX. Using a logit model, they find the choice of order type depends on the bid-ask spread, depth at the best price, price change in the last five minutes and order imbalance. Their results are similar to those in Al-Suhaibani and Kryzanowski (2001) for the Saudi stock market. In both studies, market orders are associated with greater volatility. This finding is contrary to the predictions of theoretical models such as Foucault (1999). Ronaldo (2004) also finds similar results but argues his findings could be due to statistical issues such as “collinearity and multivariate biases” (Ranaldo, 2004, p. 61).

While the empirical studies have examined the mix of limit and market orders and have attributed the choice of order type to the condition of the market, none has examined its relationship with the traders’ intention or motivation for trading. Ronaldo (2004) argues no inference can be drawn about how informed a trader is from observing his usage of market versus limit orders. Instead, the only inference possible from a trader’s choice of market or limit order is his eagerness to trade. In an earlier paper, Glosten (1994) defines eager and patient traders as market and limit order submitters, respectively. Ronaldo (2004) argues that an eager trader does not equate to an informed trader because, according to Chakravarty and Holden (1995), an informed trader may optimally choose any combination of market and limit orders.

This chapter extends the analysis of the order placement of traders by examining the aggressiveness of all market and limit orders placed and the use of limit orders in the provision of liquidity to the market. The main research question is: Does the trader type help determine the order placement strategy used? This question is addressed by examining the type of order used conditioned on the state of the market.

Limit orders provide important liquidity to traders who wish to trade immediately (Handa et al., 1998). The increased number of retail traders raises a second question: Do retail traders contribute to the depth of the limit order book? Although the analysis of the order flow in addressing the first question provides some indication of the contribution of different trader types to market depth, a more thorough analysis involves examining the bid-ask schedule over the normal trading phase.

6.2 Data and method

6.2.1 Data period and sample selection

The analysis in this chapter is limited to the 36 companies described in Chapter Four. Data on the orders submitted and trades executed over the period 1 January to 31 December 2001 inclusive are used in the analysis. Market conditions at the time of order submission are also included in the data set.

Table 6.1 reports summary statistics for the number of orders and the aggregate number of shares for each stock in the two samples examined. As expected from the construction of the sample, the number and volume of orders placed for the stocks in the first set examined (Panel A - Heavily traded stocks) are substantially higher than those for the second set (Panel B – Lightly traded stocks). The table shows, in general, a greater proportion of the number of orders and their volume were placed by institutional traders than by retail traders. For the heavily traded stocks, 49.69% of all orders (on average) were placed by institutional traders compared to the 16.85% that were placed by retail traders. In contrast, the participation by retail traders (and others) is relatively higher in the lightly traded stocks. Panel B shows 24.94% (44.41%) of the orders were placed by retail traders (others) while 30.63% of the orders were placed by institutional traders.

When considering the order volume, the contrast between the proportion of orders placed by institutional and retail traders is more striking. For example, 72.34% of the orders (measured by total number of shares) in the heavily traded stocks were placed by institutional traders compared to 5.21% by retail traders. A notable difference between the two sets of stocks is the variation in the level of order volume placed by institutional traders within each set. The greatest variation is shown in the total number of shares placed in the lightly traded stocks. For example, institutional traders placed 93.07% of the orders (measured by total number of shares) in stock PLM compared to 2.18% of the orders in stock VNA.

Table 6.1 Order flow of stocks in sample

The table presents the total number of orders and number of shares in the orders placed in each stock over the period 1 January 2001 to 31 December 2001 in the sample of stocks examined. The table also shows the percentage of orders placed by the three different trader types.

Code	Total number of orders	Percentage (%) of orders placed by			Total order volume (shares in billion)	Percentage (%) of order volume placed by		
		Institutional	Others	Retail		Institutional	Others	Retail
Panel A: Heavily traded stocks								
AMP	284,306	47.87	36.02	16.11	1,032.67	70.72	25.23	4.05
ANZ	315,173	53.69	32.37	13.95	2,074.15	75.84	20.48	3.68
BHP	526,952	54.51	31.78	13.71	4,716.25	78.11	18.39	3.50
BIL	212,093	62.68	26.39	10.93	1,013.94	79.56	16.42	4.02
CBA	423,425	45.16	34.09	20.74	1,405.05	66.29	27.46	6.25
CML	200,141	41.10	36.68	22.22	1,388.00	65.97	24.76	9.27
CSR	112,844	58.87	29.34	11.79	1,145.82	79.59	16.23	4.17
LLC	233,415	48.11	34.91	16.98	711.96	63.70	29.16	7.14
MAY	154,439	50.84	29.79	19.37	1,214.43	75.36	17.93	6.71
NAB	457,319	51.72	33.11	15.17	1,912.41	72.24	23.81	3.95
NCP	403,242	52.91	30.82	16.27	2,471.64	72.77	22.58	4.65
QAN	243,821	31.93	37.68	30.39	3,431.56	67.95	22.57	9.48
RIO	204,650	62.07	30.66	7.27	726.77	73.10	24.48	2.41
TLS	645,762	33.66	38.02	28.31	10,443.10	72.20	21.34	6.47
WBC	257,930	54.22	33.26	12.52	2,026.18	77.60	19.21	3.19
WMC	268,623	44.97	39.42	15.61	2,211.51	68.93	24.90	6.17
WOW	210,928	51.07	32.12	16.81	1,391.54	76.78	18.55	4.68
WPL	160,735	49.10	35.79	15.11	1,184.60	65.46	30.54	4.00
Mean	*295,322*	*49.69*	*33.46*	*16.85*	*2,250.09*	*72.34*	*22.45*	*5.21*
Max	*645,762*	*62.68*	*39.42*	*30.39*	*10,443.10*	*79.59*	*30.54*	*9.48*
Min	*112,844*	*31.93*	*26.39*	*7.27*	*711.96*	*63.70*	*16.23*	*2.41*
Panel B: Lightly traded stocks								
AQP	11,763	42.85	44.48	12.68	30.37	30.29	56.62	13.09
ARG	13,869	35.84	39.82	24.34	57.85	44.20	36.99	18.81
CPH	21,502	23.76	42.05	34.19	529.97	34.36	45.51	20.13
GNS	12,103	30.41	49.28	20.31	56.40	35.86	50.45	13.68
GWT	16,614	46.56	41.16	12.28	96.23	53.14	37.36	9.50
HRP	2,182	53.80	30.98	15.22	91.10	84.74	11.00	4.26
IFM	12,775	36.98	50.68	12.34	113.75	35.63	57.12	7.25
KIM	27,807	3.32	58.28	38.39	459.38	3.05	62.25	34.70
MXO	19,440	5.16	59.63	35.21	902.79	6.96	64.02	29.02
MYO	28,469	29.70	42.88	27.42	218.11	33.56	43.54	22.91
NUF	9,472	44.99	34.90	20.11	64.14	58.56	27.86	13.59
OML	20,531	39.92	35.04	25.05	210.75	45.80	34.65	19.55
PLM	1,647	40.07	40.19	19.73	50.46	93.07	5.41	1.52
RIC	16,112	21.40	46.12	32.48	265.24	26.96	50.93	22.11
SLX	18,596	37.47	42.96	19.57	57.90	29.92	50.30	19.78
TIM	28,963	14.27	52.69	33.04	435.51	7.68	59.58	32.74
VNA	36,665	2.47	53.14	44.40	1,005.10	2.18	57.09	40.73
VRL	22,830	42.69	35.16	22.15	132.46	48.58	35.43	16.00
Mean	*17,852*	*30.65*	*44.41*	*24.94*	*265.42*	*37.47*	*43.67*	*18.85*
Max	*36,665*	*53.80*	*59.63*	*44.40*	*1,005.10*	*93.07*	*64.02*	*40.73*
Min	*1,647*	*2.47*	*30.98*	*12.28*	*30.37*	*2.18*	*5.41*	*1.52*

In summary, Table 6.1 shows institutional order volume is higher in the heavily traded stocks compared to the lightly traded stocks and is consistent with previous studies that have documented greater institutional interest in the more liquid and actively traded stocks. While institutional traders contribute to the order volume in the lightly traded stocks, their order volume is, on average, lower compared to that in the more actively traded stocks. Overall, the statistics in Table 6.1 suggest the two sets of stocks should be examined separately.

6.2.2 Aggressiveness measures and ordered probit model

Orders submitted during normal trading are classified into six categories according to their aggressiveness using the scheme developed by Griffiths et al. (2000). Order aggressiveness is measured by the order price relative to the best bid and ask price on the schedule. Table 6.2 summarises the categories used for grouping the orders.

Table 6.2 Classification of new orders submitted to the market

P_O represents the price of the order, P_A represents the price of the best ask order, P_B represents the price of the best bid order, Q_A represents the quantity (number of shares) at the best ask price, Q_B represents the quantity (number of shares) at the best bid price.

Order Category	Order Type	Price Criteria		Quantity	
		Bid	Ask	Bid	Ask
1	Market orders	$P_O>P_A$	$P_O<P_B$		
2	Market orders	$P_O=P_A$	$P_O=P_B$	$Q_O>Q_A$	$Q_O>Q_B$
3	Market orders	$P_O=P_A$	$P_O=P_B$	$Q_O\leq Q_A$	$Q_O\leq Q_B$
4	In the market	$P_A<P_O<P_B$	$P_A<P_O<P_B$		
5	At the market	$P_O=P_B$	$P_O=P_A$		
6	Behind the market	$P_O<P_B$	$P_O>P_A$		

Category 1 orders are the most aggressive. Orders in this category include buy (sell) orders with order price greater (less) than the best ask (bid) price. The best ask and bid are the ask and bid orders with the highest order priority.[31] Category 1 buy (sell) orders are executed against the limit orders at the best ask (bid) and at least in part against the depth available higher (lower) in the book up (down) to the order price.

[31] See Section 4.3 for the discussion on order priority.

Category 2 and 3 buy (sell) orders have order prices equal to the best ask (bid) price. Category 2 and 3 orders are differentiated by the order size with reference to the depth at the best price on the opposite side. Category 2 orders are larger than the depth at the best price on the opposite side of the book whereas Category 3 orders are less than or equal to the depth at the best price on the opposite side. Consequently, Category 3 orders are executed immediately in full while Category 2 orders are executed immediately in part, with the unfilled part entering as a limit order. Orders in Category 1 to 3 are collectively known as market orders. Due to the dataset used, it is not possible to distinguish market from marketable limit orders.[32]

Category 4 orders have order prices that lie between the best bid and ask prices and are known as orders placed "in the market". Category 5 buy (sell) orders have prices equal to the best bid (ask). These orders are referred to as being placed "at the market". The most passive orders are in Category 6. These buy (sell) orders have their prices less (greater) than the best bid (ask) and are referred to as being placed "behind the market". Orders in Categories 4, 5 and 6 do not result in immediate execution. They are standing limit orders and provide liquidity to traders who require immediacy, i.e., traders who subsequently submit market orders.

Using the criteria described above, each order is placed into one of the six groups. Before examining the differences in the order usage by different trader types, the market conditions at the time of the order placement and the order type are analysed to verify the relationship documented in Al-Suhaibani and Kryzanowski (2001) and Verhoeven et al. (2004). Subsequently, univariate analysis is conducted to examine the differences in the use of order types by the three types of trader. Time of day differences are also examined to add to the prior research on the intraday patterns of the order types. For example, Biais et al. (1995) observe large trades at the end of the day. They hypothesise that the large trades are, among other reasons, due to fund managers being evaluated at the closing price and strategic traders unwinding their trading positions at the end of the day.

[32] Marketable limit orders are limit orders with a price equal to or better than the best existing price on the opposite side of the limit order book.

Ordered probit analysis similar to that described in Griffith et al. (2000) is used to isolate the effect of trader type on the order type selection. Let G_t^* be the unobservable continuous variable denoting the aggressiveness of the order placed at time *t*. G_t^* is assumed to depend linearly on the explanatory variables $x_{i,t}$ where *i* = 1, 2, …, *l*.

$$G_t^* = \sum_{i=1}^{l} \alpha_i x_{i,t} + \varepsilon_t$$

The observed value of G_t is determined from G_t^* using the rule:

$$G_t = \begin{cases} 1 & \text{if } -\infty < G_t^* \leq \gamma_1, \\ m & \text{if } \gamma_{m-1} < G_t^* \leq \gamma_m \text{ for } m = 2, 3, 4 \text{ and } 5 \\ 6 & \text{if } \gamma_5 < G_t^* \leq \infty \end{cases}$$

The probabilities of observing each value of G_t are given by:

$$\begin{aligned} &\Pr[G_t = 1 \mid x_i] = \Phi(\gamma_1 - \sum_{1}^{l} x_i \hat{\alpha}_i), \\ &\Pr[G_t = m \mid x_i] = \Phi(\gamma_m - \sum_{1}^{l} x_i \hat{\alpha}_i) - \Phi(\gamma_{m-1} - \sum_{1}^{l} x_i \hat{\alpha}_i) \text{ for } m = 2, 3, 4 \text{ and } 5, \\ &\Pr[G_t = 6 \mid x_i] = 1 - \Phi(\gamma_5 - \sum_{1}^{l} x_i \hat{\alpha}_i) \end{aligned}$$

where $\Phi(.)$ is the cumulative normal distribution.

The explanatory variables, $x_{i,t}$, are defined as follows:

$DumRet_t$ — is a dummy variable for orders from retail traders, taking on the value of one if a retail trader submits the order (and zero otherwise).

$DumIns_t$ — is a dummy variable for orders from institutional traders, taking on the value of one if a institutional trader submits the order.

$DepthSame_t$	is the depth at the best price on the same side of the market as the order submitted.
$DepthOpp_t$	is the depth at the best price on the opposing side of the market as the order submitted.
$\Delta DepthSame_t$	is the change in the depth at the best price on the same side of the market as the order submitted as a result of the previous market ord limit order.
$\Delta DepthOpp_t$	is the change in the depth at the best price on the opposing side of the market as the order submitted as a result of the previous market or limit order.
$Relspd_t$	is the relative bid-ask spread, which is calculated by dividing the bid-ask spread by the midpoint of the spread.
$Volume_t$	is the number of shares in the order submitted.
$LastAggressive_t$	is a dummy variable that takes on the value of one if the previous order is classified in Categories 1, 2 or 3 in terms of order aggressiveness.
$DumAsk_t$	is a dummy variable that takes on the value of one if the order is on the sell side.

The depth on both sides of the market has been shown by Griffith et al. (2000) to influence the order placement strategies of traders on the Toronto Stock Exchange. A larger depth on the same side ($DepthSame_t$) of the market encourages traders to be more aggressive, whereas a larger depth on the other side of the order book ($DepthOpp_t$) encourages more passive orders. Two variables capturing the change in the order are included: (1) $\Delta DepthSame_t$, and (2) $\Delta DepthOpp_t$. These variables measure the change in the depth on the same and opposing side of the market as the order submitted. An increase on the same side of the market would encourage more aggressive orders while a decrease on the opposing side would have the same effect.

Verhoeven et al. (2004) and Al-Suhaibani and Kryzanowski (2001) find a greater proportion of limit orders when the market spread is large. In the probit analysis, larger spread, $Relspd_t$, is expected to be associated with more passive orders. Biais et al. (1995) find positive serial correlation in order aggressiveness. It is predicted that an order is likely to be more aggressive if the previous order is also aggressive ($LastAggressive_t$).

Harris and Hasbrouck (1996) propose order placement strategy should be a joint decision in terms of the size and aggressiveness of the order. As there are costs involved in placing aggressive orders, the larger the order placed (i.e., $Volume_t$), the more passive the order is expected to be. The last explanatory variable, $DumAsk_t$, is included to allow for any differences between the aggressiveness of sell and buy orders. Keim and Madhavan (1995) find traders are more passive with buy orders, to hide their information, but more aggressive with sell orders, implying a greater urgency when they decide to sell.

6.2.3 Price step measure

This section describes the analysis that examines the position of standing limit orders placed by different trader types relative to the best bid and ask. The measure used is similar to the volume weighted bid-ask spread but better suited for this thesis, as traders may not exist on both sides of the market throughout the whole period. This is particularly so for retail traders.

All orders on the schedule are grouped according to trader type. A volume-weighted price step metric is calculated for each of the three types. Each order price, Ask_i or Bid_i, is weighted by the volume of the order, Vol_i, prior to the summation for all orders belonging to that trader type. The volume-weighted price step metric for each class of trader, *j*, is as follows:

Ask side: $$VPS_j^A = \frac{\dfrac{\sum_{i=1}^{n}\left(Ask_i \times Vol_i\right)}{\sum_{i=1}^{n} Vol_i} - Ask_{Best}}{\text{Price Step}}$$

Bid side: $$VPS_j^B = \frac{Bid_{Best} - \dfrac{\sum_{i=1}^{n}\left(Bid_i \times Vol_i\right)}{\sum_{i=1}^{n} Vol_i}}{\text{Price Step}}$$

The metric is influenced not only by the order price of the standing limit orders but also by their volume. First, the more passive are the limit orders placed by traders, the larger is the price step metric. Second, the larger the volume of the orders away from the market best bid or ask, the larger is the price step metric.

The price step metric is measured at half-hourly intervals during normal trading hours (10:00a.m. to 4:00p.m.). For example, the first interval ends at 10:30a.m. and the first snapshot of the limit order book is taken 1/100th of a second before 10:30a.m. This results in 12 measurements being taken for a typical trading day.

Stale orders are orders that remain on the schedule and have not been cancelled as there is no economic benefit to doing so. These orders are sufficiently far from the market best bid and ask prices and are unlikely to be executed. In order to mitigate noise from these orders, ask and bid orders that are ten or more price steps away from the best ask (bid) are excluded from the analysis.[33]

6.3 Results

6.3.1 Summary statistics of orders submitted

Table 6.3 presents the summary statistics for orders placed over the period 1 January 2001 to 31 December 2001 for the 18 heavily traded stocks (Panel A) and 18 lightly traded stocks (Panel B). The average price of orders placed is $15.98 and $1.68 for the heavily traded and lightly traded stocks respectively. Although the order size for

[33] The minimum price step is 0.1 cents for stocks up to 10 cents, 0.5 cents for stocks greater than 10 cents but less than or equal to 50 cents, 1 cent for stocks greater than 50 cents but less than or equal to $998.99, and $1 for stocks equal to or greater than $999 (Aitken and Comerton-Forde, 2005; ASX, 2005).

the heavily traded stocks is smaller than for the lightly traded stocks, the dollar value of each order is larger. The relative spread for the heavily traded stocks is 0.1374% and the relative spread for the lightly traded stocks is 1.428%. For both sets of stocks, the dollar spread is on average approximately two cents, which is twice the minimum price step of one cent for stocks within the price range 50 cents to $998.99.

The spreads over the period examined are smaller than those documented by Aitken and Frino (1996b) using data from June to November 1992. Aitken and Frino observe, on average, stocks in the price range of $0.10 to $10.00 have a relative spread of 4.4%. This translates to approximately six cents, which is six times the minimum price step of one cent. The probable causes for the decrease in the spreads include changes in tick size (Aitken and Comerton-Forde, 2005) and an increase in the trading volume on the ASX during the period examined.

Table 6.3 Summary statistics

The table presents the summary statistics of the orders placed over the period 1 January 2001 to 31 December 2001 for the selected sample stocks.

	Mean	Min	Max	Std	Median
Panel A: Heavily traded stocks (n= 5,315,780)					
Order Price ($)	15.982	0.001	994.500	10.248	12.050
Order Size (number of shares)	7,619	1	190,200,000	99,972	2,591
Number of trades executed	1.2775	0	450	2	1
Relative spread (%)	0.1374	0.0189	4.5375	0.1037	0.1178
Depth at best bid	38,102	1	5,268,914	112,625	10,013
Depth at best ask	35,477	1	190,180,000	155,063	10,696
Depth at bid	935,071	3,020	69,093,723	1,798,250	402,762
Depth at ask	1,367,122	1,584	190,683,566	2,442,878	473,238
Volatility	0.0339	0.0000	6.0412	0.0437	0.0221
Panel B: Lightly traded stocks (n= 321,322)					
Order Price ($)	1.677	0.007	195.000	1.817	0.992
Order Size (number of shares)	14,868	1	16,039,100	58,721	6,329
Number of trades executed	1.1219	0	115	1	1
Relative spread (%)	1.4280	0.0989	186.1592	1.1636	1.3077
Depth at best bid	61,491	1	13,898,270	232,789	17,065
Depth at best ask	48,784	1	3,566,000	111,729	15,447
Depth at bid	1,062,598	157	18,672,916	1,644,148	480,424
Depth at ask	1,142,231	48	12,809,169	1,660,537	455,004
Volatility	0.3282	0.0000	37.9312	0.4413	0.1861

The four depth measures (for both sets of stocks) exhibit skewness. In order to ensure comparability of the depth measures across stocks, they are standardised by subtracting the mean and dividing the result by the standard deviation for each stock over the period examined. The volatility measure is calculated using the root of the mean squared midpoint return for the five transactions prior to the observed order.

$$\text{Volatility} = \sqrt{\sum_{t=1}^{5} \text{Midpt Rtn}_{-t}^{2} \Big/ 5}$$

This measure of volatility is smaller in the heavily traded stocks. For robustness, volatility is recomputed using the last two and the last ten transactions respectively.

6.3.2 Market condition and order aggressiveness

Table 6.4 presents the spread, market depth and volatility prior to the placement for orders with different aggressiveness. Panel A of Table 6.4 reports the market conditions for the heavily traded stocks. To allow comparison with previous studies, the market conditions are also shown for the orders grouped as (1) market and (2) limit orders. Of the total number of orders placed, 46% are classified as market orders. Panel B shows that the proportion of market orders placed in the lightly traded stocks is similar at 42%.

As expected, the size of limit orders is larger than that of market orders. However, the difference is statistically significant only for the lightly traded stocks using both parametric and non-parametric tests.[34] The relative spread is statistically larger when a limit order is placed compared to when a market order is placed. The loadings on depth and changes in depth are consistent with prior studies. The greater the depth or the larger the increase in the depth level at the best price on the same side, the greater the incentive to place a market order. However when all orders on the schedule are included in measuring depth, the relationship is not evident. This could be due to the stale order problem described in Section 6.2.3. Also, the depth away from the best bid and ask may be less of concern to traders as it has less influence on the execution of an incoming order at the market best price.

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[34] The meaningfulness of the parametric test results depends on the validity of the assumption that the data is normally distributed. Non-parametric statistical tests are based on models that specify only very general conditions and none regarding the specific form of the distribution from which the sample was drawn (Siegel and Castellan, 1988). Both parametric (*t*-statistics) and non-parametric (Wilcoxon signed rank) tests are performed as the distribution of financial data have been found to be non-normal (Campbell et al., 1997; Gujarati, 1995).

Table 6.4 Market condition and order aggressiveness

Orders are classified by the order price relative to the best bid and ask on the market. Category 1 buy (sell) order price is greater (less) than the best ask (bid) price. Category 2 and 3 buy (sell) orders have order prices equal to the best ask (bid) price. Category 2 and 3 orders differ in that the size of Category 2 orders exceeds the depth at the priority price on the opposite side of the book whereas Category 3 does not. Category 4 orders have prices that lie between the best bid and best ask. Category 5 buy (sell) orders have prices that are equal to the best bid (ask). Category 6 buy (sell) orders have prices less (more) than the best bid (ask). Categories 1, 2 and 3 are grouped as Market Orders. Categories 4, 5 and 6 are grouped as Limit Orders. Order Size is the average number of shares per order. Relative spread is the average proportional spread calculated using the spread scaled by the midpoint price. Depth at Best Same is the market depth at the priority price on the same side of the order. ΔDepth at Best Same is the change in the market depth at the priority price on the same side of the order. Depth at Best Opposite is market depth at the priority price on the opposite side of the order. ΔDepth at Best Opposite is the change in the market depth at the priority price on the opposite side of the order. Depth at Same is the market depth on the same side of the order. ΔDepth at Same is the change in the market depth on the same side as the order. Depth at opposite is the market depth on the opposite side to the order. ΔDepth at Opposite is the change in the market depth on the same side as the order. Volatility is calculated as the square root of the mean squared return of the last five transactions before the order observed. The level of statistical significance for the two-tailed test is denoted as * significant at the 5% level and # significant at the 10% level.

