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Order placement strategies across different trading platforms: an empirical approach

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Order Placement Strategies Across Different Trading Platforms: An Empirical Approach

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CERTIFICATE

I, Anthony Flint, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Accounting, Finance and Economics, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Anthony Flint

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Synopsis

This dissertation examines order placement strategies across different trading platforms. The research provides empirical evidence on an important issue, given the growing diversity of market structures and the development of order placement strategies to adapt to these trading environments. Each chapter addresses a unique research question with scarce or conflicting prior research findings. The empirical evidence presented in this dissertation can be used by researchers, investors, and regulators to understand and manage developments in order placement strategies across financial markets.

This first issue examined in this dissertation investigates the impact of an increase in the minimum tick size on market quality using the 3-Year Treasury bond futures ("3Y T-bond") on the Sydney Futures Exchange (SFE) and the 5-Year Euro Bobl futures ("5Y Bob1") on the Eurex. On May 11, 2009, the SFE increased the minimum tick size from 0.5 to 1 basis-point for the 3Y T-bond contract. The increase in tick size from 0.5 to 1 basis-point for the 5Y Bob1 contract occurred on June 15, 2009. To examine the impact of the increase in minimum tick on market quality, two subsamples three months before and after the change are examined. For the 3Y T-bond, the pre-period is 13 May, 2008 to 13 August, 2008 and the post-period is May 13, 2009 to August 13, 2009. For the 5Y Bob1, the pre-event sample period extends from 17 June, 2008 to 17 September, 2008 and the post-event sample period extends from June 17, 2009 to September 17, 2009. Changes in liquidity before and after the increase in minimum tick may reflect changes in market conditions as opposed to the change in tick size. To control for this possibility, the 10Y T-bond and 10Y Bund contracts are used as control contracts. Results provide mixed evidence of the effect of the tick size change on market quality. The tick size increase is associated with an increase in depth at the best quotes and throughout the limit order-book for both 3Y T-bond and 5Y Bob1 contracts, which is consistent with prior studies. Bid-ask spreads (bid-ask spreads per minimum tick) for both 3Y T-bond and 5Y Bob1 contracts increase (decrease) after the change. However, the results for the control contracts imply that changes in the both 3Y T-bond and 5Y Bob1 contracts may not be due to the increase in tick size. Execution costs for both event contracts increase after the change, though the results for the control contracts suggest that this cannot be attributed to the tick size increase.

The second issue investigates the relation between algorithmic trading volume and future market quality. An internal database is directly sourced from the Australian Securities Exchange (ASX). The dataset consists of trade by trade data for the top 100 capitalised stocks listed on the ASX from July 2, 2007 to October 26, 2009. The unique feature of this dataset is that it consists of a field that identifies the source of each trade. Using this identifier, this study determines which trades are associated with human traders or computer based systems. To analyze the relation between algorithmic trading and subsequent market quality, the trading day is partitioned into multiple time intervals. The variables examined include the bid-ask spread, market depth, and short-term volatility. These variables are regressed on lagged algorithmic traded volume and a number of control factors. Over the whole sample period, results provide no evidence that algorithmic trading volume has an impact on market quality. However, when the sample is split into increasing and decreasing stock returns, results show that AT is negatively associated with future market quality when prices are falling and has no relation when prices are rising. Finally, algorithmic trading's negative association with future market quality can be explained by algorithmic traders engaging in positive feedback trading, where they systematically decrease their purchases of stocks during periods of falling prices, while increasing their level of selling.

The third issue examined measures the magnitude of execution costs of outright options and options which constitute strategies ("strategy-linked options") and examines if any differences in trade prices between these two groups is attributable to differences in market making costs on the Australian Options Markets (AOM). The data are obtained from an internal database from the AOM. The sample consists of trade by trade data for all equity options listed on the AOM. The sample period extends from January 1, 2007 to August 31, 2007. The difference in the percentage effective spread between option strategy trades and outright options is regressed on a range of option characteristics and hedging and adverse selection costs. Results reveal that execution costs for standard and tailor-made strategy-linked options are greater than outright options. Multivariate analysis shows that after controlling for a number of liquidity determinants, only tailor-made strategy-linked trades incur higher execution costs than outright options trades. Results also indicate that the difference in execution costs between tailor-made strategy-linked options and outright options is driven by the initial costs in delta hedging of option positions and not a result of higher adverse selection costs.

The fourth issue examines intraday variations in quoted depth on the Nasdaq, a competitive dealer market. The sample contains stocks listed on the Nasdaq-100 index and covers the period November 30, 2008 to April 23, 2009. The trading day is partitioned into 30-minute intervals, these one-minute intervals are averaged into 14 separate 30-minute trading intervals, from 09:30 hours to 16:00 hours (i.e. from the open to the close of trading). The variables examined include the bid-ask spread, quoted depth, volume and volatility. Consistent with prior literature, results reveal a negative relationship between the intraday patterns in quoted depth and bid-ask spreads. At the open of trading, quoted depth is relatively low and bid-ask spreads are relatively wide. Near the close of trading, quoted depth increases and bid-asks spread narrow. The pattern in spreads and depth at the close of trading on the Nasdaq is the opposite of that reported on specialist and order-driven markets. Results also show that after controlling for volume and volatility, the patterns in quoted depth and bid-ask spreads are qualitatively similar. The difference in the intraday pattern in quoted depth and bid-ask spreads on the Nasdaq relative to specialist and order-driven markets is attributed to Nasdaq dealers using both the price and the quantity of quotes to manage inventory levels at the close of trading and that this is associated with an increase in liquidity.

Chapter 1: Introduction

The provision and availability of liquidity is a crucial determinant of the success of financial markets and a key issue in the market microstructure literature. Liquidity is of important concern, given the impact it has on a diverse range of stakeholders. From the perspective of market participants, a liquid market lowers transaction costs and increases price efficiency. For exchanges, liquidity affects the ability of exchanges to attract order flow from traders and to compete for order flow with other trading venues. For firms, liquidity affects both a firm's cost of capital and optimal capital structure. A higher level of liquidity attracts more investors to a stock and that order arrival reduces the trading costs of investors because they are more likely to find counterparties willing to trade.

Liquidity and trading costs on a financial market depend not only on the characteristics of the traded security, but also on the structure of the market and the order placement strategies of market participants. Market design affects the profitability of various trading strategies and hence affects price formation and implicit execution costs. Order placement relates to the effective timing of trades using appropriate order attributes. The way market design impacts order placement strategies and consequently liquidity is therefore a fundamental issue. Market structure defines the rules of trading that affect how market participants formulate their trading strategies (O'Hara, 1995). This dissertation focuses on two market types, namely order submission strategies in (1) limit order markets where market makers are not present and (2) markets that employ designated market makers. Limit order markets do not depend on a designated market maker to provide liquidity, with the limit order book matching submitted orders at a particular price and quantity by investors. For instance, an investor submits a limit order to buy or sell a security at a particular price, whereas another investor creates a market order that matches against an existing limit order in the book. Conversely, designated market makers have an affirmative obligation to maintain a regular presence across the trading day supplying liquidity and is separately compensated to do so. Market makers derive profits through trading that provides "immediacy" to investors. For example, an investor who is keen to sell utilises a market maker's standing ability to buy the asset for itself, immediately.

Understanding the determinants of liquidity in limit order markets is important as liquidity may not be endogenously created at all times. That is, limit order markets face the problem of asynchronous order flow. For example, uncertain market conditions may reduce the likelihood of investors submitting limit orders due to the risk that the limit order will be mispriced. The probability of there being sufficient liquidity during the trading day depends on the order submission strategies of investors, such as whether an investor submits a market or limit order and cancels or amends an existing order. The literature on order placement strategies identifies a number of important factors affecting an investor's order submission decision. These include the state of the order book at the time of order submission, level of liquidity supplier competition, expected time to and probability of execution, adverse selection costs and stock return volatility (Parlour, 1998, Foucault, 1999, Foucault, Kadan, and Kandel, 2005, Goettler, Parlour, and Rajan, 2005, 2009, Roşu, 2009). These factors influence a trader's ability to execute a desired quantity at favourable prices. An exchange's trading platform affects these determinants and hence a trader's order submission strategy. Consequently, an understanding of market design and their impact on order submission strategies provides insight into the factors influencing the provision of liquidity in limit order markets.

This dissertation examines two elements of market design for limit order markets and their associated impact on market quality; the minimum price increment and algorithmic trading. One common feature in limit order markets is the presence of a minimum price increment, which is the minimum price difference in the bid-ask spread. As exchanges specify the minimum tick size, they can directly impact on available liquidity and the transaction costs imposed on investors. The overall impact of a tick size change is an empirical question. A larger tick size can encourage traders to post more limit orders, as the value for supplying liquidity is greater and the risk of front-running, that is those who move inside the bid-ask spread by submitting a limit order at a better price, is lower. Conversely, a larger tick size can come at a cost to liquidity demanders as the bid-ask spread is wider. Consequently, exchanges face a difficult task in balancing the competing interests of liquidity suppliers and investors (Harris, 1996). In addition to this difficulty, there is little experience to draw on in determining an optimal minimum tick size as exchanges rarely adjust their minimum price increment (Bollen et al., 2003). Research on the impact of changes in the minimum tick size provides important insight into its impact on market quality.

In contrast to previous research examining the impact of a reduction on the minimum price increment, the first chapter contributes to the literature by being the first to investigate the impact of an *increase* in minimum tick size on market quality for limit order markets. In response to the Global Financial Crisis that resulted in lower trading volumes on both exchanges, the Sydney Futures Exchange and the Eurex increased the minimum price increment for their medium term bonds in 2009. The increase in the tick size was designed to encourage greater liquidity in the futures markets. The literature suggests that a reduction in the minimum tick benefits small trades and liquid securities, as a lower bid-ask spread is likely to be more beneficial than reduced quoted depth (Bollen and Whaley, 1998). Futures markets offer another avenue to test this idea, as futures markets differ from equity markets in several important ways. Futures markets are more liquid than equity markets and are also dominated by institutional investors (Fleming, Ostdiek and Whaley, 1996; Frino and Oetomo, 2005). Analysing the increase in the tick size provides a unique opportunity to test whether an increase in the tick size can improve market quality for markets with high liquidity.

Another important aspect of limit order markets is the use of high frequency trading (HFT) practices, where traders use algorithms to make trades at high speeds. The impact that HFTs can have on liquidity provision is potentially significant, with the Tabb Forum estimating that over 60 per cent of trading activity in the US was conducted by HFTs in 2012. Algorithmic traders may generate earnings from trading strategies through doing a large number of small-size, small-profit trades. Due to the use of computer algorithms, HFTs can detect and act upon trading opportunities at higher speeds than their human counterparts. As HFTs are not regulated, they are able to pursue all profit maximizing short-term investment opportunities.

A number of studies suggest that HFTs act as pseudo market makers through earning profits supplying liquidity (Menkveld, 2012). One concern is that because they are not designated market makers, HFTs may destabilise markets during periods of heightened uncertainty as they rapidly withdraw and/or consume liquidity. For example, Golub and Keane (2011) suggest that HFTs that engage in market making activities quickly remove their inventory holdings when there is a significant stock price movement against their stock position. The flash crash of May 6, 2010, in which the Dow Jones Industrial Average (DJIA) fell by 600 points within minutes, is often cited as evidence that algorithmic trading can be harmful for financial markets. The cause of the crash, according to the joint SEC/CFTC report, was a sell order initiated by a large fundamental trader at 2.32pm on the E-Mini S&P 500 futures contracts. This sell order was executed rapidly over the next twenty minutes. The report noted that computerized trading was a contributing factor of the Flash Crash, with HFTs being net sellers as prices declined, accentuating the fall in prices. No research examines how the impact of algorithmic trading on market quality during market declines, of which the flash crash was an extreme event, differs from that during market upturns. Addressing this gap in the literature allows for a better understanding of risks to the provision of liquidity in limit order markets.

The second chapter addresses this gap in the literature by examining whether the relation between algorithmic trading and subsequent market quality differs across up and down markets on the Australian Stock Exchange. Analysing algorithmic trading on the ASX provides an opportunity to test this relationship as unlike the data used in other studies, this dataset identifies each specific type of participant involved in a trade. That is, each trade consists of an identifier which allows categorisation as either a computer automated or human-based trade. It further categorises each computer automated trade as either a general algorithmic trader or Broker Engines.

This thesis also examines the order submission strategies of designated market makers. As market makers have an obligation to supply liquidity, market makers adjust the bid-ask spread to offset three kinds of market making costs that have been identified in the literature of market microstructure; order-processing costs, inventory-holding costs and adverse selection costs (Stoll, 1978). In addition to adjusting the bid-ask spread, market makers also adjust their liquidity by changing the quantity dimension, the level of quoted depth (Harris, 1990). This thesis looks at the determinants for market makers adjusting bid-ask spreads and quoted depth, providing a better understanding of the factors affecting liquidity provision by market makers and its associated impact on market quality.

If an investor has private information about the fundamental value of a security (i.e. they are an informed trader), these investors will only trade when they know they will earn a return. This can include information about the timing of a news announcement and its potential impact on stock prices and returns. When trading against and informed trader, the market maker will earn a return below the market return. Therefore, market makers will moderate the size of the bid-ask spread based on the number of informed traders in the market. There is conflicting evidence on the extent to which market makers adjust bid-ask spread as a result of adverse selection costs (Vijh, 1990; Neal, 1992; Ahn et al.; 2008, Bartram et al., 2008). The options market provides an avenue to examine whether adverse selection costs are an important component when market makers determine bid-ask spreads. This is because the bid-ask spread is unlikely to vary as a result of inventory holding costs as these can be hedge in the underlying market. The literature suggests that informed traders may be more likely to act on their private information in the options market as the leverage implicit in an options contract can generate significant returns (Biais and Hillion, 1994; Easley, O'Hara, and Srinivas, 1998). Relative to outright options, options strategy trades are likely to contain information about future realized volatility (Fahlenbrach and Sandas, 2010). Analysing the determinants of execution costs for option strategy trades can shed insight how market makers adjust bid-ask spreads and whether this is driven by informed trading. Therefore, the third chapter contributes to the literature by examining the relationship between the execution costs of option strategies and the determinants of market making costs on the Australian Options Market, which is a quasi-limit order book market where liquidity is supplied by public limit orders and designated market makers.

In contrast to adverse selection costs, there is evidence that market makers adjust bid-ask spreads in relation to inventory costs. Inventory-based models of the bid-ask spread concentrate on the risk faced by market makers stemming from holding an undiversified portfolio (Tinic, 1972). Spreads exist to compensate market makers for the risk of holding unwanted inventory. This cost is equivalent to the expected difference in revenue from holding a well-diversified portfolio (Stoll, 1978). The cost of holding unwanted inventory has implications for how spreads change in response to changes in inventory holdings. Inventory-based models suggest that risk-averse market makers want to end the trading day with the desired level of inventory and thus may actively seek order flow before the close in an attempt to resolve any inventory imbalances accumulated during the day (Amihud and Mendelson, 1982). Analysis of intraday patterns in competitive dealer markets (markets where liquidity is predominantly supplied by market makers) show that market makers compete for order flow with other market makers by narrowing the bid-ask spread. A market maker resolve inventory balances by both narrowing the bid-ask spread and increasing quoted depth (Harris, 1990). The combination of the spread and depth is needed to infer overall changes in liquidity (Lee et al., 1993). Consequently, an examination of both spreads and depth at the close of trading is needed to conclude that market makers adjust for inventory imbalances and that this results in an overall improvement in liquidity. This study examines the close of trading on the Nasdaq, a competitive dealer market, to examine whether quoted depth increases, in line with inventory-based models of market makers. A dealer market like the Nasdaq is used as liquidity is predominantly supplied by market makers. Other markets such as the Australian Options Market is a hybrid market where liquidity is also supplied through limit orders. An examination of intraday patterns in those markets would mask the effect of market maker behaviour on liquidity.

Chapter 2: Literature Review

Market microstructure is how market structure influences the economics of liquidity provision. Liquidity is important as it reduces transaction costs to investors as they are more likely to find a counter-party to trade (Menkveld and Wang, 2009). The two types of literature examining liquidity provision in markets are those examining order submission strategies in electronic limit order markets and those examining liquidity provision through designated market makers. In a limit order market, liquidity is submitted by buyers and sellers without any obligation to trade. Liquidity in these markets arise endogenously and as long as there is a sufficient number of buyers and sellers, there is no need for a market maker. A number of studies examine how orders are submitted in this type of market.

Conversely, other studies examine markets with designated market makers. Market makers exist under the assumption that liquidity provision is unlikely to arise at all times. Liquidity may in fact disappear under certain market conditions, such as high levels of volatility or asymmetric information. Consequently, market makers have an obligation to provide liquidity in these circumstances. This literature review looks at order submission strategies for these two market structures and their impact on market quality. This chapter is structured as follows. Section 2.1 examines the literature concerned with order submission strategies on limit order markets, particularly relating to the minimum price increment and algorithmic trading. Section 2.2 concentrates on the literature addressing the order submission strategies of market makers, particularly in relation to the options market and intraday patterns in liquidity. Section 2.3 summarises and concludes the chapter.

2.1 Order placement Strategies in Limit Order Markets

When a trader decides to submit an order on an order-driven market, a trader faces a trade-off between submitting a limit order or a market order. An order that is submitted as a limit bid order is a quote to buy at that given price. Conversely, a limit ask order is quote to sell at that given price. The trader pays (receives) less (more) than the mid-point of the prevailing bid and ask prices using a limit bid (ask) order. Though the limit order can allow the trader to obtain a better price for the order, the cost involved with submitting a limit order is execution risk, as the time to execution is uncertain and the limit order may not execute at all. A market order has the advantage of providing the trader with immediacy as it does not face the risk of non-execution if the size of the order is less than or equal to the prevailing depth of the limit-order book. However, to obtain this immediacy the trader pays (receives) more (less) than the mid-point of the prevailing bid and ask prices. As a result of these trade-off, investors formulate optimal order submission strategies in order-driven markets to minimise costs of execution.

Determining optimal order submission strategies in the use of limit and market orders is difficult to develop as a limit order executes against a future market order, competes with existing limit orders and limit orders that may be submitted in the future. Thus, in seeking to determine the price and quantities to submit for one or more limit orders and the quantities for market orders, traders must condition on all factors that may affect the future trading process (Parlour and Seppi, 2007). Cohen et al. (1981) provide the first theoretical model examining the choice between limit and market orders. They suggest that a limit order has a 'graviational pull' property, where after a limit order is submitted, a market participant has a higher incentive to post a market order than to place another limit order near the price of the existing limit order due to the risk of non-execution.

Handa and Schwartz (1996) provide empirical evidence for the assertion of Cohen et al. (1981). They find that limit orders are associated with higher returns as the limit orders occur due in part to liquidity driven price changes which quickly revert back to the mean. However, the authors assert that the reason market orders are still used is due to the risk of non-execution. They find that limit orders subject to non-execution have negative market-adjusted returns. Further evidence is provided by Hollifield et al. (2002) who report, using a sample of stocks on the Vancouver Stock Exchange that traders with higher valuations of a stock are more likely to submit market orders.

In response to the static model of Cohen et al. (1981), Parlour (1998) and Foucault (1999) develop dynamic equilibrium of models of the choice between limit and market orders. The model of Parlour (1998) assumes traders arrive randomly in the market with different valuations for an asset. The execution probability of a limit order depends on the state of the limit order book at the time of order submission and how many market orders will arrive in the future. After a buy (sell) market order, a limit order at the ask (bid) has a higher probability of execution. As the return from submitting a limit order increases with the probability of execution, a trader who wants to sell (buy) is more likely to submit a sell (buy) limit order than a corresponding market order. Consequently, there is a 'crowding out' of market buy (sell) orders after observing market sell (buy) orders. Buy (sell) market orders are less frequent after sell (buy) market orders than after buy (sell) market orders. Consistent with Parlour (1998), Handa et al. (2003) also show that the greater the excess market depth of the buy (sell) side relative to the market depth of the sell (buy) side, the higher the execution risk to buyers (sellers). Therefore, the larger the imbalance between the buy (sell) side relative to the sell (buy) side, the more likely buyers (sellers) are to use market orders rather than limit orders.

Foucault (1999) suggests that the decision to submit a limit order is driven through price volatility. The author develops a model of price formation and order placement within a limit order market. Within this model, traders can post either limit or market orders. Limit orders enable the trader to obtain a potentially better price, but face the risk that the trade fails to execute. Foucault (1999) finds that the mix between market and limit orders are determined by the degree of price volatility. In periods of high market volatility, the probability of trading against an informed trader increases. This causes limit buy (sell) order traders to post lower (higher) bid (ask) prices and/or reduce their order sizes to compensate for the risk of being picked off by informed traders. This leads to a direct relationship between price volatility and the bid-ask spread and an inverse relationship between price volatility and quoted depth. The model of Goettler, Parlour and Rajan (2009) also suggests that speculators are less likely to supply liquidity when volatility is high.

Extending the models of Parlour (1998) and Foucault (1999), other models examine the impact of waiting costs and adverse selection costs. Foucault et al. (2005)

and Roşu (2009) suggest that traders incorporate the expected time to execution for limit orders when formulating whether to use a limit or market order, with traders categorised as patient and impatient traders. Impatient traders have a larger waiting cost per unit of time and the expected total waiting cost is determined by the product of the delay between order submission and execution, and the waiting cost per unit of time. Foucault et al. (2005) suggest that dynamics of the limit order book is determined by the mix of patient and impatient traders and the rate of order arrival. Their model has a number of predictions: impatient traders are more likely to submit a market order than a limit order; traders become more impatient at the market close, increasing the arrival rate of market orders; when the proportion of patient traders is large then traders are more likely to submit aggressive limit orders (improve upon quoted spread).

Bias et al. (1995) suggest that order placements are concentrated at the best bid and ask quotes. Examining a dataset of 40 stocks on the CAC Index, the authors report that a large proportion of trades improve upon the existing best bid and ask price, indicating that traders are trying to compete for time-priority to maximise their probability of execution. Reflecting the risk of non-execution, traders place more market orders when the spread is narrow and limit orders when the spread is wide. Al-Suhaibani and Krynowski (2000) show that the decision to place a limit or market order depends on the state of the limit order book. Examining stocks listed on the Saudi stock market, they find that market orders are more likely to be submitted when the spread (depth) is narrow (wide). Griffiths et al. (2000) reach a similar conclusion looking at 5 classifications of order aggressiveness on the Toronto Stock Exchange. They find that orders are less aggressiveness when the bid-ask spread is wide, and that greater depth on the same side of the order book encourages more aggressive orders to gain priority over other orders. Similarly, Ranaldo (2004) finds patient investors are more likely to submit aggressive orders when the same side of the book is thicker.

Cao, Hansch and Wang (2008) reveal how the state of the full limit order book affects order submission strategies as well as cancellation and amendment strategies on the Australian Stock Exchange. Consistent with Parlour (1998) and Foucault (1999), the authors show that a large inside spread discourages market orders, whereas depth at the top price step encourages more market orders. The rest of the limit order book doesn't affect order submission but does affect cancellations and amendments. The driver of this outcome is the level of order imbalance in the book; when there are a large number of limit orders on one side of the book, a trader is likely to be crowded out the other orders and is likely to improve the price of their limit order to obtain price-priority or cancel their order.

Research on the effect of volatility on order aggressiveness is less conclusive. In line with the model of Foucault (1999), Ahn et al. (2001) find that an increase in transitory volatility results in a greater placement of limit orders, as higher volatility lowers execution risk and thereby encourages limit order submissions. Beber and Caglio (2005) and document a similar relation positive relation between the placement of limit orders and volatility, as predicted by Foucault (1999). In contrast, Aitken, Brown and Wee (2007) find that limit order usage declines when volatility increases. Bloomfield et al. (2005) suggest that this is because volatility provides an information advantage to informed investors, allowing them to pick off uninformed investors.

In the market microstructure literature, investors can be segregated into informed and uninformed traders. Informed traders are those that possess information about the true value of a security that has not been impounded into the share price. Kyle (1985) suggests that traders try to maximise returns based on this information, through buying below fundamental value and waiting for the price to rise or vice versa they are short-selling. Uninformed traders are those who trade for reasons other than information. This could be because of liquidity reasons to access cash flow (Harris, 2003). Alternatively, they could be trading on noise as if it were information (Black, 1986). Black (1986) suggests that these 'noise' traders are an important source of liquidity, as uninformed traders will trade against informed traders believing they are in fact trading on 'information'.

Foster and Viswanathan (1994) develop a dynamic model that analyses strategic trading between two asymmetrically informed investors. The first informed trader knows the information seen by both informed traders and the second informed trader knows only his/her information. In this model, the lesser informed trader learns about the better informed trader's information through an analysis of the order flow. The behaviour on the part of the lesser informed trader leads the better informed trader to strategically respond by trading intensely on information common to both parties at the start of the trading day, and to trade on his own private information later in the day once the common information has dissipated through trading. This leads to the prediction that the start of the trading day is characterised by high volume, variances and spreads.

Glosten (1994) and Seppi (1997) contend that informed investors are more likely to submit market orders as they are impatient and want to capitalise on their information quickly. Conversely, uninformed investors are more likely to wait to reduce the likelihood of trading with informed investors. In contrast, the model of Chakravarty and Holden (1995) suggest that informed investors prefer to submit limit orders. This is because information about the future value of a security is not necessarily short-lived, reducing the likelihood of non-execution risk.

Kaniel and Liu (2006) suggest that the decision for an informed trader to use a market order is dependent upon the expected horizon of the informed trader's private information. The risk to using a limit order is that the order might not execute. As the expected horizon of private information increases, the probability that the limit order will be hit also increases, reducing the risk of the uncertain execution. Consequently, limit orders become more attractive to informed traders the longer the information horizon. As a test of this hypothesis, the authors find that limit orders on the NYSE convey more information than market orders about future prices, implying that informed traders prefer to submit limit orders on average.

This result is supported by Keim and Madhavan (1995), who find that institutional (informed) investors do submit limit orders. Similarly, Doung et al. (2009) find that the order submission strategy differs between individual and institutional investors. In line with Foucault (2009), both institutional and individual investors submit less aggressive orders when spreads are high for large cap stocks. For small cap stocks however individual investors are more likely to use market orders even when spreads are wide. For both institutional and individual investors, order aggressiveness declines for mid cap stocks when volatility increases. However, for large cap stocks, institutional investors increase their order aggressiveness in seeking to profit from 'picking-off' stale limit orders. Finally, institutional investors are more likely to place aggressive orders at the start of the trading day to take to exploit potential private information, whereas individual investors become more aggressive as the trading day progresses.

Beber and Caglio (2005) find that informed traders strategically place limit orders. Focusing on specific situations characterized by higher probability of information-based trading, they find that orders are less aggressive, suggesting strategic behaviour of informed traders. Analysing the Moscow Interbank Currency Exchange, Menkhoff et al. (2010) find that in response to increasing volatility, informed traders place more aggressively priced limit orders, whereas uninformed traders are insensitive to changing order book conditions. Supporting Menkhoff et al. (2010), Chung et al. (1999) and Bae et al. (2003) find that NYSE traders are more likely to place limit orders relative to market orders when the spread is large.

2.1.1 Minimum tick size and Order Submission Strategies

The imposition of a minimum tick influences the order submission strategies of traders. This is because it sets the minimum difference between bid and ask prices, the 'bid-ask spread'. A widening of the bid-ask spread resulting from the establishment of a minimum tick size changes the relative attractiveness of supplying and demanding liquidity, which may lead to an increase or decrease in overall execution costs. Whether market quality is improved by a tick size change thus becomes an empirical issue (Bessembinder, 2000).

The bid-ask spread is considered a trading cost to liquidity demanders, and is a premium received by liquidity suppliers (Harris, 2003). A wider bid-ask spread increases the marginal profitability of supplying liquidity. Traders who in the absence of a minimum tick size would have demanded liquidity using a market order may decide to supply liquidity through submitting a limit order to take advantage of this higher premium. Chung et al. (1999) examine the intraday variation in spreads established by limit-order traders and show that more investors enter limit orders when the spread is wide. Arnold and Lipson (1997) confirm that the proportion of limit order submission increases substantially after stock splits because stock splits alter pricing grids.

A widening of the bid-ask spread also reduces the likelihood of a limit order becoming stale, increasing the incentive to submit a limit order relative to a market order. A stale limit order refers to an order that no longer reflects the true value of a security, as new information has changed the security's value. These stale limit orders can be taken advantage of by traders who place a market order at the price offered by the limit order, profiting from the difference between the security's updated value and the existing price of the limit order. This is referred to as picking-off risk (Liu, 2009; Fong and Liu, 2010). For example, suppose that all traders currently agree on a security's true value. Trading only occurs in this instance as a result of liquidity reasons, with liquidity suppliers hoping an impatient trader will trade against them. Suppose now that information is released leading to the security's value being revised upwards. Some sell limit orders will now be at a price below the security's true market value, allowing traders to submit market orders against all limit orders up to the new valuation of the security, causing liquidity suppliers to lose money. The higher the risk that a limit order will become stale reduces the likelihood that traders will post limit orders. Whether a limit order become 'stale' prior to being executed is partially dependent on the size of the bid-ask spread. A wider bid-ask spread reduces the likelihood that a limit order will become stale. A wider bid-ask spread means the value of the security needs to change by a larger amount to exceed the limit order price.

A minimum tick may reduce the incidence of front running, increasing the incentive of traders to supply liquidity to the market (Harris, 1994). Front running refers to trading in front of an order in the queue, by submitting a limit order at a better price. For example, suppose that a trader place a limit order to purchase a stock at 1.00 and the order is displayed in the limit order book. Posting the limit order is costly as the trader faces the risk that the order doesn't execute. If another trader arrives offering to also post a limit order to buy at 1.00 then the new trader's order has a lower priority, with a market sell order executing against the former trader's order first. This maximises the former trader's probability of execution at the given price. If however the latter trader could post a bid a 1.000001 then the trader can move to the front of the queue without having to meaningfully improve upon the bid price.

Bacidore et al. (2003) suggest that the risk of front running may mean that if uninformed investors are disadvantaged often enough, this might result in them reducing the use of limit orders and increasing the use of market orders. Instituting a minimum tick induces a trader to meaningfully improve upon the bid by an economically significant amount in order to go the front of the queue. This increases the relative attractiveness of posting limit orders as a limit order has a greater probability of executing at a given price.

In response to the risk of front running, Goldstein and Kavajecz (2003) and Bacidore et al. (2003) report that a reduction in the minimum price increment reduces the average size of limit orders while increasing the cancellation rate of limit orders, in order to reduce the value of the trading option to other traders. High cancellation rates also helps to frustrate quote matchers as it increases the difficulty to identify a trader's intentions.

A minimum price increment can also influence the level of informed trading in the market. The transaction cost hypothesis suggests that the security with lowest transaction costs will attract informed trading. Because lower transaction costs could lead to higher profits, informed traders have more incentives to trade in the market with lower transaction costs (Booth et al, 1999).

Given the conflicting impact that the minimum tick has on liquidity demanders and suppliers, exchanges face a difficult task in balancing the competing interests of liquidity suppliers and investors (Harris, 1996). In addition to this difficulty, there is little experience to draw on in determining an optimal minimum tick size as exchanges rarely adjust their minimum price increment (Bollen et al., 2003). Research on the impact of changes in the minimum tick size provides important insight into its impact on market quality. Section 2.1.2 examines the literature assessing the impact of a tick size change on market quality.

2.1.2 Theoretical Impact of the Tick Size on Market Quality

Harris (1994) develops a cross-sectional model of the discrete bid-ask spread subject to a minimum price constraint. The minimum tick size places a lower bound limit on the size of the bid-ask spread. Harris (1994) predicts that if the minimum tick acts as a binding constraint for stocks, then a reduction in the tick size will result in a corresponding fall in the bid-ask spread. He forecasts that this will be particularly pronounced for lower priced stocks, as the tick size will have greater economic significance. The benefits of a tick size reduction should also be greatest for stocks with high trading activity, as high turnover decreases per trade fixed costs. Predictions are also given for market depth. If the minimum price variation is greater than the spreads dealers would otherwise quote, the profits to supplying liquidity are artificially increased. A decrease in the tick size under this scenario would lead to a decrease in quoted depth. Minimum price variation rules may also increase quoted depth if the exchange operates on a price-time priority, as the tick size may stop other traders from taking advantage of the information provided by an order by placing a quote at a better price.

In line with the predictions of Harris (1994), Chordia and Subrahmanyam (1995) suggest quoted bid ask spreads should decline with a reduction in the minimum tick. Looking at payment for order flow between NYSE market makers and non-NYSE market makers, when non-NYSE market makers can pay for order flow in the presence of a finite tick size, orders do not flow to the lowest cost provider of market making services. This is because there is a significant incentive for brokers to move orders off the NYSE to obtain payments offered by the non-NYSE market makers, who can offer the best quoted price without being the lowest cost provider, as the tick size acts as constraint on the spread. This suggests that lowering the tick size should lower market maker rents and improve quoted bid-ask spreads.

In the theoretical model of Cordella and Foucault (1999), the price increment which minimizes the cost of immediacy is not zero. They show that an increase in the size of the minimum tick can improve liquidity. For instance, if the current tick size is too fine, an increase in the minimum tick will increase the propensity of investors to post at the competitive spread. Second, even considering that a higher minimum tick increases the cost of immediacy, this may be offset by significant growth in limit orders, leading to an overall improvement in market quality. Seppi (1997) finds a similar result. Creating a market microstructure model of liquidity, Seppi (1997) shows that large institutional investors have a larger optimal tick size relative to retail traders, though both prefer a tick size greater than zero.

Developing a model of an order-driven market populated by discretionary liquidity traders, Foucault et al. (2005) finds that imposing a minimum tick size can improve the resiliency of the limit order market. A market is resilient if price changes that result from high order volumes quickly attract new limit orders which, in turn, pull the price back again. The authors state that actors which induce traders to post more aggressive limit orders make the market more resilient. A minimum tick size can induce traders to post more aggressive limit orders, improving the resiliency of the market.

2.1.2 Empirical Tests of the Impact of Tick Size Changes on Market Quality

Ahn, Cao and Choe (1996) is the first study to directly test the impact of reducing the tick size on transaction costs and trading activity. The event examined is the reduction in tick size from \$1/8 to \$1/16 on the American Stock Exchange (AMEX) effective 3 September, 1992. The authors find a significant reduction in both quoted and effective spreads of approximately 19% for stocks priced between \$1 and \$5 dollars. This is a result of an increase in one-sixteenth quotations and a decrease in one-eighth quotations. Traded volume and market depth remain unchanged after the tick reduction. Stocks with greater trading activity, lower prices and stronger competition from the regional exchanges experienced the greatest reductions in spreads. Van Ness, Van Ness and Pruitt (2000) however find mixed evidence on the impact of a tick size change on quoted depth. Analysing the impact of the move to sixteenths on the AMEX, Nasdaq and NYSE, Van Ness, Van Ness and Pruitt (2000) show that the number of quotes increases significantly after the change, though the effect on quoted depth is mixed, decreasing on the AMEX and NYSE and increasing on Nasdaq.

In contrast to Ahn, Cao and Choe (1996), Bacidore (1997) and Porter and Weaver (1997) show that a decline in the tick size leads to a reduction in quoted depth, in line with the predictions of Harris (1994). They examine the effect of decimalisation on the Toronto Stock Exchange (TSE) on investor welfare. In 1996, the minimum tick size was reduced from 12.5 cents to 5 cents for stocks priced over $5 and was reduced from 5 cents to 1 cent for stocks priced between $3 and $5. Stocks trading below $3 were unaffected. Following decimalization bid-ask spreads should fall and traded volume should increase. Market depth may fall if liquidity supplier profits decline because the increase in traded volume does not offset the decline in bid-ask spreads. Bacidore (1997) shows a significant decline in bid-ask spreads and quoted depth, particularly for high priced stocks. Bessembinder (2003a) also find that quotation sizes decreased 65% and 24% for the NYSE and Nasdaq respectively resulting from the change to decimalization in 2001.

Explaining the change in quote behaviour after a change in tick size, Chung and Chuwonganant (2002) authors conjecture that price discreteness has a larger effect on spread than depth revisions, as the tick size is more likely to be a binding constraint on spreads than depth. In line with this hypothesis, quote revisions involving spreads increase significantly after the change. The proportion of quote revisions involving changes in the spread is smaller for low-price, high-volume stocks both before and after the change. Furthermore, the authors find that the number of quote revisions involving changes in spread (depth) was largest (smallest) during the first hour of trading even after the change in the tick size. These results suggest that the tick size acts as a binding constraint on the bid-ask spread even after the reduction in tick size.

A change in the tick size might not just affect spreads and depth but also whether a trader exposes their order. Aitken and Comerton-Forde (2005) analyse the reduction in tick size on the Australian Stock Exchange (ASX) for stocks priced above $10 and below $A0.50 in 1995. Stocks priced between $A0.50 and $A10 are used as a control sample as they experienced no change in tick size. Liquidity is measured using the time-weighted absolute and relative bid-ask spread, depth at the best bid and ask prices and a weighted order book measure developed by Aitken and Comerton-Forde (2003) to determine the overall impact of the tick size change on market liquidity. Order exposure behaviour is also examined, where investors can decide to hide their order volume for order sizes above $A25 000. Liquidity for the control group is found to be unchanged before and after the event date. Stocks priced under $A0.50 experience a significant decrease is bid-ask spreads and depth. Using the liquidity proxy, overall liquidity improves, though order exposure is unaffected. For stocks priced above $10, liquidity for high volume stocks increased significantly, yet liquidity for low volume stocks decreased.

Porter and Weaver (1997) show that a reduced tick size primarily benefits small traders as narrower bid-ask spreads are accompanied by reduced quoted depth, which can result in higher overall transaction costs for large traders. Bacidore (1997) however shows that adverse selection costs declines and trading volume experiences no change, indicating a reduction in liquidity supplier rents. In contrast, Porter and Weaver (1997) show that internalization on the TSE is found to be unaffected. Member profits remain unchanged while revenue from commissions increases.

In line Porter and Weaver (1997), Goldstein and Kavajecz (2000) also find that a reduction in the tick size has a differential impact on small and large traders. Subsequent to the minimum price increment from an eighth to a sixteenth on the NYSE, quoted spreads and depth fell by 14.3% and 48%, respectively. More importantly, cumulative depth declines and NYSE floor members decreased the amount of liquidity they display. The combined effect has resulted in smaller traders to be better off and larger traders to be worse off. Studying the same event as Goldstein and Kavajecz (2000), Johnson and Lipson (2001) argue than an analysis of the change in quoted and effective spreads for institutional trades are not a sufficient measure of the change in market quality. This is because institutions execute a large position over multiple trades, and orders may suffer from information leakage prior to execution. Examining realised execution costs for institutional orders after the reduction in tick size, the authors find that the cost of orders below 1000 shares declines, while the cost of medium sized orders remains unchanged. Similar to Goldstein and Kavajecz (2000), large orders above 10,000 shares experience an increase of up to one-third in execution costs. The authors conclude that for the institutional orders examined, the reduction in tick size has generally lead to an increase in execution costs.

Chakravarty, Panchapagesan, and Wood (2005) examine the conclusions drawn by Johnson and Lipson (2001) by analyzing the trading costs of 34 large buy-side institutions trading NYSE stocks before and after the move to decimalisation in 2001. Confirming the results of Johnson and Lipson (2001), they present mixed evidence on the effect of decimalisation on execution costs. The authors show that the move lead to higher costs for orders that aggressively sought liquidity (those that transacted the whole order within one trading day). Partitioning trades into bid-ask spread quartiles, trading costs declined in the smallest spread quartile as the pre-decimal tick size acted as a binding constraint, while the largest spread quartile experienced an increase in trading costs, suggesting that liquidity fell for stocks not constrained by the minimum tick. The authors conclude that despite this mixed effect on different groups of investors, the change to decimalisation resulted in a significant decline in trading costs overall.

The decline in both bid-ask spreads and quoted depth as a result of the decline in the tick size means the overall impact on execution costs is uncertain. Bollen and Whaley (1998) find that that the volume-weighted quoted bid/ask spread declines by 13 percent, while quoted depth fell by 38% resulting from the NYSE's decision to change stock price quotations from 1/8ths to 1/16ths. To determine which offsetting effect dominates, they create a measure called the Market Quality Index (MQI), which is a ratio of the average share depth at the prevailing bid and ask quotes to the percentage quoted spread. The MQI suggests that the tick size change has little impact, increasing by a modest 1.44 percent. The largest gains from the tick decrease are for low priced stocks and small trades.

A reduction in the tick size might not always be optimal if bid-ask spreads are already narrow. Examining a change in the pricing grid on the Paris Bourse which raised the tick size for certain stocks and lowered it for others, Bourghelle and Declerck (2004) reveal the reduction (increase) in the tick size is associated with a decrease (increase) in quoted depth, while investors use more (less) hidden orders after the decrease (increase) in tick size. The results document no change in relative quoted and effective spreads under both an increase and decrease in tick size, suggesting a convex relationship between the tick size and bid-ask spread. They conclude that reducing the tick size is not always optimal as a coarse pricing grid may not lead to excessively large spreads, increases quoted depth and encourages liquidity providers to expose their trading interest.

In addition to potentially reducing transaction costs, a reduction in the minimum tick size may lead to improved price discovery, because stocks are traded closer to their intrinsic value, attracting greater levels of informed trading. Bacidore (2001) analyses the impact that the move to decimalization on the TSE has on traders' information acquisition. A fall in bid-ask spreads following a reduction in the minimum tick is consistent with the argument that liquidity suppliers were earning non-competitive rents before the change. The author notes that the components of the spread consist of order-processing, inventory and adverse selection costs, and the decline in the bid-ask spread may instead come from one of these components. Developing a model similar to Glosten and Milgrom (1985), Bacidore (2001) shows that the imposition of a minimum tick increases the precision of a trader's information. This is because a minimum tick increases the cost of inaccurate information. In support of the model, the author finds a positive relationship between the restrictiveness of the pre-decimalisation minimum tick regime and the decline in the adverse selection component of the spread. Similarly, Chen and Gau (2009) find that the information share of the stock market increases following the reduction in tick size Taiwan Stock Exchange (TSEC), suggesting that price discovery improves following a tightening in bid-ask spreads and a decline in transaction costs.

Hau (2006) examines the effect of the tick size on price volatility. The minimum tick size on the Paris Bourse increases for stocks priced above French Francs (FF) 500 from FF 0.1 to FF 1, providing a natural experiment to examine the effect of an increase in the tick size on volatility. Higher transaction costs may lower volatility by privileging trading based on fundamental information and discouraging destabilizing short-term speculators. Similar to other studies, the higher tick size acts as a binding constraint with effective spreads 20 percent higher for stocks priced above FF 500. Daily realised volatility is 27 percent higher for stocks trading above FF 500. Controlling for market wide volatility, the volatility differential between the two tick regimes increases on days of low index volatility. The authors conclude that an increase in tick size contributes to higher volatility.