Order Type	n	%	Order Size	Relative Spread	Depth at Best Same	ΔDepth at Best Same	Depth at Best Opposite	ΔDepth at Best Opposite	Depth at Same	ΔDepth at Same	Depth at Opposite	ΔDepth at Opposite	Volatility
Panel A: Heavily traded stocks													
Market Orders	2,431,298	46	7586	0.122	0.072	0.084	-0.039	-0.088	-0.001	-0.001	0.010	0.001	0.032
Limit Orders	2,884,482	54	7647	0.151	-0.053	-0.045	0.025	0.048	-0.015	0.001	0.007	-0.001	0.036
1	216,137	4	4024	0.131	0.005	0.092	-0.088	-0.156	0.018	-0.002	0.107	0.002	0.033
2	671,990	13	15081	0.108	0.068	0.169	-0.349	-0.478	-0.026	-0.002	-0.065	-0.002	0.038
3	1,543,171	29	4821	0.126	0.083	0.046	0.102	0.091	0.007	0.000	0.029	0.002	0.029
4	377,600	7	4864	0.219	0.070	0.235	-0.023	0.122	-0.139	-0.001	-0.113	-0.001	0.049
5	1,363,096	26	9514	0.139	-0.063	-0.114	0.055	0.017	0.009	0.001	-0.003	-0.001	0.034
6	1,143,786	22	6340	0.142	-0.081	-0.054	0.006	0.061	-0.001	0.000	0.059	0.000	0.033
Difference between Market and Limit Orders			-61	-0.029	0.125	0.129	-0.065	-0.137	0.014	-0.001	0.003	0.002	-0.004
t-statistic			(-0.67)	(-328.23)*	(140.07)*	(119.05)*	(-76.64)*	(-121.78)*	(16.04)*	(-42.19)*	(3.11)*	(56.08)*	(-115.09)*
Wilcoxon statistic			(6.74)*	(-331.47)*	(209.39)*	(134.36)*	(-107.32)*	(-233.61)*	(23.06)*	(-94.27)*	(-1.02)	(67.58)*	(-108.04)*

Order Type	n	%	Order Size	Relative Spread	Depth at Best Same	ΔDepth at Best Same	Depth at Best Opposite	ΔDepth at Best Opposite	Depth at Same	ΔDepth at Same	Depth at Opposite	ΔDepth at Opposite	Volatility
Panel B: Lightly traded stocks													
Market Orders	133,415	42	13650	1.242	0.104	0.089	-0.065	-0.087	0.054	0.000	-0.058	0.002	0.301
Limit Orders	187,907	58	15732	1.560	-0.097	-0.059	0.069	0.057	0.001	0.000	0.002	-0.001	0.348
1	9,634	3	13245	1.329	0.024	0.085	-0.169	-0.214	0.110	0.000	-0.094	0.002	0.331
2	33,402	10	23555	1.203	0.123	0.200	-0.521	-0.538	-0.060	-0.005	-0.106	-0.004	0.377
3	90,379	28	10033	1.248	0.105	0.049	0.115	0.093	0.090	0.001	-0.036	0.004	0.270
4	29,119	9	6918	2.124	-0.023	0.240	-0.047	0.107	-0.205	-0.001	-0.178	-0.003	0.449
5	87,243	27	17026	1.385	-0.122	-0.159	0.122	0.033	0.017	0.000	0.015	-0.002	0.312
6	71,545	22	17742	1.543	-0.095	-0.058	0.052	0.066	0.064	0.002	0.060	0.000	0.352
Difference between Market and Limit Orders			-2082	-0.318	0.200	0.148	-0.134	-0.144	0.053	-0.001	-0.060	0.003	-0.047
t-statistic			(-9.53)*	(-82.02)*	(55.83)*	(35.08)*	(-37.11)*	(-33.79)*	(14.63)*	(-2.79)*	(-16.94)*	(10.17)*	(-28.88)*
Wilcoxon statistic			(-42.99)*	(-90.15)*	(68.97)*	(40.05)*	(-46.96)*	(-73.17)*	(14.88)*	(-12.76)*	(-18.36)*	(-8.60)*	(-29.62)*

The volatility measure in Table 6.4 is based on the last five transactions prior to the order being placed. It is significantly higher at an average of 0.036 when limit orders are placed compared to 0.032 for market orders. This is consistent with the predictions of theoretical models such as Foucault (1999). In addition to the breakdown of market and limit orders, Table 6.4 further partitions the orders according to their aggressiveness. For the heavily traded stocks, 4% of the orders placed are classified as most aggressive and 13% are market orders with order size greater than the depth available at the best price on the opposite side of the market. A large proportion of the orders (29%) are market orders that were executed immediately at the price of the priority order on the opposite side of the market. Of the 54% that are limit orders, 7% are placed in the market, 26% at the market, and 22% are behind the market. The breakdown of the orders in the lightly traded stocks is similar to that of the heavily traded stocks.

The relationships between order aggressiveness and the variables examined (i.e., spread, depth, change in depth and volatility) are not clearly evident. The probit model examined in Section 6.3.4 is designed to provide further insight.

6.3.3 Order aggressiveness and trader type

Table 6.5 presents the average proportion of order type used by each trader type per day. Panel A reports the breakdown for the heavily traded stocks. The percentage of market orders (order types 1, 2 and 3) used by institutional traders is 45.61% and by retail traders is 46.65%. These figures are consistent with Table 6.4. While the proportions based on the general classification of market and limit orders are similar across the two trader types, the classification based on order aggressiveness demonstrates significant differences.

Of the orders placed by retail traders, 12.3% of the orders placed are classified as Category 1. This is statistically different from the 1.62% for institutional traders and 2.16% for other traders. It is possible that retail traders are impatient in their trading, but the higher proportion also could be due to their lack of knowledge of market conditions. Traders unaware of the market condition or market movements could be more inclined to place buy (sell) orders with marketable limit prices that are higher (lower) than the best ask (bid) price on the schedule. The proportion of Category 2 orders is significantly larger for institutional traders but the proportion of Category 3 orders is significantly smaller. This is expected as the size of institutional orders is larger in comparison.

Of the limit orders, a greater proportion of institutional orders are placed in the market (Category 4) compared to retail orders (0.0870 and 0.0489 respectively). These orders have prices less than the best ask and greater than the best bid. Also, a greater proportion of institutional orders are placed at the market compared to retail orders (0.3449 versus 0.1513). These orders (Category 5) are placed at the same price as the order with the highest priority on the same side. Correspondingly, a smaller proportion of institutional orders are placed behind the market (Category 6) compared to retail orders.

Table 6.5 Frequency of order type placed by different trader types

The frequency is expressed as a proportion of the total number of orders placed by that trader type on that trading day. The proportions are averaged over the period 1 January 2001 to 31 December 2001. The table shows the differences between the proportion of each order type used by (1) institutional and retail traders and (2) others and retail traders. *t*-statistic are in parentheses. The level of statistical significance for the two-tailed *t*-test is denoted as * significant at the 5% level and # significant at the 10% level.

Order				Institutional versus Retail			Others versus Retail		
Type	Institutional	Retail	Others	Diff	*t*-stat	Wilcoxon	Diff	*t*-stat	Wilcoxon
Panel A: Heavily traded stocks									
n	4,356	4,355	4,355						
1	0.016	0.123	0.022	-0.107	(-112.31)*	(-76.57)*	-0.102	(-105.98)*	(74.93)*
2	0.184	0.043	0.090	0.141	(161.50)*	(78.84)*	0.047	(-59.92)*	(-52.52)*
3	0.256	0.300	0.363	-0.044	(-28.17)*	(-24.15)*	0.063	(-30.66)*	(-31.19)*
4	0.087	0.049	0.082	0.038	(37.63)*	(39.74)*	0.033	(-30.57)*	(-32.90)*
5	0.345	0.151	0.198	0.194	(130.13)*	(76.97)*	0.047	(-36.58)*	(-36.83)*
6	0.112	0.333	0.246	-0.221	(-145.24)*	(-78.09)*	-0.087	(40.11)*	(40.79)*
Panel B: Lightly traded stocks									
n	4,009	4,048	4,229						
1	0.014	0.071	0.021	-0.057	(-27.83)*	(35.74)*	-0.050	(-24.76)*	(-25.05)*
2	0.118	0.082	0.112	0.036	(12.12)*	(-12.99)*	0.030	(12.10)*	(19.34)*
3	0.320	0.252	0.315	0.068	(14.27)*	(-13.50)*	0.063	(15.77)*	(19.16)*
4	0.137	0.098	0.120	0.039	(10.28)*	(-12.26)*	0.022	(6.50)*	(15.44)*
5	0.312	0.197	0.243	0.115	(25.98)*	(-26.26)*	0.046	(12.75)*	(15.97)*
6	0.100	0.300	0.189	-0.201	(-47.24)*	(47.30)*	-0.111	(-27.70)*	(-27.85)*

As Cho and Nelling (2000) observe, limit orders placed further away from the market are likely to take a longer time to execute. This provides some support for my conjecture that institutional traders are more eager to trade, since they are more likely to place limit orders that are in the market or at the market rather than behind it. The results for the lightly traded stocks in Panel B are similar to those for the heavily traded stocks. The percentage of limit and market orders are similar for both institutional and retail traders at 45.3% and 44.8% respectively. Retail traders have a greater proportion of orders that are aggressively priced (Category 1). They also have a greater proportion of orders that are passively priced (Category 6) than institutional traders.

Table 6.6 presents the breakdown of order types placed by the different trader types across the trading day. Across all three, the number of orders placed exhibits a U-shape that is consistent with prior studies on intraday trading patterns (Aitken et al., 1993b; McInish and Wood, 1990). The number of orders placed is lowest during the middle of the trading day. The U-shaped pattern exists for both sets of stocks examined.

In examining the proportion of market orders across the trading day, there is a statistically significant increase in the more aggressive orders placed by all three trader types. This is inconsistent with the findings of Biais et al. (1995) for the Paris Bourse. They find that market orders were most frequent during the earlier part of the trading day, followed by the period towards the end of the day. It is least frequent during the middle of the day. The increase in the proportion of market orders through the day is also evident in the lightly traded stocks. This phenomenon could be driven by traders becoming more eager to unwind their positions before the end of the day. For example, day traders on the NASDAQ are known to be reluctant to hold their positions overnight (Harris and Schultz, 1998). As a result, trading volume from day traders increases before the market closes.

Table 6.6 Proportion of order type used by different trader types during the normal trading hours

The table presents the average proportion of order type used by the three different trader types during the normal trading hours. The trading day is partitioned into three segments: (1) 10am-12pm (2) 12pm-2pm and (3) 2pm-4pm. The last two columns show the differences between the proportion of market orders placed over the following periods (1) 10am-12pm versus 12pm-2pm and (2) 12pm-2pm versus 2pm-4pm. The level of statistical significance for the two-tailed test is denoted as: * significant at the 5% level and # significant at the 10% level.

Trader type	Time of the day	N	Number of orders	Order type						Market Orders	Proportion of Market Orders for 10am-12pm minus 12pm-2pm			Proportion of Market Orders for 12pm-2pm minus 2pm-4pm		
				1	2	3	4	5	6		Diff	*t*-stat	Wilcoxon	Diff	*t*-stat	Wilcoxon
Panel A: Heavily traded stocks																
Institutional	10am-12pm	4,352	244	0.018	0.190	0.241	0.099	0.329	0.124	0.449						
	12pm-2pm	4,327	90	0.013	0.165	0.279	0.078	0.344	0.120	0.458	0.009	(5.26)*	(5.46)*			
	2pm-4pm	4,281	263	0.016	0.182	0.264	0.078	0.363	0.097	0.462				0.0047	(2.82)*	(2.31)*
Others	10am-12pm	4,353	181	0.025	0.093	0.338	0.093	0.197	0.254	0.456						
	12pm-2pm	4,325	82	0.016	0.081	0.395	0.068	0.183	0.257	0.492	0.036	(13.72)*	(13.84)*			
	2pm-4pm	4,281	154	0.020	0.089	0.387	0.073	0.207	0.224	0.496				0.0040	(1.42)	(1.93)#
Retail	10am-12pm	4,352	91	0.128	0.045	0.278	0.053	0.137	0.359	0.451						
	12pm-2pm	4,320	55	0.122	0.038	0.314	0.041	0.139	0.346	0.474	0.023	(8.85)*	(8.87)*			
	2pm-4pm	4,277	72	0.120	0.042	0.326	0.046	0.174	0.291	0.489				0.0149	(5.45)*	(5.57)*
Panel B: Lightly traded stocks																
Institutional	10am-12pm	3,629	9	0.014	0.119	0.299	0.155	0.311	0.102	0.432						
	12pm-2pm	3,087	5	0.013	0.118	0.322	0.122	0.325	0.100	0.453	0.021	(2.62)*	(1.59)			
	2pm-4pm	3,448	10	0.016	0.118	0.341	0.126	0.319	0.080	0.475				0.0218	(2.65)*	(-3.36)*
Others	10am-12pm	4,054	17	0.022	0.111	0.292	0.128	0.246	0.201	0.425						
	12pm-2pm	3,800	9	0.017	0.101	0.322	0.103	0.246	0.211	0.440	0.015	(2.50)*	(1.80)#			
	2pm-4pm	3,914	12	0.022	0.117	0.353	0.108	0.236	0.164	0.492				0.0523	(8.55)*	(-9.40)*
Retail	10am-12pm	3,674	11	0.068	0.084	0.230	0.098	0.202	0.318	0.382						
	12pm-2pm	3,466	7	0.070	0.073	0.247	0.085	0.194	0.331	0.390	0.008	(1.20)	(-0.23)			
	2pm-4pm	3,514	8	0.072	0.083	0.282	0.087	0.205	0.272	0.436				0.0465	(6.37)*	(-7.45)*

6.3.4 Ordered probit analysis

Table 6.7 presents the results from ordered probit analysis. Due to the large number of data points and computational limitations, it was not possible to generate the model based on the whole data set.[35] The model was generated for the two sets of stocks used and for two months, March 2001 and September 2001, separately to give some assurance that the results are generalisable across the whole period.[36]

The dependent variable is order aggressiveness ranked from the most to the least aggressive. A negative coefficient indicates that the probability of observing more aggressive orders increases with each positive change of that variable. The model fitted to March 2001 (September 2001) data for heavily traded stocks has a negative coefficient on *DumIns* of -0.192 (-0.104). This indicates that the probability of observing a more aggressive order is higher when the order is placed by an institutional trader. The coefficient on *DumRet* of 0.086 indicates that the probability of observing a more aggressive order is lower when the order is placed by a retail trader. The latter coefficient is -0.047 when using the September 2001 data, indicating that the orders placed by retail traders are more aggressive than those placed by "other" traders but are still more passive than those placed by institutional traders.

The other explanatory variables such as *DepthSame*, Δ*DepthSame, DepthOpp*, Δ*DepthOpp*, *Relsp, LastAggressive* and *DumAsk* exhibit their predicted signs. Larger and increasing market depth on the same side of the market as the order increases the probability of observing a more aggressive order. Larger market depth and increasing depth on the opposite side decreases the probability of observing a more aggressive order. More limit orders are observed when the spread on the market is large. Also,

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[35] The large number of observations is likely to bias the analysis in finding significant independent variables. Thus, care needs to be exercised when interpreting the findings.

[36] The trading activity in the month of September may not reflect trading during other parts of the year because the majority of Australian companies release their financial results in September (using earnings announcement data available for 2000, 53% of Australian listed companies were found to release their preliminary final statements in September). The information asymmetry is likely to higher in September and the trader types that are active in the market during September may be different to other months.

the probability of observing a more aggressive order increases when the previous order is aggressive. These findings are consistent with results reported in prior studies such as Biais et al. (1995), who they find the probability of observing the same order type in sequence is higher than observing two different order types in sequence. The *DumAsk* variable shows the probability of observing a more aggressive order increases given the order is a sell order.

Table 6.7 Ordered probit analysis of order type usage

The analysis for the 36 stocks used data from March 2001 and September 2001. Orders are classified into six different levels of aggressiveness. Category 1 buy (sell) order price is greater (less) than the best ask (bid) price. Category 2 and 3 buy (sell) orders have order prices equal to the best ask (bid) price. Category 2 and 3 orders differ in that the size of Category 2 orders exceeds the depth at the priority price on the opposite side of the book whereas Category 3 orders do not. Category 4 orders have prices that lie between the best bid and best ask. Category 5 buy (sell) orders have prices that are equal to the best bid (ask). Category 6 buy (sell) orders have prices less (more) than the best bid (ask). $DumRet_t$ is the dummy variable for orders from retail traders; it takes on the value of one if a retail trader submits the order. $DumI_t$ is the dummy variable for orders from institutional traders; it takes on the value of one if an institutional trader submits the order. $DepthSame_t$ is the depth at the best price on the same side of the market as the order submitted. $DepthOpp_t$ is the depth at the best price on the opposing side of the market as the order submitted. $\Delta DepthSame_t$ is the change in the depth at the best price on the same side of the market as the order submitted. $\Delta DepthOpp_t$ is the change in the depth at the best price on the opposing side of the market as the order submitted. *Relspd* is the relative bid-ask spread, which is calculated by dividing the bid-ask spread by the midpoint of the spread. $Volume_t$ is the number of shares in the order submitted. $LastAggressive_t$ is a dummy variable that takes on the value of one if the previous order is classified in Categories 1, 2 or 3 in terms of order aggressiveness. $DumAsk_t$ is a dummy variable that takes on the value of one if the order is on the sell side. For the z-statistic, * indicates significance at the 5% and # significant at the 10% level..

	Coefficient	Z-Statistic	Coefficient	Z-Statistic
	Panel A: Heavily traded stocks			
	(March 2001 n=436,660)		(September 2001 n=583,509)	
DumIns	-0.192	-54.053 *	-0.104	-33.290 *
DumRet	0.086	17.597 *	-0.047	-11.956 *
DepthSame	-0.066	-38.887 *	-0.038	-26.959 *
ΔDepthSame	-0.044	-36.606 *	-0.036	-32.563 *
DepthOpp	0.076	40.794 *	0.040	31.667 *
ΔDepthOpp	0.044	37.454 *	0.044	41.644 *
Relspd	0.954	59.380 *	0.732	61.501 *
Volume/1,000,000	-0.129	-5.372 *	-0.908	-14.832 *
Volatility	-0.522	-12.146 *	-0.590	-20.477 *
DumAft	0.045	9.917 *	0.016	4.173 *
DumLate	0.000	0.136	-0.013	-4.393 *
LastAggressive	-0.055	-15.039 *	-0.062	-19.825 *
DumAsk	-0.048	-14.971 *	-0.029	-10.407 *
Partition boundaries				
γ1	-1.946	-332.741 *	-1.554	-353.911 *
γ2	-1.007	-204.247 *	-0.886	-221.032 *
γ3	-0.082	-17.062 *	-0.062	-15.822 *
γ4	0.123	25.564 *	0.126	32.088 *
γ5	0.905	184.228 *	0.783	195.437 *

	Coefficient	Z-Statistic	Coefficient	Z-Statistic
	Panel B: Lightly traded stocks			
	(March 2001 n=24,796)		(September 2001 n=3,775)	
DumIns	-0.137	-8.247 *	0.046	2.705 *
DumRet	0.222	13.622 *	0.113	6.177 *
DepthSame	-0.093	-12.602 *	-0.035	-5.886 *
ΔDepthSame	-0.049	-8.541 *	-0.046	-8.096 *
DepthOpp	0.129	17.945 *	0.041	6.313 *
ΔDepthOpp	0.042	7.561 *	0.031	5.754 *
Relspd	0.128	14.962 *	0.055	10.824 *
Volume/1,000,000	0.462	2.066	0.416	2.564
Volatility	-0.075	-4.029 *	-0.033	-2.709 *
DumAft	-0.025	-1.441	0.007	0.360
DumLate	-0.150	-9.564 *	-0.129	-7.823 *
LastAggressive	-0.191	-11.954 *	-0.251	-14.686 *
DumAsk	-0.054	-4.005 *	-0.214	-14.667 *
Partition boundaries				
$\gamma 1$	-2.043	-78.794 *	-1.844	-79.626 *
$\gamma 2$	-1.109	-52.186 *	-1.195	-58.773 *
$\gamma 3$	-0.194	-9.428 *	-0.308	-15.915 *
$\gamma 4$	0.055	2.661 *	0.019	0.984
$\gamma 5$	0.798	38.334 *	0.856	43.270 *

The explanatory variables that are inconsistent with prior expectations include *Volume*, *Volatility* and *DumLate*. The sign on the order size variable is contrary to the prediction that larger orders are more passive because of the higher cost of executing large aggressive orders. The results are, however, consistent with Keim and Madhavan (1995), where institutional traders are found to be impatient (thus aggressive) in their trading. The coefficient on the variable *Volatility* is also contrary to the prediction of the theoretical models but consistent with empirical findings (e.g., Foucault, 1999; Ranaldo, 2004). The coefficient on the dummy variable *DumLate* is not significant in the model using March 2001 data but has the correct sign and is statistically significant using September 2001 data.

Panel B presents the coefficients for the ordered probit model using data for the lightly traded stocks. The implications of the results are similar to those for the heavily traded stocks, the only notable difference being the coefficient of *Volume*, whose sign is now consistent with predictions.

In summary, the analysis shows that orders from institutional traders are more aggressive than retail traders. However, institutional traders appear to be more aware of market conditions. Furthermore, limit orders placed by institutional traders are more likely to be in the market or at the market, which increases their probability of being executed.

6.3.5 Trader type and market depth

The volume-weighted price metric is calculated for each trader type in each month of the period examined. Table 6.8 reports the average volume-weighted price metric for the three different trader types. The volume-weighted price metric for institutional traders is compared to that for retail traders each month. Table 6.8 shows the number of months in which the volume-weighted price metric is larger for retail traders.

For the heavily traded stocks, standing limit orders placed by retail traders are further away from the market best bid and ask compared to institutional traders. Standing bid and ask limit orders from retail traders are, on average, 5.46 price steps away from the market's best bid and ask while standing limit orders from institutional traders are, on average, 3.28 price steps away. Standing limit orders placed by retail traders are consistently further from the market in all 12 months of data analysed for the 18 heavily traded stocks.

For the lightly traded stocks, the average volume weighted price metric of standing limit orders placed by retail traders is also further from the market (5.19 price step) compared to orders placed by institutional traders (4.08). However, the results presented for the individual stocks show that the aggregated results are not necessarily representative of all 18 stocks in that subset. In some stocks, such as KIM and MXO, institutional traders are shown to have standing limit orders further away from the market.

Table 6.8 Monthly average price steps of standing limit orders

The table presents the monthly average price steps, VPS_t^A and VPS_t^B, for the stocks using data from the period 1 January 2001 to 31 December 2001. The significance column shows the average *t*-statistic over the 12 month period and the number of months where the difference in the average price step between institutional traders and retail traders are significantly different at the 5% level.

	Average Price Step			Significance	
ASX Code	Institution	Others	Retail	*t*-stat	5% significant
Panel A: Heavily traded stocks					
AMP	3.575	4.355	5.521	12.77	12
ANZ	3.343	4.355	5.516	16.12	12
BHP	3.679	4.574	5.570	16.33	12
BIL	3.194	4.092	4.971	8.76	12
CBA	3.745	4.370	5.349	10.23	12
CML	2.992	4.713	5.933	25.44	12
CSR	2.551	4.218	5.535	23.14	12
LLC	3.466	4.605	5.646	15.09	12
MAY	3.142	4.828	5.602	20.31	12
NAB	3.852	4.336	5.462	9.74	12
NCP	3.694	4.549	5.515	13.17	12
QAN	2.695	4.893	5.488	30.03	12
RIO	3.679	3.725	4.729	4.01	11
TLS	2.635	4.575	5.607	39.75	12
WBC	3.198	4.490	5.546	17.35	12
WMC	3.207	4.500	5.314	16.84	12
WOW	3.098	4.553	5.637	20.2	12
WPL	3.201	4.104	5.265	13.45	12
Mean	*3.275*	*4.435*	*5.456*		
Panel B: Lightly traded stocks					
AQP	2.106	2.742	3.555	5.08	12
ARG	4.317	4.683	4.991	6.1	9
CPH	3.728	5.071	6.065	18.91	11
GNS	3.451	3.926	4.365	4.8	8
GWT	4.129	4.788	5.401	8.55	11
HRP	1.746	3.313	3.176	15.73	11
IFM	2.870	3.515	4.784	8.74	11
KIM	6.004	5.008	5.212	-5.6	2
MXO	6.533	5.748	5.714	-4.1	5
MYO	3.923	5.107	5.843	12.18	12
NUF	2.794	3.966	4.875	10.77	12
OML	2.778	4.404	4.998	15.49	11
PLM	2.625	3.504	2.521	0.96	4
RIC	3.273	3.814	4.491	15.5	11
SLX	2.980	4.067	4.926	9.02	12
TIM	4.150	4.866	5.406	6.81	9
VNA	13.722	12.812	11.702	-3.79	1
VRL	2.218	4.452	5.319	23.43	12
Mean	*4.075*	*4.766*	*5.186*		

Figures 6.1 and 6.2 show the variation in the number of price steps that standing limit orders are away from the market best bid and ask through the normal trading day, for

the heavily traded stocks and lightly traded stocks respectively. In both figures, market spread is relatively wider in the first interval (market spread captured prior to 10:30a.m.) The spread decreases over the trading day and increases near the closing. This pattern is generally consistent with the intra-day bid-ask spread pattern found in Aitken, et al. (1993a) for the ASX.

The volume-weighted price step metric for institutional traders is consistently lower than for retail traders across the whole day. While the intraday variation is small, the volume-weighted price step metric for institutional traders is highest at the middle of the day. The results from Table 6.6 discussed earlier showed that the proportion of aggressive orders submitted by institutional traders is largest between 2 p.m. and 4 p.m. The proportion of the most passive order type (Category 6) is highest in the first two hours of trading (10 a.m. to 12 p.m.). The results suggest that the price step metric will be highest at the beginning of trading for institutional traders. However, Figure 6.1 does not support this inference.

The price step metric for institutional traders is smallest near the end of the trading phase and is consistent with the analysis of order aggressiveness. However, the price step metric for institutional traders during the middle of the day is larger than for the beginning of the day, when more passive orders are submitted. The difference found here is likely to be due to the relative size of the order types. Table 6.6 analyses the proportions of different order types placed and does not provide any measure of aggressiveness weighted by the size of the orders. Combining the results from Table 6.6 and Figure 6.1, it can be inferred that, while orders placed during the middle of the day may be more aggressive than those placed at the beginning of the day, aggressive orders around midday are also likely to be smaller in size.