Studies also examine the impact of a reduction on the minimum tick in a futures market setting, which largely align with the literature in equities markets. ap-Gwilym, McManus, and Thomas (2005) is the first study to investigate the impact of a reduction in the minimum tick in a futures market setting. The reduction in tick size occurred on the UK Long Gilt Futures on LIFFE, which experienced a change in quotation from fractions to decimal quotes in 1998. The results reported by the authors are largely consistent with the evidence for equity markets. Price clustering increases, with zero being the most frequently used digit after the change to decimal pricing. Quoted and effective spreads measured as a proportion of ticks increases following the reduction in tick size, however the monetary value of the spread declines. Trade size decreases as quoted depth declines after the change. However, results show a significant increase in daily traded volume, with the authors concluding that the benefits of narrower spreads offsets the negative impact of reduced depth.

2.1.3 Order Submission Strategies of Algorithmic Traders

Algorithmic trading refers to trades conducted by computer algorithms, with little or no human intervention. Algorithmic trading refers to the use of algorithms to conduct and manage trades. These programs are used to trade under both agency and proprietary contexts. These uses extend to minimizing execution costs by splitting larger orders into smaller packages, or finding price patterns for minute arbitrage opportunities, referred to as high frequency trades. Initial studies concerning algorithmic trading focus on the effect it can have on an investor's transaction costs. Kisell and Malamut (2006) argue that an important use of algorithmic trading models is to aim at achieving or beating a specified benchmark for their executions. Bertsimas and Lo (1998) find that the optimal strategy for traders with large positions trying to minimize execution costs is to break the order into smaller pieces. Konishi (2002) develops an optimal slicing strategy for VWAP trades. Although these execution strategies predate the rise of algorithmic trading, such strategies are suited for Algorithmic Traders (ATs). Domowitz and Yegerman (2005) show algorithmic trading is less expensive than alternative means based on a measure of implementation shortfall. However, these algorithms underperform human execution for order sizes greater than 10 % of average daily volume. VWAP algorithms have an underperformance of 2bps relative to the VWAP benchmark, but the authors suggest that this can be compensated by the lower fees attached to computer algorithms relative to human brokers.

Algorithmic traders may generate earnings from trading strategies through doing a large number of small-size, small-profit trades. Due to the use of computer algorithms, HFTs can detect and act upon trading opportunities at higher speeds than their human counterparts. As HFTs are not regulated, they are able to pursue all profit maximizing short-term investment opportunities. These high-frequency trading opportunities may roughly be divided into liquidity-providing trading strategies and liquidity-consuming trading strategies.

Liquidity-consuming trading strategies consists of placing market orders to take advantage of directional movements in prices. When HFTs use trade and order flow information to determine where prices may go in the future, they consume part of the available limit orders that other investors might have used to trade. One such liquidity consuming strategy (Hirschey, 2013) is to anticipate and trade ahead of the order flow of other investors. For example, a trader may anticipate the trades of an institutional investor if the investor splits their large order into numerous smaller orders and their initial trades reveal information about their future trading intentions. The algorithmic trader can profit from this by trading ahead of the institutional investor, profiting from the price impact of the investor's subsequent trades. This strategy can be complemented through the practice of quote-stuffing, where traders generate a large amount of message traffic which other investor's must process, allowing the algorithmic trader to trade ahead of them (Brogaard, 2011).

Brogaard et al. (2014) reveal that HFTs engage in both directional and contrarian trading strategies. Using a subset of HFTs operating on the NASDAQ for a sample of stocks, the authors decompose stock price movements into permanent and temporary components. Permanent price movements reflect new information that changes the fundamental value of the security, whereas the temporary component is interpreted as pricing errors. The authors find that HFTs trade in the direction of permanent price movements and in the opposite direction of transitory pricing errors using market orders. Foucault et al. (2016) suggest that their ability to do this arises from their ability to process information slightly ahead of the rest of the market. Consequently, Brogaard et al. (2014) show that HFTs can predict price changes over horizons of less than 3 to 4 seconds.

Another strategy is the use of statistical arbitrage or pairs trading, where a long position and an offsetting short-position is taken in two highly correlated instruments. When the correlation between the two stocks temporarily diverges, an arbitrage position is taken where a short position is taken in the outperforming instrument and a long position is taken in the underperforming instrument. The profitability from the trade occurs from the spread between the two instruments converging. Brogaard (2011) examines the propensity for algorithmic traders to either provide or take liquidity around news events. Algorithmic traders during stock-specific news events increase their frequency in providing liquidity and reduce the frequency of taking liquidity. The opposite result is found for macro-economic announcements. As stock-specific news relates only to the stock, the information released from the announcement allows trader's to trade the stock's correlated pairs. As macro-economic announcements affect all stocks, the pairs trading strategy is less effective.

Algorithmic traders can also engage in market-making, posting bid and ask quotes that allows them to earn a liquidity premium through the bid-ask spread. Employing two proprietary datasets from Chi-X and Euronext that contain anonymized broker IDs for trades in Dutch index stocks, Menkveld (2012) examines the entry of a large high frequency trader to Chi-X in September 2007. The trader has an upper bound latency of 1.67 milliseconds, engages in proprietary trading, generates a high number of trades, and finishes the trading day with a net zero inventory position. The authors key finding is that 78 per cent of the of the trader's quotes are passive market maker quotes. He concludes that HFTs provide liquidity and are the new market makers. Whereas traditional market making occurs in a single stock, Gerig and Michayluk (2010) show that automated market makers can also make money by trading in similar stocks in a way that traditional market makers do in a single stock. They consider a model whereby an automated market maker is confronted by two traders in different but similar stocks. If one trader is selling and the other buying at the same time, the HFT can provide liquidity by taking the opposite side of each order. This lowers the losses automated market makers incur to informed traders because the opposite direction of the trades makes it more likely one or both of the investors are uninformed.

One of the issues with HFTs acting as market makers is that as they don't have affirmative obligations to provide liquidity, HFTs may not provide liquidity during periods of market stress. A Designated Primary Market Maker (DPM) is a specialized market maker approved by an exchange to guarantee that he or she will take the position in a particular assigned. These designated market makers have affirmative obligations to provide liquidity to market participants, through providing quotes on both sides of the market, contributing to the depth of the market and maintaining market activity. These obligations can take the form of maximum spread width, minimum quoted volume, location of the market makers spread width relative to the best bid and offer, minimum percentage of the day the market maker must quote and minimum time in force for market maker quotes. Alternatively, HFTs make money through providing liquidity by turning over shares quickly while minimising exposure to adverse price movements during these brief holding periods. If the likelihood of adverse price movements increase, HFTs can respond through reducing their liquidity provision or withdraw from the market altogether as they have no obligation to make markets.

Though not specifically related to HFTs, Anand and Venkataraman (2013) study the trades of Endogenous Liquidity Providers (ELPs), who supply liquidity because it is a profitable activity, and those of Designated Market Makers (DMMs), who have exchange-assigned obligations to maintain markets on the Toronto Stock Exchange. The authors find that during market conditions reflecting high inventory risk, such as periods with low volume or one-sided order flow (more buy orders than sell orders and vice versa), DMMs participate in undesirable trades, especially for less active stock where they are the only reliable counterparties to available to investors. The authors suggest that the obligations of DMMs oblige them to supply liquidity during periods of high inventory risk. Conversely, ELPs exercise the option to withdraw from the market during these times. These results suggest that HFTs are likely to withdraw their supply of liquidity during periods when liquidity is already weak.

The Australian Securities and Investments Commission (2012) provides evidence supporting the contention that HFTs reduce the supply of liquidity and increase their liquidity demand during periods of high volatility. ASIC (2012) considers the impact of high frequency trading on the quality and integrity of Australia's financial markets over the period of January to September 2012. ASIC (2012) finds that high frequency trading is concentrated in the most liquid securities, the S&P/ASX 200 (the largest 200 stocks on the exchange). In the S&P/ASX 50, HFTs buy and sell more during times when prices are around the daily average and reduced their participation when prices diverged from the daily average. For the S&P/ASX 150-200 (the least liquid proportion), HFTs reduced their participation in the market when prices fell of increased by around 1.8 to 2 standard deviations from the average price.

Korajczyk and Murphy (2014) also report that HFTs reduce their supply of liquidity during stressful periods. The authors find that HFTs provide significantly more liquidity than designated market makers to large institutional trades. Utilising a unique data set that provides all orders, trades and trader identities, the authors are able to identify designated market makers and HFTs on the Toronto Stock Exchange. In line with the findings of ASIC (2012), the authors find that despite HFTs providing more liquidity than market makers to larger trades, liquidity provision changes significantly when the large trade is considered stressful. When the trading volume of a large trade as a proportion of total trading volume is in the upper quintile, the proportion of liquidity supplied by HFTs decline significantly. Further, HFTs reduce liquidity provision on days in which the stock price is particularly stressful.

Hu (2013) examines the factors that influence liquidity provision by high frequency traders. The author suggests that interactions between HFTs are one reason for why HFTs supply less liquidity when markets are volatile. Specifically, the author provides evidence that information asymmetry induced by the liquidity consuming strategies undertaken by certain HFTs induces HFTs that engage in market-making activities to supply less liquidity. For example, if a liquidity-providing HFT and a liquidity-taking HFT have the same reaction speed on average, then the liquidity-providing HFT will be faster 50 per cent of the time and vice versa. Half the time, the liquidity-taking HFT submits a market-order before the liquidity-providing HFT has had a chance to adjust their quotes. At these times, the liquidity-providing HFT has been adversely selected. If the liquidity-providing HFT takes this issue into account, the trader provide less liquidity on average and will supply even less liquidity as the level of information asymmetry increases. Using the NASDAQ-100 Exchange Traded Fund, the author finds that information asymmetry increases as volatility increases, resulting in HFTs supplying less liquidity.

Golub et al. (2012) suggest that HFTs that engage in market making activities quickly remove their inventory holdings when there is a significant stock price movement against their stock position. The authors examine mini flash crashes using six years of U.S. stock market data. Mini flash crashes are abrupt and severe flash crashes that occur in an extremely short period. The authors use the example of a flash crash that occurred on 16th April 2010 in the stock of Goldman Sachs Group, Inc. where a -1.9% price change occurred in less than 50 milliseconds. Their analysis of the speed and magnitude of the flash crashes suggested that these are caused by HFT activity. Their hypothesis is that when a stock price has a distinct price movement, market makers receive a significant increase in orders that increase their inventory risk. For example, if there is a distinct decline in the stock price, a market maker will receive an increase in sell orders, forcing market makers to be the buyers. If the stock price continues to decline, the inventory exposure of market makes continues to increase. When the market maker's risk management limits are breached, comprised of the size of the inventory and the unrealised profit and loss, the market maker has to stop providing liquidity and aggressively take liquidity by selling back the shares purchased previously. For HFTs without affirmative obligations who trade in short increments, they do no wait for prices to revert to favourable levels and therefore remove their accumulated inventory as quickly as possible. The authors state that this action is likely to cause a sharp movement in the stock price.

The literature examining the order submission strategies on algorithmic traders suggest that they engage in both liquidity supplying and consuming strategies. The overall impact of these strategies on market quality is uncertain, which is examined in the next section.

2.1.4 Theoretical impact of Algorithmic Trading on Market Quality

Cvitanic and Kirilenko (2010) build the first theoretical model to address how HFTrs affect market conditions through their order submission strategies. They model an electronic market populated by low frequency traders (humans) and add a high frequency trader (machine). This machine is assumed to be uninformed, similar to a market maker. The advantage of the machine relative to a human trader is its higher speed in submitting and cancelling orders. The authors find that the presence of HFTs yield transaction prices that differ from the HFT-free price; when a HFTr is present, the distribution of transaction prices will have thinner tails and are concentrated near the mean. Their second finding is that as humans increase their order submissions, intertrade duration decreases and trading volume increases in proportion to higher human order arrival rates. The implication is that the presence of HFTs results in an increase in liquidity. Alternatively, Gsell (2008) creates a simulated environment which examines the impact that implemented algorithmic trading concepts have on market outcomes, which the paper limits to market prices and volatility. The outcome of the simulation shows that an increase in high frequency trading had a negative impact on market prices, though it significantly reduced volatility.

Gerig and Michayluk (2010) develop a theoretical model that seeks to explain the increasing dominance of algorithmic trading and to understand its effect on the market. Their model shows that automated liquidity providers are able to price securities more accurately than human market makers. This is because they can trade almost instantaneously and can accurately model complex relationships between securities. Consequently, automated liquidity providers come to transact the majority of trades at prices that are more efficient than provided by human market makers. This has a number of positive market effects: informed investors make less profits and uninformed investors have smaller losses. This can lead to a situation where uninformed investors increase their trading activity, increasing total traded volume and lowering overall transaction costs.

A distinguishing feature of algorithmic trading is that trades are conducted at much higher speed and higher frequency relative to other traders on the market. The investment time horizon of ATs is therefore a lot shorter. Outside the algorithmic trading literature, other work has examined the impact of different investment time horizons on market quality. Froot et al. (1992) show that short term speculators decrease the informational quality of asset prices. In standard models of informed trading, informational externalities are negative; returns to acquiring information falls as other traders possess this information. In contrast, the authors show that a market with short-term speculators creates positive informational externalities; as more speculators study a piece of information, the information is disseminated into the market, impacting the price. Therefore, profits from that information are inversely related to how early it is learnt. This leads to a situation where traders ignore some fundamental information, which fails to get impounded into the price, leading to a fall in price discovery. In contrast to the theoretical predictions of Froot et al. (1992), Vives (1995) show that short term speculators can increase or decrease the informational efficiency of prices depending on the temporal pattern of information arrival. In the model of Vives (1995), short-term trading intensity is a function of the pattern of information arrival, with short-term traders reducing price informativeness with concentrated arrival of information, and enhances it with diffuse arrival of information.

2.1.5 Empirical Tests of the Impact of Algorithmic Trading on Market Quality

The brief literature modelling the potential effect of algorithmic traders on market quality provide conflicting outcomes as to whether the effect is positive or negative. Consequently, academic research has begun to empirically examine the potential impact of algorithmic trading on market dynamics. Despite the growing academic interest in this area, the empirical literature concerning algorithmic trading is still brief. This is primarily due to data constraints, which are unable to clearly identify trades belonging to an algorithmic trader. The studies that do look at the impact of algorithmic trading on market characteristics employ traditional proxies of market quality, including bid-ask spreads, market depth, stock volatility and price discovery.

Employing a unique dataset from Nasdaq OMX that distinguishes between high frequency and non-high frequency trades, Brogaard (2010) finds that HFTs have a positive impact on market quality, as they improve the price discovery process without affecting volatility. Similarly, Castura et al. (2010) show that market quality has improved for a broad range of stocks on the Russel 1000 and Russell 200 index, coinciding with automation on exchanges. Governed by the theory that an efficient stock price should exhibit no serial autocorrelation, the authors report that prices are more efficient, finding a reduction in the mean reversion of mid-market quotes. However, Castura et al. (2010) don't show causality between algorithmic trading and market quality. Using the implementation of auto-quoting on the NYSE is treated as an exogenous instrument for algorithmic trading, Hendershottet et al. (2011) show that algorithmic trading improves quoted and effective spreads, but reduces market depth. The degree of price discovery that is correlated with trading is shown to decrease after the introduction of autoquote, indicating that algorithms respond quickly to order flow information and reduce adverse selection in the market. The authors interpret these results as indicating that algorithmic trading causally improves liquidity.

Conflicting evidence is presented on the impact of algorithmic trading on volatility. Chaboud et al. (2009) find that the correlation between algorithmic trades is higher relative to non-algorithmic trades on the foreign exchange market. However, the evidence suggests that despite this higher correlation of trades, algorithmic trading does not contribute to higher volatility, though it does contribute to improve price discovery. Similarly, Hendershott and Riordan (2011) find that algorithmic traders on the Deutchse Bourse closely monitor changes in liquidity and time their trades to demand liquidity when it is cheap and supply liquidity when it is expensive, moderating movements in prices.

However, Smith (2010) reveals the increase in algorithmic trading on U.S markets has resulted in a marked change in the correlation structure of stock trading, leading to an increase in short-term volatility. Smith (2010) examines the Hurst exponent of traded value over short time scales (15 minutes or less). The Hurst exponent measures the long term memory of a time series, i.e the autocorrelations of a time series and the rate at which these decrease as the distance between two values increases. The author shows that the increase in the Hurst exponent of U.S stocks occurs prominently after the implementation of Order Protection Rule (Rule 611). This rule mandates that trades are to automatically trade at the best price offered across all exchange venues, and lead to a substantial growth in algorithmic trading. A Hurst Exponent greater than 0.5 points towards increasing volatility on the U.S market, as more participants in the market generate more volatility, not more predictable behaviour.

HFTs may have a negative impact on liquidity as they may increase the level of information asymmetry in the market. Jovanovic and Menkveld (2011) develop a theoretical model of algorithmic traders as market makers in electronic limit order markets, and assess the effect this role has on investor welfare. In limit-order markets without middlemen, newly placed limit orders are either matched with existing limit orders or are added to the order book. The placement of a limit order faces the risk that the order becomes stale due to the arrival of new information, creating a trading option that may be picked off by a later investor. Traders in limit order markets therefore face adverse selection costs, which hampers trading activity. As algorithmic trading is the use of computer algorithms to analyse market data and make trades, the introduction of ATs to a limit order market may reduce information friction if the information between two investor arrivals is hard, machine-processable information. Alternatively, ATs may reduce investor welfare if the there is no information friction between the early and late investor with respect to hard information. Jovanovic and Menkveld (2011) assess the validity of this model using the natural experiment provided by the introduction of Chi-X to compete with Euronext. The features of Chi-X make it attractive to ATs, as it provides a subsidy to a quote that leads to execution, relative to Euronext, who charge a fee for price quote changes. The authors find that entry of an HFT to the market was accompanied by a 23% reduction in adverse selection costs and a 17% increase in trade frequency.

One issue with determining the effect of HFTs on liquidity is how often they demand and supply liquidity in the market. Employing two proprietary datasets from Chi-X and Euronext that contain anonymized broker IDs for trades in Dutch index stocks, Menkveld (2012) examines the impact of a HFT on these two markets. The author identifies a trader that enters both markets simultaneously, who fits the profile of an HFT. Menkveld (2012) notes that the entry of the HFT coincided with a 50% fall in the bid-ask spread and that the HFT contributed to liquidity across both markets, supplying liquidity 80% of the time.

Even if HFTs act as a market maker on average, one key difference between them and designated market makers is that they are under no obligation to supply liquidity to the market at all times. Consequently, they may exacerbates volatility and destabilizes financial markets during periods of heightened volatility. The author tests whether volatility causes HFTs to increase or decrease their trading activity. Using macro and stock-specific news as exogenous sources of volatility, HFTs tend to decrease their liquidity demand during stock specific news periods and tend to take more liquidity during macro news periods. Finally, using the natural experiment afforded by the removal of a fraction of HFT participants after the short sale ban of 2008, Brogaard (2011) documents that HFTs reduces intraday volatility.

Examining the Flash Crash of 6 May, 2009 Kirilenko et al. (2011) hypothesize that the Flash Crash occurred as a result of a large sell order that was executed rapidly on the E-Mini Index. HFTs contributed to the price decline as they were initial buyers of the sell order, but quickly became aggressive net sellers to balance their inventory positions. The results show that HFTs exhibit a number of characteristics that can have a negative impact on market stability. They exhibit trading patterns inconsistent with traditional market makers, trading aggressively in the direction of price changes and do not accumulate significant inventory positions. Thus, HFTs do not supply liquidity when prices move against their trading position. Furthermore, they can exacerbate price movements by competing for liquidity as they try to rebalance their inventory positions.

2.1.6 Empirical Tests of Latency and Market Quality

Latency refers to the amount of time it takes to submit and receive feedback about an order. Financial markets have witnessed a significant reduction in latency over the last couple of decades, driven by exchange co-location services, improved market infrastructure and trade automation. Not surprisingly, algorithmic trading and latency are strongly related, with reductions in latency contributing to the growth of algorithmic trading. The arguments put forth for and against reduced latency are similar to the arguments governing algorithmic trading; increased latency allows better monitoring of the market and gives investors the ability to more easily rebalance their portfolio to changes in fundamental information, though it can also be used to take advantage of the option granted by limit order traders, discouraging liquidity provision. Given the relationship between algorithmic trading and latency, understanding the effect that reductions in latency have on market quality can provide further insight into algorithmic trading.

A number of studies have examined the effect of trading speed on market quality. Riordan and Storkenmaier (2011) use the natural experiment provided by the reduction in latency on the Deutchse Bourse in 2002 to test the effect of speed on liquidity and price discovery. The authors findings show a decrease in both quoted and effective spreads in the post-event period. This decrease was driven primarily by a reduction in the adverse selection component of the spread. Similar to the results presented by Hendershott et al. (2011), the decline in the adverse selection component was partially offset by an increase in the realised spread, suggesting that liquidity suppliers were able to increase their revenues after the change. Drawing the same conclusion as Hendershott et al. (2011), liquidity suppliers are interpreted as being able to increase their revenues due to a reduction in the competition between liquidity suppliers. Price efficiency shows a significant improvement in the post-event period, with the contribution of quotes to price discovery doubling to 90%. The results of the paper are similar to the empirical literature on algorithmic trading, showing reduced latency leads to improvements in market quality.

The studies reviewed above examine reductions in latency during a period where ATs were becoming prominent in the market. Other studies have analysed the effect a reduction in latency has on market quality in earlier time periods. Easley et al. (2009) examine the impact on stock prices of an upgrade to NYSE's infrastructure in 1980. The upgrade consisted of two phases; phase 1 introduced on 14 July, 1980 improved dissemination of quotes and the reporting of floor transactions to off-floor traders and phase 2 introduced a technology upgrade that reduced latency from 2 minutes pre-upgrade to 20 seconds post-upgrade. The upgrades reduced the trading option granted by limit order traders to the specialist on-floor traders. The authors hypothesise that because limit order traders require compensation for adverse selection, the upgrades should be associated with positive abnormal stock returns. For phase 2, the results indicate that the total return over the next 20 days was 4 percent, and this excess return result is robust to Fama French, momentum and industry factors. A reduction in latency is therefore associated with a reduction in adverse selection risk and an improvement in market quality. Analysing trading activity in the millisecond environment using Nasdaq order-level data, Hasbrouck and Saar (2012) also find that a decline in latency is associated with tighter quoted spreads, increased depth, reduced price impact and lower volatility.