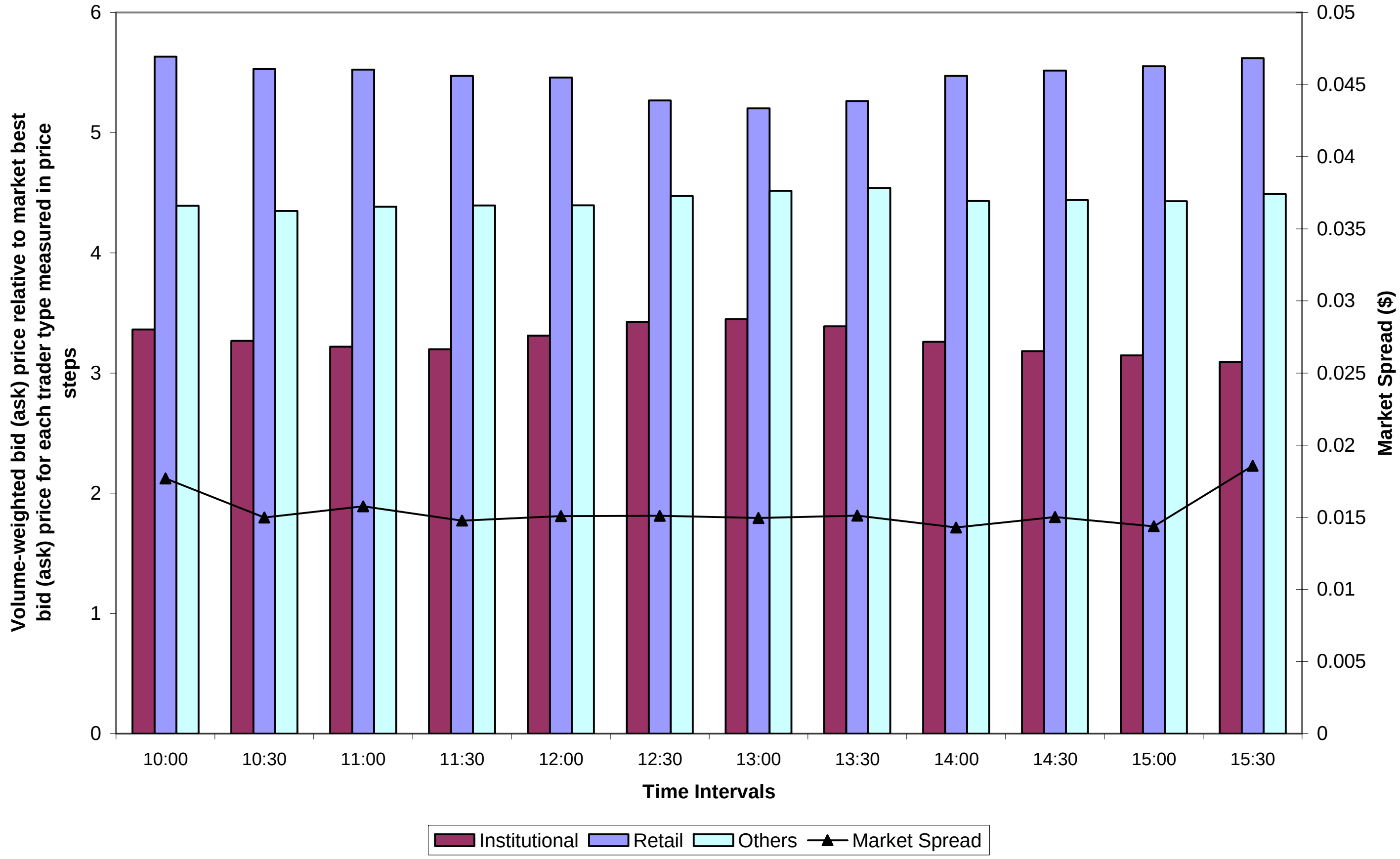

Figure 6.1 Volume-weighted bid (ask) price relative to the market best bid (ask) price for each trade type in the heavily traded stocks. The volume-weighted prices are expressed in price steps. The volume-weighted prices are measured at the end of each half hour interval from 10:00am to 4:00pm.

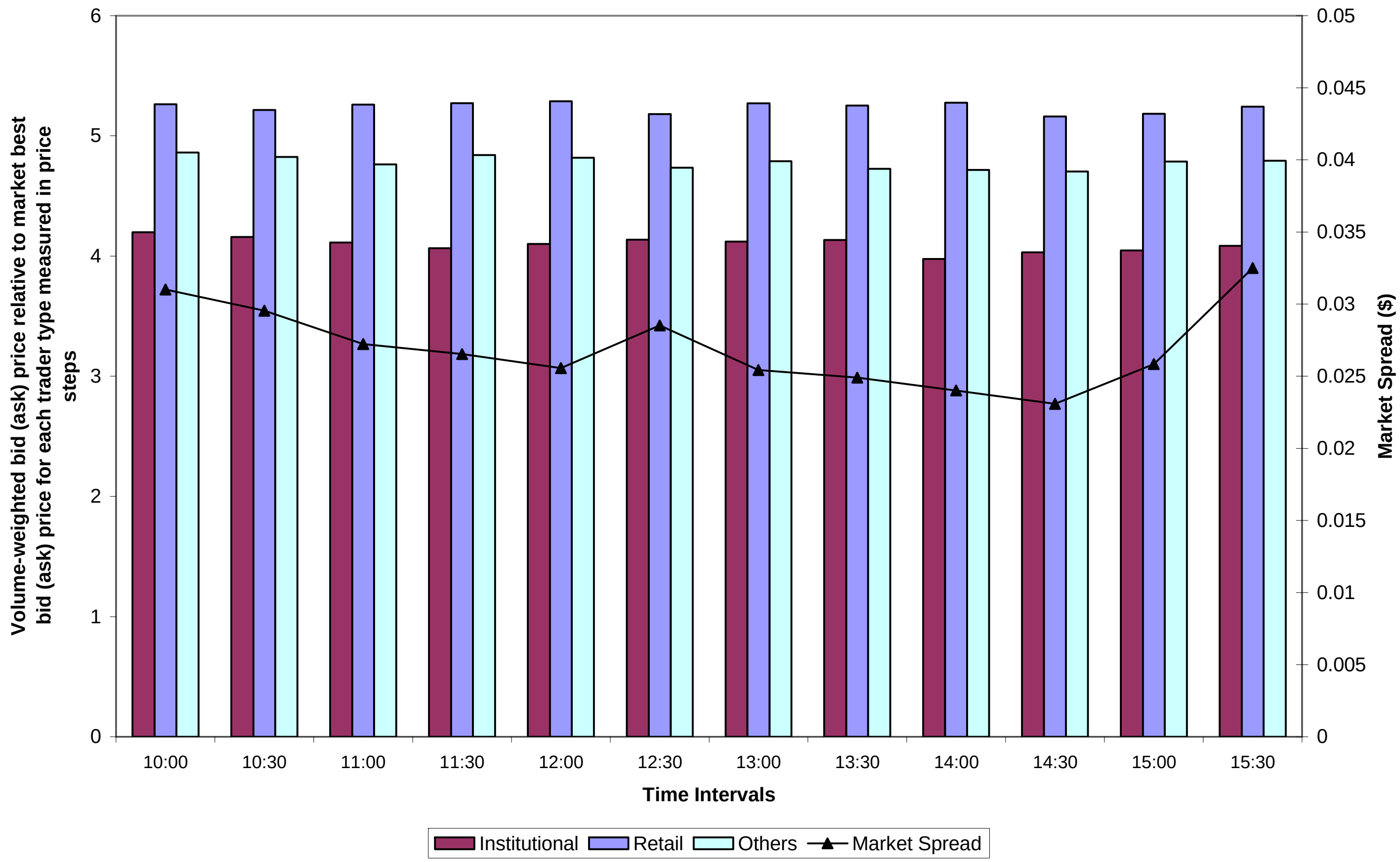

Figure 6.2 Volume-weighted bid (ask) price relative to the market best bid (ask) price for each trade type in the lightly traded stocks. The volume-weighted prices are expressed in price steps. The volume-weighted prices are measured at the end of each half hour interval from 10:00am to 4:00pm.

The volume-weighted price step metric for retail traders is lowest at the middle of the trading phase. The higher price step metrics at the beginning and end of trading suggest retail traders are aware of the greater risk of being "picked off" by an informed trader, thus pricing their limit orders further from the market best bid and ask. However, this suggestion contradicts the earlier discussion based on order aggressiveness, where retail traders are believed to be less aware of market conditions when placing their orders.

Figure 6.2 relates to lightly traded stocks. It shows that, again, standing limit orders placed by institutional traders are closer to the market best bid and ask compared to similar orders placed by retail traders. The intraday pattern found in Figure 6.1 is not evident in Figure 6.2. A reason could be the lack of activity in these stocks. On average, 88 orders are placed per stock day for the stocks in the second set (lightly traded stocks). Given that almost half of them are market orders, the analysis of the remaining orders is limited.

In summary, the results from Table 6.8 and Figures 6.1 and 6.2 provide support for the hypothesis (H_4), that the standing limit orders placed by retail traders are further away from the market compared to those placed by institutional traders. The following inferences can be drawn. First, the contribution to market liquidity that is likely to be consumed by market traders is highest from institutional traders. Second, a premium appears to be charged by retail traders for the information asymmetry to which they are exposed at the beginning and end of trading, when strategic traders are more likely to trade. This evidence is found for the more heavily traded stocks but it is less clear for the lightly traded stocks.

6.4 Conclusion

Handa and Schwartz (1996) describe the securities market as an ecological system where different type of trader operate in different ways. The economics that drive order-driven markets are intricate and their viability is not obvious. Handa and Schwartz show that accentuated volatility is required to compensate limit order traders, whereas the non-execution of limit orders induces more eager traders to submit market orders.

This chapter examined the aggressiveness of orders placed and found that, on average, institutional orders are more aggressive. Retail traders seem to be less aware of the state of the market when placing aggressive orders. It was also found that significant differences exist between the contributions of institutional and retail traders to the depth of the limit-order book. Retail standing limit orders were found to be further from the market; and the differences between limit orders placed by retail and institutional traders were larger at the beginning and end of the trading phase, when strategic traders are known to be more likely to trade.

CHAPTER SEVEN
INTERACTION OF ORDER PLACEMENT WITH TRANSIENT VOLATILITY

7.1 Introduction

The results in Chapter Five show orders placed by institutional traders in heavily traded stocks are associated with larger permanent price changes but smaller temporary changes. They suggest that institutional traders are informed and can time their order placements when the market has sufficient liquidity. Thus, the discount (premium) incurred when institutional traders sell (buy) is minimised. While the earlier analyses suggest that retail traders are less informed, the concern that retail activity adversely affects share price volatility remains unexamined.

In his survey, Karpoff (1987) cites many studies that document a positive relation between price volatility and trading volume. Bessembinder and Seguin (1993) suggest that the volatility-volume relation in financial markets may depend on the type of trader. However, there is no agreement in the literature on the effect of trading by different trader types on price volatility. For example, Daigler and Wiley (1999) show the positive volatility-volume relation in futures markets is driven by "the general public", which includes individual speculators, managed funds and small hedgers. On the other hand, Sias (1996) finds a positive contemporaneous relation between the level of institutional ownership and security return volatility after accounting for capitalisation.[37]

The literature to date on online traders has associated their trading with characteristics such as naivety and noise. For example, Ahmed et al. (2003) argue that online traders are typically unsophisticated, have never traded before and may not appreciate the risk involved. They find that the increase in the proportion of naïve investors in the market increases the differential interpretation of public information,

[37] While Daigler and Wiley (1999) and Sias (1996) provide conflicting findings, this may be a function of the differences in the markets examined, i.e., a futures market versus a stock market respectively.

resulting in larger stock price and volume reactions to earnings announcements. Hong and Kumar (2002) argue that, due to their relative lack of sophistication, small individual investors are likely to be a dominant source of noise trading in the market.

In this thesis, retail traders are hypothesised to be uninformed and consequently their activity and trading cause volatility in the market. This chapter examines the effect of order placement by retail and institutional traders on share price volatility on the Australian Stock Exchange (ASX). The analysis of the relation between retail volume and price volatility on the ASX will contribute to the literature on the relationship between volume and volatility.

7.2 Data and method

The data used for the analysis are transaction data for the whole of 2001. There are 24 15-minute intervals for each normal trading day (see Table 7.1). For each 15-minute interval, the order volume and order placement frequency of each trader type are aggregated and share price volatility is calculated. This section describes measures of order activity and volatility and also the Vector Auto-regressive (VAR) models used in examining the interaction between order activity and volatility.

Table 7.1 Intervals for each normal trading day

Interval	Time	Interval	Time
1	10:00:00 - 10:14:59	13	13:00:00 - 13:14:59
2	10:15:00 - 10:29:59	14	13:15:00 - 13:29:59
3	10:30:00 - 10:44:59	15	13:30:00 - 13:44:59
4	10:45:00 - 10:59:59	16	13:45:00 - 13:59:59
5	11:00:00 - 11:14:59	17	14:00:00 - 14:14:59
6	11:15:00 - 11:29:59	18	14:15:00 - 14:29:59
7	11:30:00 - 11:44:59	19	14:30:00 - 14:44:59
8	11:45:00 - 11:59:59	20	14:45:00 - 14:59:59
9	12:00:00 - 12:14:59	21	15:00:00 - 15:14:59
10	12:15:00 - 12:29:59	22	15:15:00 - 15:29:59
11	12:30:00 - 12:44:59	23	15:30:00 - 15:44:59
12	12:45:00 - 12:59:59	24	15:45:00 - 15:59:59

The opening and closing differ from the continuous double-sided auction in place during normal trading. Stocks on SEATS open using a single price call auction where orders are batched before the matching of the orders occur. Also, the stocks on SEATS are split into five groups and the groups are staggered for opening between

9:59.45am to 10:09.15am. The closing single price auction takes place at 4:05pm to 4:06pm after batching the orders between 4:00pm to 4:05pm. As the volatility under different trading systems is found to differ, only orders placed during continuous trading, defined to be Intervals 2-24, are included in the subsequent analysis.

7.2.1 Order volume and frequency

Instead of trade activity, order placement activity is used to indicate participation by the different trader types. While order flow does not represent what is being traded, it provides a better indication of the total trader activity. A flaw with the use of aggregate order flow is that it does not differentiate between aggressive and passive orders but gives both order types the same weighting. Passive orders are limit orders placed further away from the best bid and ask and have a relatively low probability of execution. These orders are likely to become “stale” as they remain unexecuted. On the other hand, aggressive orders are market orders or marketable limit orders that have a higher probability of execution.

Another issue is the use of frequency or volume in measuring the quantity of trades executed or orders placed. The literature on the volume and volatility relationship has debated the role of volume or frequency of orders and trades though no conclusion has been reached (see Chan and Fong, 2000; Jones et al., 1994b). As a robustness check, two measures are used in the subsequent analysis: (1) the number of orders and (2) the total number of shares (volume) of the orders.

7.2.2 Measure of volatility

Two measures of volatility are used in this analysis. The first, *V1*, measures the fluctuation in price in the time interval t by $\sum_{i=1}^{N} r_i^2$, where r_i is the return of the i^{th} transaction during time interval t, and N is the total number of transactions within the interval. The return measure is defined as the difference between the natural logarithms of two successive midpoint spreads and is calculated whenever an order is placed, i.e., $r_t = \ln(MPS_t / MPS_{t-1})$.[38] The use of spread midpoint instead of trade price mitigates the effect of bid-ask bounce, which inflates the volatility measure.

This volatility measure differs from the variance measure ($1/N \sum_{i=1}^{N} \left(r_i - \bar{r}\right)^2$) that has been commonly used in that the mean return, $\bar{r}$, is assumed to be zero, since the average return within the intraday interval is close to zero (Ahn et al., 2001). Also, the sum of squared returns is not standardised by the total number of observations as the measure is used to capture the cumulative price fluctuation within the interval and not the average price fluctuation for each transaction. As a result, the increase in the number of order placements will, by nature of the measure, increase the calculated volatility measure.

Another volatility measure examined is that used by Grossman (1988) in analysing the interaction between program trading and volatility. The measure is computed using the natural log of the ratio of the highest spread midpoint, P_H, to the lowest spread midpoint, P_L, during each fifteen-minute interval between 10:00 a.m. and 4:00 p.m. That is,

$$V2 = 100 \times \ln\left(\frac{P_H}{P_L}\right)$$

This measure differs from the first as it considers the maximum spread of values within the interval. The effects of minimum price variation (price tick) and the magnitude of the share price may have different impacts on this measure. $V2$ is bounded by zero ($V2 \geq 0$) where the highest spread midpoint is equal to the lowest spread midpoint in the interval.

7.2.3 Granger causality

To investigate the causal relationship between volatility and trader activity, the concept of Granger (1969) causality is used to measure how much two variables

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[38] The placement of an order may result in the execution of a trade or the creation of a standing limit order. The placement of an aggressive order, such as a limit order that is in the market or a market order, will result in the change in the midpoint spread giving a non-zero $r_{i,t}$.

precede each another. The following bi-variate VAR model is used to estimate the relationship between volatility and retail trader activity. Battalio, Hatch and Jennings (1997) used a similar model to test the effect of Small Order Execution System (SOES) trades on stock price volatility on Nasdaq. As discussed in Chapters 5 and 6, the extent to which each trader type participates in a stock depends on the stock examined. Consequently, the following system is estimated separately for each of the 36 selected stocks:

$$R_t = a_1 + \sum_{i=1}^{n} b_{1,i} R_{t-i} + \sum_{i=1}^{n} c_{1,i} V_{t-i} + \sum_{i=2}^{5} d_{1,i} day_i + \sum_{i=2}^{3} f_{1,i} time_i + g_1 T_t + e_{1,t}$$
$$V_t = a_2 + \sum_{i=1}^{n} b_{2,i} R_{t-i} + \sum_{i=1}^{n} c_{2,i} V_{t-i} + \sum_{i=2}^{5} c_{2,i} day_{i,t} + \sum_{i=2}^{3} f_{2,i} time_{i,t} + g_2 T_t + e_{2,t}$$

where R_t is the proportion of retail trade activity, V_t is the volatility measure, *day* is the dummy variable for day of the week, $time_i$ is the dummy variable for time of the day, and T_t is the total number of trades in the 15-minute intervals.

While the number of lags, *n,* for each of the variables will be determined by the data available, the relationship is not expected to last more than one trading day (i.e., 23 lags). Brown et al. (1997) found the bi-directional causality between order imbalance and return to not last beyond a single day. Although not discussed in their paper, the closing of the market at the end of the day appears to provide a break in the relationship examined. The Schwartz Bayesian Criterion (SBC) is used to estimate the optimal lag length. Other criteria such as the Akaike Information Criterion can be used, but it has been suggested that more parsimonious models are achieved by using the SBC (Lutkepohl, 1991, p.138).

Exogenous variables, *day*, *time* and T_t, are included in the model as they affect volatility (Jones et al., 1994b; Wood et al., 1985) and order placements by different trader types. The trading period is divided into three intervals as time-of-the-day effects are found for the earlier and later parts of the trading period: (1) 10:15am - 11:59am (2) 12:00pm - 1:59pm (3) 2:00pm to 4:00pm.

7.3 Results

7.3.1 Summary statistics

Table 7.2 presents summary statistics of trading by trader type and price volatility in the 23 15-minute intervals. Panel A shows, on average, 47% (24 of 51) of the orders placed in the heavily traded stocks during a 15-minute interval are by institutional traders and 18% (9 of 51) are by retail traders. The difference between institutional and retail order flow is more apparent when order flow is measured using the volume of shares placed. Institutional traders contributed 73% (283,828 of 391,310) of the total order flow during an average 15-minute interval and retail traders contributed 6% (22,684 of 391,310). The large contribution to the order flow by institutional traders is not found for the lightly traded stocks (see Panel B). Instead, the order flow from retail traders is larger than from institutional traders both in terms of frequency and volume of orders placed. The table shows that 31% (32,648 of 105,387) of the share order volume is placed by retail traders compared to 24% (25,614 of 105,387) by institutional traders.

Table 7.2 also shows the proportion of the orders placed by each trader type that are classified as aggressive. Aggressive orders include marketable limit orders, market orders and limit orders placed in the market. These orders result in trades being executed immediately and, generally, a change in the bid-ask spread.[39] For the heavily traded stocks, the proportion of orders placed by institutional traders that are aggressive is similar to that placed by retail traders, at 54% and 52% respectively. However, the differences are more apparent in the lightly traded stocks where 57% of the orders placed by institutional traders are aggressive and 47% of the orders placed by retail traders. These results are similar to those presented in Table 6.5. The similarity in the aggressiveness measures suggests that the trading of the two different trader types should not have a significant impact on share price volatility in the heavily traded stocks. However, differences may be observed in the lightly traded stocks.

[39] Some market or marketable limit orders result in trades being executed but do not affect the bid-ask spread. These are generally smaller orders that do not consume the entire depth offered at the best price on the opposing side of the market.

Table 7.2 Summary statistics of the average order activity in a 15-minute interval

The analysis uses data from the period 1 January 2001 to 31 December 2001 for the selected sample of stocks. The summary statistics are presented for two samples comprising heavily traded stocks (Panel A) and lightly traded stocks (Panel B), respectively. The “frequency of orders placed” shows the total number of orders placed by each trader type in a 15-minute interval. “Volume transacted” shows the number of shares in the orders placed. “Proportion of aggressive orders” shows the proportion of orders (calculated using order frequency) that are aggressive. The criterion for being classified as aggressive is that the price on the bid (ask) order is greater (less) than or equals to the best bid (ask). *V1* is the summation of the square midpoint return in the interval. *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval.

	Frequency of orders placed				Volume transacted			Proportion of aggressive orders				
	All	Instn	Retail	Others	Instn	Retail	Others	Instn	Retail	Others	*V1*	*V2*
Panel A: Heavily traded stocks												
N	98,486	98,486	98,486	98,486	97,482	93,458	97,138	97,482	93,458	97,138	98,486	98,486
Mean	51	24	9	17	283,828	22,684	84,798	54%	52%	56%	0.15	0.27
Median	38	18	6	12	128,292	7,603	38,979	54%	50%	56%	0.06	0.20
Max	1,276	347	461	586	191,350,000	40,019,038	100,060,000	100%	100%	100%	226.06	9.75
Min	1	0	0	0	1	1	1	0%	0%	0%	0.00	0.00
Std Dev	47	22	12	19	815,539	140,832	383,500	18%	27%	22%	1.31	0.26
Panel B: Lightly traded stocks												
N	70,804	70,804	70,804	70,804	34,995	37,959	49,492	34,995	37,959	49,492	70,804	70,804
Mean	4	1	1	2	25,614	32,648	47,125	57%	47%	55%	1.47	0.40
Median	3	0	1	1	6,000	9,000	10,383	67%	50%	50%	0.00	0.00
Max	601	57	263	320	22,165,103	4,721,818	6,436,264	100%	100%	100%	7434.85	67.39
Min	1	0	0	0	1	1	1	0%	0%	0%	0.00	0.00
Std Dev	8	2	3	5	186,732	106,534	164,461	42%	43%	41%	30.27	0.89

The first volatility measure, *V1*, shows the heavily traded stocks (*V1* = 0.149) are less volatile than the lightly traded stocks (*V1* = 1.473). The standard deviation of *V1*, for the lightly traded stocks (30.27) is more than 20 times larger than for for heavily traded stocks (1.31). The alternative volatility measure, *V2*, has a much smaller standard deviation for both samples but yields a similar conclusion. That is, the heavily traded stocks are less volatile and there are larger variations in the measure for the lightly traded stocks. The higher volatility in smaller stocks could be driven by the tick size of the stocks examined in the two samples. The heavily traded stocks generally have a lower proportional spread so that percentage price changes between transactions are likely to be smaller.

7.3.2 Time of the day differences in volatility and order activity

Figures 7.1 and 7.2 show the intraday variation in the proportion of orders placed by different trader types and price volatility for the heavily and lightly traded stocks respectively.[40] For the heavily traded stocks, the proportion of orders placed by institutional traders is higher than by retail traders in every interval over the trading period. This is not so in the lightly traded stocks. The proportion of orders from retail traders exceeds that from institutional traders during the middle of the trading period, i.e., between 12:30pm to 13:45pm. This is consistent with Table 7.2 where the difference between the average proportion of order flow contributed by institutional and retail traders for the lightly traded stocks is less than for the heavily traded stocks.

Table 7.3 presents the tests for differences in the intraday variation in volatility, retail trading activity and institutional trading activity. The 23 intervals are grouped into the following three periods: (1) "*Morn*" (2) "*After*" and (3) "*Late*". "*Morn*" comprises Intervals 2 to 8, "*After*" comprises Intervals 9 to 16 while "*Late*" comprises Intervals 17 to 24.

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[40] Figures 7.1 and 7.2 do not present the proportion of order volume placed. The intraday pattern in proportion of order volume is reported in Table 7.2.

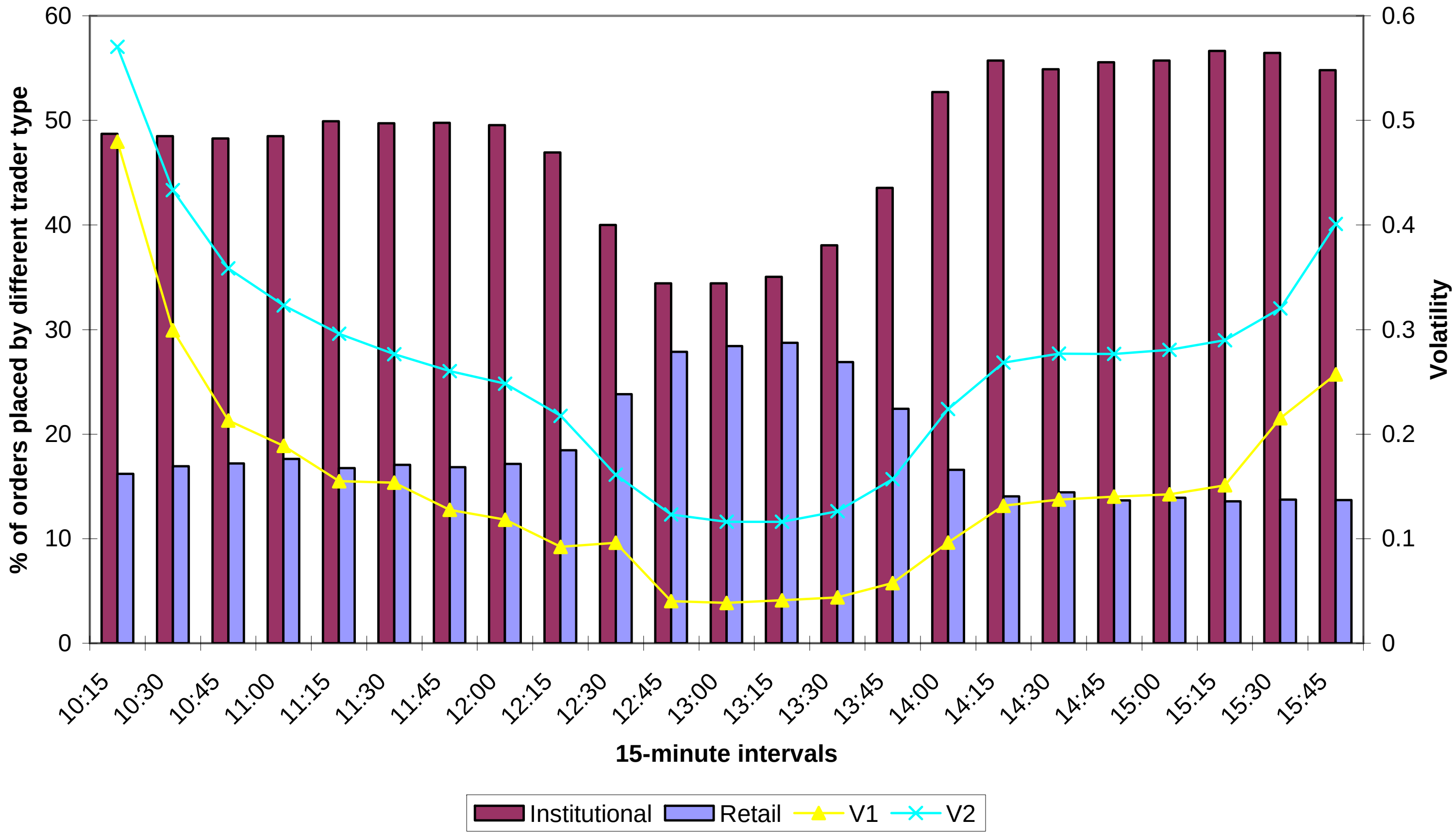

Figure 7.1 Intraday variation in the proportion of orders placed by institutional and retail traders and the volatility measures (*V1* and *V2*) in each 15-minute interval. The sample comprises the 18 stocks in the heavily traded category.

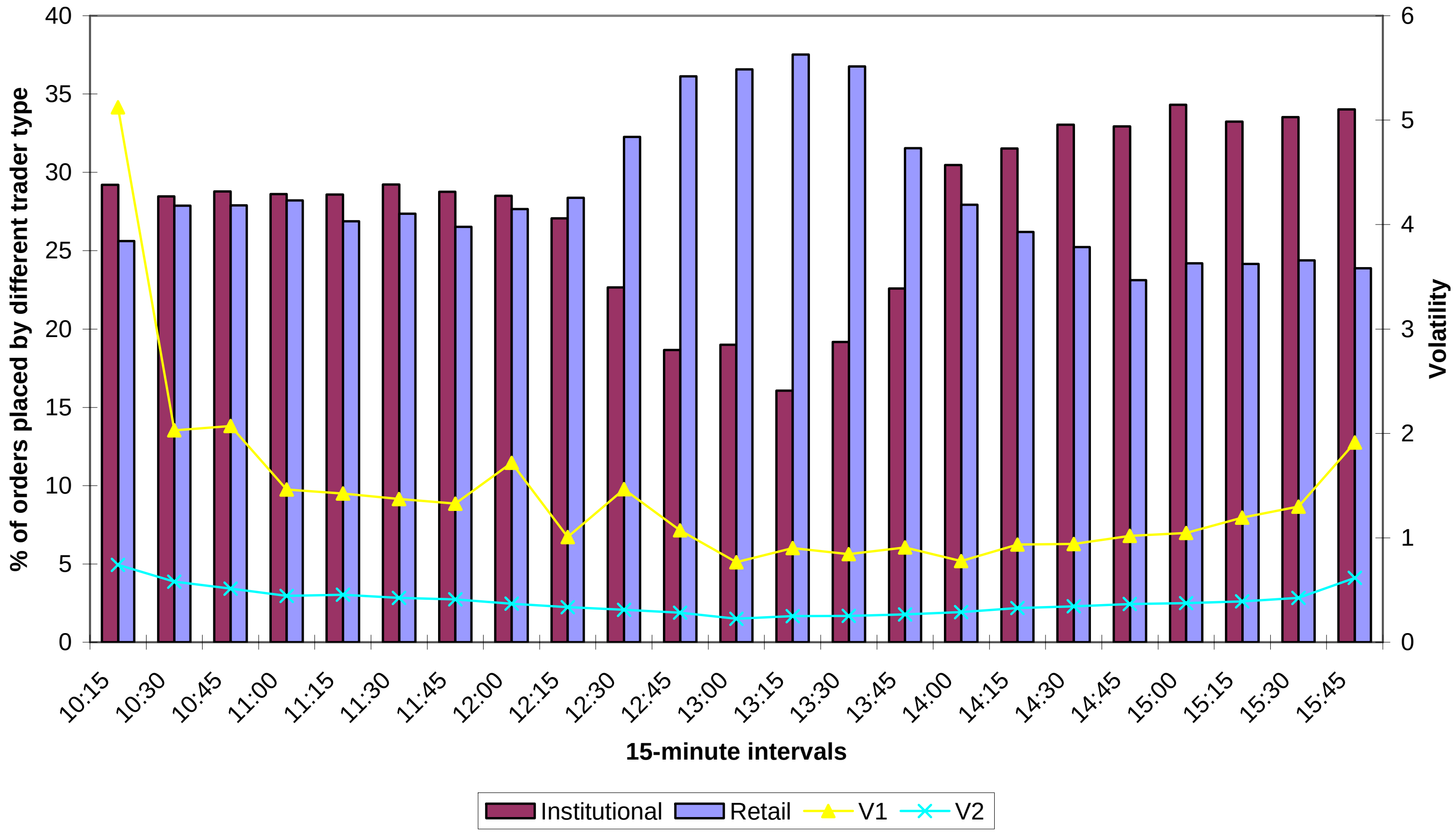

Figure 7.2 Intraday variation in the proportion of orders placed by institutional and retail traders and the volatility measures (*V1* and *V2*) in each 15-minute interval. The sample comprises the 18 stocks in the lightly traded category.

Table 7.3 Panel A shows that the orders placed by institutional traders accounted for about half of the order flow (49.1%) during the first two hours of trading ("*Morn*") for the heavily traded stocks. This proportion decreases to 40.3% in the "*After*" period and increases during the last two hours of trading to 55.3%. The differences in the three periods are significant at the 5% level using a *t*-test and Wilcoxon signed rank test. The retail traders' order placement pattern is opposite to that found for institutional traders.[41] Retail activity is highest (24.2%) during the "*After*" period and is lower during the "*Morn*" period (16.9%) and the "*Late*" period (14.2%). The differences are, again, significant at the 5% level. The results for both institutional traders and retail traders are similar when order placement is measured using volume of shares placed (*I_V* and *R_V*) instead of frequency of orders placed (*I_F* and *R_F*).

Both volatility measures, *V1* and *V2*, show that there are significant differences in the volatility in the three periods. Volatility is highest in the morning ("*Morn*") followed by before the close ("*Late*") and is lowest in the "*After*" period. The volatility pattern observed is consistent with that found in previous Australian and US studies. For example, Aitken et al. (1993) observe higher return volatility at the beginning and end of trading on the ASX while Wood, McInish and Ord (1985) report the same for the NYSE.

Table 7.3 Panel B reports the results for lightly traded stocks. While the overall contribution to order placement by institutional (retail) traders is lower (higher) compared to the heavily traded stocks, the intraday variation in the proportion of order flow contributed by institutional and retail traders is similar for both samples of stocks. The U-shaped pattern is found for institutional trading (*I_F*) and the inverse U-shaped pattern is found for retail trading (*R_F*). Both the *t*-test and the Wilcoxon signed ranks test show that the three periods are significantly different from each other.

[41] If the "other" category of trader were to account for a constant fraction of trading, this result would of course be guaranteed.

Table 7.3 Comparison of order placement and volatility

The table presents the comparison of the variables in the three periods ("*Morn*", "*After*" and "*Late*") between 1 January 2001 and 31 December 2001 for the selected sample stocks. "*Morn*" comprises intervals 2-8, "*After*" comprises intervals 9-16 and "*Late*" comprises intervals 17-24. The results are presented for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). *I_F* (*R_F*) is the proportion of orders placed by institutional (retail) traders measured using the frequency of order placements. *I_V* (*R_V*) is the proportion of orders placed by institutional (retail) traders measured using the volume of shares placed. *V1* is the summation of the squared returns using the midpoint spread in the 15 minute interval. *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. * significance at the 5% level and # significance at the 10% level.

Variable	Periods	N	Mean	Comparison	*t*-stat	Wilcoxon
			Panel A: Heavily traded stocks			
I_F	*Morn*	30,372	0.491	*Morn* vs *After*	-63.90*	-62.59*
	After	34,326	0.403	*After* vs *Late*	111.73*	-104.52*
	Late	33,788	0.553	*Morn* vs *Late*	51.60*	51.76*
R_F	*Morn*	30,372	0.169	*Morn* vs *After*	70.47*	11.34*
	After	34,326	0.242	*After* vs *Late*	-100.46*	44.62*
	Late	33,788	0.142	*Morn* vs *Late*	-35.09*	-36.93*
I_V	*Morn*	30,372	0.679	*Morn* vs *After*	-48.40*	-35.70*
	After	34,326	0.597	*After* vs *Late*	84.30*	-71.54*
	Late	33,788	0.735	*Morn* vs *Late*	41.75*	42.93*
R_V	*Morn*	30,372	0.064	*Morn* vs *After*	56.94*	41.09*
	After	34,326	0.115	*After* vs *Late*	-73.42*	68.81*
	Late	33,788	0.051	*Morn* vs *Late*	-23.02*	-33.37*
V1	*Morn*	30,372	0.231	*Morn* vs *After*	-14.21*	-120.19*
	After	34,326	0.066	*After* vs *Late*	12.27*	-105.04*
	Late	33,788	0.159	*Morn* vs *Late*	-6.00*	-24.37*
V2	*Morn*	30,372	0.360	*Morn* vs *After*	-100.56*	-117.71*
	After	34,326	0.158	*After* vs *Late*	81.19*	-97.80*
	Late	33,788	0.292	*Morn* vs *Late*	-31.19*	-30.74*
			Panel B: Lightly traded stocks			
I_F	*Morn*	23,688	0.288	*Morn* vs *After*	-20.73*	29.63*
	After	21,782	0.221	*After* vs *Late*	32.93*	37.24*
	Late	25,334	0.329	*Morn* vs *Late*	12.81*	9.92*
R_F	*Morn*	23,688	0.272	*Morn* vs *After*	17.85*	-0.56
	After	21,782	0.330	*After* vs *Late*	-25.32*	-5.94*
	Late	25,334	0.248	*Morn* vs *Late*	-8.19*	-6.53*
I_V	*Morn*	23,688	0.281	*Morn* vs *After*	-16.76*	28.47*
	After	21,782	0.223	*After* vs *Late*	28.58*	35.25*
	Late	25,334	0.323	*Morn* vs *Late*	12.26*	8.64*
R_V	*Morn*	23,688	0.265	*Morn* vs *After*	15.99*	-7.89*
	After	21,782	0.320	*After* vs *Late*	-23.90*	-18.31*
	Late	25,334	0.239	*Morn* vs *Late*	-8.50*	-11.96*
V1	*Morn*	23,688	2.148	*Morn* vs *After*	-3.05*	33.24*
	After	21,782	1.109	*After* vs *Late*	0.42	19.77*
	Late	25,334	1.156	*Morn* vs *Late*	-3.05*	-14.96*
V2	*Morn*	23,688	0.513	*Morn* vs *After*	-25.56*	34.57*
	After	21,782	0.291	*After* vs *Late*	15.24*	24.50*
	Late	25,334	0.396	*Morn* vs *Late*	-13.38*	-11.61*

The same patterns are observed when the proportion of orders placed is measured by volume of orders (*I_V* and *R_V*) instead of frequency of orders placed (*I_F* and *R_F*). The differences between the three periods in the proportion of orders placed are significant using both parametric and non-parametric tests. The variation in volatility, measured by both *V1* and *V2*, is also similar to that found for the heavily traded stocks. The differences in the volatility for the three periods (*Morn*, *After* and *Late*) are generally found to be statistically significant at the 5% level.

The results in Table 7.3 highlight some of the problems with using *V1* as the volatility measure. The comparison of *V1* in Panel B shows that volatility in the "after" period and "late" period are statistically different when the Wilcoxon signed rank test is used but not so when the *t*-test is used. In further analysis where two of the outliers were excluded from the "after" period, the differences are shown to be statistically different using the parametric test. The volatility measurement, *V1*, is much larger for the lightly traded stocks (*V1*=2.148) compared to the heavily traded stocks (*V1*=0.231). This is possibly due to the small number of order placements in the 15-minute interval in the lightly traded stocks sample and the average return for the interval not equating to zero as previously assumed. As the volatility measure *V1* is affected by the frequency of order placement, only *V2* is used in further analyses.

7.3.3 Autocorrelations, contemporaneous and lagged cross-correlations

Table 7.4 reports the correlations between order activities of the three trader types. There is a strong correlation between the measures of the proportion of order submissions calculated using frequency of orders placed and the volume of shares placed (for example, between *I_F* and *I_V)*. Correlations between the measures are higher for lightly traded stocks (ranging from 0.92 to 0.93) compared to heavily traded ones (ranging from 0.70 to 0.71). This is most likely caused by the lower order activity and variability in the size of orders in lightly traded stocks. The correlation between institutional and retail activity is negative for both samples and varies in magnitude depending on the measurement and the sample examined. The results show that an increase in the proportion of orders placed by retail traders (*R_V* or *R_F*) generally implies a decrease in the proportion of orders by institutional trader. Again, this result is partly by construction. However, the order activities from both institutional and retail investors are less negatively correlated in the lightly traded stocks.

Table 7.4 Correlation between measures of order submission

I_F, O_F and *R_F* are the proportion of order submissions measured using frequency of order placements for institutional, other and retail traders respectively. *I_V, O_V* and *R_V* are the proportion of order submissions measured using volume of shares placed by institutional, other and retail traders respectively. Correlations between the variables are calculated for each stock separately and averaged across the stocks in the samples.

	I_F	*O_F*	*R_F*	*I_V*	*O_V*
			Panel A: Heavily traded stocks		
O_F	-0.70				
R_F	-0.58	-0.17			
I_V	0.74	-0.58	-0.36		
O_V	-0.60	0.71	0.01	-0.86	
R_V	-0.45	-0.07	0.70	-0.50	0.01
			Panel B: Lightly traded stocks		
O_F	-0.54				
R_F	-0.38	-0.54			
I_V	0.92	-0.50	-0.35		
O_V	-0.50	0.92	-0.49	-0.55	
R_V	-0.35	-0.50	0.93	-0.37	-0.54

Table 7.5 reports the autocorrelations, contemporaneous and lagged cross-correlations between volatility (*V2*) and proportion of orders placed by retail traders (*R_F*). The proportion of orders placed by each trader type is calculated using the number of orders. The correlation results are recalculated using the proportion of orders and are reported in Table E.1 in Appendix E, as they are similar to Table 7.5. Table 7.5 Panel A presents the results for the sample comprising heavily traded stocks.

The contemporaneous correlation between the proportion of orders placed by retail traders and volatility is -0.20, indicating intervals with a larger proportion of retail activity are associated with lower volatility. The cross-correlation between volatility and lag values of retail activity are negative for the first seven lags and are significant for more than half the stocks in the sample (at least 10 of the 18 stocks) for the first five lags. The autocorrelation coefficients for volatility (*V2*) show that, of the 18 stocks examined in the heavily traded sample, the autocorrelation is positive and significant up to the eighth lag for more than half. The results show after an interval of high volatility, volatility remains high for the next two hours. The average autocorrelation becomes negative in the ninth lag, showing a delayed reversal in share price volatility. The correlation between retail activity and lag values of volatility is negative for the first three lags. The negative correlation coefficient is significant for more than half the sample (*n*>9) for only the first two lags.

Retail order activity, *R_F*, is positively correlated with its own lagged values. The autocorrelation is positive and significant for more than half the sample up to 10 lags. The positive autocorrelation found here is consistent with prior literature that has examined the conditional probability of order placement (Biais et al., 1995). When retail traders are active in the market, they are likely to continue to remain in the market for much of the trading day.

Table 7.5 Autocorrelations, contemporaneous and lagged cross-correlations between *V2* and *R_F*

The table presents the autocorrelations contemporaneous and lagged cross-correlations between volatility, *V2*, and the proportion of retail order submissions measured using number of orders placed, *R_F*, for sample firms between 1/1/2001 to 31/12/2001. *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. The results are shown for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). The "Mean *t*-stat" shows the mean *t*-statistic of the 18 firms in each sub-sample. The "no. of significant coeff" shows the number of firms in each sample that has a correlation coefficient significant at the 0.10 level or better.

	$V2_0$	Mean *t*-stat	No. of significant coeff	R_F_0	Mean *t*-stat	No. of significant coeff
Panel A: Heavily traded stocks (n=18)						
$V2_0$	1.000			-0.200	-15.136	18
$V2_{-1}$	0.504	38.130	18	-0.094	-7.072	17
$V2_{-2}$	0.371	22.770	18	-0.052	-3.920	12
$V2_{-3}$	0.286	16.094	18	-0.018	-1.349	9
$V2_{-4}$	0.226	12.087	18	0.012	0.885	6
$V2_{-5}$	0.180	9.376	18	0.040	3.020	10
$V2_{-6}$	0.144	7.336	17	0.065	4.940	12
$V2_{-7}$	0.099	4.911	16	0.092	6.967	18
$V2_{-8}$	0.056	2.677	10	0.120	9.107	18
$V2_{-9}$	-0.001	-0.253	5	0.158	11.967	18
$V2_{-10}$	-0.054	-2.938	11	0.201	15.180	18
$V2_{-11}$	-0.086	-4.552	15	0.229	17.296	18
$V2_{-12}$	-0.096	-4.994	15	0.225	16.986	18
R_F_0	-0.200	-15.136	18	1.000		
R_F_{-1}	-0.141	-10.640	18	0.393	29.734	18
R_F_{-2}	-0.120	-9.043	17	0.311	20.143	18
R_F_{-3}	-0.098	-7.412	17	0.245	14.708	18
R_F_{-4}	-0.073	-5.486	18	0.176	10.123	18
R_F_{-5}	-0.050	-3.752	15	0.125	7.040	17
R_F_{-6}	-0.026	-1.932	9	0.088	4.911	14
R_F_{-7}	-0.008	-0.595	3	0.073	4.012	13
R_F_{-8}	0.022	1.646	3	0.058	3.108	10
R_F_{-9}	0.074	5.605	16	0.052	2.796	10
R_F_{-10}	0.138	10.448	18	0.047	2.456	10
R_F_{-11}	0.182	13.795	18	0.042	2.203	9
R_F_{-12}	0.210	15.851	18	0.039	2.054	10

Panel B: Lightly traded stocks (n=18)						
$V2_0$	1.000			-0.058	-3.711	10
$V2_{-1}$	0.222	14.626	17	-0.013	-0.891	3
$V2_{-2}$	0.161	9.990	17	-0.003	-0.167	1
$V2_{-3}$	0.136	7.892	17	0.003	0.252	1
$V2_{-4}$	0.118	6.835	14	0.008	0.529	0
$V2_{-5}$	0.100	5.582	15	0.000	0.037	1
$V2_{-6}$	0.077	4.234	10	0.011	0.715	0
$V2_{-7}$	0.066	3.694	13	0.018	1.078	3
$V2_{-8}$	0.065	3.498	10	0.007	0.596	2
$V2_{-9}$	0.054	2.846	9	0.016	1.087	2
$V2_{-10}$	0.046	2.420	9	0.017	1.080	3
$V2_{-11}$	0.039	2.050	6	0.014	0.974	3
$V2_{-12}$	0.043	2.275	6	0.009	0.673	1
R_F_0	-0.058	-3.711	10	1.000		
R_F_{-1}	-0.019	-1.317	3	0.121	7.579	18
R_F_{-2}	-0.011	-0.723	2	0.088	5.460	15
R_F_{-3}	-0.009	-0.610	1	0.077	4.563	15
R_F_{-4}	-0.001	-0.237	1	0.064	3.719	12
R_F_{-5}	-0.005	-0.402	3	0.058	3.532	14
R_F_{-6}	-0.004	-0.294	1	0.061	3.564	15
R_F_{-7}	-0.001	-0.166	1	0.053	3.219	12
R_F_{-8}	0.010	0.691	0	0.051	3.016	11
R_F_{-9}	0.011	0.731	0	0.047	2.817	8
R_F_{-10}	0.013	0.885	1	0.043	2.548	8
R_F_{-11}	0.014	0.867	3	0.037	2.176	7
R_F_{-12}	0.014	0.818	0	0.043	2.396	7

Table 7.5 Panel B reports the results for the 18 lightly traded stocks. While the results are generally similar to those of the previous sample, there are some differences. Volatility is correlated with its own lagged values but unlike the heavily traded stocks, volatility does not mean revert within the 12 lags examined. There is again strong autocorrelation in retail order activity. The main differences between the two samples are in the significance of the negative contemporaneous correlation and the cross correlation between volatility and order activity. The negative contemporaneous correlations between *V2* and *R_F* are significant for 10 of the 18 lightly traded stocks compared to all 18 stocks in the sample of heavily traded stocks. Also, the cross-autocorrelations between *R_F* and lagged values of *V2* and between *V2* and lagged values of *R_F* are not significant for most lightly traded stocks. As total order flow comprises orders placed by institutional investors, retail investors and others, the increase in institutional order flow does not necessarily equate to a decrease in retail order flow. As a robustness check, Table 7.5 presents the autocorrelation, contemporaneous and lagged cross-correlations between volatility

($V2$) and the proportion of institutional order submissions (I_F) measured using the frequency of orders placed.[42]

Table 7.6 Panel A reports, for heavily traded stocks, volatility is on average positively correlated with the contemporaneous and eight lagged values of institutional order activity. The positive cross-correlations are significant for more than half the sample of heavily traded stocks up to the seventh lag, *I_F(-7)*.

Table 7.6 Autocorrelations, contemporaneous and lagged cross-correlations between *V2* and *I_F*

The table presents the autocorrelations, contemporaneous and lagged cross-correlations between volatility, *V2*, and proportion of institutional order submissions measured using number of orders placed, *I_F*, for sample firms between 1/1/2001 to 31/12/2001. *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. The results are shown for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). The "Mean *t*-stat" shows the mean *t*-statistic of the 18 firms in each sub-sample. The "no. of significant coeff" shows the number of firms in each sample that has a correlation coefficient significant at the 0.10 level or better.

	$V2_0$	Mean *t*-stat	No. of Significant	I_F_0	Mean *t*-stat	No. of significant
Panel A: Heavily traded stocks (n=18)						
$V2_0$	1.000			0.139	10.477	17
$V2_{-1}$	0.504	38.130	18	0.046	3.477	13
$V2_{-2}$	0.371	22.770	18	0.014	1.042	8
$V2_{-3}$	0.286	16.094	18	-0.016	-1.221	7
$V2_{-4}$	0.226	12.087	18	-0.037	-2.809	8
$V2_{-5}$	0.180	9.376	18	-0.062	-4.665	13
$V2_{-6}$	0.144	7.336	17	-0.088	-6.651	18
$V2_{-7}$	0.099	4.911	16	-0.110	-8.293	18
$V2_{-8}$	0.056	2.677	10	-0.134	-10.141	18
$V2_{-9}$	-0.001	-0.253	5	-0.168	-12.718	18
$V2_{-10}$	-0.054	-2.938	11	-0.204	-15.449	18
$V2_{-11}$	-0.086	-4.552	15	-0.219	-16.575	18
$V2_{-12}$	-0.096	-4.994	15	-0.203	-15.312	18
I_F_0	0.139	10.477	17	1.000		
I_F_{-1}	0.116	8.731	17	0.483	36.483	18
I_F_{-2}	0.117	8.838	17	0.400	24.824	18
I_F_{-3}	0.107	8.085	17	0.321	18.011	18
I_F_{-4}	0.087	6.558	15	0.245	13.001	18
I_F_{-5}	0.062	4.691	14	0.184	9.454	18
I_F_{-6}	0.044	3.316	13	0.142	7.184	17
I_F_{-7}	0.030	2.293	10	0.125	6.297	17
I_F_{-8}	0.006	0.471	5	0.114	5.674	16
I_F_{-9}	-0.046	-3.503	11	0.113	5.590	17
I_F_{-10}	-0.105	-7.976	17	0.116	5.732	17
I_F_{-11}	-0.155	-11.693	18	0.115	5.611	16
I_F_{-12}	-0.190	-14.401	18	0.114	5.507	16

[42] Table E.2 presents a similar table where the proportion of institutional orders is calculated using the number of shares placed to ensure robustness. The results are similar.