In contrast, Hendershott and Moulton (2011) find that the reduction in latency on the NYSE had mixed effects on market quality. On 24 June, 2007, the NYSE converted to a hybrid market system, where trades could take place on the trading floor or electronically. The introduction of the Hybrid market reduced the execution time of market orders from 10 seconds to less than a second. Hendershott and Moulton (2011) find that the reduction in latency on the NYSE had mixed effects on market quality. On average, from the month prior to the stock's activation date to the month after, quoted spreads increase from 7.9 basis points to 8.3 basis points, and effective spreads increase from 5.6 basis points to 5.9 basis points. Decomposing the spread, the authors report an increase in the adverse selection component of the spread. However, the authors also note that price noise dropped after the introduction of the Hybrid system, indicating an improvement in price efficiency.

2.2 Order Submission Strategies of Market Makers

Bloomfield et al. (2005) suggests there is no need for a market maker as market participants provide liquidity in limit order markets. However, a fundamental issue in trading is the asynchronous arrival of buyers and sellers. A mismatch of buyers and sellers leads to uncertainty in both the time it takes to complete a trade and the price the trade will transact at (Demsetz, 1968). This uncertainty can be mitigated by the presence of liquidity suppliers who serve as counterparties to the trade, providing immediacy of execution (Venkataraman and Waisburd, 2007). Market makers play an integral part in the provision of liquidity in various financial markets, including derivative markets. Market making primarily involves the submission of non-marketable resting orders that provide liquidity to the marketplace at specified prices. A market maker's trading strategy involves quoting both a buy and a sell price for a financial instrument or commodity, seeking to profit from the difference between the two prices, known as the bid-ask spread. An important component of this strategy is to always quote competitive buy and sell prices, with the intention of buying and selling equal components of the financial instrument being traded.

The market maker's profits from the bid-ask spread is to offset three kinds of market making costs that have been identified in the literature of market microstructure; order-processing costs, inventory-holding costs and adverse selection costs (Stoll, 1978). Order processing costs involve the fixed cost of market making (Demetz, 1968). Demsetz (1968) argues that the bid-ask spread partly compensates market makers for the operating costs incurred in providing immediacy. Inventory-holding costs arise from the market maker managing his/her inventory positions (Tinic, 1972, Stoll, 1978, Amihud and Mendelson, 1980, 1982, Ho and Stoll, 1981). Adverse selection costs occur as market makers, in supplying liquidity, may trade with individuals who are better informed about the true value of the underlying security (Bagehot, 1971, Glosten and Milgrom, 1985, Kyle, 1985, Amihud and Mendelson, 1986, Easley and O'Hara, 1987, Glosten and Harris, 1988, and Admati and Pfleiderer, 1988). The market maker minimises the costs of inventory and adverse selection costs through adjusting their quoted bid and ask prices.

Inventory-based models of the bid-ask spread concentrate on the risk faced by market makers stemming from holding an undiversified portfolio (Tinic, 1972). Spreads exist to compensate market makers for the risk of holding unwanted inventory (Stoll, 1978, Amihud and Mendelson, 1980, 1982, and Ho and Stoll, 1981, 1983). This cost is equivalent to the expected difference in revenue from holding a well-diversified portfolio (Stoll, 1978). The cost of holding unwanted inventory has implications for how spreads change in response to changes in inventory holdings. In the model of Amihud and Mendelson (1980), transaction prices result from the execution of randomly arriving sell and buy orders at the market-maker's bid and ask prices. These prices are set so as to move the specialist to a desired inventory position. At this desired inventory position, the bid-ask spread is minimized. The authors demonstrate that as long as the specialist is managing his inventory, a monopolistic specialist will widen spreads from this preferred position as inventory imbalances accrue.

Alternatively, Ho and Stoll (1983) develop an inventory model of a competitive dealer market, made up of competing market makers who differ only in their inventory positions and risk preferences. According to Ho and Stoll (1983), the reservation fee of a market maker depends on his/her risk aversion and inventory level. Controlling for risk aversion, a market maker's quotes become a monotone function of his/her inventory level, where market makers with long (short) positions post competitive ask (bid) prices. In other words, when an order imbalance occurs that moves the market maker away from his/her desired inventory positions, he/she adjusts the bid-ask spread to move back to the desired inventory position.

A number of studies support the inventory-holding models of bid-ask spreads. Hansch et al. (1998) undertake an empirical test of Ho and Stoll's (1983) inventory model of competitive dealership markets on the London Stock Exchange (LSE). The authors provide empirical evidence supporting the model of Ho and Stoll (1983), revealing that a market maker's inventory position is significantly related to the ability of the market maker to execute large trades, changes in quotes are strongly correlated to changes in inventories and inventory positions are mean reverting with the strength of mean reversion increasing as a function of his/her inventory level.

Order-flow imbalances give rise to the inventory holding cost component of the bid-ask spread (Stoll, 1978; Ho and Stoll, 1981). The process of equilibrating order imbalances may cause the market maker's inventory position to deviate from optimal levels, resulting in an increase in inventory holding costs. Chordia et al. (2003) examine the effect of order imbalances on liquidity and market returns on the NYSE. Employing the Lee and Ready (1991) algorithm to designate transactions as buyer-initiated or seller-initiated, the authors calculate the daily aggregate order imbalance for each stock (buy orders less sell orders). The authors find that after an event resulting in a large order imbalance, specialists alter the quotes to motivate investors to take the other side of the trade, consistent with inventory models of the spread (Stoll, 1978).

Harris (1990) points out that liquidity has both a price and quantity dimension, meaning overall changes in liquidity cannot be determined by analysing one dimension alone. Harris (1990) argues that a market maker can adjust his/her liquidity by changing both the price dimension (the bid-ask spread) and the quantity dimension (the quoted depth). Ye (1995) examines the function of quoted depth in mitigating the risk of adverse selection on the part of the market maker. He develops a framework for analysing a specialist's optimal quotation strategy. The author finds that when the probability that the specialist is providing liquidity to an informed trader increases, the specialist will both widen the spread and reduce depth to protect themselves from losses. Similarly, Kavajecz (1999) reveals that a market maker responds to information events by adjusting the quoted depth in addition to quoted prices.

Madhavan and Sofianos (1998) show that designated market makers actively monitor their inventory positions, being more likely to be sellers when holding long inventory positions and vice versa. Consequently, market makers do not just adjust bid-ask spreads to control their inventory positions, they also selectively time the size and direction of their trades. However, Panayides (2007) states that designated market makers are most likely to engage in inventory rebalancing when they are not constrained by their market making obligations.

Information-based models are concerned with adverse selection costs faced by liquidity providers in the presence of information asymmetry. As liquidity providers have less information about the true value of a security relative to informed traders, liquidity suppliers can expect to lose money when transacting against informed traders (see Bagehot, 1971, Copeland and Galai, 1983, Easley and O'Hara, 1987, and Glosten and Milgrom, 1985). Market makers widen spreads to offset the expected cost of transacting with informed traders. Copeland and Gelai (1983) argue that the dealer's bid-ask spread is a trade-off between expected losses to informed traders and expected gains from liquidity traders. The pricing strategy of the dealer is equivalent to offering an out-of-the-money option straddle for a fixed number of shares during a fixed time interval. The exercise prices of the straddle determine the bid-ask spread, with the profit maximizing spread occurring at the point where the expected total revenues from liquidity trading balance the expected total losses from informed trading. Similar to Copeland and Gelai (1983), Glosten and Milgrom (1985) demonstrate that adverse selection gives rise to bid-ask spreads when all other transaction costs are zero and dealers are risk neutral and perfectly competitive.

Easley and O'Hara (1987) provide an alternative explanation to the inventory hypothesis of why dealers adjust prices in response to a large incoming order. Under the inventory model, large trades force the dealer away from his/her desired inventory position, with bid-ask spreads being compensation for bearing this inventory risk. The authors show that as informed traders want to trade, they will trade larger amounts at any given price. Large trades are transacted at less favourable prices, as market makers try to offset losses when transacting with informed traders.

2.2.1 Market Makers in Option Markets

In the option market, there are unique factors that affect the cost of liquidity provision relative to the equity market for market makers. In the options market, managing inventory levels are a much bigger problem for market makers relative to the equity market. In the model of Biais and Hillion (1994), the reservation buying and selling prices depends on the volatility of the underlying security. As a result of the implicit leverage of the options market, the volatility of an option position is much larger than an equal dollar position in the equities market, causing higher inventory holding costs. As discussed by Jamesone and Wilhelm (1992), not only is option volatility larger relative to stock volatility, but is dependent upon the underlying stock price. Over a particular time period for a stock, if the volatility is constant then the risk per dollar of investment is nonstochastic. For options however, the volatility changes with changes in the price of the underlying stock, making the risk stochastic. This results in higher inventory costs for option market makers.

The evidence by Lakonishock et al. (2007) suggest that option market makers face less control over their inventory positions relative to equity market makers. The authors provide detailed descriptive statistics on purchased and written open interest and open buy and sell volumes across a number of investor types. For both calls and puts, written option positions are more common than purchased positions, leading to an imbalance in order flow that moves the market maker away from his/her optimal inventory position. Battalio and Schultz (2011) suggest that other factors impede the market maker in managing inventory levels, including options being split over numerous strike prices and expiration dates, order flow differing for options at, in or out of the money and the option's time to maturity.

Market makers in the options market are also likely to face greater adverse selection costs relative to equity market makers. If informed investors regard options as a superior investment vehicle relative to the underlying stock, then the implied stock prices from options are likely to reveal information about the future equilibrium value of the observed stock price. Stephan and Whaley (1990) find that both stock prices and volumes lead option prices and volumes. The authors claim that the findings of Manaster and Rendleman (1982) and Anthony (1998) are seriously undermined from the use of closing prices, as the option market closes ten minutes after the stock market. The information lead of options may be a result of information that was disseminated between the closing times of the two markets. Stephan and Whaley (1990) overcome these issues by employing intraday transaction data and examines the direct lead/lag relationship between option and stock prices and volumes. The authors find that options do not contain information, with stock prices and volumes leading option prices and volumes.

However, a number of studies find that options are informative. Manaster and Rendleman (1982) test whether options provide information on future stock values by forming portfolios based on the differences between the implied stock price of an option and the observed price, and compare the returns earned on the different portfolios. The results show that closing option prices contained information that was not contained in stock prices for a period of up to 24 hours. Similarly, Anthony (1998) finds that option volume on the Chicago Board of Options Exchange (CBOE) is informative, with option volume leads stock trading volume by a one day lag.

Back's (1993) model of informed option trading predicts that a component of option returns that are independent of the underlying stock return, will exist due to the presence of informed trading. Sheikh and Ronn (1994) conjecture that strategic behaviour by informed traders will lead to similar patterns in the return series of stocks and options. Supporting this hypothesis, Sheikh and Ronn (1994) find a strong similarity in both the means of day end stock returns and adjusted option returns, and the variances of intraday stock and option returns.

Easley et al. (1998) investigate the informational role of transaction volumes in the options market. In line with the findings of Stephan and Whaley (1990), stock price changes lead option volumes whereas option volumes do not lead stock price changes. However, when aggregating option trades into positive and negative news trades, option trades are shown to be informative, with option volumes leading stock price changes. Building on Easley et al. (1998), Chan et al. (2002) suggest that the inferred information content of option trades may originate from stock trades, which Easley et al. (1998) do not examine. Their results show that stock net trade volume is informative for stock and option quote revisions, suggesting informed traders initiate trades in the stock market only.

Charkravarty et al. (2004) provide evidence that option trading contributes to the price discovery process in the underlying market. Previous studies examining the lead-lag relationship between option and stock prices combine permanent and temporary price changes, whereas permanent price changes is the only component that represents information. Employing the price discovery methodology of Hasbrouck (1995), the evidence indicates that 17 to 18% of price discovery occurs in the options market. Furthermore, price discovery is greater when the ratio of option volume to stock volume is high and the option bid-ask spread is narrow relative to stock bid-ask spreads.

The above evidence suggests that market makers in the options market face greater inventory and adverse selection costs relative to market makers in equity markets. This means that market makers will quote greater spreads in option markets relative to equity markets and that changes in quoted prices will also be greater (Cho and Engle, 1998, Kaul et al. 2004).

2.2.3 Determinants of Bid-Ask Spreads in Options Market

Jameson and Wilhelm (1992) discuss how market makers face risks that are unique to options. These risks include the inability of option market makers to continuously rebalance their inventory position and the uncertainty about the return volatility of the underlying stock. Employing the inventory model specification of Ho and Stoll (1983), the authors find that after controlling for variation in spreads produced by costs generally associated with market making, discrete hedge rebalancing (gamma risks) and stochastic stock return volatility (vega risks) are not fully diversifiable and account for 8% and 4.5% of the option bid-ask spread, respectively. These costs, unique to the option market, are given as the reason why option bid-ask spreads are greater relative to stocks. George and Longstaff (1993) provide supporting evidence for this conclusion, examine the cross-sectional distribution of bid-ask spreads on the

S&P 100 index options market. The authors find that the determinants of market making costs explain 70 percent of the variation in bid-ask spreads. Specifically, bid-ask spreads are negatively related to the option's delta and level of trading activity and positively related to the option's price and time to maturity. Wei and Zheng (2010) examine the effect of trading activities on the liquidity of US equity options and come to similar conclusions. Several liquidity determinants are found to affect the proportional spread, including time to maturity, moneyness, stock return volatility, option return volatility, option trading volume and option price. This supports the inventory model of option bid-ask spreads, with changes in these liquidity determinants altering the market makers inventory risk.

In addition to vega and gamma risks, time to maturity will also effect bid-ask spread. An option's term-to-maturity has two opposing effects on its bid-ask spread. Market makers face higher gamma and theta risks trading in option contracts with a shorter time-to-maturity. However, market makers face higher credit risks holding longer term options, which may cause them to widen spreads as compensation for the higher credit risk exposure. Chong et al. (2003) show option bid-ask spreads to be negatively related to their term-to-maturity. This result holds after controlling for competition, trading activity and price. The results suggest a market risk effect in trading shorter term contracts, as market makers are exposed to greater theta and gamma risks.

Cho and Engle (1999) proposed a new theory called "derivative hedge theory" in which bid-ask spreads in the option market are determined by option activity and activity in the underlying stock. If market makers in derivative markets can perfectly hedge their position using the underlying security, then spreads in the option market will be determined by spreads in the underlying market. Examining S&P 100 index options, the authors find that option market spreads are positively related to spreads in the underlying market, supporting their derivative hedge theory. Option market duration does not affect bid-ask spreads, with slow and fast markets leading to wider spreads. As inventory costs predicts wide spreads in slow markets and information asymmetry predicts wider spreads in slow markets, neither outcome would occur if the underlying market provided a perfect hedge. The authors conclude that the market maker is only able to imperfectly hedge his/her position in the underlying securities market.

However, Kaul et al. (2004) argue that the derivative hedge theory of Cho and Engle (1999) accounted for the initial hedging cost only. That is, the percentage delta is related to the cost of setting up the hedge position, but this does not account for rebalancing costs. The authors calculate rebalancing costs as proportional to vega multiplied by the spread of the underlying stock. Their results imply a large proportion of the bid-ask spread is attributable to inventory management costs; 50% attributable to setting up a delta neutral position and 6.93% associated with discrete rebalancing. Similar results are found by Patrella (2006), who develops a model of the option bid-ask spread that incorporates a reservation bid-ask spread applied by market makers to protect themselves from scalpers. In line with Kaul et al. (2004), the model includes the main determinants of option market making costs, including initial hedging, rebalancing and order-processing costs. Examining a sample of covered warrants on the Italian Stock Exchange, the model explains 64% of the total variation in bid-ask spreads, and that the inclusion of the reservation spread increases the explanatory power of the model from 20 to 54 percentage points. Engle and Neri (2010) however state that the cost of rebalancing the hedging position is proportional both to gamma and to the volatility of the underlying stock. Employing a significantly greater dataset than both prior studies by examining the whole US options market, the authors find that these three costs account for a significant proportion of the bid-ask spread.

In addition to hedging costs, spreads may also be affected by informed trading. The literature provides conflicting evidence on the adverse selection component on the bid-ask spread. Vijh (1990) is the first to examine the relationship between information asymmetry and bid-ask spreads on the CBOE. He argues that the greater implicit leverage of options relative to equities attracts both informed and noise traders. Results show price effects are absent surrounding large option trades, providing evidence against informed option trading. Examining the adverse selection component of the bid-ask spread, results show information asymmetry to be an insignificant determinant of option spreads. Similar results are found by Neal (1992), who calculates the adverse selection component of the bid-ask spread using the method of Glosten and Harris (1988). He finds that adverse selection is an insignificant determinant of the bid-ask spread, accounting for 3% of the average spread.

Conversely, Ahn et al. (2008) test the level of informed trading on the KOPSI 200 Index options traded on the Korean Exchange using the spread decomposition model developed by Madhaven et al. (1997). Estimating the adverse selection component of the bid-ask spread, the authors find that information asymmetry accounts for 34.99% of the bid-ask spread for call options and 39.14% of the bid-ask spread for put options. The authors find that adverse selection costs are positively related with option delta.

Bartram et al. (2008) also show that informed traders are attracted to the options market, by assessing the impact of adverse selection on option bid-ask spreads by examining two markets with different levels of information asymmetry. The authors compare the EuRex, a traditional derivatives exchange, with EuWax which specializes in bank-issued options. The level of adverse selection is lower on the EuWax as market makers know the identity of the investors with whom they trade. In contrast to Vijh (1990) and Neal (1992), the results from comparing similar option contracts across both markets show that bid-ask spreads on the EuWax are tighter (4.2%) compared to bid-ask spreads on the EuRex (8.8%). The authors also reveal that inventory costs are a significant determinant of bid-ask spreads. Ask prices on EuWax are systematically higher than on EuRex, which is consistent with the idea that market makers are unable to control their inventory and incur hedging costs to cover their net short positions.

Extending the results of Vijh (1990) and Neal (1992), Lee and Yi (2001) suggest that informed trading may only be important for some trade types. They find that informed trading in the options market is primarily driven by small investors, with the adverse selection component of the bid-ask spread on the CBOE greater than on the NYSE, with the opposite result found for large trades. This suggests that there are some investors who prefer to trade in options relative to stocks, with option markets playing an important role in the price discovery process. The authors also show that adverse selection costs are negatively related to the option’s delta, implying that options with greater leverage attract greater levels of informed trading.

2.2.4 Option Trading Strategies

Option strategies involve the purchase and/or sale of different call options at the same time. Despite the significant market microstructure literature covering option markets, there are a scant number of studies examining option strategies. This is surprising, given the importance of strategy trades in option markets. Chaput and Ederington (2003) document the use of option strategies by traders for options on Eurodollar Futures. The authors find that spread and combination trading collectively account for over 55% of large trades in the Eurodollar options market and almost 75% of the trading volume due to large trades. The four most heavily traded combinations are straddles, ratio spreads, vertical spreads and strangles, representing about two thirds of all strategy trades. The authors find that effective bid-ask spreads are higher on orders exceeding 500 contracts and on combinations that short volatility.

Fahlenbrach and Sandas (2010) study trading in option strategies using a sample covering all strategy and individual option trades on the FTSE-100 Index. They find strategy trades represent 37% of all option trades and account for 75% of the number of contracts traded. The authors document that the most actively traded combinations are strangles, straddles, bull and bear spreads, calendar spreads and covered calls and puts. Furthermore, the most popular strategy trades are delta neutral trades that have exposure to volatility. Volatility trades, with little or no delta exposure that consists of only option trades, are found to have information about the future volatility of the underlying stock. However, the authors find that volatility trades consisting of both options and futures, do not contain information about future volatility, as these trades are likely used for hedging reasons. Directional option strategies, which are long or short delta with little or no vega exposure, do not contain information about future returns. The results suggest that informed traders use volatility strategies, not directional strategies.

2.2.5 Market Makers and Intraday Patterns in Liquidity

A number of studies examine how market makers account for inventory imbalances and how this affects the intraday variation in liquidity. Transaction demand at the opening is greater and less elastic as a result of new overnight information, changing the investors' optimal portfolio. Inelastic demand at the close results from the imminent non-trading period leading to different optimal portfolios relative to the continuous trading period. On a specialist market, a specialist is designated by the exchange to make a market in a particular security. This allows the monopolist market maker to charge higher prices at these periods of heavy and inelastic demand. Brock and Kleidon's (1992) show that this model predicts high volume at the open and close of trading, which is contemporaneously associated with wide spreads.

McInish and Wood (1992) examine the intraday behaviour of time-weighted bid-ask spreads on the NYSE. Examining minute-by-minute spreads across the trading day, spreads are found to be highest near the open of trading, declines over the course of the trading day and increases near the close of trading. The authors also split the day into 13 half hour intervals. Using a linear regression model, spreads are found to be significantly related to trading activity, risk, information content and competition. Including time dummies into the regression, parameter estimates of the dummy variables for each interval reveal spreads are higher at the start and end of the trading day relative to the interim period. The results support the contention of Brock and Kleidon (1992) that wide spreads at the open and close are driven by the inelastic demand of investors.

The monopolistic power of the specialist on the NYSE allows them to widen the bid-ask spread in response to the inelastic demand of investors. However, when market markers have to compete with one another on a competitive dealer market, bid-ask spreads do not widen at the close despite inelastic demand. Chan et al. (1995a) show that spreads on the Chicago Board Options Exchange (a competitive dealer market) are narrow at the close of trading relative to the NYSE. The reason for this is that at the close of trading, inventory effects are particularly acute at the close of trading, as dealers face the risk of holding undesired inventory overnight. This can lead the market maker with long positions to decrease both their bid and ask prices (making ask quotes more competitive and bid quotes less competitive) to attract buy orders, while short positions lead to an increase in bid and ask quotes. This results in a narrowing of the inside spread (the highest bid price and lowest ask price) near the close of trading. In an analysis of intraday patterns in bid-ask spreads on the Nasdaq (a competitive dealer market), Chan et al. (1995b) the authors report that inside spreads on the Nasdaq narrow significantly near the close of trading and that this arises from a minority of dealers moving within the spread.

Lee et al. (1993) posit the impossibility of making inferences about liquidity changes on the basis of spreads or depth alone. The authors illustrate with a simple pricing function of a dealer using ordered pairs of the ask-price and ask-size and bid-price and bid-size that the combination of the spread and depth is needed to infer overall changes in liquidity. A simple examination of the bid-ask spread can therefore be misleading in inferring patterns in liquidity without also examining changes in quoted depth. Lee et al. (1993) test the general relation between spreads, depth and volume on the NYSE as well as testing the relation between these three variables conditioned on an information event; quarterly earnings announcements. The authors find that traded volume and bid-ask spreads follow an intraday U-shaped pattern while quoted depth follows a reverse U-shaped pattern. Results show that bid-ask spreads widen and quoted depth decreases after periods of high trading volume.

Lee, Mucklow and Ready (1993) posit the impossibility of making inferences about liquidity changes on the basis of spreads or depth alone. The authors illustrate with a simple pricing function of a dealer using ordered pairs of the ask-price and ask-size and bid-price and bid-size that the combination of the spread and depth is needed to infer overall changes in liquidity. A simple examination of the bid-ask spread can therefore be misleading in inferring intraday liquidity patterns without also examining changes in quoted depth. Lee, Mucklow and Ready (1993) test the general relation between spreads, depth and volume on the NYSE as well as testing the relation between these three variables conditioned on an information event; quarterly earnings announcements. The authors find that traded volume and bid-ask spreads follow an intraday U-shaped pattern while quoted depth follows a reverse U-shaped pattern. Results show that bid-ask spreads widen and quoted depth decreases after periods of high trading volume.

In a test of the inventory model of Ho and Stoll (1983), Chung and Zhao (2004a) analyse the quote revision behaviour of Nasdaq market makers by examining their inter-temporal changes in both spread and depth quotes. The authors find that the intraday variation in the number of quoted revisions follows a U-shaped pattern, indicating liquidity management is higher around the open and close of trading relative to the middle of the day. They attribute the high number of quote revisions during the last hour of trading as consistent with inventory models such as Amihud and Mendelson (1980) and Ho and Stoll (1983), with the large number of quote revisions reflecting the market maker's attempt to seek desired order flows.

2.7 Summary

This chapter reviews the literature concerned with order placement strategies across limit order driven markets and markets with a designated market maker that will be used to inform several hypotheses that are tested in the following chapters. The first essay assesses the effect of a tick size change on market quality in a futures market setting. The second essay examines the impact of algorithmic trading on market quality on the ASX. The third essay analyses the execution costs of option strategies and their determinants on the Australian Options Market. The fourth essay documents intraday patterns in liquidity on the Nasdaq.

Chapter 3: Market Quality Surrounding a Tick Size Increase

3.1 Introduction

The literature reviewed in Section 2.4 provides mixed conclusions with respect to the impact of a tick size change on market quality. The literature examining reductions in the minimum price increment find that bid-ask spreads decline in the post-event period. However, the evidence indicates that quoted depth increases after a reduction in the tick size. An issue with these studies therefore is determining which of the two changes has the greatest impact on liquidity. The literature on this issue studies the impact of a tick size reduction; the effect of a tick size increase is yet to be examined.

The objective of this essay is to bridge this gap in the literature by investigating a tick size increase in a futures market setting. More specifically, this essay examines the impact of increasing the tick size on market quality using the 3-Year Treasury bond futures ("3Y T-bond") on the Sydney Futures Exchange (SFE) and the 5-Year Euro Bobl futures ("5Y Bob1") on the Eurex. The remainder of this chapter is structured as follows. Section 3.2 presents the data. Section 3.3 outlines the research design and presents the empirical results. Section 3.4 summarises the chapter.

3.2 Hypotheses on Minimum Price Increment

The tick size is the smallest increment that a trading price can move and acts as the lower bound of the bid-ask spread. As discussed in Section 2.3.1, the relationship between tick size adjustments and liquidity is a contentious issue, with disagreement occurring on what constitutes an optimal tick size. For instance, Cordella and Foucault (1999) establish that transaction costs are not minimized by setting the minimum tick to zero. Consider a liquidity supplier who observes the competitive price (the price equaling the expected asset value rounded to the nearest tick) is below the current best price. In the presence of a minimum tick regime, this trader has the option to either post at the competitive price or post one tick below the current best price. A larger tick size creates a bigger wedge between the competitive price and the expected asset value, providing a greater profit to the trader. This results in liquidity suppliers being more willing to post at the competitive price, leading to a quicker price adjustment. The larger tick size therefore does not necessarily increase transaction costs for liquidity demanders. Whether a change in the tick size increases or decreases liquidity is dependent upon its effect on both bid-ask spreads and quoted depth.

In a competitive market, a reduction in the minimum price increment allows liquidity suppliers to post competitive quotes, leading to a reduction in the bid-ask spread. This is particularly the case if the minimum tick acts as a binding constraint, which occurs when the bid-ask spread is equal to one tick. Kurov and Zabotina (2005) argue that a binding minimum tick indicates the tick size is above its competitive level, which impedes price competition. In this situation, a limit order that improves the current price becomes a market order. A trader that wishes to earn the bid-ask spread must place a limit order at the current best price, which due to price-time priority rules, places the trader's order at the end of the queue. The minimum tick prevents the trader from increasing his/her probability of execution through narrowing the spread, causing bid-ask spreads to be higher in the presence of a minimum tick size than without. If the tick size is binding, a reduction in the tick-size will therefore lead to a reduction in bid-ask spreads. The evidence from prior literature suggests that bid-ask spreads tighten after a reduction in the minimum tick (see Goldstein and Kavajecz, 2000, Jones and Lipson 2001, Bessembinder 2003, ap Gwilym et al 2005).

Conversely, an increase in the minimum tick may lead to an increase in the bid-ask spread. However, this depends on whether the new tick size causes artificially wide bid-ask spreads. Bourghelle and Declerck (2004) report that a coarser pricing grid on the Paris Bourse does not result in higher bid-ask spreads as the proportion of one tick spreads is about 10% prior to the tick size reduction. The empirical evidence on the tick size in futures markets shows that a high percentage of bid-ask spreads trade at the minimum tick. In a study of the UK Long Gilt Futures, ap Gwilym et al. find that over 96% of quoted spreads under fractional pricing and 79% of bid-ask spreads under decimal pricing trade at the minimum tick.

Hypothesis$_{3.1}$: *Bid-ask spreads will increase after the increase in minimum tick*

An increase in the minimum tick increases the premium paid to liquidity suppliers for providing liquidity to the market. The increase in liquidity supplier revenues may encourage greater participation by liquidity suppliers on the exchange. If the minimum tick is a binding constraint on the spread, spreads are artificially inflated making it profitable to submit limit orders. Grossman and Miller (1988) contend that dealers can more easily cover their fixed costs under a large minimum tick regime, thereby encouraging dealer participation on the exchange which increases liquidity.

An increase in the minimum tick has implication for market depth at the best quotes and throughout the limit order book. Liquidity suppliers who previously posted limit orders outside the best quotes may choose to place their order at the best bid and ask prices, leading to an increase in quoted depth at the best quotes. Lau and McInish (1995) and Goldstein and Kavajecz (2000) argue that a tick size reduction causes liquidity providers to reduce depth at the best quotes and away from the best quotes. Under a tick increase, as the cost of liquidity has risen, liquidity demanders may now choose to place limit orders instead of market orders leading to an increase in cumulative depth.

A larger tick size may also make investors more willing to expose orders. For instance, Harris (1991) argues a coarse pricing grid enforces time priority by acting as a disincentive to step ahead of the current quote, thereby encouraging traders to post liquidity. The following hypothesis predicts the increase in the tick size will lead to higher depth at the best quotes and throughout the limit order book.

Hypothesis$_{3.2}$: *Quoted depth will be larger at the best bid and ask quotes after the increase in minimum tick*

Hypothesis$_{3.3}$: *Total quoted depth visible in the limit order book will larger after the increase in minimum tick*

Lee et al. (1993) note that studies examining liquidity provision need to simultaneously examine changes in both spreads and depth. Prior literature has consistently documented reduced spreads and depth after a tick size reduction. A change in tick size therefore has opposing effects on liquidity, leading to difficulty in estimating the effect of the tick size change on market quality. Several studies have examined the overall impact of the tick size change on liquidity. Bacidore (1997) finds that execution costs on the Toronto exchange decline after the reduction in the minimum tick. Goldstein and Kavajecz (2000) report the combined effect of reduced bid-ask spreads and quoted depth benefited small orders but increased the transaction costs of large orders. In contrast, Bessembinder (2003a) report reduced transaction costs for both small and large traders. Using the Aitken and Comerton-Forde (2003) measure of liquidity, Aitken and Comerton-Forde (2005) find a lower tick size results in a significant increase in liquidity. An important determinant of the impact of a tick size increase on liquidity is the proportion of trades executed at the best quotes. If before the change a high proportion of trades are executed within the best quotes, an increase in market depth may not reduce transaction costs as sufficient depth to transact against already exists. Alampieski and Lepone (2009) report that 99 percent of all trades are executed against the best prevailing quotes and all trades are executed within the best two quotes on the SFE. This leads to the following hypothesis.

Hypothesis$_{3.4}$: *An increase in the tick size will lead to a reduction in the level of market liquidity.*

3.3 Eurex and Sydney Futures Exchange

Eurex is Europe's largest futures and options exchange. The Sydney Futures Exchange (SFE) is the largest futures exchange in the Asia-Pacific Region. Trading on both the

SFE and the Eurex operates through a fully automated electronic limit order book. The two main trader types, local participants and full participants, enter orders directly into the order-book with trades taking place based on price and time precedence rules.

The 3-Year Treasury bond futures (“3Y T-bond”), 10-Year Treasury bond futures (“10Y T-bond”) and the 5-Year Euro Bobl futures (“5Y Bob1) and the 10-Year Euro bund futures (“10Y Bund) follow a quarterly expiration cycle. For the 3Y T-bond and 10Y T-bond futures, contracts expire on the 15th of March, June, September, and December with settlement occurring three days before expiration. Both bonds have face values of AUD 100,000 and are quoted on a “100-yield” basis (yield deducted from an index of 100.00). The trading hours for both contracts are between 8:30 and 16:30 hours for daytime trading and 17:10 and 7:00 hours for night time trading during US daylight savings time.[1] The delivery date for the 5Y Bobl and 10Y Bund contracts falls on the tenth calendar day of the respective quarterly month. Both bonds have face values of EUR 100,000 and are quoted on a “100-yield” basis. Trading hours for both contracts are between 8:00 and 22:00 hours.

The 3Y T-bond contracts has a minimum tick of 0.5 basis points and pre-trade transparency of five levels either side of the limit order-book before May 11, 2009 and a minimum tick of 1 basis point after that date and pre-trade transparency of three levels either side of the limit order-book. The 5Y Bob1 contracts have a minimum tick of 0.5 basis points before June 15, 2009 and a minimum tick of 1 basis points after that date and pre-trade transparency of ten levels either side of the limit order-book. The

[1] Trading is between 17:10 and 7:10 hours for night time trading during US non daylight savings time.

10Y T-bond contracts have a minimum tick of 0.5 basis points and pre-trade transparency of five levels either side of the limit order-book and the 10Y Bund has a minimum tick of 0.5 basis points and pre-trade transparency of ten levels either side of the limit order-book. On both the SFE and Eurex, traders can view in real time prices and order volume on each side of the order book and the traded volume and price of each trade that occurs. Trading identity however is anonymous as broker mnemonics are not visible.

3.3 Data

The data used in this study are provided by Securities Industry Research Centre of Asia Pacific (SIRCA) and contain a record describing each transaction, including the contract code, date, time, price, and volume. The data also provide the prices and volumes of prevailing bid and ask quotes throughout the limit order-book, which are time-stamped to the nearest second. On May 11, 2009, the SFE increased the minimum tick size from 0.5 to 1 basis-point for the 3Y T-bond contract.[2] The increase in tick size from 0.5 to 1 basis-point for the 5Y Bob1 contract occurred on June 15, 2009.

To examine the impact of the increase in minimum tick on market quality, we examine two subsamples three months before and after the change. For the 3Y T-bond, the pre-period is 13 May, 2008 to 13 August, 2008 and the post-period is May 13, 2009 to August 13, 2009. For the 5Y Bob1, the pre-event sample period extends from 17 June, 2008 to 17 September, 2008 and the post-event sample period extends from June 17, 2009 to September 17, 2009. The day of the change is excluded for both events. In line with Frino and McKenzie (2002) who find abnormal levels of liquidity motivated trading near expiry, this study excludes the five days prior to expiration. In line with Bortoli et al. (2006), analysis is restricted to the nearest to expiry contract only.

[2] The change in tick size on May 11, 2009 coincided with a reduction in the visibility of the order book in the 3-Year bond futures from five to three price levels.

3.4 Research Design and Empirical Results

Changes in liquidity before and after the increase in minimum tick may reflect changes in market conditions as opposed to the change in tick size. To control for this possibility, the 10Y T-bond and 10Y Bund contracts are used as control contracts. The two futures contracts on each exchange are regarded as potential substitutes as they trade on the same platform during the same hours, with underlying assets being risk-free government bonds. The minimum tick size of 0.5 basis points and the level of transparency of 5 price levels on each side of the order-book for the 10Y T-bond remained constant over the sample period. The tick size and the level of transparency also remains constant for the 10Y Bund, with a minimum tick size of 1 basis point and transparency of 10 price levels either side of the order book.

In an analysis of the Sydney Futures Markets, Alampieski and Lepone (2009) state that market activity, volatility, and trading in interest rate futures contracts follow seasonal patterns. As a result, the impact of an increase in transparency may be indistinguishable from seasonal trading patterns. To further ensure the change in liquidity results from the increase in the minimum tick and not the impact of seasonality in trading, a year-on-year analysis is conducted. The post period is compared to the period 13 May, 2008 to 13 August, 2008 for the 3Y T-bond and 17 June, 2008 to 17 September, 2008 for the 5Y Bob1.

The variables used to assess changes in market quality after the transition are the bid-ask spread, quoted depth, traded volume, and volatility. The bid-ask spread is calculated using two measures. Following Frino et al. (2008), the first is the absolute bid-ask spread in points, measured as the ask-price minus the bid-price.

Following Alampieski and Lepone (2009), the second measure employed divides the absolute bid-ask spread by the minimum tick. The bid-ask spread is sampled over 5-minute intervals for the day trading sessions and then averaged over each trading session.

Lee et al. (1993) establish that an examination of liquidity must involve an analysis of both spreads and depth. Harris suggests that a tick size increase may reduce the with Harris (1994) arguing that changes in liquidity can only be determined by assessing changes in depth throughout the limit order book. Goldstein and Kavajecz (2000) note that an analysis of depth at the best prices omits valuable information as to whether the change in tick size results in a sufficient change to cumulative depth to change the transaction costs of large orders. Alternatively, Cao et al. (2009) find that order book information beyond the best quotes is moderately informative. Consequently, quoted depth is examined using two measures; best depth and total depth. Best depth is defined as the combined volume of shares available at both the best bid price and best ask price at the end of each interval. Total depth is the sum of the volume of contracts at each bid and ask price throughout the visible limit-order book at the end of each interval. Similar to bid-ask spreads, best and total depth are sampled over 5-minute intervals for the day and then averaged over each trading day.

Traded volume is included as a measure of market quality because if transaction costs increase, trade volume should decrease (Harris, 1994). This is because a higher bid-ask spread would increase the cost associated with trading as the spread is a transaction cost paid by liquidity suppliers (Harris, 2003). Trading volume is calculated as the total number of shares traded during the trading session. Schwartz (1993) defines volatility as unexpected changes in prices. The tick size can effect volatility as prices deviate from fundamental value. A greater tick size will increase this difference between price and value. Volatility is measured as the natural logarithm of the highest traded price divided by the lowest traded price for each trading session.

3.3.1 Univariate Analysis

Table 3-1 provides descriptive statistics of the market quality indicators surrounding the structural transitions for both event (3Y T-bond and 5Y Bobl) and control (10Y T-bond and 10Y bund) contracts. Prior literature including Ahn et al., (1996, 1998), Goldstein and Kavajecz (2000) and Aitken and Comerton-Forde (2005) indicate reductions in the minimum tick lead to lower bid -ask spreads. In line with these findings, there is a significant increase of 0.0050 (0.0046) basis points in the bid-ask spread for the 3Y T-bond (5Y Bob1) contracts. For the control for 3Y T-bond (i.e., 10Y T-bond), bid-ask spreads decline significantly at the 1% level, while those for the control for 5Y Bob1 (i.e., 10Y Bund) increase significantly at the 1% level. Supporting the prediction of hypothesis $H_{3,1}$, results suggest that the increase in the bid-ask spread for the 3Y T-bond is due to the tick-size increase since the market for the 10Y T-bond contracts experiences the opposite change. This is in line with a number of These are in line with a number of studies showing that tick size reductions are associated with lower bid-ask spreads. With respect to the 5Y Bob1 contract, the increase in the bid-ask spread could result from a market-wide change as bid-ask spreads for the 5Y Bob1 and 10Y Bund change in the same direction, in contradiction to hypothesis $H_{3,1}$.

Bid-ask spreads per minimum tick for the 3Y T-bond (5Y Bob1) contracts decrease by 0.028 (0.128) ticks, which is significant at the 1% level. For the 10Y T-bond, bid-ask spreads per minimum tick decline significantly at the 1% level, while those for the 10Y Bund increase significantly at the 1% level. As opposed to the bid-ask spread results, only the change in the 5Y Bob1 bid-ask spread per minimum tick can be attributed to the tick size increase since the change for the 10Y Bund occurs in the opposite direction. In regards to the bid-ask spread per minimum tick for the 3Y T-bond, it is not possible to conclude whether the tick size increase is the cause of the decrease as the control contract (i.e., 10Y T-bond) experiences a qualitatively similar change.

Table 3-1
Descriptive Statistics

This table present descriptive statistics for measures of market liquidity surrounding the increase in minimum tick for the 3Y T-bond and the 5Y Bob1 contracts. The tick size of the 3Y T-bond contracts was increased from half to a full-basis point on May 11, 2009. The pre-event sample period extends from 13 May, 2008 to 13 August, 2008. The post-event sample period extends from 13 May, 2009 to 13 August, 2009. The tick size of the 5Y Bob1 contracts was increased from half to a full-basis point on June 15, 2009. The pre-event sample period extends from 17 June, 2008 to 17 September, 2008. The post-event sample period extends from 17 June, 2009 to 17 September, 2009. Bid-ask spreads and depth are sampled every 5 minutes (15 minutes) and then averaged for each day. *Bid-Ask Spread* is the best ask price minus the best bid price in contract points. *BAS* is calculated as the bid-ask spread divided by the minimum tick. *Best Depth* is the aggregate order volume at the best bid and best ask price. *Total depth* is the aggregate order volume throughout the limit-order book. *Volatility* is the natural logarithm of the highest traded price divided by the lowest traded price for each day. *Volume* is the average daily traded volume. * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

Panel A: SFE						
	3Y T-bond (Event Contract)			10Y T-bond (Control Contract)		
	Pre	Post	Post - Pre	Pre	Post	Post - Pre
Bid-Ask Spread	0.0052	0.0102	0.0050**	0.0053	0.0052	-0.0001**
BAS	1.043	1.015	-0.028**	1.059	1.034	-0.025**
Best Depth	531	1,179	648**	192	148	-44**
Total Depth	3,471	4,686	1,215**	1,227	865	-362**
Volatility	0.0860	0.1008	0.0148*	0.0860	0.0921	0.0061*
Volume	48,939	51,461	2,522	19,662	15,356	-4,306**
Panel B: Eurex						
	5Y Bob1 (Event Contract)			10Y Bund (Control Contract)		
	Pre	Post	Post - Pre	Pre	Post	Post - Pre
Bid-Ask Spread	0.0059	0.0105	0.0046**	0.0105	0.0107	0.0002**
BAS	1.176	1.051	-0.125**	1.052	1.069	0.017**
Best Depth	259	651	392**	375	335	-40**
Total Depth	3,719	9,889	6,170**	7,128	6,029	-1,099**
Volatility	0.4819	0.3653	-0.1166**	0.6721	0.5691	-0.1030**
Volume	491,517	315,963	-175,554**	794,117	588,931	-205,186**

Harris (1994) predicted a reduction in the tick size would decrease quoted depth as liquidity provision is less profitable and more risky. In line with this prediction, quoted depths at both the best quotes and throughout the limit order book increase for the 3Y T-bond (an increase of 648 (1,215) contracts for best (total) depth) and 5Y Bob1 contracts (an increase of 392 (6,170) contracts for best (total) depth), in contrast to the control contracts where both best and total depth levels decline: a reduction of 44 (362) contracts for best (total) depth in the 10Y T-bond and that of 40 (1,099) contracts for best (total) depth in the 10Y Bund. All changes in (both best and total) quoted depths reported in Table 3-1 are statistically significant at the 1% level. This is line with the predictions of the second hypothesis. In contrast to the results for bid-ask spreads and bid-spreads per minimum tick, results clearly indicates that the increases in (both best and total) quoted depths for the two event contracts are due to the tick size increase rather than a market-wide event, as the changes for the corresponding control contracts are in the opposite direction.