Panel B: Lightly traded stocks (n=18)						
$V2_{0}$	1.000			0.018	0.949	7
$V2_{-1}$	0.222	14.626	17	-0.001	-0.081	4
$V2_{-2}$	0.161	9.990	17	-0.001	-0.310	3
$V2_{-3}$	0.136	7.892	17	-0.005	-0.432	2
$V2_{-4}$	0.118	6.835	14	-0.010	-0.754	2
$V2_{-5}$	0.100	5.582	15	-0.008	-0.594	3
$V2_{-6}$	0.077	4.234	10	-0.011	-0.870	4
$V2_{-7}$	0.066	3.694	13	-0.022	-1.409	6
$V2_{-8}$	0.065	3.498	10	-0.016	-1.203	6
$V2_{-9}$	0.054	2.846	9	-0.020	-1.316	5
$V2_{-10}$	0.046	2.420	9	-0.020	-1.346	6
$V2_{-11}$	0.039	2.050	6	-0.021	-1.264	4
$V2_{-12}$	0.043	2.275	6	-0.015	-1.033	2
I_F_{0}	0.018	0.949	7	1.000		
I_F_{-1}	-0.001	-0.087	2	0.194	12.456	18
I_F_{-2}	0.007	0.340	2	0.163	9.947	17
I_F_{-3}	0.001	0.147	3	0.142	8.287	16
I_F_{-4}	0.003	0.205	3	0.128	7.256	16
I_F_{-5}	0.004	0.213	3	0.126	7.093	17
I_F_{-6}	0.003	0.155	3	0.107	5.937	14
I_F_{-7}	0.002	0.066	2	0.108	5.862	15
I_F_{-8}	-0.006	-0.512	2	0.096	5.032	13
I_F_{-9}	-0.013	-0.984	4	0.087	4.521	12
I_F_{-10}	-0.015	-1.055	3	0.092	4.797	13
I_F_{-11}	-0.018	-1.033	3	0.087	4.559	13
I_F_{-12}	-0.022	-1.332	4	0.087	4.479	13

Institutional activity is positively and significantly correlated with the first two lagged values of volatility for more than half the stocks in the sample. The subsequent lagged values of volatility are negatively and significantly correlated with institutional activity for most stocks. Also consistent with prior studies is the strong autocorrelation in institutional order placement in the heavily traded stocks.

Panel B shows for the lightly traded stocks, the positive autocorrelations between volatility and lagged institutional order placement and between institutional order activity and lagged volatility values are not evident, unlike the results for the heavily traded sample. For example, institutional activity is positively correlated with the contemporaneous value of volatility but negatively correlated with the lagged values.

In summary, consistent with previous findings, there is strong positive autocorrelation in retail activity and institutional activity. Volatility is negatively cross-correlated with lagged values of retail activity and positively cross-correlated with lagged values of institutional activity. However, the negative cross-correlation of retail activity with lagged values of volatility and the positive cross-correlation of institutional activity with lagged values of volatility are found over a shorter time period. Also, the cross-correlation relationship is found to be significant only in the heavily traded stocks.

7.3.4 VAR modelling and Granger causality results

While the above results suggest a relationship between retail order activity and volatility, they do not isolate the time of day effects, nor infer causality. The bivariate VAR described in Section 7.2.3 is used to investigate the causal relationship between volatility and order activity. The VAR systems can be estimated by ordinary least squares (OLS) if each regression contains the same lagged endogenous variables (Enders, 1995, p. 313; Gujarati, 1995, p. 747).

7.3.4.1 Choice of lag length

The VAR systems were estimated for each of the companies in the sample. Imposing a maximum lag length of 23, the lag length that minimises the SBC is found for each stock. The results are reported in Table 7.7. The lag lengths range from two to 12 15-minute intervals depending on the endogenous variables and stocks examined. The median lag length of three is found to minimise the SBC for the models with *R_F* and *V2* as endogenous variables. The same lag length was found to minimise the SBC with *R_F* and *V2* as endogenous variables. To achieve parsimonious models, we present the models using lags of four periods (n=4). Models using 12 lags are also generated and presented in Appendix E as part of the robustness checks.

An issue of concern is whether the variables in a VAR need to be stationary. Sims (1995) recommends against differencing even if the variables contain a unit root. Gujarati (1995) suggests all variables should be (jointly) stationary. Each variable was tested for stationarity using the Dicky-Fuller test and the null hypothesis of unit root was rejected for all stocks at the 1% significance level.

Table 7.7 Lag lengths that minimise the Schwartz Bayesian Criterion

The table presents the lag lengths that minimises the Schwartz Bayesian Criterion (SBC) for the VAR systems modelling the interaction between trading activity and volatility for each stock. Proportion of order activity by the retail trader is measured using frequency of orders placed (*R_F*) and volume of shares in the orders (*R_V*). The volatility measure, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval.

	R_F vs *V2*		*R_V* vs *V2*	
Company	SBC	Lag	SBC	Lag
Panel A: Heavily traded stocks				
AMP	-17.88	3	-17.99	2
ANZ	-18.07	3	-18.40	3
BHP	-18.55	11	-18.95	4
BIL	-17.14	9	-17.30	4
CBA	-18.25	10	-18.42	9
CML	-16.84	12	-16.75	3
CSR	-16.40	2	-16.40	2
LLC	-16.71	3	-16.74	3
MAY	-16.12	3	-16.12	3
NAB	-18.28	11	-18.75	3
NCP	-17.18	10	-17.57	3
QAN	-15.78	3	-15.47	3
RIO	-17.64	2	-17.85	2
TLS	-18.15	10	-17.98	3
WBC	-18.00	3	-18.39	3
WMC	-17.08	11	-17.13	3
WOW	-17.22	10	-17.41	2
WPL	-16.94	3	-17.10	3
Panel B: Lightly traded Stocks				
AQP	-12.80	3	-12.67	3
ARG	-14.33	2	-14.20	2
CPH	-12.71	2	-12.53	2
GNS	-12.69	2	-12.61	2
GWT	-13.29	4	-13.10	4
HRP	-14.01	2	-13.99	2
IFM	-12.03	2	-11.91	2
KIM	-11.47	2	-11.33	2
MXO	-11.52	2	-11.41	2
MYO	-12.34	2	-12.09	2
NUF	-13.02	3	-12.94	2
OML	-12.41	2	-12.22	2
PLM	-12.29	2	-12.29	2
RIC	-12.72	2	-12.58	2
SLX	-11.34	2	-11.16	2
TIM	-11.94	3	-11.72	3
VNA	-10.53	3	-10.37	3
VRL	-12.94	2	-12.76	2

7.3.4.2 Granger causality test

Table 7.8 presents the Granger causality test of the relation between order activity of different trader types and volatility. For 14 of the 18 heavily traded stocks, volatility is found to Granger-cause retail order activity and retail order activity is found to Granger-cause volatility. The results are similar when volume of shares is used instead of frequency of orders in the calculation of the proportion of order activity. Similarly, institutional order activity is found to Granger-cause volatility and volatility is found to cause institutional order activity in the heavily traded stocks. When the above tests are repeated for the lightly traded stocks, the causality relationships between order activity and volatility are not significant. It is probable that the break down of the relationship in the lightly traded sample is due to infrequent trading. A coarser partitioning of time may be more appropriate for these stocks.[43] The next section provides further discussion of the VAR models and the coefficients found.

Table 7.8 Causality test of the VAR models with volatility and proportion of order activity of both retail traders and institutional traders

The proportion of order activity is measured using frequency of order placement (*R_F* and *I_F*) and also volume of shares in the orders (*R_V* and *I_V*). Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. The results are shown for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). The symbol "*V2* → *R_F*" indicates that *R_F* is the dependent variable and the explanatory variables are lagged values of *R_F* and *V2* and the exogenous variables. The exogenous variables include dummy variables for time of the day, day of the week and also the number of orders placed during that interval. The "*Chi-sq*" shows the average *Chi-sq* for the 18 stocks in each sample. The "significance" shows the number of times the observed causal effect is not a chance event in that we are 90% confident the causality is not random.

Causality	*Chi-sq*	Significance	Causality	*Chi-sq*	Significance
		Panel A: Heavily traded stocks			
V2 → *R_F*	23.76	16	*V2* → *R_V*	14.22	14
R_F → *V2*	27.46	15	*R_V* → *V2*	15.55	14
V2 → *I_F*	29.50	16	*V2* → *I_V*	23.76	16
I_F → *V2*	38.24	16	*I_V* → *V2*	27.46	15
		Panel B: Lightly traded stocks			
V2 → *R_F*	4.55	4	*V2* → *R_V*	3.98	2
R_F → *V2*	4.61	2	*R_V* → *V2*	4.50	1
V2 → *I_F*	7.08	4	*V2* → *I_V*	4.55	4
I_F → *V2*	5.06	2	*I_V* → *V2*	4.61	2

[43] One of the robustness tests involves partitioning the day into hourly intervals instead of 15-minute intervals.

7.3.4.3 VAR - proportion of retail order submissions (*R_F*) measured using order frequency

Table 7.8 presents the results of the VAR modelling where the proportion of order submissions is measured using the frequency of orders, *R_F*. Panel A reports the results for the sample of heavily traded stocks. The autocorrelations in the order submission, *R_F*, and volatility, *V2*, are strongly evident. These results are consistent with the findings of previous studies such Biais, Hillion and Spatt and that of previous chapters in this thesis. In order to analyse the relationship between retail order activity and volatility, the following discussion focuses on the lag terms of *V2* on *R_F* and of *R_F* on *V2*. In the *R_F* equation, the average coefficient on $V2_{-1}$ is positive and 11 of the 18 coefficients are positive and significant at the 10% level. In the *V2* equation, the coefficient on R_F_{-1} is negative but only 5 of the 18 coefficients are significant. The results suggest retail traders are attracted to volatile markets but their trading does not increase volatility in subsequent periods. Contrary to hypothesis H_5, which predicts that periods with a higher proportion of retail activity are associated with higher volatility, periods subsequent to periods of high retail activity were found to have lower volatility.

Table 7.8 Panel B shows the results for the sample comprising lightly traded stocks. The strong autocorrelation between retail activity with its own lag values and also volatility with its own lagged values is again evident. However, the effects of the lagged values of retail activity on volatility and the lagged values of volatility on retail activity are not consistent with those found for the heavily traded stocks. While the average coefficients on the lagged terms of *V2* in the *R_F* equation are mostly positive, they are not statistically significant for most stocks. The average coefficients on the lagged terms of retail activity in the *V2* equation are positive but again not significant for most stocks.

Table 7.9 Results of the VAR modelling using four lags for each of the endogenous variables - *R_F* and *V2*

Proportion of order submission, *R_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	R_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.0915	14.80	[18, 0]	0.0539	4.56	[13, 3]
T	-0.0003	-5.61	[0, 17]	0.0041	42.80	[18, 0]
Day_2	-0.0044	-1.04	[0, 5]	-0.0143	-1.91	[0, 11]
day_3	-0.0058	-1.33	[0, 7]	-0.0044	-0.56	[2, 3]
day_4	-0.0048	-1.14	[0, 4]	-0.0066	-0.97	[0, 7]
day_5	0.0000	0.06	[1, 1]	-0.0073	-0.89	[1, 5]
$time_2$	0.0443	11.77	[18, 0]	-0.0279	-3.94	[0, 16]
$time_3$	-0.0232	-6.31	[0, 18]	-0.0311	-4.71	[0, 18]
R_F_{-1}	0.2201	16.20	[18, 0]	-0.0208	-0.73	[1, 5]
R_F_{-2}	0.1146	8.30	[18, 0]	-0.0007	0.03	[1, 2]
R_F_{-3}	0.0779	5.69	[18, 0]	-0.0004	0.05	[2, 1]
R_F_{-4}	0.0534	4.00	[16, 0]	0.0125	0.57	[5, 0]
$V2_{-1}$	0.0168	2.42	[11, 0]	0.1881	15.09	[18, 0]
$V2_{-2}$	0.0176	2.47	[12, 0]	0.0540	4.28	[17, 0]
$V2_{-3}$	0.0117	1.65	[10, 0]	0.0173	1.38	[8, 1]
$V2_{-4}$	0.0104	1.49	[8, 0]	0.0102	0.86	[5, 0]
R^2			0.27			0.49
F-Value			142.95			356.34
Eqn with significant (<10%) *F*-Values			18			18
Panel B: Lightly traded stocks						
Constant	0.2268	12.58	[18, 0]	0.0446	0.24	[6, 4]
T	-0.0071	-3.41	[0, 15]	0.0757	28.50	[18, 0]
day_2	-0.0055	-0.19	[0, 4]	-0.0150	-0.40	[0, 2]
day_3	-0.0066	-0.48	[1, 1]	-0.0125	-0.54	[0, 5]
day_4	-0.0035	-0.24	[2, 2]	-0.0081	-0.32	[1, 2]
day_5	-0.0056	-0.32	[1, 2]	-0.0070	-0.21	[0, 2]
$time_2$	0.0378	2.79	[13, 0]	-0.0554	-1.90	[0, 8]
$time_3$	-0.0230	-1.92	[0, 11]	-0.0212	-0.61	[1, 3]
R_F_{-1}	0.0916	5.60	[18, 0]	0.0016	0.05	[2, 0]
R_F_{-2}	0.0610	3.75	[15, 0]	0.0144	0.28	[1, 0]
R_F_{-3}	0.0484	2.90	[15, 0]	0.0101	0.27	[1, 1]
R_F_{-4}	0.0439	2.57	[12, 0]	0.0160	0.37	[3, 1]
$V2_{-1}$	0.0027	0.26	[2, 2]	0.0996	6.86	[16, 0]
$V2_{-2}$	-0.0003	0.30	[1, 0]	0.0419	2.92	[15, 0]
$V2_{-3}$	0.0073	0.61	[2, 0]	0.0349	2.13	[12, 0]
$V2_{-4}$	0.0040	0.29	[0, 0]	0.0349	2.46	[12, 0]
R^2			0.04			0.24
F-Value			11.33			92.96
Eqn with significant (<10%) *F*-Values			18			18

7.3.4.4 VAR - proportion of retail order submissions (R_V) measured using volume of shares

The VAR modelling is repeated using volume of shares in the calculation of the proportion of retail activity, *R_V*. The results are presented in Table 7.10 and are similar to those found using frequency of order placement. The only significant difference is in the coefficient of the lagged terms of retail activity, *R_V*, in the volatility equation. Instead of a negative relation, retail activity is found to increase volatility in subsequent periods. However, the effect of retail activity on volatility is only weakly significant.

7.3.4.5 Robustness checks – VAR using institutional activity

As a robustness check, the models are recomputed using institutional order activity. Table 7.11 presents the VAR modelling results using the frequency of orders placed in computing the proportion of institutional order activity. The expectation is that the institutional order activity relationship with volatility is the inverse of the relationship between volatility and retail order activity. The optimal lag lengths are found using the Schwartz Bayesian Criterion and are presented in Table E.3 in the appendix. While the optimal lag length for most systems is longer than that found using retail activity and volatility as endogenous variables, a maximum of 12 is found for all models regardless of the measurement of order activity used. Similar to the earlier analysis of retail activity, the following discussion presents the results using a lag length of four. Models using a lag length of 12 are also computed and the results of these models are presented in Appendix E.

Table 7.11 Panel A reports, for the heavily traded stocks, volatility causes a subsequent reduction in the proportion of orders placed by institutional traders. Also, the proportion of orders placed by institutional traders increases volatility in subsequent periods. While the effect of volatility on institutional order placement is significant for all 18 of the heavily traded stocks, the effect of institutional order placement on volatility is found for only eight.

Table 7.10 Results of the VAR modelling using four lags for each of the endogenous variables - *R_V* and *V2*.

Proportion of order submission, *R_V*, is measured using the volume of shares placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	R_V			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.0446	8.76	[18, 0]	0.0447	4.50	[14, 2]
T	-0.0003	-5.34	[0, 18]	0.0041	42.76	[18, 0]
Day_2	-0.0018	-0.53	[0, 3]	-0.0138	-1.87	[0, 11]
Day_3	-0.0035	-0.98	[0, 6]	-0.0040	-0.53	[2, 3]
Day_4	-0.0027	-0.80	[0, 7]	-0.0061	-0.93	[1, 7]
Day_5	-0.0004	-0.09	[1, 1]	-0.0073	-0.90	[1, 5]
$Time_2$	0.0323	9.07	[18, 0]	-0.0303	-4.26	[0, 16]
$Time_3$	-0.0126	-3.53	[0, 17]	-0.0309	-4.69	[0, 18]
R_V_{-1}	0.1828	13.50	[18, 0]	0.0090	0.38	[3, 1]
R_V_{-2}	0.0983	7.18	[18, 0]	0.0078	0.32	[2, 0]
R_V_{-3}	0.0675	4.95	[18, 0]	0.0202	0.75	[3, 0]
R_V_{-4}	0.0507	3.79	[17, 0]	0.0262	0.92	[7, 0]
$V2_{-1}$	0.0091	1.46	[9, 0]	0.1911	15.42	[18, 0]
$V2_{-2}$	0.0089	1.38	[7, 0]	0.0546	4.35	[17, 0]
$V2_{-3}$	0.0076	1.18	[6, 0]	0.0182	1.45	[9, 1]
$V2_{-4}$	0.0047	0.75	[4, 0]	0.0103	0.88	[6, 0]
R^2			0.17			0.49
F-Value			74.66			355.48
Eqn with significant (10%) *F*-Values			18			18
Panel B: Lightly traded stocks						
Constant	0.2353	12.35	[18, 0]	0.0446	0.22	[6, 4]
T	-0.0090	-4.16	[0, 16]	0.0757	28.50	[18, 0]
Day_2	-0.0061	-0.24	[1, 3]	-0.0147	-0.40	[0, 2]
Day_3	-0.0071	-0.47	[1, 2]	-0.0124	-0.54	[0, 5]
Day_4	-0.0046	-0.28	[1, 2]	-0.0078	-0.32	[1, 2]
Day_5	-0.0045	-0.24	[1, 2]	-0.0069	-0.21	[0, 2]
$Time_2$	0.0345	2.31	[9, 0]	-0.0559	-1.93	[0, 8]
$Time_3$	-0.0269	-2.07	[0, 11]	-0.0214	-0.62	[1, 3]
R_V_{-1}	0.0791	4.75	[17, 0]	0.0035	0.13	[2, 1]
R_V_{-2}	0.0553	3.42	[16, 0]	0.0157	0.42	[1, 0]
R_V_{-3}	0.0449	2.71	[14, 0]	0.0079	0.18	[1, 1]
R_V_{-4}	0.0402	2.35	[15, 0]	0.0174	0.51	[2, 0]
$V2_{-1}$	0.0014	0.17	[1, 0]	0.0998	6.87	[16, 0]
$V2_{-2}$	-0.0018	0.15	[1, 0]	0.0421	2.94	[15, 0]
$V2_{-3}$	0.0057	0.41	[1, 0]	0.0349	2.13	[12, 0]
$V2_{-4}$	0.0053	0.33	[1, 1]	0.0351	2.47	[11, 0]
R^2			0.04			0.24
F-Value			9.72			92.93
Eqn with significant (10%) *F*-Values			18			18

Table 7.11 Results of the VAR modelling using four lags for each of the endogenous variables - *I_F* and *V2*.

Proportion of order submissions, *I_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	I_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.2244	22.57	[18, 0]	0.0270	1.90	[11, 2]
T	0.0001	1.63	[9, 1]	0.0041	42.90	[18, 0]
Day_2	0.0056	1.03	[4, 0]	-0.0148	-2.01	[0, 11]
Day_3	0.0086	1.55	[8, 0]	-0.0054	-0.72	[1, 3]
Day_4	0.0059	1.13	[5, 0]	-0.0068	-1.05	[0, 7]
Day_5	-0.0013	-0.26	[1, 2]	-0.0073	-0.92	[1, 5]
$Time_2$	-0.0523	-10.67	[0, 18]	-0.0253	-3.46	[1, 14]
$Time_3$	0.0463	9.52	[18, 0]	-0.0321	-4.82	[0, 18]
I_F_{-1}	0.2760	20.27	[18, 0]	0.0284	1.50	[8, 0]
I_F_{-2}	0.1423	10.20	[18, 0]	0.0159	0.88	[3, 0]
I_F_{-3}	0.0833	6.01	[18, 0]	0.0141	0.61	[3, 1]
I_F_{-4}	0.0570	4.29	[17, 0]	-0.0085	-0.42	[1, 4]
$V2_{-1}$	-0.0315	-3.48	[0, 17]	0.1868	15.06	[18, 0]
$V2_{-2}$	-0.0204	-2.21	[0, 12]	0.0527	4.19	[16, 0]
$V2_{-3}$	-0.0125	-1.36	[0, 6]	0.0160	1.28	[8, 1]
$V2_{-4}$	-0.0036	-0.38	[1, 0]	0.0103	0.87	[6, 0]
R^2			0.34			0.49
F-Value			197.33			357.08
Eqn with significant (10%) *F*-Values			18			18
Panel B: Lightly traded stocks						
Constant	0.1634	8.75	[18, 0]	0.0691	1.10	[6, 4]
T	0.0066	1.44	[9, 3]	0.0759	28.54	[18, 0]
Day_2	-0.0055	-0.29	[0, 2]	-0.0154	-0.40	[0, 3]
Day_3	-0.0012	-0.05	[0, 3]	-0.0128	-0.56	[0, 5]
Day_4	-0.0116	-0.63	[1, 3]	-0.0096	-0.36	[1, 3]
Day_5	-0.0157	-0.82	[0, 1]	-0.0080	-0.23	[0, 2]
$Time_2$	-0.0348	-2.63	[1, 13]	-0.0570	-1.97	[0, 8]
$Time_3$	0.0436	3.18	[14, 0]	-0.0210	-0.60	[0, 3]
I_F_{-1}	0.1320	8.32	[18, 0]	-0.0236	-0.82	[0, 2]
I_F_{-2}	0.0935	5.85	[17, 0]	-0.0121	-0.25	[1, 0]
I_F_{-3}	0.0781	4.75	[16, 0]	-0.0140	-0.15	[1, 2]
I_F_{-4}	0.0738	4.51	[17, 0]	-0.0043	-0.09	[1, 3]
$V2_{-1}$	-0.0030	-0.42	[0, 2]	0.0996	6.86	[16, 0]
$V2_{-2}$	0.0044	-0.02	[2, 3]	0.0413	2.90	[15, 0]
$V2_{-3}$	-0.0060	-0.33	[0, 0]	0.0349	2.10	[12, 0]
$V2_{-4}$	-0.0023	-0.12	[1, 1]	0.0335	2.39	[11, 0]
R^2			0.09			0.24
F-Value			28.33			93.17
Eqn with significant (10%) *F*-Values			18			18

Table 7.11 Panel B shows the relationship between volatility and institutional order placement is not evident in the lightly traded stocks. On average, volatility (*V2*) is found to have a negative impact on the proportion of orders placed by institutional traders. However, the relationship is significant for only two of the 18 lightly traded stocks. The proportion of orders placed by institutional traders is found to have, on average, a negative impact on volatility. Again, the relationship is significant for only two of the 18 stocks in the sample.

Table 7.12 shows the results for the VAR modelling using volume of shares placed in calculating the proportion of order placement. The results are similar to those found in Table 7.11 with the main difference being in the effect of institutional activity on volatility. The positive, albeit weak, relationship between institutional activity and the next period's volatility is no longer evident. Panel A shows that, for the heavily traded stocks, lagged volatility decreases the proportion of shares placed by institutional traders. Also, volatility in the subsequent period decreases when the activity by institutional traders increases. However, the relationship of lagged institutional activity on volatility is found to be significant in only one of the 18 stocks. Panel B shows that the results are similar to those found using frequency of orders placed in measuring proportion of order activity.

7.3.4.6 Robustness checks – VAR using 12 lags

Appendix E presents the VAR modelling using 12 lags of the endogenous variables. Tables E.4 and E.5 present the results for the VAR modelling for retail order activity using the two measures of order activity. The results are similar to those found using four lags. Table E.4 shows that for the heavily traded stocks, there is some evidence of volatility attracting retail activity and that of retail activity decreasing the volatility in the subsequent period. However, these results are not found when the proportion of order activity is measured using volume of shares (see Table E.5). For the lightly traded stocks, the relationship between retail activity and volatility is generally weak.

Table 7.12 Results of the VAR modelling using 4 lags for each of the endogenous variables - *I_V* and *V2*.

Proportion of order submissions, *I_V*, is measured using the volume of shares placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of the day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficient while the second is the number of negative and significant coefficients.

	I_V			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.3325	22.61	[18, 0]	0.0669	4.38	[15, 0]
T	0.0003	2.50	[13, 0]	0.0041	42.77	[18, 0]
Day_2	0.0067	0.91	[4, 0]	-0.0137	-1.88	[0, 11]
Day_3	0.0124	1.64	[8, 0]	-0.0038	-0.52	[2, 3]
Day_4	0.0101	1.42	[8, 0]	-0.0061	-0.94	[1, 7]
Day_5	0.0021	0.25	[1, 1]	-0.0073	-0.91	[1, 5]
$Time_2$	-0.0514	-7.67	[0, 18]	-0.0307	-4.26	[0, 15]
$Time_3$	0.0448	6.76	[18, 0]	-0.0308	-4.64	[0, 18]
I_V_{-1}	0.2341	17.34	[18, 0]	-0.0071	-0.46	[0, 1]
I_V_{-2}	0.1228	8.91	[18, 0]	-0.0011	0.03	[0, 1]
I_V_{-3}	0.0833	6.08	[18, 0]	-0.0036	-0.28	[0, 3]
I_V_{-4}	0.0684	5.13	[18, 0]	-0.0157	-1.07	[0, 8]
$V2_{-1}$	-0.0371	-3.01	[0, 17]	0.1911	15.48	[18, 0]
$V2_{-2}$	-0.0177	-1.41	[0, 7]	0.0541	4.32	[17, 0]
$V2_{-3}$	-0.0108	-0.82	[0, 2]	0.0167	1.34	[9, 1]
$V2_{-4}$	0.0019	0.16	[1, 0]	0.0096	0.82	[5, 0]
R^2			0.23			0.49
F-Value			108.35			355.59
Eqn with significant (10%) *F*-Values			18			18
Panel B: Lightly traded stocks						
Constant	0.1675	8.36	[18, 0]	0.0693	1.11	[7, 4]
T	0.0087	1.96	[9, 3]	0.0759	28.53	[18, 0]
Day_2	-0.0027	-0.11	[0, 2]	-0.0153	-0.40	[0, 3]
Day_3	0.0003	0.04	[1, 2]	-0.0128	-0.56	[0, 5]
Day_4	-0.0068	-0.32	[1, 4]	-0.0093	-0.36	[1, 2]
Day_5	-0.0146	-0.66	[0, 1]	-0.0079	-0.23	[0, 2]
$Time_2$	-0.0303	-2.01	[0, 11]	-0.0569	-1.97	[0, 8]
$Time_3$	0.0430	2.92	[13, 0]	-0.0200	-0.57	[0, 3]
I_V_{-1}	0.1133	7.08	[18, 0]	-0.0315	-1.05	[0, 3]
I_V_{-2}	0.0855	5.32	[17, 0]	-0.0133	-0.33	[1, 2]
I_V_{-3}	0.0692	4.21	[15, 0]	-0.0185	-0.18	[2, 2]
I_V_{-4}	0.0661	4.02	[17, 0]	0.0023	-0.02	[1, 2]
$V2_{-1}$	-0.0023	-0.21	[0, 2]	0.1001	6.89	[16, 0]
$V2_{-2}$	0.0054	0.03	[2, 2]	0.0417	2.92	[15, 0]
$V2_{-3}$	-0.0051	-0.31	[0, 0]	0.0351	2.11	[12, 0]
$V2_{-4}$	-0.0030	-0.13	[1, 2]	0.0339	2.42	[12, 0]
R^2			0.07			0.24
F-Value			20.72			93.10
Eqn with significant (10%) *F*-Values			17			18

Tables E.6 and E.7 present the results for the VAR modelling for institutional order activity. Again, the results are similar to those found using four lags. Volatility decreases institutional order activity. Institutional activity increases volatility but only if activity is measured using frequency of orders placed. The relationship between the two variables is weak for lightly traded stocks.