Table 3-1 also reports changes in trading volume and volatility surrounding the tick size increase. Trading volume is significantly higher for the 3Y T-bond, but is significantly lower for the 10Y T-bond, while volatility is significantly higher across both contracts. However, these are in line with the changes in the control contract, suggesting that the change in tick size has not had an impact on traded volume. For example, Ahn et al. (2007) finds no increase in volume on the Tokyo Stock Exchange following the 1997 tick reduction. There is a significant decline in traded volume and volatility for the 5Y Bob1 and 10Y Bund contracts.

3.1.2 Multivariate Analysis

As documented by Chordia et al. (2000), changes in market quality measures such as bid-ask spreads and quoted depth are associated with changes in market-wide liquidity factors. To better isolate the impact of the tick size increase on bid-ask spreads and quoted depth, the following regressions ("market wide regressions", hereafter) are estimated:

$$BAS_i = \alpha_0 + \alpha_1 Change_i + \alpha_2 ControlBAS_i + \varepsilon_i \qquad (3.1)$$

$$Ln(BestDepth)_i = \alpha_0 + \alpha_1 Change_i + \alpha_2 Ln(ControlBestDepth_i) + \varepsilon_i \qquad (3.2)$$

$$Ln(ToalDepth)_i = \alpha_0 + \alpha_1 Change_i + \alpha_2 Ln(ControlTotalDepth_i) + \varepsilon_i \qquad (3.3)$$

where $Change_i$ is a dummy variable assigned the value of one if the observation is taken from the post-event sample and zero otherwise. BAS_i is the bid-ask spread, $Ln(BestDepth)_i$ is the logarithm of the aggregate order volume at the best bid and best ask price, and $Ln(ToalDepth)_i$ is the logarithm of the aggregate order volume throughout the limit-order book for the event contracts. The variables $ControlBAS_i$, $Ln(ControlBestDepth_i)$, and $Ln(ControlTotalDepth_i)$ represent bid-ask spreads, the logarithm of best depth, and the logarithm of total depth for the control contracts, respectively. In Equation (1), the bid-ask spread is used as the dependent variable. As a falsification test, these three regressions are re-estimated using the control contracts as dependent variables.

As presented in Panel A of Table 3-2, the bid-ask spread regression results for the 3Y T-bond contracts indicate a significant increase in bid-ask spreads at the 1% level. In contrast, the results for the 10Y T-bond contracts show a negative coefficient on the dummy variable (at the 5% level), indicating that spreads narrow over the period. As reported in Panel B and C of Table 3-2, best depth and total visible depth for the 3Y T-bond contracts increase significantly (at the 1% level) in the post-period after controlling for depth in the 10Y T-bond contract. The regressions for the control contract (10Y T-bond) show a reduction in both best and total depths after the tick size increase, with both of these changes significant at the 1% level.

Table 3-2
Market Wide Regressions

This table reports the regression results of spreads and depth around the move to full-basis point trading in the 3Y T-bond and 5Y Bob1 contracts. For the 3Y T-bonds, the pre-event sample period for extends from 13 May, 2008 to 13 August, 2008. The post-event sample period extends from 13 May, 2009 to 13 August, 2009. For the 5Y Bobl, the pre-event sample period extends from 17 June, 2008 to 17 September, 2008. The post-event sample period extends from 17 June, 2009 to 17 September, 2009. The regression equations (1), (2), and (3) are estimated for the event (3Y T-bond and 5Y Bob1) contracts as the dependent variables. As a falsification test, these three regressions are re-estimated using the control contracts as dependent variables. * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

	Intercept	Change	10Y T-bond	3Y T-bond	10Y Bund	5Y Bob1	R^2
Panel A: Bid-Ask Spread							
SFE							
3Y T-bond	0.0044**	0.0050**	0.1483				0.9974
10Y T-bond	0.0044**	-0.0009*		0.1655			0.184
Eurex							
5Y Bob1	0.0037**	0.0046**			0.2071*		0.9931
10Y Bund	0.0090**	-0.0010*				0.2519*	0.1693
Panel C: Best Depth							
SFE							
3Y T-bond	3.4770**	1.0110**	0.5102**				0.7707
10Y T-bond	2.8810**	-0.5580**		0.3591**			0.3451
Eurex							
5Y Bob1	1.134	0.9810**			0.7240**		0.8921
10Y Bund	3.0700**	-0.5338**				0.4771**	0.3927
Panel D: Total Depth							
SFE							
3Y T-bond	5.3250**	0.4616**	0.3892**				0.3559
10Y T-bond	4.7560**	-0.4414**		0.2840**			0.4468
Eurex							
5Y Bob1	2.6380**	1.0690**			0.6224**		0.9524
10Y Bund	2.9340**	-0.8574**				0.7195**	0.5531

Table 3-2 also shows the market wide regression results for the 5Y Bob1 contracts. Bid-ask spreads for the 5Y Bob1 are significantly wider after the change at the 1% level, as indicated by the positive dummy variable coefficient. In contrast, there is a significant decrease in bid-ask spreads for the control contract at the 5% level. Both best depth and total depth for the 5Y Bob1 increase significantly after the tick change. For the 10Y Bund contracts, the negative dummy coefficients indicate a significant decline (at the 1% level) in best depth and total depth in the post-period. These results support hypotheses $H_{3,1}$ and $H_{3,2}$ for both event contracts.

Chordia et al. (2000) find that liquidity measures are dependent on factors specific to the particular financial instrument in addition to market-wide liquidity factors. Harris (1994) argues that two important determinants of the bid-ask spread and quoted depth are trading volume and price volatility. To control for both market-wide and security specific factors on the bid-ask spread and quoted depth, this study follows Frino, Gerace, and Lepone (2008) and estimates the following equations:

$$BAS_i = \alpha_0 + \alpha_1 Change_i + \alpha_2\, Ln(ControlVolume_i) + \alpha_3 ControlVolatility + \alpha_3\, Ln(Volume_i) + \alpha_5 Volatility_i + \varepsilon_i \quad (3.4)$$

$$Ln(TotalDepth)_i = \alpha_0 + \alpha_1 Change_i + \alpha_2\, Ln(ControlVolume_i) + \alpha_3 ControlVolatility_i + \alpha_3\, Ln(Volume_i) + \alpha_5 Volatility_i + \varepsilon_i \quad (3.5)$$

$$Ln(TotalDepth)_i = \alpha_0 + \alpha_1 Change_i + \alpha_2\, Ln(ControlVolume_i) + \alpha_3 ControlVolatility_i + \alpha_3\, Ln(Volume_i) + \alpha_5 Volatility_i + \varepsilon_i \quad (3.6)$$

where BAS_i, $Ln(BestDepth_i)$, $Ln(TotalDepth_i)$, and $Change_i$ are as described in Equations (1), (2), and (3). $Ln(ControlVolume_i)$ is the logarithm of the average daily traded volume, $ControlVolatility_i$is the natural logarithm of the highest traded price divided by the lowest traded price for each day in the control contracts. $Ln(Volume_i)$

and $Volatility_i$ represent daily traded volume and volatility in the event contracts, respectively. As a falsification test, these three regressions are also re-estimated using the control contracts as dependent variables.

Panel A of Table 3-3 shows that after controlling for volatility and volume for the 3Y T-bond contract, bid-ask spreads experience a significant increase at the 1% level after the change in tick size. Supporting hypothesis $H_{3,1}$, the increase in spreads is isolated to the 3Y T-bond contract, with bid-ask spreads for the 10Y T-bond contract showing a significant decrease at the 1% level after the change. In line with the hypothesis $H_{3,2}$, the regression results in Panel B and C of Table 3-3 show a significant improvement in both the best and total depth levels for the 3Y T-bond contracts after the increase in tick size: this result is specific to the 3Y T-bond contracts, with the coefficients on the change dummy variables for the 10Y T-bond contracts being negative at the 1% level. The results of the combined regressions for the 5Y Bob1 contracts are also presented in Table 3-3. The positive dummy coefficient for the 5Y Bob1 (presented in Panel A) indicate that the bid-ask spread widens in the post-period. Bid-ask spreads for the 10Y Bund contract are wider in the post-period, as indicated by the poisitive dummy coefficient (significant at the 1% level), however the economic size of the coefficient is much smaller than for the 5Y Bobl at 0.0002 relative to 0.0047, also supporting hypothesis $H_{3,1}$ with regards to the 5Y Bobl contract. As shown in Panel B, the dummy variable coefficients for best and total depths are both highly significant and positive at the 1% level, indicating an increase in depth levels after the tick increase for the 5Y Bob1. On the contrary, the 10Y Bund contracts experience a significant decrease in both best and total depths at the 1% level, thus supporting hypothesis $H_{3,2}$.

The results of the analysis suggest that in line with the literature, the increase in the tick size resulted in both higher bid-ask spreads, and greater depth. The increase in spreads is not surprising, as the average quoted spread was close to the minimum tick size prior to the increase in the tick size for both the 3Y T-bond contract and 5Y Bob1. Harris (1994) suggests that an increase in the tick size will improve quoted depth as it reduces the cost of front-running an order, as it increase the price a trader has to pay to obtain price-time priority. The higher tick size therefore provides protection against quote matchers and front-runners, reducing the cost of displaying quotes on the limit order book. Furthermore, the greater tick size reduces the likelihood that a liquidity supplier will trade with a limit order trader (Anshuman and Kalay, 1998).

Table 3-3
Combined Regressions

This table reports the regression results of spreads and depth around the move to full-basis point trading in the 3Y T-bond and 5Y Bob1 contracts. For the 3Y T-bonds, the pre-event sample period for extends from 13 May, 2008 to 13 August, 2008. The post-event sample period extends from 13 May, 2009 to 13 August, 2009. For the 5Y Bobl, the pre-event sample period extends from 17 June, 2008 to 17 September, 2008. The post-event sample period extends from 17 June, 2009 to 17 September, 2009. The regression equations (4), (5), and (6) are estimated for the event (3Y T-bond and 5Y Bob1) contracts as the dependent variables. As a falsification test, these three regressions are re-estimated using the control contracts as dependent variables. * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

	Intercept	Change	Volume (10Y T-bond)	Volatility (10YT-bond)	Volume (3Y T-bond)	Volatility (3Y T-bond)	Volume (10Y Bund)	Volatility (10Y Bund)	Volume (5Y Bob1)	Volatility (5Y Bob1)	R^2
Panel A: Bid-Ask Spread											
SFE											
3Y T-bond	0.0053**	0.0049**	-0.0000	-0.0012*	-0.0000	0.0014*					0.9974
10Y T-bond	0.0053**	-0.0002**	-0.0000	-0.0002	0.0000	0.0005					0.1825
Eurex											
5Y Bob1	0.0059**	0.0047**					0.0000	-0.0000	0.0000	-0.0000	0.9927
10Y Bund	0.01038	0.0002**					-0.0000	0.0003	0.0000	-0.0003	0.1698
Panel C: Best Depth											
SFE											
3Y T-bond	1.755	0.8727**	-0.0668	-0.0002	0.4870**	-2.980**					0.1804
10Y T-bond	2.5580**	-0.1040*	0.4294*	0.5729	0.4151*	-1.435*					0.4046
Eurex											
5Y Bob1	3.3130*	0.9778**					-0.2926	0.1774	0.4522*	-0.5155	0.128
10Y Bund	2.362	-0.0718					0.3123*	-0.0488	0.1397	-0.2202	0.1875

Table 3, continued

Panel D: Total Depth

SFE											
3Y T-bond	4.3510**	0.3273**	-0.044	-0.3102	0.4151**	-3.147**					0.4345
10Y T-bond	5.6300**	-0.2330**	0.3562**	-0.2891	-0.1888*	-0.5096					0.4843
Eurex											
5Y Bob1	6.4900**	0.9915**					-0.0039	-0.1102	0.1397	-0.2165	0.9216
10Y Bund	6.7520**	-0.1711**					0.2997*	-0.2032	-0.1427	-0.1254	0.2945

3.3.3 *Execution Costs*

To provide a more comprehensive assessment of the change in liquidity after the increase in minimum tick (i.e., whether the change in bid-ask spreads dominates the change in quoted depth), this section tests the third hypothesis by examining the price impact of executing orders. The pre-trade benchmark represents the price that would have prevailed had the trade not executed (Domowitz et al., 2001), while the post-trade benchmark represents the equilibrium price after all short-term price pressure has dissipated (Harris, 2003). A significant price impact would suggest that the increase in quoted depth did not offset the cost of the increase in the bid-ask spread.

Trades are classified as buyer- and seller-initiated using the method of Ellis, Michaely, and O'Hara (2000). Each trade is classified into four mutually exclusive quartiles based on trade size. The first quartile contains the smallest 25% of trade sizes and the fourth quartile contains the largest 25% of trade sizes. Studies employ different different pre- and post-trade benchmarks. Berkman et al. (2005) use an intraday benchmark of mid-quotes five seconds before and five minutes after transactions. However, studies of intraday show patterns in liquidity in order-driven markets shows that traded volume follows a U-shape pattern, meaning that the number of trades within 5 minutes is not constant across the trading day (Ahn and Cheung, 1999). Therefore consistent with Gemmill (1996), the transaction price five trades prior to the trade is used as the pre-trade benchmark, where the price impact of each trade is measured as the basis point change from the pre-trade benchmark price to the trade price. This is averaged across each day and then across each sample period.

Results of the price impact analysis for the 3Y T-bond contracts are shown in Table 3-4. There is a significant increase in execution costs across all quartiles for both buyer and seller-initiated trades at the 1% level. For purchases, execution costs for the first quartile averaged 0.1109 basis points before the tick increase and 0.2105 basis points after, a significant change of 0.0996 basis points at the 1% level. Similar results are found for the other three quartiles.

Qualitatively comparable results are obtained for sales. For the first and second quartiles, price impact increases significantly by 0.1000 and 0.0610 basis points at the 1% level respectively, while the third and fourth quartiles show a significant increase of 0.0600 and 0.0920 basis points (both at the 1% level). Table 3-4 also reveals that results for the 5Y Bob1 contracts are qualitatively similar to those for the 3Y T-bond contracts.

Table 3-4
Execution Costs

Price impact results are presented before and after the change in tick size for the 3Y T-bond and 5Y Bobl contracts. For the 3Y T-bonds, the pre-event sample period extends from 13 May, 2008 to 13 August, 2008. The post-event sample period extends from 13 May, 2009 to 13 August, 2009. For the 5Y Bobl, the pre-event sample period extends from 17 June, 2008 to 17 September, 2008. The post-event sample period extends from 17 June, 2009 to 17 September, 2009. Trades are classified as buyer and seller initiated using the methodology of Ellis, Michaely, and O'Hara (2000). The price impact of each trade is measured as the change from the transaction price five trades prior to the trade price. This is averaged across each day and then across each sample period. Each trade is classified into four mutually exclusive quartiles based on trade size. The first quartile contains the smallest 25% of trade-sizes and the fourth quartile contains the largest 25% of trade-sizes. Price impact is reported in basis points. * indicates statistical significance at the 5% level. ** indicates statistical significance at the 1% level.

	Quartile 1		Quartile 2		Quartile 3		Quartile 4		All	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Panel A: Pre-period										
SFE										
3Y T-bond	0.1109	-0.1140	0.1047	-0.1260	0.1099	-0.1410	0.1544	-0.1710	0.1194	-0.1380
10Y T-bond	0.1418	-0.1260	0.1425	-0.1360	0.1460	-0.1540	0.1810	-0.1900	0.1584	-0.1610
Eurex										
5Y Bob1	0.1637	-0.1555	0.1412	-0.1421	0.1507	-0.1507	0.1437	-0.1517	0.1484	-0.1509
10Y Bund	0.3424	-0.3367	0.3147	-0.3146	0.3108	-0.3078	0.3346	-0.3415	0.3255	-0.3245
Panel B: Post-period										
SFE										
3Y T-bond	0.2105	-0.2140	0.2233	-0.1870	0.2424	-0.2010	0.2985	-0.2630	0.2394	-0.2160
10Y T-bond	0.1655	-0.1700	0.1474	-0.1470	0.1461	-0.1560	0.1629	-0.1790	0.1555	-0.1630
Eurex										
5Y Bob1	0.2805	-0.2652	0.2702	-0.2575	0.2855	-0.2726	0.3197	-0.3110	0.2889	-0.2856
10Y Bund	0.3076	-0.3177	0.2883	-0.3005	0.2973	-0.2919	0.3879	-0.3986	0.3203	-0.3292
Panel C: Post - Pre										
SFE										
3Y T-bond	0.0996**	-0.1000**	0.1186**	-0.0610**	0.1325**	-0.0600**	0.1441**	-0.0920**	0.1200**	-0.0780**
10Y T-bond	0.0237**	-0.0440**	0.0049	-0.0110	0.0001	-0.0020	-0.0181**	0.011	-0.0029*	-0.0020
Eurex										
5Y Bob1	0.1168**	-.01097**	0.1290**	-.01154**	0.1347**	-0.1218**	0.1760**	-0.1596**	0.1405**	-0.1347**
10Y Bund	-0.0348**	0.0190**	-0.0264**	0.0141**	-0.0136**	0.0160**	0.0533**	-0.0570**	0.0051	-0.0038

In contrast to the results for the event contracts, those for the control (10Y T-bond and 10Y Bund) contracts are mixed. With respect to the total sample, results for both control contracts indicate that there is no significant change in execution costs for both purchases and sales at the 1% level. Results are not uniform across the four quartile groups for both control contracts, however when costs are seen to increase this is still less than for the 3Y T-bond and 5Y Bob1 contracts. For example, for purchases of the 3Y T-bond, the difference in execution costs for the first quartile averaged 0.1109 basis points, relative to 0.0237 basis points. This means that the changes in execution costs for the event contracts is likely to be attributed to the tick size increase, supporting hypothesis $H_{3,3}$. These results suggest that increasing the minimum price increment has a negative impact on market quality, where the cost of increasing the bid-ask spread more than offset the increase in quoted depth. This is likely the result of there being already sufficient liquidity in futures markets prior to the tick increase to absorb the impact of market orders. This is in line with studies that find that the impact of a reduction in tick size primarily benefits small trades and liquid securities (Bollen and Whaley, 1998).

3.5 Summary

This essay investigates the impact of the *increase* in minimum tick size on market quality using the 3-Year Treasury bond futures (“3Y T-bond”) on the Sydney Futures Exchange (SFE) and the 5-Year Euro Bobl futures (“5Y Bob1”) on the Eurex, which is distinguished from prior studies that examine tick size reductions. The literature for both equity and futures markets provide evidence that a reduction in the tick size is associated with lower spreads and quoted depth. As these changes have conflicting effects on liquidity, certain studies attribute the change in spreads and depth as indicative of an improvement in liquidity, while other studies conclude a reduction in overall liquidity, which warrants a re-examination of this issue.

This essay provides evidence that a tick size increase is associated with an increase in depth at the best quotes and throughout the limit order-book for both 3Y T-bond and 5Y Bob1 contracts, which is consistent with results in prior studies. However, with respect to both bid-ask spreads, this paper finds mixed evidence. The results show that the change in tick size lead to wider bid-ask spreads for the 3Y T-bond and the 5Y Bob1. This chapter suggest that the increase in the tick size lead to an increase in execution costs, indicating that the increase in the bid-ask spread has more than offset the increase in quoted depth.

Chapter 4: Algorithmic Trading and Market Quality

4.1 Introduction

This study investigates the relation between algorithmic trading volume and future market quality. Recent academic research has begun to focus on the impact of algorithmic trading on market quality such as liquidity and volatility (Hendershott and Riordan, 2011, Hasbrouck and Sarr, 2011, Brogaard, 2010, and Jones and Menkveld 2011). Although the evidence suggests that algorithmic traders (ATs) are not associated with reduced market quality, there are concerns that ATs can exacerbate market instability by increasing (decreasing) their demand (supply) of liquidity when liquidity is scarce. Despite these concerns, none of them examines how the impact of algorithmic trading on market quality during market declines differs from that during market upturns. The aim of this study is to bridge this gap in the literature by examining whether the relation between algorithmic trading and market quality differs across up and down markets. Furthermore, it examines whether market conditions affect the behaviour of ATs, which differentially impacts the market.

The remainder of this paper is structured as follows. Section 2 develops the hypotheses on the impact of algorithmic trading on market quality. Section 3 gives an overview of the institutional details of the Australian Stock Exchange (ASX) provides an overview of the data and presents descriptive statistics. Section 3 describes the research design. Section 4 presents the results. Section 5 summarises.

4.2 Hypotheses on Algorithmic Trading

Algorithmic trading involves automating order executions according to a set of pre-specified conditions such as prices, volatility etc. This enables algorithmic trading programs to be more efficient at processing and utilizing trading information relative to human market makers (Gerig and Michayluk, 2010). One of the other distinguishing features of algorithmic trading is its speed of execution, with latency speeds measured in milliseconds. ATs can thus transact on the information they acquire instantaneously. Hendershott and Riordan (2011) suggest that the AT's superior ability to process trade data and their fast execution speed enable efficient monitoring and adjustment of limit orders in response to new public information. This reduces the cost of the option provided by limit orders, leading to an improvement in liquidity. Furthermore, the ability of algorithms to continuously monitor the market can allow ATs to supply liquidity when it is cheap and take liquidity when it is expensive, thereby moderating short-term volatility. The empirical literature for equity and foreign exchange markets document that ATs improve market quality. Higher algorithmic trading leads to a narrowing of bid-ask spreads and effective spreads, price discovery increases and short-term volatility either reduces or does not increase (see Brograad, 2010; Chaboud et al., 2011; Hendershott et al., 2011; Hendershott and Riordan, 2011). The following hypothesis predicts that algorithmic trading has either no impact or leads to an improvement in market quality.

Hypothesis$_{4.1}$: *An increase in algorithmic trading will either have no impact or lead to an improvement in market quality.*

Jovanovic and Menkveld (2011) model ATs as a new form of market maker on limit order markets. If a trader places a limit order, a common value innovation occurring after the placement can leave the order stale and provides a trading option that can be picked off by other traders. This increases the adverse selection costs faced by the limit order trader, resulting in higher execution costs. The superior information processing speed of ATs creates an edge in quickly updating limit orders as public information arrives. ATs may therefore act as middlemen in limit order markets for other limit order traders, as their limit orders are continuously refreshed, which inhibits informed traders from taking advantage of this trading option.

Kirilenko et al. (2011) however find that during periods of market stress, algorithmic traders display behaviour inconsistent with traditional market makers. A designated market maker differs from a strategic trader as they have an affirmative obligation to maintain two-sided markets during exchange hours and to buy and sell at their displayed bids and offers. An analysis of the behaviour of HFTs during the flash crash of 6 May, 2010 reveals that HFTs trade aggressively in the direction of price changes and comprise a large percentage of total trading activity, but do not accumulate significant inventory positions. They are not willing to either accumulate large positions or sustain large losses and in rebalancing their positions, they may also compete for liquidity, thus amplifying price volatility. An implication of this result is that algorithmic traders may have a negative impact on market quality during intraday price falls. The following hypothesis predicts that algorithmic trading leads to a decline in market quality during intraday periods of negative returns.

Hypothesis$_{4.2}$: *During intraday periods of negative returns, an increase in algorithmic trading will lead to a reduction in market quality.*

There is also the possibility that algorithmic trading may differentially impact market quality during different market environments. However, the empirical evidence suggests that this is not the case. Hasbrouck and Saar (2012) find that the impact of low latency activity (a proxy for algorithmic trading) enhances market quality over periods dominated by flat or rising prices and during periods dominated by falling prices and economic uncertainty. Brogaard (2012) examines the effect of HFTs on volatility over the 2008-09 period, which is a time period characterized by heightened volatility. Examining the short sale ban in 2008 that removed a fraction of HFT participants, the author finds HFTs reduce volatility. The following hypothesis predicts that the effect of algorithmic trading on market quality should be similar across different market conditions.

Hypothesis$_{4.3}$: *There is no difference in the effect of algorithmic trading on market quality during bull and bear markets.*

Contrarian traders are traders that increase their buying when prices fall and increase their selling when prices are rising. Kaniel et al. (2008) argue that contrarian traders act as liquidity providers. Institutional investors requiring immediacy offer price concessions to encourage other investors to take the other side of the trade. Momentum traders conversely act as liquidity demanders. The results of Kirilenko et al. (2011) show that during the Flash Crash HFTs acted as momentum traders, aggressively selling to keep inventories near a target inventory level. Herding and positive-feedback trading by ATs may result in a reduction in market quality (Culter et al., 1990). The following hypothesis predicts that ATs engage in momentum trading during intraday periods of negative returns.

Hypothesis$_{4.4}$: *Algorithmic traders act as liquidity demanders during price falls.*

4.3 Australian Securities Exchange

The Australian Securities Exchange (ASX) was formed in July 2006 through the merger of the Australian Stock Exchange and the Sydney Futures Exchange. The ASX operates as a fully automated continuous order-driven market. Orders are submitted electronically by buyers and sellers through the ASX Trade, an electronic order book for securities listed on the ASX. ASX Trade replaced the Integrated Trading System (ITS) in November 2010, which earlier replaced the Stock Exchange Automated Trading System (SEATS) in October 2006. The system facilitates the trading of equities, debt securities and warrants on ASX's markets. Orders are automatically matched based on price and time priority. Submitted orders are filled by crossing with either the best bid (if it is a sell order) or the best ask (in the case of a buy order). Unfilled orders become standing limit orders which fill the bid-ask schedule. The information available to all market participants on the bid-ask schedule include any standing limit orders, its order type, volume and price. A short series of the most recent executions are also visible.

The ASX facilitates trades during exchange-open hours between 10:00 am to 4:00 pm. Brokers can submit orders in the pre-open from 7:00-10:00 am in preparation for the market opening. A single price call auction takes place for each stock between 10:00-10:09:15 am using a specific algorithm. To prevent brokers from distorting prices, the actual opening time is generated randomly and occurs within 15 seconds of the prescribed opening time. Normal trading takes place between 10:00 am and 4:00 pm under a continuous double-sided auction where price and time priority rules apply. Trading ceases at 4:00 pm and the market is placed in pre-close until 4:10 pm. Brokers enter, amend and cancel orders in preparation for the closing single price auction which takes place between 4:10 pm and 4:12 pm.

4.2 Data and Descriptive Statistics

An internal database is directly sourced from the ASX. The dataset consists of trade by trade data for the top 100 capitalised stocks listed on the ASX from July 2, 2007 to October 26, 2009. The unique feature of this dataset is that it consists of a field that identifies the source of each trade. Using this identifier, this study determines which trades are associated with *human traders* or *computer based systems*. This field, which is a five character user code, consists of two types of user code. The first group of user code is five *letter* user code that consists of a username of a market participant associated with each submitted order indicate the actions of a human trader.[3] The second group of user code is five *alphanumeric* characters which indicate that the order is submitted through a computer based system gateway.

[3] User code consists of four characters of the participant's surname, followed by a single character of his/her first name. For example, the participant whose name is Anthony Flint is identified as "FLINA".

Note that the first (second) group is a *proxy* for human (computer) based trading; it is possible that human traders submit their orders through the computer based system gateway, and that a computer based trading strategy is executed through a terminal classified as human based.[4][5] This study further classifies the group of computer based system as either ATs or other computer based trading platform, referred to as Broker Engines (BEs), based on the average trade size and trading frequency from the relevant gateway, with BE's trading in both larger size and lower frequency than algorithmic trading gateways.[6]

This study combines the ASX internal dataset with ten levels of order book data sourced from Thompson Reuters Tick History (TRTH) provided by the Securities Industry Research Centre of Asia Pacific (SIRCA). The combined dataset provides a reconstruction of the full order book for each trade. For each trade, the following information is provided in the dataset: (*i*) the direction of the trade (i.e., buy/sell), (*ii*) the share volume, (*iii*) stock code, (*iv*) date, (*v*) time stamp to the nearest hundredth of a second, (*vi*) initiator indication (indicating which participant initiated the trade), (*vii*) market participant identifier (ASX internal field described above), and (*viii*) bid and ask quotes and share volume at each of the ten depth levels. Information from the liquidity suppliers includes trade price, volume, and user code.

[4] Further information about each user code is contained in the "ASX source file". This file indicates that each participant can be associated with multiple user codes through which they can process orders.

[5] This classification scheme originally identifies retail brokers (such as Commonwealth Securities Limited ("CommSec") and ETRADE Australia Securities Ltd ("E*TRADE Australia")) as computer based traders; however, these brokers are predominantly retail-based, and are subsequently classified as human traders.

[6] To further test the robustness of the computerised user code classifications, the sample is cross tested by applying a filter based on the frequency of trades and average dollar volume across each six month sub-sample.

Table 6-1 reports summary statistics for the 100 sample stocks by trader type. The average dollar traded volume per 15-minute interval is $2,787,462, suggesting a high level of trading activity in our sample stocks. A significant proportion of trading volume is conducted by ATs, averaging $996,473 in dollar traded volume over each 15-minute interval. Algorithmic trading dollar volumes are split evenly between buys and sells, with average dollar buy volumes accounting for about 51% of algorithmic trading dollar volumes.

Table 4-1
Descriptive Statistics

This table presents summary statistics for average trading activity per 15-minute interval over the period from 2 July, 2007 to 26 October, 2009 for 100 sample stocks. *Algorithmic Trades* are trades classified as originating from a computer algorithm. *All Trades* include all trades for the entire sample period. *Total Ratio*, *Buy Ratio,* and *Sell Ratio* are the trading activity ratios. Each ratio is calculated by dividing the trading value contributed by the AT by order type by total dollar volume transacted in the interval.

	Algorithmic Trades			*All Trades*
	Total	*Buy*	*Sell*	*Total*
Panel A: Average trading activity in a 15-minute interval as measured by dollar volume transacted				
Mean	996,473	507,264	489,209	2,787,462
Median	387,253	189,545	183,542	880,095
Max	114,105,434	109,810,983	42,726,422	2,390,425,843
Min	0	0	0	1
Standard Deviation	1,013,692	970,294	927,707	6,616,942
Panel B: Average trading activity in a 15-minute interval as measured by share volume transacted				
Mean	84,291	42,751	41,238	263,255
Median	40,432	19,433	18,635	92,526
Max	25,523,166	24,564,580	8,904,090	148,207,452
Min	0	0	0	1
Standard Deviation	186,482	104,276	97,569	842,649
Panel C: Average trading activity in a 15-minute interval as measured by number of trades				
Mean	61	32	29	107
Median	40	20	18	70
Max	1,573	1,125	1,077	2,709
Min	0	0	0	1
Standard Deviation	67	37	35	118
Panel D: Average trading activity in a 15-minute interval as measured by trading ratios				
	Total Ratio	*Buy Ratio*	*Sell Ratio*	
Mean	0.4954	0.2519	0.2435	
Median	0.4956	0.2239	0.2148	
Max	1	1	1	
Min	0	0	0	
Standard Deviation	0.2133	0.1640	0.1614	

4.3 Research Design

To analyze the relation between algorithmic trading and subsequent market quality, the trading day is partitioned into multiple time intervals. However, the length of the time interval depends on two contradicting factors. First, as ATs can react fast to changing market conditions, the time interval should not be too long to ensure the effects of algorithmic trading on market quality are captured. However, the time interval should not be too short to limit the number of transactions within each interval. Hendershott et al. (2014) examine liquidity measures in 5 and 30 minute intervals. In this study, each trading day is divided into 15-minute intervals. Trading hours on the ASX are between 10:00 and 16:00. A single price call auction takes place between 10:00-10:10 through the use of a specific algorithm. This time period is removed from the sample, as the nature of the orders submitted during this period is fundamentally different from the continuous double sided auction that takes place on the ASX limit order book.

Hendershott (2011) state that algorithmic trading should be normalised by trading volume, otherwise it would proxy for overall changes in trading volume. Following Lakanishok et al. (1992), Chordia and Subrahmanyam (2004), and Li and Wang (2010), algorithmic trading volume is measured as:

$$TOTAL_{it} = \frac{AT\_Buying\ Volume_{it} + AT\_Selling\ Volume_{it}}{Total\ Trading\ Volume_{it}} \tag{4.1}$$

where $AT\_Buying\ Volume_{it}$ ($AT\_Selling\ Volume_{it}$) is the total dollar value of market and limit order purchases (sales) made by ATs for stock i in interval t. This consists of trades undertaken by an AT, and does not include broker engine trades. $Total\ Trading\ Volume_{it}$ is the total dollar value of all market and limit order buys and sells for stock i in interval t. This includes algorithmic, broker engine and human trades. Trading volume ratios for buys and sells are also calculated separately, where algorithmic trading buy volume is measured as:

$$BUY_{it} = \frac{AT\_Buying\ Volume_{it}}{Total\ Trading\ Volume_{it}} \tag{4.2}$$

and algorithmic trading sell volume is measured as:

$$SELL_{it} = \frac{AT\_Selling\ Volume_{it}}{Total\ Trading\ Volume_{it}} \tag{4.3}$$

where algorithmic trading buying, selling, and total trading volume is calculated as before.

Following Harris (1994), liquidity indicators analysed include the bid-ask spread, market depth, and short-term volatility. The bid-ask spread is defined as:

$$PBAS_t = \frac{inside\ ask_t - inside\ bid_t}{\left(\frac{inside\ ask_t + inside\ bid_t}{2}\right)} \tag{4.4}$$

where $PBAS_t$ is the percentage bid-ask spread for stock i at time period t, the inside ask is the lowest ask price at time period t, and the inside bid is the highest bid price at period t. The mid-point is used to avoid problems associated with bid-ask bounce. It is computed for every trade for each stock, and is averaged over all trades in each interval. As a robustness test, the percentage effective spread is also employed, and is defined as twice the difference between the actual execution price and the market quote at the time of each trade. Market depth is calculated using two measures. Best depth is defined as the logarithm of the total number of shares available at the best bid and the best ask (Harris, 1994). It is computed for every trade for each stock and is averaged across all trades for each 15-minute interval. The second measure is defined as the sum of the volume of shares at each bid and ask price throughout the limit-order book. Volatility is measured using the intraday high-low price range estimator proposed by Parkinson (1980). The volatility measure is given as follows:

$$\sigma = \sqrt{\frac{(\ln high - \ln low)^2}{4ln2}}, i = 1, 2, \ldots, N; t = 1,2, \ldots, T. \quad (4.5)$$

where volatility is calculated for the i^{th} stock in the t^{th} time interval; $high$ and low refers to the highest traded price and lowest traded price in each 15-minute interval. To avoid the effect of bid-ask bounce, the midpoint of the prevailing bid-ask spread is used as the traded price.

4.4 Results

4.4.1 Multiple Regressions of Market Quality on Lagged Algorithmic Volume

To determine the impact of algorithmic trading volume on market quality, Hendershott et al. (2014) use an instrumental variable regression to determine causal impacts. They argue that the decision to engage in algorithmic trading may depend on liquidity. To account for this potential endogeneity issue, the lagged ratio of algorithmic trading volume to total volume is used as an instrument. The intuition behind this is that lagged algorithmic trading precedes changes in market quality indicators. This may not overcome all endogeneity issues however if the liquidity variables are serially correlated. Consequently, when submitting an order using an algorithm, traders may form expectations about future bid-ask spreads and depth. In estimating the impact of algorithmic trading on market quality, Hendershott et al. (2011) include trading volument and volatility as control variables in their regression. Hendershott et al. (2011) note that the quoted bid-ask spread is problematic as traders may be willing to trade inside the bid-ask quote. Consequently, both the quoted bid-ask spread and effective spread are included. To examine the relation between algorithmic trading volume and subsequent market quality, the following regressions are estimated for each individual stock:

$$\begin{aligned} BAS_t = \ & \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} \\ & + \beta_4 BAS_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t, \end{aligned} \tag{4.6}$$

$$\begin{aligned} QD_t = \ & \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} \\ & + \beta_4 QD_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t, \end{aligned} \tag{4.7}$$

$$\begin{aligned} \sigma_t = \ & \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} \\ & + \beta_4 BAS_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t, \end{aligned} \tag{4.8}$$

$$\begin{aligned} \sigma_t = \ & \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} \\ & + \beta_4 QD_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t, \end{aligned} \tag{4.9}$$

where BAS_t represents the percentage bid-ask spread and effective spread for time interval t, respectively; QD_t represents the natural logarithm of the best and total depth at time interval t; σ_t is the intraday high-low price range estimator; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}) and sell ($SELL_{t-1}$) ratios; and NT_t is the number of trades executed during time interval t. BAS_{t-1}, QD_{t-1}, and σ_{t-1} are to control for serial-autocorrelation in the dependent variables. M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day, and zero otherwise; and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours, and zero otherwise. The inclusion of intraday time dummy variables controls for intraday variation. The volatility regression is estimated four times, with each liquidity variable ($PBAS_{t-1}$,PES_{t-1},BQD_{t-1}, and TQD_{t-1}) used as an explanatory variable in the regression. Each equation is estimated separately for each stock using the Generalized Method of Moments (GMM); the resulting *t*-statistics are robust to heteroskedasticity and autocorrelation (Newey and West, 1987).

The regression results for percentage spreads are reported in Table 4-2, which are estimated using the total number of algorithmic trades in the interval, as well as algorithmic buy and sell trades. Table 4-2 reports the cross-sectional means of the coefficients and associated *t*-statistics. Results show that for total algorithmic trades, both bid-ask spread measures are positively associated with lagged algorithmic trading volume; the average *t*-statistic for the bid-ask spread (effective spread) is 2.36 (2.36). In contrast, examining buy and sell trades individually, the coefficients on the ratios are not distinguishable from zero. This is different to Hendershott et al. (2014) who show that algorithmic trading resulted in a reduction in bid-ask spreads.

Table 4-2
Percentage Spreads and Lagged Algorithmic Trading Volume

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression model is specified as follows:

$$BAS_t = \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} + \beta_4 BAS_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t$$

where BAS_t represents the percentage bid-ask spread ($PBAS_{t-1}$) and effective spread (PES_{t-1}) during time interval t; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; σ_{t-1} is the intraday high-low price range estimator at time interval $t-1$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average t-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficients for $RATIO_{t-1}$, NT_t, M_t, and $A_t$are multiplied by 10^5, and those for *Constant*, σ_{t-1}, $PBAS_{t-1}$, and PES_{t-1} are multiplied by 10^2.

	Total		*Buy*		*Sell*	
	$PBAS_t$	PES_t	$PBAS_t$	PES_t	$PBAS_t$	PES_t
Constant	0.02	0.03	0.02	0.03	0.02	0.03
	(12.08)	(12.00)	(12.90)	(12.82)	(12.74)	(12.66)
$RATIO_{t-1}$	2.00	4.00	2.00	2.00	2.00	3.00
	(2.36)	(2.36)	(1.06)	(1.06)	(1.84)	(1.84)
NT_t	-0.07	-0.10	-0.07	-0.10	-0.07	-0.10
	(-1.91)	(-1.90)	(-1.89)	(-1.89)	(-1.90)	(-1.90)
σ_{t-1}	1.03	1.55	1.02	0.015	0.010	0.015
	(6.07)	(6.06)	(6.02)	(6.01)	(6.03)	(6.02)
$PBAS_{t-1}$	85.33		85.42		85.41	
	(162.43)		(163.69)		(163.98)	
PES_{t-1}		85.29		85.38		85.37
		(161.58)		(162.83)		(163.13)
M_t	-0.20	-0.30	-0.20	-0.30	-0.20	-0.30
	(-2.57)	(-2.56)	(-2.61)	(-2.61)	(-2.61)	(-2.60)
A_t	0.10	0.10	0.10	0.10	0.10	0.10
	(0.80)	(0.79)	(0.70)	(0.69)	(0.74)	(0.73)
R^2	0.79	0.79	0.79	0.79	0.79	0.79

An important determinant of market quality is the available size to trade at both the bid and ask side of the market. For larger market participants, a reduction in depth at or near the best quotes may result in worse execution prices as traders consume liquidity to fill the order. Harris (1990) argues that liquidity has both a price dimension (i.e., bid-ask spread) and a quantity dimension (i.e., depth). For instance, if an AT efficiently picks off stale limit orders, limit order traders may reduce their order size in response. Hendershott et al. (2011) show that higher algorithmic trading volume is negatively associated with market depth.

Table 4-3
Quoted Depths and Lagged Algorithmic Trading Volume

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression model is specified as follows:

$$QD_t = \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} + \beta_4 QD_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t$$

where QD_t represents the natural logarithm of the best quoted depth (BQD_{t-1}) and total quoted depth (TQD_{t-1}) during time interval t; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; σ_{t-1} is the intraday high-low price range estimator at time interval $t-1$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average t-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficient for NT_t is multiplied by 10^4, and the coefficients for $RATIO_{t-1}$, M_t, and A_t are multiplied by 10^2.

	Total		*Buy*		*Sell*	
	BQD_t	TQD_t	BQD_t	TQD_t	BQD_t	TQD_t
Constant	1.08	0.53	1.06	0.52	1.07	0.52
	(28.26)	(19.81)	(28.73)	(19.93)	(28.92)	(20.02)
$RATIO_{t-1}$	-1.23	-0.76	-0.13	-0.38	-1.69	-0.86
	(-1.16)	(-1.70)	(-0.20)	(-0.76)	(-1.23)	(-1.40)
NT_t	2.30	-0.30	2.30	-0.30	2.30	-0.30
	(2.60)	(-0.58)	(2.53)	(-0.64)	(2.54)	(-0.64)
σ_{t-1}	-6.64	-2.29	-6.58	-2.26	-6.59	-2.27
	(-7.73)	(-4.98)	(-7.68)	(-4.94)	(-7.70)	(-4.95)
BQD_{t-1}	0.89		0.89		0.89	
	(282.44)		(285.08)		(284.79)	
TQD_{t-1}		0.95		0.95		0.95
		(561.90)		(566.76)		(565.89)
M_t	1.01	1.08	1.04	1.09	1.02	1.09
	(1.57)	(3.52)	(1.62)	(3.56)	(1.59)	(3.55)
A_t	2.05	0.76	2.07	0.78	2.05	0.77
	(4.64)	(3.07)	(4.68)	(3.13)	(4.66)	(3.12)
R^2	0.81	0.92	0.81	0.92	0.81	0.92

Table 4-3 shows the regression results for both best and total depth. In contrast to Hendershott et al. (2011), the relationship between algorithmic trading volume and subsequent market depth is insignificant for both depth measures.

Table 4-4
Volatility and Lagged Algorithmic Trading Volume

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression models are specified as follows:

$$\sigma_t = \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{it-1} + \beta_4 BAS_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t$$
$$\sigma_t = \beta_0 + \beta_1 RATIO_{t-1} + \beta_2 NT_t + \beta_3 \sigma_{t-1} + \beta_4 QD_{t-1} + \beta_5 M_t + \beta_6 A_t + \varepsilon_t$$

where σ_t is the intraday high-low price range estimator at time interval t; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; BAS_t represents the percentage bid-ask spread ($PBAS_{t-1}$) and effective spread (PES_{t-1}) during time interval t; QD_t represents the natural logarithm of the best quoted depth (BQD_{t-1}) and total quoted depth (TQD_{t-1}) during time interval t; NT_t is the number of trades executed during time interval$t$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average *t*-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficient for *Constant*, $RATIO_{t-1}$, NT_t, PES_{t-1}, TQD_{t-1}, M_t, and A_t are multiplied by 10^4.