7.3.4.7 Robustness checks – VAR using different interval widths

Another concern with the findings (or the lack thereof) is the size of the interval used. This is more of an issue for the lightly traded stocks as the level of trading in these stocks is low. Table 7.2 reports, on average, 51 orders are placed in a 15-minute interval for the heavily traded sample but only four for the lightly traded. Furthermore, a large number of intervals in the lightly traded stocks are found not to have any order activity.[1] As part of the robustness checks, wider intervals of 60-minutes and two-hours are used to collate the order flow and compute the volatility measures for the lightly traded stocks. The results are presented in Table E.8 and Table E.9.

The VAR models are generated using a lag length of six when 60-minute intervals are used and lag length of three when two-hour intervals are used. These lag lengths are chosen to allow the observation of the relationship within a normal trading day cycle (i.e., normal trading excluding the opening and closing). The results from the tables are consistent with those found using the smaller intervals of 15-minutes.

7.3.5 Summary

Retail traders are more active after periods of higher volatility, in that the number of orders placed and the volume of shares transacted increases. On the other hand, institutional traders are less active after periods of higher volatility. The effect of volatility on the mix of traders in the market is statistically significant in heavily traded stocks but not in lightly traded stocks. Furthermore, the effect of the order activity from different trader types on volatility differs depending on the measure of

[1] Table 7.1 shows that there was order activity in 98,486 stock intervals for the heavily traded stocks but order activity was found only in 70,804 intervals for the lightly traded stocks.

the order mix. A higher proportion of orders placed by retail traders reduces volatility. This can be explained by a simultaneous increase in the proportion of orders placed by institutional traders, who are believed to be better informed. The actions of the informed traders move prices, creating greater volatility. However, an increase in the proportion of order volume placed by retail traders increases volatility. It is possible that larger retail traders are not as informed about market conditions, so that their trades cause temporary price changes and a larger share price variation.

An alternative explanation is given by the stealth trading hypothesis. When informed institutional traders attempt to camouflage their actions, they are more likely to transact in smaller order sizes. Thus a smaller proportion of order volume of institutional traders would be evidence of informed trading, which is accompanied by higher volatility.

CHAPTER EIGHT
CONCLUSION

The first section of this chapter summarises the findings that were presented in Chapters Five, Six and Seven. The second section discusses the contribution to the literature and the third outlines limitations of my study and proposes areas for further research.

8.1 Summary of findings

This thesis has examined the trading patterns of retail and institutional traders. Three aspects of their trading were of particular interest: (1) the information content of their trades, (2) their order placement strategies, and (3) the impact of their trading on share price volatility.

Chapter Five presented the results on the first set of research questions concerning the short run price effect of transactions by retail and institutional traders. It was hypothesised (H_1) that trades made on the basis of private information, such as those by institutional traders, are associated with larger permanent price changes. On the other hand, trades that are made by uninformed traders, such as retail traders, were hypothesised to be associated with smaller permanent price effects. The analysis found support for these predictions among the heavily traded stocks. The second hypothesis (H_2) proposed that institutional trades are associated with a smaller total price effect when compared to retail trades. The rationale is that the inventory cost or price-pressure effect is smaller for institutional traders than for retail traders. The analysis found support for the prediction that retail traders are less informed in their order placement and incur higher market impact costs when executing their orders.

Having found evidence that retail traders are less informed than institutional traders, Chapter Six compared their trading strategies. The trading strategy of informed traders has been debated in the market microstructure literature. The issues of order size, order type and frequency of trading have prompted much theoretical and empirical research. In order to profit from their potentially short-lived information advantage, informed traders are expected to place more aggressive orders. While the study of order price aggressiveness does not necessarily provide an indication of whether the trader is informed, it provides some insight into retail and institutional traders' strategies and demand for immediacy. The results in Chapter Six showed that, consistent with hypothesis H_3, institutional orders were more aggressive. Furthermore, retail traders were found to be less aware of the state of the market when placing aggressive orders. For example, when placing a marketable buy limit order, the limit price was set "much higher" than the best ask price.

A related question with order aggressiveness is the provision of liquidity to a limit order market by the different trader types. The results presented in the second section of Chapter Six revealed significant differences between the contributions of institutional and retail traders to the depth of the limit-order book. Retail standing limit orders are found to be further from the market with the differences being larger at the beginning and end of the trading phase where strategic traders are known to be more likely to trade. The results are consistent with the hypothesis (H_4) that limit orders placed by retail traders have a greater expected adverse selection component.

Chapter Seven examined the effect of trading by retail and institutional traders on price volatility. Hypothesis H_5 predicted periods with a greater proportion of retail trader activity are associated with higher stock price volatility, as retail traders trade on noise. Retail traders were found to be more active and institutional traders were found to be proportionally less active after periods of high volatility. However, the effect of volatility on the mix of traders in the market depended on the sample examined, with the results being statistically significant in heavily traded stocks.

In addition, the effect of order activity from different trader types on volatility differed depending on the measure of the order mix. A lower proportion of orders placed (measured by order frequency) by retail traders and the accompanying increase in the proportion of orders placed by institutional traders increased volatility. The actions of these informed traders moved prices, creating greater volatility. However, an increase in the proportion of order volume placed by retail traders increased volatility. It is likely the smaller proportion of order volume of institutional traders is associated with stealth trading rather than liquidity trading, thus increasing price volatility.

8.2 Contribution to literature

The increase in retail investor activity in the late 1990s and early 2000s raised serious concerns for regulators and stock exchange operators. Research on the impact of different trader types on the stock market has been scarce. The availability of data and increased awareness of the growing importance of retail traders has prompted further research. Hong and Kumar (2002) argue individual investors are a dominant source of noise trading, given their lack of sophistication. The results in this thesis provide further support for the prediction that retail traders are less informed than institutional traders.

The analysis suggests that the motivation of the trader is an important factor when examining the type of order used. Consistent with Keim and Madhavan (1995), institutional traders are found to be impatient (i.e., aggressive) in their trading. In addition to being uninformed, retail traders are found to factor a higher expected adverse selection cost component into their standing limit orders. The findings in this thesis provide support for work on modelling the order placement decision in a limit order book environment.

Earlier studies suggest retail traders cause larger fluctuations in share prices and influence the speed of price adjustment to new information (Greene and Smart, 1999). Others such as Hirshleifer, Myers, Myers and Teoh (2003) do not find individual investors were the main source of the post-earnings announcement drift. Jackson (2003) finds the noise trader risk discussed by De Long et al. (1990a) is caused by institutional and not retail traders. The results in this thesis provide mixed evidence on the effect of different types of trader on volatility. While an increase in order volume from retail traders is associated with higher volatility, an increase in order frequency is associated with lower volatility.

8.3 Limitations and directions for future research

Trading in 36 stocks during calendar year 2001 was examined, with the stocks selected from the two extreme deciles of the top 200 companies in Australia ranked by trading volume. Stocks were selected from these deciles to provide a contrast of the heavily and lightly traded companies. The 18 heavily traded stocks were found to account for 59% of the total dollar volume traded in 2001 while the 18 lightly traded stocks accounted for less than 1% of total trading. While the 18 lightly traded stocks are thinly traded, they were included in the analysis because they are representative of many stocks listed on the Australian Stock Exchange (ASX). The results discussed were generally consistent with the hypotheses for the heavily traded stocks but not so for the lightly traded stocks. Thus, the findings may not necessarily apply to other companies in the top 200 list and to the many smaller companies traded on the ASX.

The information content of the market and marketable limit orders placed by different trader types were examined using narrow transaction time windows (t=1 and t=5). The findings of the price impact type analysis of orders can be compared to the performance of orders over a wider window of one month as robustness testing. However, it is unclear from the current literature what window would be appropriate or would correspond to the investment horizon of a retail or institutional investor. Furthermore, previous studies suggest informed traders are likely to use both market and limit orders (Anand et al., 2005; Bloomfield et al., 2005; Chakravarty and Holden, 1995). The exclusion of limit orders in the information content analysis may bias the results if there is a systematic preference of informed retail traders for limit orders. An extension would involve studying the performance of both limit and market orders placed by different trader types.

The aggressiveness of the orders placed and the position of limit orders are studied without consideration of the penalty of failed execution. Harris and Hasbrouck (1996) argue that when studying the performance of traders' order placement, it is important to factor opportunity costs into the analysis. An extension of the study on the order placement strategies of different trader types could involve examining the execution probability and the time to execution from the initial placement of a limit order. This will provide an insight into the cost of non-execution. The conjecture is that limit orders placed by retail traders, hypothesised to be uninformed, are likely to have a lower probability of execution and take a longer time to execute than limit orders placed by institutional traders. This could accord with the ecological system of the limit order book discussed in Handa et al. (1998).

The ordered probit analysis of the order aggressiveness was conducted using data for two months, March 2001 and September 2001. Trading activity in the month of September may not reflect trading at other times of the year because most Australian companies have June as the financial year-end and release their annual results in September. Kim and Verrecchia (1994) suggest that information asymmetry around the time of a major announcement is higher than in other periods. Information asymmetry during September may be higher and trader types that are active in the market may be different compared to other months of the year. Further analysis involving other months could verify that the results are not period specific.

The analysis of the volume and share price volatility relationship provided mixed results. The use of volume and trading frequency, respectively, provided conflicting evidence on the effect of retail trading on volatility. The impact of the frequency of trading and trading volume on volatility has been the subject of debate in the literature. For example, Jones et al. (1994b) argue that the frequency of trades is related to volatility and that the size of the trades has no information content. Further work could involve exploring the effect of retail trading on volatility by segmenting the order flow from retail traders to account for the non-linear relationship between order size and volatility (Chan and Fong, 2000).

The stealth trading hypothesis of Barclay and Warner (1993) suggests informed traders are likely to use medium sized orders. Others such as Walsh (1998) have found large trades on the ASX are associated with larger price movements. Heflin and Shaw (2005) argue changes in the quoted depth represent shifts in the price-quantity schedule; implying that, when studying the price effects of orders, order size should be measured relative to the market condition at the time the order was placed. Heflin and Shaw (2005) suggest informed traders placing market orders for immediate execution take into account the depth at the best quotes, and choose the size of their order accordingly. Informed traders want to trade as large a quantity as possible to fully exploit their informational advantage but will adjust their order placement according to market conditions. Segmenting the order flow from both retail and institutional traders by the size of order could provide better insight into the trading activity and volatility relationship.

The increase in retail trading has plateaued somewhat since the introduction of online trading. The latest share ownership survey published by the ASX shows that the percentage of direct share ownership in Australia increased steadily during the late 1980s and 1990s. The trend peaked in 1999 at 41%. The percentage ownership hovered around the 40% after 1999 and increased slightly to 44%, in 2004 (International Share Ownership, 2005). The sample year of 2001 used in the study could be argued to be an unusual period in that many of the retail traders had only just entered the market and were inexperienced. Some of the analysis conducted in this thesis could be repeated with more recent data, providing further evidence on the trading strategies of more experienced retail investors. It is likely that retail traders on the whole will have learned from their experience and further research will allow the analysis of any changes that have resulted.

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APPENDIX A

ORDER AND TRADE RECORD DETAILS

There are six order type records examined.

- ENTBID and ENTASK – These records represent new bid and ask orders entered. These orders can be market, limit or marketable limit orders. When market orders are placed, they result in trades as the order is executed against a standing limit order.
- AMDBID and AMDASK – These records represent amendments to bid and ask orders that have been entered. These entries result in the cancellation of the original order, and a new order is created with the new order being placed at the end of the price queue.
- TIKBID and TIKASK – These records are similar to the amendments and represent the cancellations of standing limit orders. Whenever a tick order is placed, a new order is created which is one price step closer to the market.

The following fields are available for the order records.

Field	Description
Date	DDMMYYYY
Time	HH:MM:SS.SS, the time is shown to the nearest hundredth of a second
Stock Code	Company
Order type	The six order types are: (1) ENTBID, (2) ENTASK, (3) AMDBID, (4) AMDASK, (5) TIKBID, and (6) TIKASK.
Price	Order price or new order price for amendments and tick orders.
Volume	The volume includes both disclosed and undisclosed volume – number of shares.
Broker identifier	Three categories are used: (1) Institutional, (2) Retail and (3) Others.

There are two trade record types used.

- TRADES: These records include all on market trades which arise as a result of a matching bid and ask order.
- OFFTRD: These records trades which have executed off market, pursuant the ASX trading rules and reported to the market via SEATS.

The following fields are available for trade records:

Field	Description
Date	DDMMYYYY
Time	HH:MM:SS.SS, the time is shown to the nearest hundredth of a second
Stock code	Company
Trade type	This denotes if the trade is executed on-market or off-market.
Price	Trade price
Volume	Number of shares traded.
Buy broker identifier	Three categories are used: (1) Institutional, (2) Retail and (3) Others.
Sell broker identifier	Three categories are used: (1) Institutional, (2) Retail and (3) Others.

APPENDIX B

CLASSIFICATION OF BROKER HOUSES

Table B.1 Classification of broker houses

Panel A lists the broker houses that are classified as institutional. Panel B lists the broker houses that are classified as retail. Panel C lists the broker houses that are classified as others.

Panel A: Institutional
ABN AMRO Equities Australia Limited
Credit Suisse First Boston Australia
Deutsche Securities Australia Ltd
Goldman Sachs (Australia) Pty Ltd
J.P. Morgan Securities Australia Limited (formerly Ord Minnett)
JB Were Limited
Macquarie Equities Limited
Merrill Lynch Australia
Morgan Stanley Dean Witter Australia Securities
Salomon Smith Barney Australia Securities Pty Ltd
UBS Warburg Australia Equities
Panel B: Retail
Andrew West & Co Limited
Barton Capital Securities Pty Ltd
Commonwealth Securities Ltd
E-Trade Australia Securities Ltd
HP JDV Ltd
ITG Australia Ltd
National Online Trading Limited
Salomon Smith Barney Private Clients (ANZ Securities)
Sanford Securities Pty Ltd
UBS Warburg Private
Panel C: Others
ABN AMRO Morgans Limited
ANZ Securities Limited
AOT Australia Pty Ltd
AOT Securities Pty Ltd
ASX International Services (Singapore)
Austock Brokers Pty Ltd
Baker Young Stockbrokers Ltd
Bell Potter Securities Limited
BNP Equities (Australia) Ltd
BNP Equities Private
Bridges Financial Services Pty Ltd
Burdett Buckeridge & Young Ltd
Burrell Stockbroking Pty Ltd
C.J. Weedon & Co.
Cameron Securities Ltd
Cazenove Australia Pty Ltd
Challenger First Pacific Limited
Charles Schwab Australia Pty Limited
Chartpac Securities Limited
CIBC World Markets Australia Ltd
ComSec Trading Limited
D.J. Carmichael Pty Ltd

Daiwa Securities SWCM Stockbroking Ltd
Dicksons Limited
E.L. & C. Baillieu Stockbroking Limited
Euroz Securities Limited
F.W. Holst & Co. Pty Ltd
Falkiners Stockbroking Limited
Findlay & Co Stockbrokers Limited
Foster Stockbroking Pty Ltd
Grange Securities Ltd
Hogan & Partners / Aberdeen Hogan
HSBC InvestDirect (Aust) Ltd
Hudson Securities Pty Ltd
Hull Trading Pty Ltd
Intersuisse Limited
Johnson Taylor Potter Limited
Joseph Palmer & Sons
J.P. Morgan Private(formerly Ord Minnett)
K.J. Polkinghorne & Co. Pty Ltd
Kirke Securities Pty Ltd
Knight Financial
Lodge Partners Pty Ltd
Lonsdale Securities Ltd
M.J. Wren & Partners Stockbrokers
Merrill Lynch Private Australia Ltd
Montagu Pty Ltd
Mortimer & Chua
Optiver Australia Ltd
Paterson Ord Minnett Ltd
Peake Lands Kirwan Pty Ltd
Reynolds & Company Pty Ltd
Rivkin Discount Stockbroking
SG Australia Equities Limited
Shadforths Limited
SHAW Stockbroking Limited
Southern Cross Equity Limited
State One Stockbroking Limited
Statton Securities
Taylor Collison Limited
TD Waterhouse Investor Services Ltd
Terrain Securities Pty Ltd
Timber Hill Australia Pty Ltd
TIR Securities Australia Ltd
Tolhurst Noalls
Tricom Equities Limited
Westpac Securities Limited
William Noall Limited
Wilson HTM Ltd

APPENDIX C
OFF-MARKET TRADES

Orders that are automatically executed on SEATS are known as on-market trades. These trades normally occur between 10:00am and 4:05pm Sydney time. Trades that are not automatically executed by SEATS are known as off-market trades. These trades comprise orders that are matched off SEATS and entered into the system by the seller. There are two main categories of off-market trades: (1) trades that take place outside Normal Trading, and (2) Special Crossings.

Trades that take place outside Normal Trading comprise late trades and overnight trades. Late trades take place after the market has closed over the Closing Phase (4:05pm to 5:00pm) and after-hour adjust phase (5:00pm to 7:00pm). Overnight trades take place over the Enquiry Phase (7:00pm to 7:00am). Late trades must take place according to the price-time priority and with reference to the SEATS limit order book. Brokers submit their orders through SEATS to indicate their intention to trade. Where orders overlap, the broker contacts the counterparties in price-time priority to execute the orders. When the trades are executed, the sellers have the responsibility to enter the trade details into SEATS. Overnight trades take place by telephone. As SEATS is not available during this time, the buyer and seller mutually agree to the price of the trade. The sellers are required to enter the overnight trades into SEATS by 9.45am before the market re-opens.

Special crossings may take place off-market at any time including during Normal Trading and where the same broker is on both the buy and the sell side. The two most common types of crossings are (1) block specials and (2) portfolio specials. A block special is a crossing with a value of over $1 million and a portfolio special is a crossing comprising trades in at least ten securities with each trade having a value of at least $200,000 and the total value of the portfolio trade is greater than $5 million. The traders do not need to check the market prices as special crossings can take placed with no reference to the current market. This is contrast to on-SEATS crossings, where the crossings are essentially traded at the market prices.

APPENDIX D

PRICE EFFECTS

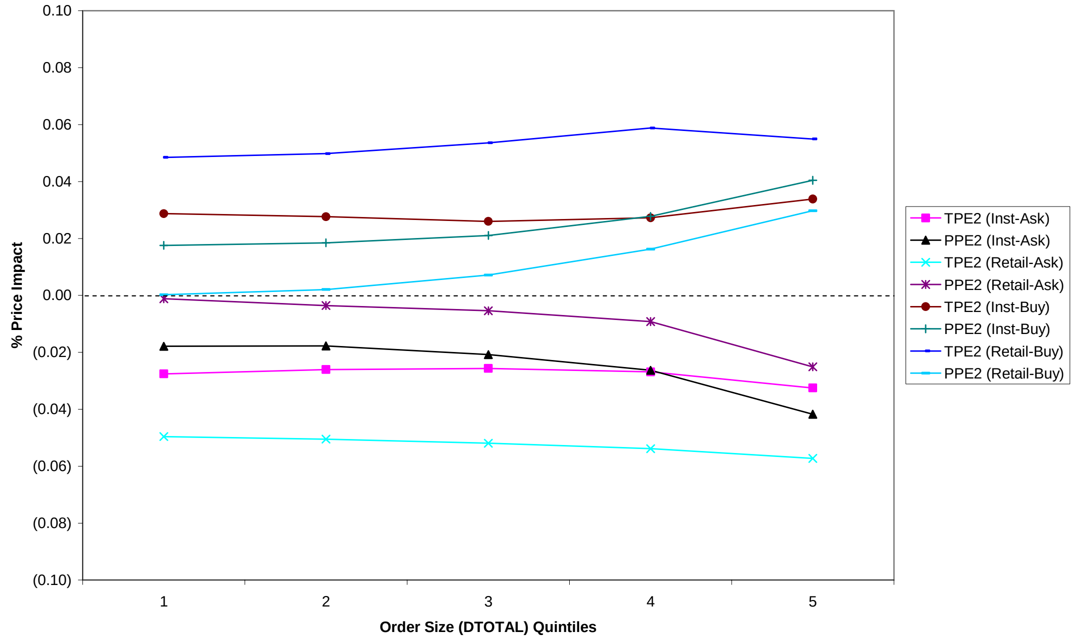

Figure D.1 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 1 (i.e., heavily traded stocks). Orders are ranked and grouped into quintiles based on DTOTAL (order size as a percentage of the number of shares traded on the day) where Quintile 1 comprises the smallest orders. Price effect is computed using *k*=*j*=5.

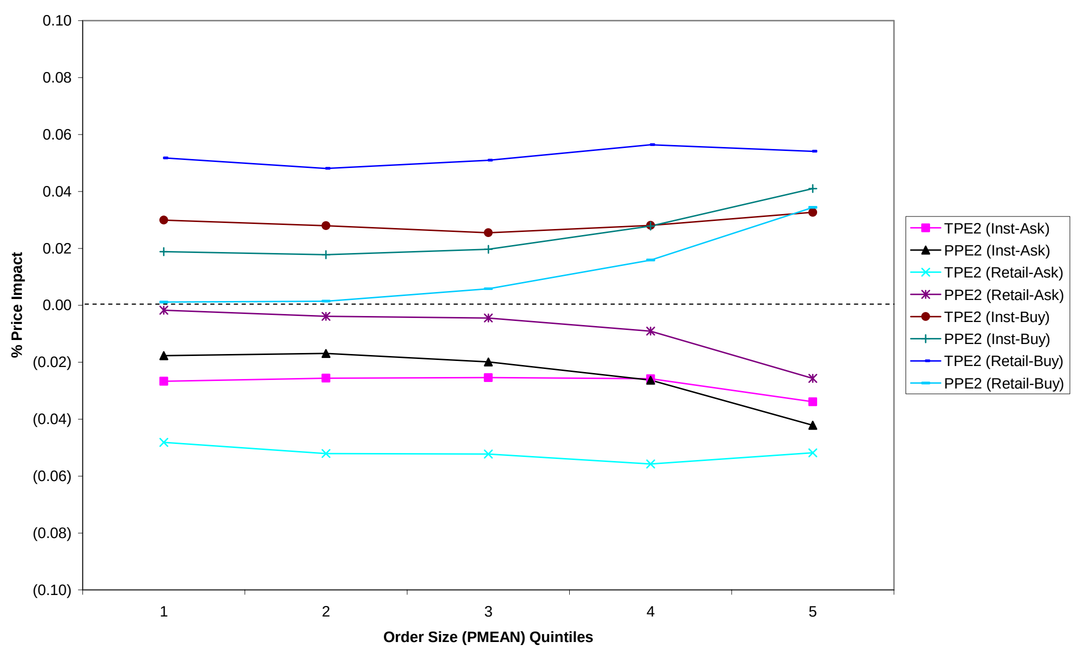

Figure D.2 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 1 (i.e., heavily traded stocks). Orders are ranked and grouped into quintiles based on PMEAN (order size as a percentage of average daily number of shares traded over the sample period for the company) where Quintile 1 comprises the smallest orders. Price effect is computed using *k*=*j*=5.

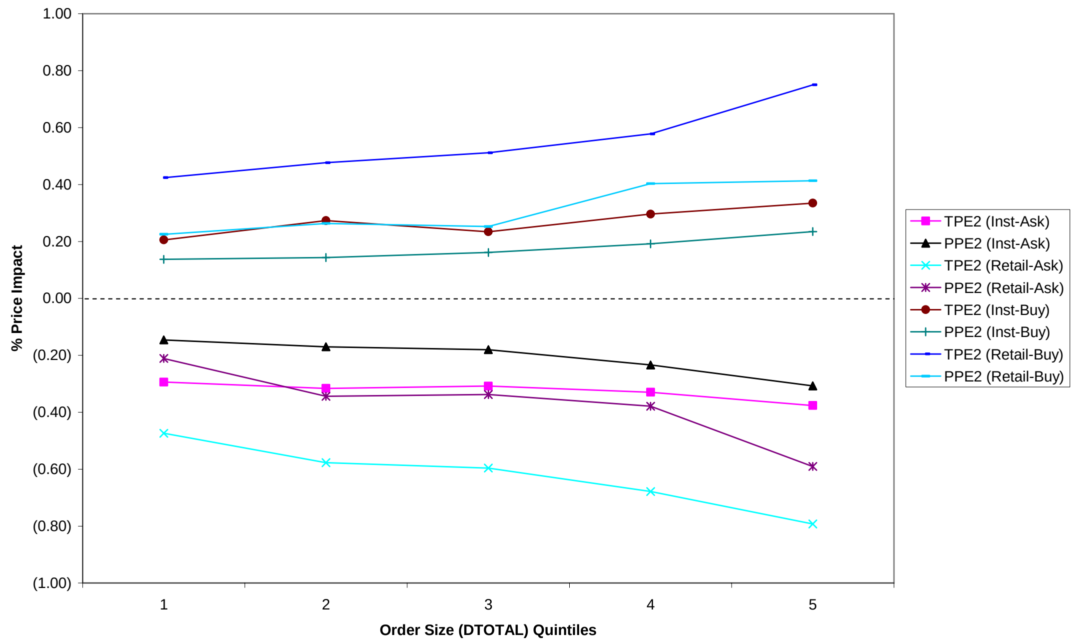

Figure D.3 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 10 (i.e., lightly traded stocks). Orders are ranked and grouped into quintiles based on DTOTAL (order size as a percentage of the number of shares traded on the day) where Quintile 1 comprises the smallest orders. Price effect is computed using $k=j=5$.

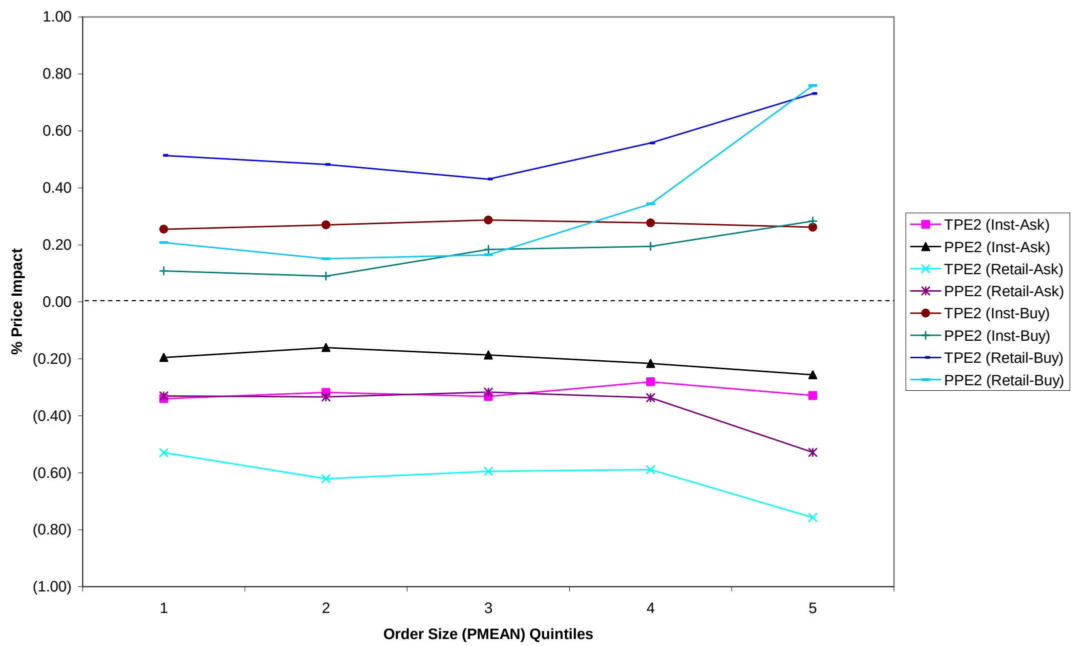

Figure D.4 Total and permanent price effect of orders placed by institutional and retail traders for stocks in Decile 10 (i.e., lightly traded stocks). Orders are ranked and grouped into quintiles based on PMEAN (order size as a percentage of average daily number of shares traded over the sample period for the company) where Quintile 1 comprises the smallest orders. Price effect is computed using k=j=5.

APPENDIX E

VOLUME AND VOLATILITY RELATION

Table E.1 Autocorrelations, contemporaneous and lagged cross-correlations between *V2* and *R_V*

The table presents the autocorrelations, contemporaneous and lagged cross-correlations between volatility, *V2*, and proportion of retail order submission measured using number of shares placed, *R_V*, for our sample firms between 1 January 2001 and 31 December 2001. *V2*, is computed by 100*(log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. The results are shown for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). The "Mean *t*-stat" shows the mean *t*-statistic of the 18 firms in each sub-sample. The "no. of significant coeff" shows the number of firms in each sample that has a correlation coefficient significant at the 0.10 level.

	$V2_0$	Mean *t*-stat	No. of significant coeff	R_V_0	Mean *t*-stat	No. of significant coeff
Panel A: Heavily traded stocks (n=18)						
$V2_0$	1.000			-0.160	-12.102	18
$V2_{-1}$	0.504	38.130	18	-0.088	-6.679	18
$V2_{-2}$	0.371	22.770	18	-0.060	-4.568	16
$V2_{-3}$	0.286	16.094	18	-0.037	-2.804	9
$V2_{-4}$	0.226	12.087	18	-0.018	-1.340	4
$V2_{-5}$	0.180	9.376	18	0.004	0.301	2
$V2_{-6}$	0.144	7.336	17	0.024	1.829	4
$V2_{-7}$	0.099	4.911	16	0.039	2.972	9
$V2_{-8}$	0.056	2.677	10	0.065	4.923	15
$V2_{-9}$	-0.001	-0.253	5	0.092	6.947	18
$V2_{-10}$	-0.054	-2.938	11	0.136	10.247	18
$V2_{-11}$	-0.086	-4.552	15	0.161	12.161	18
$V2_{-12}$	-0.096	-4.994	15	0.159	12.014	18
R_V_0	-0.160	-12.102	18	1.000		
R_V_{-1}	-0.113	-8.563	18	0.293	22.111	18
R_V_{-2}	-0.099	-7.445	18	0.225	15.493	18
R_V_{-3}	-0.078	-5.920	17	0.175	11.491	18
R_V_{-4}	-0.057	-4.317	16	0.128	8.187	18
R_V_{-5}	-0.038	-2.833	11	0.090	5.640	18
R_V_{-6}	-0.021	-1.598	7	0.068	4.210	16
R_V_{-7}	-0.011	-0.790	3	0.060	3.740	12
R_V_{-8}	0.006	0.450	3	0.054	3.302	11
R_V_{-9}	0.038	2.847	9	0.050	3.072	10
R_V_{-10}	0.084	6.378	17	0.041	2.502	9
R_V_{-11}	0.124	9.393	17	0.042	2.536	7
R_V_{-12}	0.150	11.312	18	0.035	2.098	7

Panel B: Lightly traded stocks (n=18)						
$V2_{0}$	1.000			-0.069	-4.434	15
$V2_{-1}$	0.222	14.626	17	-0.019	-1.259	2
$V2_{-2}$	0.161	9.990	17	-0.010	-0.596	2
$V2_{-3}$	0.136	7.892	17	-0.003	-0.180	0
$V2_{-4}$	0.118	6.835	14	0.004	0.249	0
$V2_{-5}$	0.100	5.582	15	-0.003	-0.177	2
$V2_{-6}$	0.077	4.234	10	0.004	0.292	0
$V2_{-7}$	0.066	3.694	13	0.013	0.760	2
$V2_{-8}$	0.065	3.498	10	0.002	0.258	1
$V2_{-9}$	0.054	2.846	9	0.009	0.640	1
$V2_{-10}$	0.046	2.420	9	0.012	0.726	1
$V2_{-11}$	0.039	2.050	6	0.010	0.699	1
$V2_{-12}$	0.043	2.275	6	0.004	0.360	2
R_V_{0}	-0.069	-4.434	15	1.000		
R_V_{-1}	-0.022	-1.554	6	0.104	6.441	17
R_V_{-2}	-0.014	-0.983	2	0.077	4.808	15
R_V_{-3}	-0.013	-0.895	3	0.068	4.060	13
R_V_{-4}	-0.004	-0.482	2	0.056	3.318	10
R_V_{-5}	-0.009	-0.656	2	0.053	3.272	12
R_V_{-6}	-0.007	-0.545	2	0.053	3.114	11
R_V_{-7}	-0.005	-0.426	2	0.046	2.814	9
R_V_{-8}	0.005	0.334	0	0.044	2.666	10
R_V_{-9}	0.006	0.379	0	0.042	2.580	8
R_V_{-10}	0.008	0.507	1	0.039	2.326	7
R_V_{-11}	0.010	0.573	1	0.034	2.017	5
R_V_{-12}	0.011	0.576	0	0.039	2.191	6

Table E.2 Autocorrelations, contemporaneous and lagged cross-correlations between *V2* and *I_V*

The table presents the autocorrelations, contemporaneous and lagged cross-correlations between volatility, *V2*, and proportion of institutional order submission measured using number of shares placed, *I_V*, for our sample firms between 1 January 2001 and 31 December 2001. *V2*, is computed by 100*(log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. The results are shown for heavily traded stocks (Panel A) and lightly traded stocks (Panel B). The "Mean *t*-stat" shows the mean *t*-statistic of the 18 firms in each sub-sample. The "no. of significant coeff" shows the number of firms in each sample that has a correlation coefficient significant at the 0.10 level.

	$V2_0$	Mean *t*-stat	No. of significant coeff	I_V_0	Mean *t*-stat	No. of significant coeff
			Panel A: Heavily traded stocks (n=18)			
$V2_0$	1.000			0.091	6.877	16
$V2_{-1}$	0.504	38.130	18	0.030	2.234	9
$V2_{-2}$	0.371	22.770	18	0.011	0.855	3
$V2_{-3}$	0.286	16.094	18	-0.004	-0.323	2
$V2_{-4}$	0.226	12.087	18	-0.012	-0.925	3
$V2_{-5}$	0.180	9.376	18	-0.029	-2.182	6
$V2_{-6}$	0.144	7.336	17	-0.052	-3.899	14
$V2_{-7}$	0.099	4.911	16	-0.065	-4.939	17
$V2_{-8}$	0.056	2.677	10	-0.084	-6.338	18
$V2_{-9}$	-0.001	-0.253	5	-0.107	-8.072	18
$V2_{-10}$	-0.054	-2.938	11	-0.137	-10.363	18
$V2_{-11}$	-0.086	-4.552	15	-0.153	-11.547	18
$V2_{-12}$	-0.096	-4.994	15	-0.143	-10.808	18
I_V_{-1}	0.091	6.877	16	1.000		
I_V_{-2}	0.079	5.982	16	0.374	28.297	18
I_V_{-3}	0.084	6.345	17	0.300	19.922	18
I_V_{-4}	0.076	5.744	17	0.245	15.181	18
I_V_{-5}	0.058	4.410	15	0.194	11.521	18
I_V_{-6}	0.040	3.009	10	0.153	8.844	18
I_V_{-7}	0.028	2.109	8	0.128	7.293	17
I_V_{-8}	0.020	1.477	4	0.118	6.604	17
I_V_{-9}	0.004	0.328	2	0.112	6.221	17
I_V_{-10}	-0.028	-2.106	7	0.112	6.170	17
I_V_{-11}	-0.067	-5.037	16	0.113	6.208	18
I_V_{-12}	-0.106	-8.012	18	0.116	6.295	16
I_V_{-1}	-0.138	-10.421	18	0.113	6.077	17

Panel B: Lightly traded stocks (n=18)						
$V2_{0}$	1.000			0.026	1.511	11
$V2_{-1}$	0.222	14.626	17	0.004	0.303	5
$V2_{-2}$	0.161	9.990	17	0.003	-0.036	3
$V2_{-3}$	0.136	7.892	17	0.000	-0.119	2
$V2_{-4}$	0.118	6.835	14	-0.008	-0.554	2
$V2_{-5}$	0.100	5.582	15	-0.004	-0.316	3
$V2_{-6}$	0.077	4.234	10	-0.006	-0.532	3
$V2_{-7}$	0.066	3.694	13	-0.017	-1.047	4
$V2_{-8}$	0.065	3.498	10	-0.011	-0.829	2
$V2_{-9}$	0.054	2.846	9	-0.013	-0.854	3
$V2_{-10}$	0.046	2.420	9	-0.013	-0.907	5
$V2_{-11}$	0.039	2.050	6	-0.016	-0.908	3
$V2_{-12}$	0.043	2.275	6	-0.011	-0.717	2
I_V_{0}	0.026	1.511	11	1.000		
I_V_{-1}	-0.002	-0.120	2	0.163	10.371	18
I_V_{-2}	0.008	0.398	2	0.138	8.471	16
I_V_{-3}	0.002	0.272	2	0.118	7.009	16
I_V_{-4}	0.006	0.414	3	0.107	6.241	16
I_V_{-5}	0.008	0.472	4	0.109	6.270	17
I_V_{-6}	0.004	0.225	2	0.089	5.140	14
I_V_{-7}	0.004	0.210	3	0.093	5.244	15
I_V_{-8}	-0.003	-0.236	1	0.080	4.402	13
I_V_{-9}	-0.008	-0.618	3	0.073	4.008	12
I_V_{-10}	-0.009	-0.653	2	0.074	4.049	12
I_V_{-11}	-0.012	-0.638	2	0.073	4.093	13
I_V_{-12}	-0.015	-0.830	3	0.075	4.051	13

Table E.3 Lag lengths that minimise the Schwartz Bayesian Criterion

The table presents the lag lengths that minimise the Schwartz Bayesian Criterion (SBC) for the VAR systems modelling the interaction between trading activity and volatility for each stock. Proportion of order activity by institutional trader is measured using frequency of orders placed (*I_F*) and volume of shares in the orders (*I_V*). The volatility measure, *V2*, is computed by 100*(log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval.

	I_F vs V2		*I_V vs V2*	
Company	SBC	Lag	SBC	Lag
Panel A: Heavily traded stocks				
AMP	-8.09	10	-7.28	3
ANZ	-8.21	12	-7.68	11
BHP	-8.55	10	-8.09	4
BIL	-7.15	3	-6.77	3
CBA	-8.58	10	-7.83	3
CML	-7.34	11	-6.46	3
CSR	-6.58	4	-6.17	2
LLC	-7.02	9	-6.40	9
MAY	-6.43	3	-5.87	4
NAB	-8.39	11	-7.84	3
NCP	-7.53	10	-7.04	3
QAN	-6.50	10	-5.39	10
RIO	-7.52	7	-7.15	4
TLS	-17.97	10	-16.63	3
WBC	-17.18	11	-16.65	3
WMC	-16.50	10	-15.81	10
WOW	-16.70	12	-16.15	10
WPL	-16.30	3	-15.77	3
Panel B: Lightly traded Stocks				
AQP	-3.03	3	-2.88	3
ARG	-5.03	2	-4.83	2
CPH	-3.97	6	-3.61	5
GNS	-3.52	5	-3.33	5
GWT	-3.47	4	-3.29	4
HRP	-4.23	2	-4.20	2
IFM	-2.35	4	-2.23	2
KIM	-4.20	2	-4.05	2
MXO	-3.70	2	-3.47	2
MYO	-3.21	3	-2.95	3
NUF	-3.55	3	-3.44	3
OML	-3.02	4	-2.84	4
PLM	-2.83	3	-2.76	2
RIC	-3.84	3	-3.61	3
SLX	-11.10	3	-10.95	3
TIM	-12.18	4	-12.13	6
VNA	-12.30	3	-12.27	3
VRL	-12.74	5	-12.51	3

Table E.4 Results of the VAR modelling using 12 lags for each of the endogenous variables - *R_F & V2*

Proportion of order submission, *R_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*(log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets shows the number of positive and significant coefficient while the second is the number of negative and significant coefficients.

	R_V			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
			Panel A: Heavily traded stocks			
Constant	0.0566	8.15	[18, 0]	0.0469	3.35	[12, 3]
T	-0.0004	-7.50	[0, 17]	0.0041	41.35	[18, 0]
day_2	-0.0023	-0.55	[0, 0]	-0.0145	-1.94	[0, 11]
day_3	-0.0020	-0.44	[0, 2]	-0.0042	-0.52	[2, 3]
day_4	-0.0012	-0.25	[0, 0]	-0.0065	-0.95	[0, 6]
day_5	0.0026	0.70	[3, 0]	-0.0069	-0.83	[2, 5]
$time_2$	0.0410	9.96	[18, 0]	-0.0320	-4.12	[0, 16]
$time_3$	-0.0404	-9.64	[0, 18]	-0.0261	-3.43	[0, 16]
R_F_{-1}	0.1866	13.74	[18, 0]	-0.0255	-0.92	[0, 5]
R_F_{-2}	0.0925	6.75	[18, 0]	-0.0063	-0.20	[1, 3]
R_F_{-3}	0.0595	4.35	[18, 0]	-0.0060	-0.19	[0, 3]
R_F_{-4}	0.0279	2.04	[9, 0]	0.0080	0.33	[3, 0]
R_F_{-5}	0.0291	2.11	[11, 0]	0.0021	0.14	[1, 3]
R_F_{-6}	0.0267	1.93	[11, 0]	0.0064	0.23	[2, 0]
R_F_{-7}	0.0319	2.30	[14, 0]	-0.0166	-0.66	[0, 2]
R_F_{-8}	0.0317	2.28	[13, 0]	-0.0381	-1.50	[0, 4]
R_F_{-9}	0.0519	3.75	[18, 0]	-0.0095	-0.33	[1, 2]
R_F_{-10}	0.0508	3.70	[18, 0]	0.0182	0.78	[1, 0]
R_F_{-11}	0.0421	3.10	[18, 0]	0.0346	1.45	[7, 1]
R_F_{-12}	0.0398	2.98	[16, 0]	0.0175	0.65	[3, 1]
$V2_{-1}$	0.0109	1.61	[7, 0]	0.1843	14.71	[18, 0]
$V2_{-2}$	0.0133	1.89	[9, 0]	0.0516	4.07	[17, 0]
$V2_{-3}$	0.0083	1.18	[6, 0]	0.0139	1.10	[6, 1]
$V2_{-4}$	0.0061	0.80	[2, 0]	0.0042	0.33	[4, 1]
$V2_{-5}$	0.0076	1.08	[4, 0]	-0.0009	-0.09	[1, 1]
$V2_{-6}$	0.0007	0.05	[1, 0]	0.0032	0.25	[3, 2]
$V2_{-7}$	-0.0087	-1.22	[0, 5]	0.0106	0.83	[5, 0]
$V2_{-8}$	-0.0024	-0.31	[0, 3]	0.0046	0.36	[1, 0]
$V2_{-9}$	0.0074	1.11	[7, 0]	0.0074	0.58	[4, 0]
$V2_{-10}$	0.0143	2.01	[11, 0]	0.0011	0.09	[3, 1]
$V2_{-11}$	0.0144	1.98	[11, 0]	0.0050	0.41	[3, 0]
$V2_{-12}$	0.0051	0.79	[3, 0]	0.0201	1.69	[7, 0]
R^2			0.30			0.49
F-Value			79.26			174.46
Eqn with significant (10%) *F*-Values			18			18

Panel B: Lightly traded stocks						
Constant	0.1841	8.88	[18, 0]	0.0224	-0.40	[5, 6]
T	-0.0074	-3.50	[0, 15]	0.0751	28.04	[18, 0]
day_2	-0.0061	-0.22	[0, 4]	-0.0162	-0.44	[0, 2]
day_3	-0.0066	-0.51	[1, 2]	-0.0119	-0.53	[0, 4]
day_4	-0.0026	-0.18	[1, 2]	-0.0061	-0.26	[1, 2]
day_5	-0.0052	-0.30	[0, 2]	-0.0060	-0.19	[1, 2]
$time_2$	0.0381	2.74	[13, 0]	-0.0690	-2.36	[0, 12]
$time_3$	-0.0270	-2.22	[0, 11]	-0.0238	-0.70	[0, 3]
R_F_{-1}	0.0832	5.06	[18, 0]	-0.0001	0.00	[2, 0]
R_F_{-2}	0.0519	3.17	[14, 0]	0.0130	0.22	[1, 0]
R_F_{-3}	0.0389	2.31	[15, 0]	0.0084	0.21	[1, 0]
R_F_{-4}	0.0319	1.81	[10, 0]	0.0142	0.32	[3, 0]
R_F_{-5}	0.0310	1.97	[12, 0]	0.0064	0.03	[0, 0]
R_F_{-6}	0.0293	1.76	[10, 0]	0.0059	-0.02	[2, 0]
R_F_{-7}	0.0243	1.56	[8, 0]	-0.0016	0.00	[0, 0]
R_F_{-8}	0.0287	1.73	[11, 0]	0.0232	0.62	[5, 0]
R_F_{-9}	0.0281	1.83	[12, 0]	0.0042	0.17	[1, 0]
R_F_{-10}	0.0183	1.16	[5, 0]	-0.0059	-0.18	[1, 2]
R_F_{-11}	0.0164	0.94	[4, 0]	-0.0054	0.15	[2, 1]
R_F_{-12}	0.0236	1.40	[7, 0]	0.0030	0.09	[0, 1]
$V2_{-1}$	0.0020	0.18	[2, 2]	0.0965	6.60	[16, 0]
$V2_{-2}$	-0.0014	0.21	[1, 0]	0.0383	2.67	[14, 0]
$V2_{-3}$	0.0065	0.53	[1, 0]	0.0305	1.79	[12, 0]
$V2_{-4}$	0.0029	0.22	[0, 0]	0.0278	1.91	[6, 0]
$V2_{-5}$	-0.0019	-0.07	[1, 1]	0.0219	1.28	[7, 0]
$V2_{-6}$	0.0003	0.10	[0, 1]	0.0041	0.32	[2, 0]
$V2_{-7}$	0.0023	0.19	[1, 0]	0.0043	0.39	[3, 2]
$V2_{-8}$	-0.0011	0.00	[1, 2]	0.0134	0.95	[4, 0]
$V2_{-9}$	0.0034	0.33	[1, 0]	0.0116	0.71	[4, 1]
$V2_{-10}$	0.0033	0.12	[0, 1]	0.0087	0.56	[3, 0]
$V2_{-11}$	0.0017	0.17	[2, 0]	0.0084	0.55	[2, 1]
$V2_{-12}$	0.0005	0.00	[0, 0]	0.0126	0.82	[4, 0]
R^2			0.05			0.25
F-Value			7.08			45.87
Eqn with significant (10%) *F*-Values			18			18

Table E.5 Results of the VAR modelling using 12 lags for each of the endogenous variables - R_V & V2

Proportion of order submission, *R_V*, is measured using the volume of shares placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	R_V			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.0324	5.91	[18, 0]	0.0329	3.02	[12, 3]
T	-0.0003	-5.66	[0, 18]	0.0041	41.75	[18, 0]
day_2	-0.0010	-0.33	[0, 3]	-0.0136	-1.85	[0, 11]
day_3	-0.0022	-0.61	[0, 5]	-0.0034	-0.44	[2, 2]
day_4	-0.0014	-0.41	[0, 2]	-0.0057	-0.87	[1, 7]
day_5	0.0004	0.14	[2, 1]	-0.0068	-0.83	[2, 5]
$time_2$	0.0306	7.80	[18, 0]	-0.0351	-4.57	[0, 16]
$time_3$	-0.0222	-5.72	[0, 17]	-0.0291	-3.95	[0, 18]
R_V_{-1}	0.1654	12.18	[18, 0]	0.0032	0.16	[2, 1]
R_V_{-2}	0.0850	6.20	[18, 0]	0.0016	0.10	[0, 1]
R_V_{-3}	0.0541	3.96	[16, 0]	0.0113	0.42	[1, 0]
R_V_{-4}	0.0320	2.34	[10, 0]	0.0150	0.50	[3, 0]
R_V_{-5}	0.0241	1.75	[10, 0]	0.0140	0.51	[1, 0]
R_V_{-6}	0.0229	1.66	[10, 0]	0.0164	0.56	[2, 1]
R_V_{-7}	0.0286	2.07	[13, 0]	0.0010	-0.02	[1, 1]
R_V_{-8}	0.0278	2.01	[12, 0]	-0.0270	-1.03	[0, 4]
R_V_{-9}	0.0372	2.69	[15, 0]	-0.0218	-0.77	[1, 2]
R_V_{-10}	0.0309	2.25	[11, 0]	0.0201	0.76	[4, 0]
R_V_{-11}	0.0328	2.41	[15, 0]	0.0420	1.61	[10, 0]
R_V_{-12}	0.0230	1.71	[10, 0]	0.0340	1.19	[7, 0]
$V2_{-1}$	0.0069	1.13	[6, 0]	0.1872	15.05	[18, 0]
$V2_{-2}$	0.0072	1.11	[6, 0]	0.0525	4.16	[17, 0]
$V2_{-3}$	0.0061	0.94	[5, 0]	0.0149	1.18	[6, 1]
$V2_{-4}$	0.0027	0.37	[1, 0]	0.0041	0.33	[5, 1]
$V2_{-5}$	0.0039	0.61	[0, 0]	-0.0004	-0.04	[1, 1]
$V2_{-6}$	-0.0006	-0.09	[2, 2]	0.0035	0.27	[3, 2]
$V2_{-7}$	-0.0092	-1.40	[0, 6]	0.0123	0.97	[5, 0]
$V2_{-8}$	-0.0032	-0.48	[0, 3]	0.0061	0.49	[1, 0]
$V2_{-9}$	0.0029	0.51	[3, 1]	0.0066	0.52	[4, 0]
$V2_{-10}$	0.0125	1.94	[10, 0]	-0.0006	-0.04	[2, 3]
$V2_{-11}$	0.0111	1.63	[8, 0]	0.0033	0.27	[3, 0]
$V2_{-12}$	0.0016	0.30	[2, 1]	0.0189	1.60	[7, 0]
R^2			0.18			0.49
F-Value			40.39			174.08
Eqn with significant (10%) *F*-Values			18			18

Panel B: Lightly traded stocks						
Constant	0.1944	8.96	[18, 0]	0.0218	-0.47	[4, 6]
T	-0.0091	-4.15	[0, 17]	0.0750	28.04	[18, 0]
day_2	-0.0067	-0.26	[0, 3]	-0.0156	-0.43	[0, 2]
day_3	-0.0071	-0.48	[1, 2]	-0.0115	-0.52	[0, 4]
day_4	-0.0036	-0.22	[1, 2]	-0.0057	-0.25	[1, 2]
day_5	-0.0040	-0.21	[1, 2]	-0.0057	-0.18	[1, 2]
$time_2$	0.0355	2.31	[9, 0]	-0.0689	-2.37	[0, 11]
$time_3$	-0.0305	-2.30	[0, 12]	-0.0239	-0.73	[0, 3]
R_V_{-1}	0.0720	4.29	[17, 0]	0.0019	0.08	[1, 1]
R_V_{-2}	0.0477	2.93	[15, 0]	0.0150	0.38	[1, 0]
R_V_{-3}	0.0366	2.20	[12, 0]	0.0064	0.12	[1, 0]
R_V_{-4}	0.0303	1.72	[7, 0]	0.0157	0.46	[1, 0]
R_V_{-5}	0.0281	1.82	[9, 0]	0.0087	0.15	[1, 1]
R_V_{-6}	0.0248	1.49	[6, 0]	0.0044	0.01	[1, 0]
R_V_{-7}	0.0236	1.52	[6, 0]	-0.0043	-0.08	[0, 0]
R_V_{-8}	0.0259	1.55	[9, 0]	0.0202	0.61	[3, 0]
R_V_{-9}	0.0289	1.86	[10, 0]	0.0023	0.12	[1, 0]
R_V_{-10}	0.0201	1.26	[7, 0]	-0.0011	-0.01	[2, 1]
R_V_{-11}	0.0185	1.06	[5, 0]	-0.0043	0.15	[2, 0]
R_V_{-12}	0.0201	1.17	[5, 0]	0.0070	0.20	[1, 0]
$V2_{-1}$	0.0007	0.11	[0, 1]	0.0969	6.62	[16, 0]
$V2_{-2}$	-0.0027	0.10	[1, 0]	0.0385	2.68	[15, 0]
$V2_{-3}$	0.0049	0.35	[0, 0]	0.0305	1.79	[12, 0]
$V2_{-4}$	0.0046	0.31	[3, 0]	0.0281	1.92	[6, 0]
$V2_{-5}$	-0.0017	-0.06	[1, 1]	0.0220	1.29	[7, 0]
$V2_{-6}$	0.0000	-0.02	[0, 1]	0.0041	0.33	[2, 0]
$V2_{-7}$	0.0028	0.26	[1, 0]	0.0041	0.38	[3, 2]
$V2_{-8}$	-0.0016	-0.10	[1, 2]	0.0135	0.96	[4, 0]
$V2_{-9}$	0.0026	0.28	[1, 0]	0.0114	0.71	[3, 1]
$V2_{-10}$	0.0029	0.10	[0, 0]	0.0090	0.58	[3, 0]
$V2_{-11}$	0.0025	0.28	[2, 0]	0.0086	0.56	[2, 1]
$V2_{-12}$	-0.0006	-0.12	[1, 0]	0.0129	0.83	[4, 0]
R^2			0.05			0.25
F-Value			6.14			45.83
Eqn with significant (10%) *F*-Values			18			18

Table E.6 Results of the VAR modelling using 12 lags for each of the endogenous variables - *I_F* & *V2*.

Proportion of order submission, *I_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets shows the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	I_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.1204	9.49	[18, 0]	0.0062	0.20	[7, 4]
T	0.0003	3.84	[15, 0]	0.0041	41.54	[18, 0]
day_2	0.0033	0.60	[1, 0]	-0.0148	-2.02	[0, 11]
day_3	0.0037	0.69	[3, 0]	-0.0052	-0.71	[1, 3]
day_4	0.0018	0.33	[2, 1]	-0.0068	-1.05	[0, 6]
day_5	-0.0034	-0.71	[1, 5]	-0.0068	-0.86	[1, 5]
$time_2$	-0.0492	-9.17	[0, 18]	-0.0283	-3.55	[0, 15]
$time_3$	0.0745	13.40	[18, 0]	-0.0242	-3.06	[0, 14]
I_F_{-1}	0.2353	17.30	[18, 0]	0.0295	1.51	[7, 0]
I_F_{-2}	0.1181	8.55	[18, 0]	0.0200	1.06	[4, 0]
I_F_{-3}	0.0630	4.55	[17, 0]	0.0187	0.82	[4, 0]
I_F_{-4}	0.0249	1.80	[8, 0]	-0.0068	-0.31	[0, 3]
I_F_{-5}	0.0252	1.81	[11, 0]	-0.0046	-0.21	[0, 1]
I_F_{-6}	0.0228	1.64	[9, 0]	-0.0060	-0.22	[0, 2]
I_F_{-7}	0.0335	2.39	[13, 0]	0.0163	0.83	[4, 0]
I_F_{-8}	0.0393	2.80	[15, 0]	0.0389	1.96	[11, 0]
I_F_{-9}	0.0559	4.00	[17, 0]	0.0161	0.79	[5, 1]
I_F_{-10}	0.0567	4.09	[17, 0]	-0.0060	-0.42	[2, 2]
I_F_{-11}	0.0374	2.72	[16, 0]	-0.0266	-1.35	[0, 7]
I_F_{-12}	0.0377	2.85	[14, 0]	-0.0222	-1.01	[1, 6]
$V2_{-1}$	-0.0257	-2.90	[0, 16]	0.1832	14.71	[18, 0]
$V2_{-2}$	-0.0166	-1.87	[0, 9]	0.0510	4.04	[17, 0]
$V2_{-3}$	-0.0111	-1.21	[0, 4]	0.0133	1.05	[5, 1]
$V2_{-4}$	-0.0030	-0.27	[1, 0]	0.0047	0.37	[5, 1]
$V2_{-5}$	-0.0050	-0.58	[0, 3]	-0.0008	-0.08	[1, 1]
$V2_{-6}$	-0.0024	-0.20	[1, 2]	0.0028	0.22	[3, 2]
$V2_{-7}$	0.0158	1.59	[9, 0]	0.0098	0.77	[3, 0]
$V2_{-8}$	0.0045	0.41	[1, 0]	0.0050	0.40	[1, 0]
$V2_{-9}$	-0.0109	-1.17	[0, 4]	0.0082	0.65	[4, 0]
$V2_{-10}$	-0.0187	-2.04	[0, 10]	0.0017	0.13	[3, 1]
$V2_{-11}$	-0.0088	-0.88	[0, 5]	0.0055	0.45	[3, 0]
$V2_{-12}$	0.0059	0.63	[3, 0]	0.0227	1.92	[9, 0]
R^2			0.37			0.50
F-Value			108.88			175.28
Eqn with significant (10%) *F*-Values			18			18

Panel B: Lightly traded stocks						
Constant	0.1172	5.77	[17, 0]	0.0573	0.77	[4, 3]
T	0.0068	1.63	[9, 2]	0.0752	28.05	[18, 0]
day_2	-0.0054	-0.28	[2, 2]	-0.0174	-0.45	[0, 3]
day_3	-0.0012	-0.05	[0, 2]	-0.0134	-0.58	[0, 5]
day_4	-0.0120	-0.65	[1, 3]	-0.0082	-0.32	[1, 3]
day_5	-0.0136	-0.69	[0, 1]	-0.0077	-0.22	[0, 3]
$time_2$	-0.0377	-2.73	[0, 13]	-0.0693	-2.38	[0, 12]
$time_3$	0.0492	3.57	[14, 0]	-0.0230	-0.70	[0, 2]
I_F_{-1}	0.1162	7.26	[18, 0]	-0.0239	-0.81	[0, 1]
I_F_{-2}	0.0763	4.76	[15, 0]	-0.0112	-0.20	[1, 0]
I_F_{-3}	0.0588	3.50	[15, 0]	-0.0124	-0.10	[1, 1]
I_F_{-4}	0.0482	2.87	[15, 0]	-0.0014	-0.05	[1, 2]
I_F_{-5}	0.0444	2.72	[14, 0]	-0.0039	-0.01	[1, 1]
I_F_{-6}	0.0295	1.91	[12, 0]	0.0171	0.24	[1, 1]
I_F_{-7}	0.0271	1.69	[7, 0]	0.0041	0.27	[0, 0]
I_F_{-8}	0.0232	1.33	[7, 0]	-0.0192	-0.61	[0, 2]
I_F_{-9}	0.0275	1.59	[9, 0]	-0.0067	-0.23	[0, 1]
I_F_{-10}	0.0282	1.72	[10, 0]	0.0013	0.11	[1, 1]
I_F_{-11}	0.0245	1.55	[9, 0]	-0.0042	-0.30	[0, 1]
I_F_{-12}	0.0264	1.63	[8, 0]	-0.0005	0.17	[1, 1]
$V2_{-1}$	-0.0020	-0.33	[0, 2]	0.0969	6.63	[16, 0]
$V2_{-2}$	0.0050	0.05	[2, 3]	0.0380	2.66	[15, 0]
$V2_{-3}$	-0.0055	-0.28	[1, 0]	0.0308	1.78	[12, 0]
$V2_{-4}$	-0.0022	-0.10	[1, 1]	0.0268	1.88	[5, 0]
$V2_{-5}$	0.0066	0.23	[2, 0]	0.0215	1.25	[7, 1]
$V2_{-6}$	0.0002	-0.10	[1, 0]	0.0037	0.31	[2, 0]
$V2_{-7}$	-0.0076	-0.37	[1, 1]	0.0033	0.33	[3, 2]
$V2_{-8}$	-0.0043	-0.09	[1, 1]	0.0124	0.90	[3, 0]
$V2_{-9}$	-0.0008	-0.19	[1, 2]	0.0111	0.68	[3, 1]
$V2_{-10}$	0.0003	-0.09	[0, 0]	0.0083	0.53	[3, 0]
$V2_{-11}$	-0.0035	-0.11	[2, 0]	0.0083	0.54	[2, 1]
$V2_{-12}$	-0.0017	-0.25	[0, 1]	0.0126	0.81	[4, 0]
R^2			0.11			0.25
F-Value			16.48			45.92
Eqn with significant (10%) *F*-Values			18			18

Table E.7 Results of the VAR modelling using 12 lags for each of the endogenous variables - *I_V* & *V2*.

Proportion of order submission, *I_V*, is measured using the volume of shares placed. Volatility, *V2*, is computed by 100*(log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets shows the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	I_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.2070	10.96	[18, 0]	0.0691	3.44	[11, 0]
T	0.0003	3.09	[15, 0]	0.0041	41.78	[18, 0]
day_2	0.0057	0.79	[3, 0]	-0.0134	-1.84	[0, 10]
day_3	0.0084	1.13	[4, 0]	-0.0028	-0.42	[2, 3]
day_4	0.0068	0.96	[6, 0]	-0.0055	-0.88	[1, 7]
day_5	0.0005	0.02	[1, 1]	-0.0068	-0.85	[1, 5]
$time_2$	-0.0499	-6.81	[0, 18]	-0.0351	-4.51	[0, 16]
$time_3$	0.0685	9.37	[18, 0]	-0.0288	-3.79	[0, 16]
I_V_{-1}	0.2066	15.26	[18, 0]	-0.0032	-0.21	[0, 0]
I_V_{-2}	0.1020	7.41	[18, 0]	0.0030	0.30	[0, 1]
I_V_{-3}	0.0625	4.55	[18, 0]	0.0010	0.02	[1, 2]
I_V_{-4}	0.0383	2.79	[16, 0]	-0.0102	-0.67	[0, 3]
I_V_{-5}	0.0327	2.36	[15, 0]	-0.0055	-0.36	[0, 2]
I_V_{-6}	0.0251	1.81	[9, 0]	-0.0082	-0.48	[0, 3]
I_V_{-7}	0.0285	2.05	[11, 0]	0.0011	0.13	[0, 0]
I_V_{-8}	0.0342	2.46	[15, 0]	0.0123	0.91	[3, 0]
I_V_{-9}	0.0413	2.98	[17, 0]	0.0094	0.74	[4, 1]
I_V_{-10}	0.0456	3.31	[17, 0]	-0.0052	-0.40	[0, 1]
I_V_{-11}	0.0332	2.43	[12, 0]	-0.0195	-1.37	[0, 9]
I_V_{-12}	0.0332	2.48	[14, 0]	-0.0199	-1.34	[0, 7]
$V2_{-1}$	-0.0322	-2.63	[0, 16]	0.1873	15.11	[18, 0]
$V2_{-2}$	-0.0152	-1.23	[0, 5]	0.0521	4.15	[17, 0]
$V2_{-3}$	-0.0101	-0.77	[0, 1]	0.0140	1.11	[5, 1]
$V2_{-4}$	0.0014	0.11	[0, 1]	0.0040	0.32	[5, 1]
$V2_{-5}$	0.0000	-0.01	[0, 0]	-0.0007	-0.07	[1, 1]
$V2_{-6}$	-0.0035	-0.24	[0, 0]	0.0031	0.24	[3, 2]
$V2_{-7}$	0.0194	1.47	[8, 0]	0.0120	0.95	[5, 0]
$V2_{-8}$	0.0095	0.69	[3, 0]	0.0075	0.59	[1, 0]
$V2_{-9}$	-0.0049	-0.36	[1, 1]	0.0076	0.60	[4, 0]
$V2_{-10}$	-0.0216	-1.70	[1, 13]	-0.0009	-0.07	[2, 2]
$V2_{-11}$	-0.0121	-0.90	[0, 3]	0.0019	0.16	[3, 0]
$V2_{-12}$	0.0050	0.37	[2, 1]	0.0182	1.55	[7, 0]
R^2			0.25			0.49
F-Value			59.51			174.22
Eqn with significant (10%) *F*-Values			18			18

Panel B: Lightly traded stocks						
Constant	0.1207	5.54	[17, 0]	0.0573	0.78	[4, 4]
T	0.0089	2.06	[10, 3]	0.0752	28.06	[18, 0]
day_2	-0.0034	-0.15	[1, 2]	-0.0172	-0.45	[0, 3]
day_3	-0.0008	0.00	[1, 1]	-0.0131	-0.58	[0, 5]
day_4	-0.0082	-0.38	[1, 1]	-0.0080	-0.31	[1, 3]
day_5	-0.0142	-0.63	[0, 1]	-0.0073	-0.21	[0, 2]
$time_2$	-0.0326	-2.05	[0, 11]	-0.0698	-2.41	[0, 12]
$time_3$	0.0482	3.27	[14, 0]	-0.0225	-0.69	[0, 2]
I_V_{-1}	0.0992	6.14	[18, 0]	-0.0327	-1.06	[0, 3]
I_V_{-2}	0.0703	4.37	[16, 0]	-0.0131	-0.28	[1, 1]
I_V_{-3}	0.0523	3.14	[15, 0]	-0.0183	-0.14	[2, 3]
I_V_{-4}	0.0445	2.66	[14, 0]	0.0039	0.01	[0, 1]
I_V_{-5}	0.0457	2.78	[13, 0]	-0.0042	0.02	[1, 1]
I_V_{-6}	0.0279	1.81	[10, 0]	0.0172	0.09	[1, 2]
I_V_{-7}	0.0284	1.75	[10, 0]	-0.0007	0.18	[0, 0]
I_V_{-8}	0.0217	1.21	[6, 0]	-0.0146	-0.61	[0, 2]
I_V_{-9}	0.0265	1.57	[10, 0]	0.0026	-0.04	[0, 0]
I_V_{-10}	0.0257	1.54	[9, 0]	-0.0056	-0.04	[1, 1]
I_V_{-11}	0.0260	1.69	[9, 0]	-0.0063	-0.23	[0, 1]
I_V_{-12}	0.0257	1.60	[9, 0]	0.0069	0.28	[3, 1]
$V2_{-1}$	-0.0015	-0.14	[0, 1]	0.0974	6.65	[16, 0]
$V2_{-2}$	0.0058	0.08	[2, 2]	0.0382	2.68	[15, 0]
$V2_{-3}$	-0.0044	-0.24	[1, 0]	0.0309	1.79	[12, 0]
$V2_{-4}$	-0.0028	-0.10	[0, 1]	0.0272	1.90	[5, 0]
$V2_{-5}$	0.0051	0.14	[2, 1]	0.0217	1.27	[7, 1]
$V2_{-6}$	0.0007	-0.04	[1, 0]	0.0041	0.34	[2, 0]
$V2_{-7}$	-0.0086	-0.39	[0, 2]	0.0033	0.33	[3, 2]
$V2_{-8}$	-0.0022	0.00	[0, 0]	0.0127	0.92	[3, 0]
$V2_{-9}$	0.0006	-0.08	[1, 0]	0.0108	0.67	[3, 1]
$V2_{-10}$	-0.0005	-0.14	[1, 0]	0.0086	0.55	[4, 0]
$V2_{-11}$	-0.0047	-0.18	[0, 0]	0.0085	0.56	[2, 1]
$V2_{-12}$	-0.0010	-0.24	[0, 2]	0.0130	0.83	[4, 0]
R^2			0.09			0.25
F-Value			12.39			45.92
Eqn with significant (10%) *F*-Values			18			18

Table E.8 Results of the VAR modelling using six lags (60-minutes interval) for each of the endogenous variables - *R_F* & *V2*.

Proportion of order submission, *R_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	R_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.0413	4.83	[17, 0]	0.2371	4.50	[15, 0]
T	0.0000	-0.92	[1, 4]	0.0024	19.74	[18, 0]
Day_2	-0.0041	-0.91	[0, 3]	-0.0374	-1.35	[0, 6]
day_3	-0.0025	-0.53	[0, 2]	-0.0055	-0.19	[1, 1]
day_4	-0.0018	-0.38	[0, 1]	-0.0107	-0.44	[0, 2]
day_5	0.0036	0.81	[3, 1]	-0.0246	-0.79	[1, 4]
$time_2$	0.0520	9.37	[18, 0]	-0.1662	-4.86	[0, 18]
$time_3$	-0.0455	-8.40	[0, 18]	-0.1309	-3.97	[0, 18]
R_F_{-1}	0.2786	12.09	[18, 0]	-0.0315	-0.19	[2, 3]
R_F_{-2}	0.1510	5.61	[18, 0]	-0.2638	-1.56	[0, 8]
R_F_{-3}	0.1253	5.22	[18, 0]	0.4518	3.07	[14, 0]
R_F_{-4}	0.0725	2.70	[16, 0]	-0.3528	-2.08	[0, 14]
R_F_{-5}	-0.0354	-1.51	[1, 8]	-0.1079	-0.70	[1, 2]
R_F_{-6}	0.1139	4.52	[18, 0]	0.0345	0.22	[0, 0]
$V2_{-1}$	0.0070	1.74	[9, 0]	0.1165	4.72	[17, 0]
$V2_{-2}$	0.0004	0.07	[2, 0]	0.0435	1.75	[11, 0]
$V2_{-3}$	0.0062	1.55	[8, 0]	0.0178	0.72	[3, 0]
$V2_{-4}$	-0.0004	-0.06	[3, 2]	0.0348	1.42	[7, 0]
$V2_{-5}$	0.0063	1.52	[7, 0]	0.0006	0.01	[2, 2]
$V2_{-6}$	-0.0014	-0.36	[1, 0]	0.0579	2.45	[12, 0]
R^2			0.49			0.46
F-Value			76.21			65.62
Eqn with significant (<10%) *F*-Values			18			18

Panel B: Lightly traded stocks						
Constant	0.1707	6.72	[18, 0]	0.3512	2.39	[13, 2]
T	-0.0028	-2.34	[0, 12]	0.0411	14.71	[18, 0]
Day_2	-0.0051	-0.21	[0, 3]	-0.0147	-0.25	[0, 2]
Day_3	-0.0078	-0.57	[0, 1]	-0.0240	-0.42	[0, 3]
Day_4	-0.0020	-0.14	[1, 3]	-0.0219	-0.33	[0, 2]
Day_5	-0.0038	-0.23	[0, 1]	-0.0109	-0.19	[0, 1]
$time_2$	0.0423	2.60	[13, 0]	-0.2413	-3.05	[0, 16]
$time_3$	-0.0176	-1.35	[0, 7]	-0.0988	-1.04	[1, 7]
R_F_{-1}	0.1096	4.02	[17, 0]	0.0404	0.26	[2, 1]
R_F_{-2}	0.0723	2.59	[14, 0]	0.0801	0.39	[2, 0]
R_F_{-3}	0.0643	2.26	[13, 0]	0.0048	0.16	[2, 0]
R_F_{-4}	0.0540	1.95	[12, 0]	-0.0220	-0.06	[0, 0]
R_F_{-5}	0.0392	1.39	[6, 0]	0.0123	0.19	[2, 0]
R_F_{-6}	0.0472	1.77	[10, 0]	-0.0287	-0.18	[0, 1]
$V2_{-1}$	0.0037	0.53	[2, 0]	0.1503	5.84	[17, 0]
$V2_{-2}$	-0.0004	0.06	[0, 1]	0.0599	2.27	[13, 0]
$V2_{-3}$	0.0039	0.34	[0, 0]	0.0401	1.33	[6, 0]
$V2_{-4}$	0.0024	0.28	[1, 0]	0.0290	1.15	[8, 0]
$V2_{-5}$	0.0008	0.13	[0, 0]	0.0297	1.13	[7, 0]
$V2_{-6}$	0.0006	0.24	[2, 0]	0.0166	0.69	[4, 1]
R^2			0.09			0.28
F-Value			6.88			28.92
Eqn with significant (<10%) *F*-Values			18			18

Table E.9 Results of the VAR modelling using three lags (2-hours interval) for each of the endogenous variables - *R_F* & *V2*

Proportion of order submission, *R_F*, is measured using the frequency of orders placed. Volatility, *V2*, is computed by 100*log(P_H/P_L) where P_H (P_L) is the highest (lowest) midpoint spread in the 15-minute interval. day_i is the dummy variable for day of the week. E.g., day_2 denotes Tuesday and day_3 denotes Wednesday. $time_i$ is the dummy variable for time of day. The trading period is segmented into three periods 10am-12pm, 12-2pm ($time_2$=1) and 2-4pm ($time_3$=1). The coefficient (Coeff), *t*-statistic (*t*-stat), R^2 and *F*-values are averaged across all 18 stocks in each sample. The number of coefficients significant at the 10% level is shown in square brackets. The first figure in each set of brackets is the number of positive and significant coefficients while the second is the number of negative and significant coefficients.

	R_F			*V2*		
	Coeff	*t*-stat	Significance	Coeff	*t*-stat	Significance
Panel A: Heavily traded stocks						
Constant	0.0479	5.03	[17, 0]	0.4418	4.50	[16, 0]
T	0.0000	0.90	[9, 2]	0.0018	14.86	[18, 0]
Day_2	-0.0057	-1.09	[0, 4]	-0.0668	-1.27	[0, 5]
day_3	-0.0039	-0.74	[0, 3]	-0.0124	-0.26	[0, 1]
day_4	-0.0026	-0.48	[0, 2]	-0.0227	-0.47	[0, 3]
day_5	0.0031	0.60	[3, 1]	-0.0471	-0.81	[1, 4]
$time_2$	0.0484	6.95	[18, 0]	-0.3062	-4.23	[0, 17]
$time_3$	-0.0480	-7.32	[0, 18]	-0.2634	-4.00	[0, 17]
R_F_{-1}	0.3869	10.36	[18, 0]	-0.2960	-0.76	[0, 5]
R_F_{-2}	0.1533	3.92	[17, 0]	-0.0971	-0.18	[0, 2]
R_F_{-3}	0.1174	3.21	[14, 0]	0.0588	0.14	[0, 0]
$V2_{-1}$	0.0065	1.95	[10, 0]	0.1106	3.26	[14, 0]
$V2_{-2}$	0.0028	0.84	[4, 0]	0.0352	1.03	[5, 1]
$V2_{-3}$	-0.0002	-0.06	[0, 0]	0.0509	1.54	[9, 0]
R^2			0.54			0.47
F-Value			69.43			49.33
Eqn with significant (<10%) *F*-Values			18			18
Panel B: Lightly traded stocks						
Constant	0.1750	6.49	[18, 0]	0.8198	3.32	[15, 1]
T	-0.0014	-1.50	[0, 7]	0.0291	9.91	[18, 0]
Day_2	-0.0032	-0.13	[1, 3]	-0.0804	-0.52	[0, 3]
Day_3	-0.0058	-0.43	[2, 1]	-0.0571	-0.49	[0, 3]
Day_4	-0.0006	-0.08	[1, 3]	-0.0883	-0.58	[0, 3]
Day_5	-0.0039	-0.23	[0, 1]	-0.0430	-0.30	[0, 1]
$time_2$	0.0409	2.31	[11, 0]	-0.5054	-3.37	[0, 16]
$time_3$	-0.0212	-1.42	[0, 8]	-0.2667	-1.56	[1, 8]
R_F_{-1}	0.1660	4.38	[17, 0]	0.1607	0.38	[1, 1]
R_F_{-2}	0.0945	2.47	[15, 0]	-0.1133	-0.08	[1, 1]
R_F_{-3}	0.0884	2.33	[13, 0]	0.0282	0.08	[4, 1]
$V2_{-1}$	0.0024	0.62	[2, 1]	0.1834	5.10	[17, 0]
$V2_{-2}$	-0.0001	-0.01	[0, 0]	0.0674	1.80	[11, 0]
$V2_{-3}$	0.0046	0.55	[2, 1]	0.0578	1.62	[7, 0]
R^2			0.13			0.28
F-Value			7.90			22.30
Eqn with significant (<10%) *F*-Values			18			18