	Total				*Buy*				*Sell*			
	$PBAS_t$	PES_t	BQD_t	TQD_t	$PBAS_t$	PES_t	BQD_t	TQD_t	$PBAS_t$	PES_t	BQD_t	TQD_t
Constant	-1.60	-1.60	17.60	32.00	-1.40	-1.40	17.90	32.20	-1.40	-1.40	17.80	32.10
	(-1.06)	(-1.05)	(5.14)	(5.72)	(-0.69)	(-0.68)	(5.43)	(5.92)	(-0.79)	(-0.78)	(5.41)	(5.87)
$RATIO_{t-1}$	0.50	0.50	0.60	0.40	0.30	0.30	0.20	0.04	0.30	0.30	0.40	0.20
	(0.84)	(0.84)	(0.73)	(0.56)	(0.32)	(0.32)	(0.17)	(0.06)	(0.64)	(0.64)	(0.53)	(0.40)
NT_t	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
	(8.77)	(8.77)	(8.35)	(8.45)	(8.78)	(8.78)	(8.36)	(8.45)	(8.78)	(8.78)	(8.37)	(8.46)
σ_{t-1}	0.72	0.72	0.73	0.73	0.72	0.72	0.73	0.73	0.72	0.72	0.73	0.73
	(43.74)	(43.74)	(47.32)	(46.20)	(43.74)	(43.75)	(47.38)	(46.28)	(43.78)	(43.78)	(47.44)	(46.33)
$PBAS_{t-1}$	0.56				0.58				0.58			
	(6.22)				(6.29)				(6.28)			
PES_{t-1}		-1.40				-1.40				-1.40		
		(-4.45)				(-4.54)				(-4.52)		
BQD_{t-1}			0.38				0.38				0.38	
			(6.22)				(6.28)				(6.27)	
TQD_{t-1}				-2.40				-2.40				-2.40
				(-5.34)				(-5.40)				(-5.37)
M_t	-0.10	-0.10	0.10	0.10	-0.10	-0.10	0.10	0.10	-0.10	-0.10	0.10	0.10
	(-0.57)	(-0.57)	(-0.33)	(-0.30)	(-0.57)	(-0.57)	(-0.34)	(-0.31)	(-0.58)	(-0.57)	(-0.34)	(-0.30)
A_t	1.70	1.70	1.70	1.70	1.70	1.70	1.70	1.70	1.70	1.70	1.70	1.70
	(2.30)	(2.30)	(2.47)	(2.42)	(2.29)	(2.29)	(2.46)	(2.41)	(2.29)	(2.29)	(2.47)	(2.42)
R^2	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59

The last market quality variable examined is volatility. The literature examining algorithmic and high frequency trading find that the presence of algorithmic trading does not contribute to higher volatility, and may actually lower it (Hendershott and Riordan, 2011). Hendershott and Riordan (2011) suggest that algorithmic trading is more likely to dampen volatility than to increase it, as ATs can monitor the market and demand liquidity when it is cheap and supply liquidity when it is expensive, thereby moderating changes in liquidity. Table 4-4 shows the relation between algorithmic trading volume on subsequent volatility. In line with Hendershott and Riordan (2011), algorithmic trading does not contribute to higher volatility. Across all regression specifications, the coefficients on algorithmic trading variables are not distinguishable from zero, consistent with the first hypothesis ($H_{4,1}$).

4.4.2 Algorithmic Trading Volume during Periods of Market Stress

The results in the previous section show that market quality is not associated with lagged algorithmic trading volume (except for the total ratio). This is similar to other studies finding that algorithmic trading does not result in a deterioration in market quality. However, Kirilenko et al. (2011) document that algorithmic trading had a negative impact on the market during one period of extreme market stress. Examining the flash crash of May 6, 2010, the authors find that HFT was not responsible for the crash, though their responses exacerbated market volatility during the period. Kirilenko et al. (2011) find that HFTs exhibit trading patterns inconsistent with traditional market makers, through trading aggressively in the direction of price changes and not accumulating significant inventory positions. Thus, HFTs do not supply liquidity when prices move against their trading position. Further, they can exacerbate price movements by competing for liquidity as they try to rebalance their inventory positions. The results of Kirilenko et al. (2011), however, apply to one extreme event. It is unknown whether such behaviour is representative of algorithmic trading during less extreme market episodes.

To test this, each time interval is classified into up and down intervals for each stock, based on whether the return is positive or non-positive. This is defined as:

$$D_{it}^{Up} \equiv \begin{cases} 1 \; if \; R_{it} > 0 \\ 0 \; if \; R_{it} < 0 \end{cases} \tag{4.10}$$

$$\text{and } D_{it}^{Down} \equiv 1 - \; D_{it}^{Up} \tag{4.11}$$

The following regression models are then estimated for each stock:

$$\begin{gathered} BAS_t = \beta_0 + \beta_1 RATIO_{t-1}^{+} + \beta_2 RATIO_{t-1}^{-} + \beta_3 NT_t + \beta_4 \sigma_{t-1} \\ + \beta_5 BAS_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t \end{gathered} \tag{4.12}$$

$$\begin{gathered} QD_t = \beta_0 + \beta_1 RATIO_{t-1}^{+} + \beta_2 RATIO_{t-1}^{-} + \beta_3 NT_t + \beta_4 \sigma_{t-1} \\ + \beta_5 QD_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t \end{gathered} \tag{4.13}$$

$$\begin{gathered} \sigma_t = \beta_0 + \beta_1 RATIO_{t-1}^{+} + \beta_2 RATIO_{t-1}^{-} + \beta_3 NT_t + \beta_4 \sigma_{t-1} \\ + \beta_5 BAS_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t \end{gathered} \tag{4.14}$$

$$\begin{gathered} \sigma_t = \beta_0 + \beta_1 RATIO_{t-1}^{+} + \beta_2 RATIO_{t-1}^{-} + \beta_3 NT_t + \beta_4 \sigma_{t-1} \\ + \beta_5 QD_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t \end{gathered} \tag{4.15}$$

where $RATI0_{t-1}^{+} \equiv RATIO_{t-1} \times D_{t-1}^{Up}$ and $RATIO_{t-1}^{-} \equiv D_{t-1}^{Down}$. The findings of Kirilenko, Kyle, Samadi and Tuzun (2011) suggest that algorithmic trading can have a negative impact on trading during market downturns if algorithmic trading increase their demand for liquidity, or reduce their supply of liquidity, as total liquidity contracts, or both.

Table 4-5 shows the results for bid-ask spreads and effective spreads. Panel A of Table 4-5 shows that lagged algorithmic trading volume is positively related to bid-ask spreads and effective spreads only for down intervals. This positive relation is significant during down intervals with an average *t*-statistic of 2.97 for both bid-ask spreads and effective spreads, and insignificant for up intervals with an average *t*-statistic of 1.64 and 1.63, respectively. These results are consistent across buy and sell trades, with the coefficients in the regressions for both spread measures positive and significant for down intervals, and insignificant for up intervals. These results show that the relation between market quality and lagged algorithmic trading volume is not independent of market conditions, suggesting that the findings of Kirilenko et al. (2011) can be extended to less extreme market falls.

The results for market depth are shown in Table 4-6. After controlling for lagged depth and volatility, intraday variation and trading activity, total depth is significantly and negatively related to lagged algorithmic trading volume. Examining all trades, the average coefficient on the lagged algorithmic trading volume during down intervals is significantly negative with an average *t*-statistic of -2.97. The relationship between lagged algorithmic trading volume and market depth is, however, insignificant when QD_t is computed using the best quotes (average *t*-statistic of -1.96), suggesting that the main impact of lagged algorithmic trading volume is on depth throughout the limit order book. Similar to the spread results, β_1 is insignificant for both best and total depth. The results are similar for buys and sells, with β_1 being insignificant across both best and total depth, while β_2 is significantly negative for total depth, not best depth.

Table 4-5
Percentage Spreads and Lagged Algorithmic Trading Volume during Up and Down Markets

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression model is specified as follows:

$$BAS_t = \beta_0 + \beta_1 RATIO^{+}_{t-1} + \beta_2 RATIO^{-}_{t-1} + \beta_3 NT_t + \beta_4 \sigma_{t-1} + \beta_5 BAS_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t$$

where BAS_t represents the percentage bid-ask spread ($PBAS_{t-1}$) and effective spread (PES_{t-1}) during time interval t; $RATIO^{+}_t$ and $RATIO^{-}_t$ denote the algorithmic trading variables on up and down intervals, respectively; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; σ_{t-1} is the intraday high-low price range estimator at time interval $t-1$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average t-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficients for $RATIO^{+}_{t-1}$, $RATIO^{-}_{t-1}$, NT_t, M_t, and $A_t$are multiplied by 10^5, and those for *Constant*, σ_{t-1}, $PBAS_{t-1}$, and PES_{t-1} are multiplied by 10^2.

	Total		*Buy*		*Sell*	
	$PBAS_t$	PES_t	$PBAS_t$	PES_t	$PBAS_t$	PES_t
Constant	0.02	0.03	0.02	0.03	0.02	0.03
	(11.82)	(11.74)	(12.64)	(12.56)	(12.47)	(12.39)
$RATIO^{+}_t$	2.00	3.00	1.00	2.00	1.00	1.00
	(1.64)	(1.63)	(0.46)	(0.46)	(0.94)	(0.93)
$RATIO^{-}_t$	3.00	5.00	3.00	4.00	3.00	4.00
	(2.97)	(2.97)	(2.04)	(2.04)	(2.71)	(2.71)
NT_t	-0.08	-0.10	-0.08	-0.10	-0.08	-0.10
	(-2.16)	(-2.16)	(-2.15)	(-2.15)	(-2.15)	(-2.15)
σ_{t-1}	1.07	1.62	1.07	1.61	1.07	1.61
	(6.27)	(6.26)	(6.23)	(6.22)	(6.23)	(6.23)
$PBAS_{t-1}$	84.71		84.80		84.79	
	(134.93)		(136.15)		(136.04)	
PES_{t-1}		84.68		84.77		84.76
		(134.16)		(135.37)		(135.26)
M_t	-2.00	-3.00	-2.00	-3.00	-2.00	-3.00
	(-2.45)	(-2.44)	(-2.49)	(-2.48)	(-2.48)	(-2.47)
A_t	1.00	1.00	1.00	1.00	1.00	1.00
	(0.77)	(0.77)	(0.68)	(0.67)	(0.73)	(0.73)
R^2	0.79	0.78	0.79	0.78	0.79	0.78

Table 4-6
Quoted Depths and Lagged Algorithmic Trading Volume during Up and Down Markets

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression model is specified as follows:

$$QD_t = \beta_0 + \beta_1 RATIO^+_{t-1} + \beta_2 RATIO^-_{t-1} + \beta_3 NT_t + \beta_4 \sigma_{t-1} + \beta_5 QD_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t$$

where QD_t represents the natural logarithm of the best quoted depth (BQD_{t-1}) and total quoted depth (TQD_{t-1}) during time interval t; $RATIO^+_t$ and $RATIO^-_t$ denote the algorithmic trading variables on up and down intervals, respectively; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; σ_{t-1} is the intraday high-low price range estimator at time interval $t-1$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average t-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficient for NT_t is multiplied by 10^4, and the coefficients for $RATIO^+_{t-1}$, $RATIO^-_{t-1}$, M_t, and A_t are multiplied by 10^2.

	Total		*Buy*		*Sell*	
	BQD_t	TQD_t	BQD_t	TQD_t	BQD_t	TQD_t
Constant	1.18	0.56	1.16	0.55	1.17	0.55
	(27.77)	(19.41)	(28.20)	(19.54)	(28.41)	(19.61)
$RATIO^+_t$	-1.46	-0.48	-0.05	0.12	-1.81	-0.32
	(-1.01)	(-0.87)	(-0.02)	(0.04)	(-0.82)	(-0.35)
$RATIO^-_t$	-2.10	-1.48	-1.58	-1.65	-2.50	-1.89
	(-1.96)	(-2.97)	(-1.36)	(-2.54)	(-1.88)	(-2.94)
NT_t	3.30	-0.20	3.30	-0.20	3.20	-0.20
	(3.49)	(-0.15)	(3.42)	(-0.19)	(3.42)	(-0.20)
σ_{t-1}	-7.02	-2.47	-6.97	-2.44	-6.96	-2.44
	(-7.75)	(-5.11)	(-7.71)	(-5.05)	(-7.72)	(-5.06)
BQD_{t-1}	0.88		0.88		0.88	
	(244.37)		(246.75)		(246.39)	
TQD_{t-1}		0.95		0.95		0.95
		(485.73)		(489.58)		(489.45)
M_t	1.24	1.16	1.27	1.17	1.26	1.17
	(1.67)	(3.48)	(1.71)	(3.51)	(1.69)	(3.50)
A_t	2.12	2.12	2.15	2.12	2.13	2.12
	(4.61)	(3.09)	(4.65)	(3.16)	(4.62)	(3.12)
R^2	0.79	0.91	0.79	0.91	0.79	0.91

The results for volatility presented in Table 4-7 are similar, with a rise in lagged algorithmic trading volume generally being related to an increase in volatility during periods of decreasing prices, though not during periods of increasing prices. Focusing on β_1 for all trades using $PBAS_{t-1}$ as a regressor, the average coefficient is negative with an average t-statistic of -0.44. The average coefficient estimate for $Ratio^-_t$, however, is positive with an average *t*-statistic of 2.30. Similar results are found using effective spreads and both depth measures as control variables. These results hold for both buys and sells.

In line with previous literature, the results in Section 4.4.1 indicate that higher algorithmic trading volume in the market is not associated with a deterioration in market quality. In contrast, this section suggests that such results could be biased as they fail to take into account the direction of prices. Dividing the sample into periods of increasing and decreasing prices, results reveal that lagged algorithmic trading volume is related to a reduction in liquidity and an increase in volatility during periods when the market is falling, and has no association with market quality during periods when the market is increasing. This is consistent with the second hypothesis ($H_{4,2}$). This aligns with the findings such as Kirilenko et al. (2011) that document that algorithmic trading had a negative impact on the market during periods of market stress.

Table 4-7
Volatility on Lagged Algorithmic Trading Volume during Up and Down Markets

This table reports the GMM estimates from the regressions estimated for each of the 100 stocks ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to October 26, 2009. The regression models are specified as follows:

$$\sigma_t = \beta_0 + \beta_1 RATIO^{+}_{t-1} + \beta_2 RATIO^{-}_{t-1} + \beta_3 NT_t + \beta_4 \sigma_{t-1} + \beta_5 BAS_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t$$

$$\sigma_t = \beta_0 + \beta_1 RATIO^{+}_{t-1} + \beta_2 RATIO^{-}_{t-1} + \beta_3 NT_t + \beta_4 \sigma_{t-1} + \beta_5 QD_{t-1} + \beta_6 M_t + \beta_7 A_t + \varepsilon_t$$

where σ_t is the intraday high-low price range estimator at time interval t; BAS_t represents the percentage bid-ask spread ($PBAS_{t-1}$) and effective spread (PES_{t-1}) during time interval t; QD_t represents the natural logarithm of the best quoted depth (BQD_{t-1}) and total quoted depth (TQD_{t-1}) during time interval t; $RATIO^{+}_t$ and $RATIO^{-}_t$ denote the algorithmic trading variables on up and down intervals, respectively; $RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; σ_{t-1} is the intraday high-low price range estimator at time interval $t-1$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average *t*-statistics are in parentheses. The R^2 is the cross-sectional average adjusted R-square. To adjust the units for presentation, the coefficients for *Constant*, $RATIO^{+}_t$, $RATIO^{-}_t$, NT_t, BQD_{t-1}, TQD_{t-1}, M_t, and A_t are multiplied by 10^4, and those for σ_{t-1}, $PBAS_{t-1}$, and PES_{t-1} are multiplied by 10^2.

	Total				*Buy*				*Sell*			
	$PBAS_t$	PES_t	BQD_t	TQD_t	$PBAS_t$	PES_t	BQD_t	TQD_t	$PBAS_t$	PES_t	BQD_t	TQD_t
Constant	-2.10	-2.10	25.10	41.60	-2.00	-1.90	24.90	41.20	-2.00	-1.90	41.50	41.50
	(-1.24)	(-1.23)	(6.02)	(6.41)	(-0.94)	(-0.93)	(6.22)	(6.56)	(-1.00)	(-0.99)	(6.56)	(6.56)
$RATIO^{+}_t$	-0.80	-0.80	-1.30	-1.40	-1.30	-1.30	-1.90	-2.00	-2.20	-2.20	-2.70	-2.70
	(-0.44)	(-0.44)	(-1.04)	(-1.10)	(-0.83)	(-0.83)	(-1.35)	(-1.39)	(-1.18)	(-1.18)	(-1.70)	(-1.70)
$RATIO^{-}_t$	2.20	2.30	2.00	2.00	3.00	3.00	2.70	2.70	3.00	3.00	3.00	3.00
	(2.30)	(2.31)	(2.06)	(2.04)	(2.13)	(2.13)	(2.03)	(2.04)	(2.74)	(2.74)	(2.70)	(2.70)
NT_t	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
	(8.77)	(8.77)	(8.44)	(8.51)	(8.77)	(8.77)	(8.43)	(8.49)	(8.78)	(8.78)	(8.51)	(8.51)
σ_{t-1}	70.25	71.80	70.26	71.38	70.19	71.76	70.19	71.33	70.24	71.39	70.24	71.39
	(42.80)	(46.54)	(42.81)	(45.45)	(42.76)	(46.55)	(42.77)	(45.47)	(42.82)	(45.54)	(42.82)	(45.54)
$PBAS_{t-1}$	59.75				59.94				59.96			
	(5.93)				(6.00)				(5.99)			
PES_{t-1}		39.66				39.78				39.79		
		(5.93)				(5.99)				(5.98)		
BQD_{t-1}			-2.10				-2.10				-3.20	
			(-5.50)				(-5.51)				(-6.15)	
TQD_{t-1}				-3.20				-3.20				-3.20
				(-6.18)				(-6.13)				(-6.15)
M_t	0.10	0.10	0.30	0.30	0.10	0.10	0.30	0.30	0.10	0.10	0.40	0.40
	(-0.39)	(-0.39)	(-0.17)	(-0.10)	(-0.40)	(-0.40)	(-0.18)	(-0.11)	(-0.39)	(-0.39)	(-0.09)	(-0.09)
A_t	1.80	1.80	2.00	1.90	1.80	1.80	2.00	1.90	1.80	1.80	1.90	1.90
	(2.30)	(2.30)	(2.57)	(2.47)	(2.29)	(2.29)	(2.56)	(2.46)	(2.31)	(2.31)	(2.50)	(2.50)
R^2	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57

4.4.4 Feedback Trading and Market Quality

The findings of Kirilenko et al.(2011) imply that algorithmic trading could harm market quality during price declines if they increase their demand for liquidity during these periods. Kaniel et al. (2008) argue that contrarian traders act as liquidity providers. Institutional investors requiring immediacy offer price concessions to encourage other investors to take the other side of the trade. Momentum traders conversely act as liquidity demanders. Herding and positive-feedback trading may result in a reduction in market quality (Culter et al., 1990).

To test whether ATs systematically engage in herding and positive-feedback trading, the following regression is estimated:

$$RATIO_t = \beta_0 + \beta_1 D_t^{Down} + \beta_2 NT_t + \beta_3 RATIO_{t-1} + \beta_4 M_t + \beta_5 A_t + \varepsilon_t \tag{6.16}$$

where the algorithmic trading buy and sell ratios are examined separately to determine whether ATs systematically reduce their buying, and increase their selling, during price declines. Table 6-14 shows that β_1 is significantly negative for buys and significantly positive for sells; *t*-statistics are very large, being -12.98 for buys and 12.59 for sells. These results indicate a certain degree of herding by ATs. ATs reduce their buying in stocks with falling prices, while increasing their selling. This lends support to the conjecture that ATs increase their demand for liquidity during price falls, and that this reduces market quality, which is consistent with previous studies examining the trading strategies of ATs (Anand and Venkataraman, 2013; ASIC 2012; Korajczyk and Murphy 2014; Hu, 2013; Golub et al., 2012).

Table 6-14
Momentum Trading During Down Markets

This table reports the GMM estimates from the regressions estimated for each of the 100 ASX stocks based on 15-minute intervals. The sample period extends from July 2, 2007 to March 6, 2009. The regression model is specified as follows:

$$RATIO_t = \beta_0 + \beta_1 D_t^{Down} + \beta_2 NT_t + \beta_3 RATIO_{t-1} + \beta_4 M_t + \beta_5 A_t + \varepsilon_t$$

$RATIO_{t-1}$ is the algorithmic total ($TOTAL_{t-1}$), buy (BUY_{t-1}), and sell ($SELL_{t-1}$) ratio, respectively; NT_t is the number of trades executed during time interval$t$; M_t is a dummy variable that takes the value of one from 10:15 to 11:00 hours of the trading day and zero otherwise, and A_t is a dummy variable that takes the value of one from 15:00 to 16:00 hours and zero otherwise; and ε_{it} is a random error term. Regression coefficients are cross-sectional averages from the 100 stocks. Average t-statistics are in parentheses. To adjust the units for presentation, the coefficients for D_t^{Down}, NT_t, M_t, and A_t are multiplied by 10^2.

	Buy Ratio	*Sell Ratio*
Constant	0.10	0.09
	(42.44)	(37.53)
D_t^{Down}	-2.61	2.41
	(-12.98)	(12.59)
NT_t	-0.01	-0.01
	(-1.16)	(-1.06)
$RATIO_{t-1}$	0.65	0.65
	(114.69)	(112.91)
M_t	-0.39	-0.25
	(-2.09)	(-1.45)
A_t	-0.40	-0.56
	(-2.13)	(-2.85)

4.5 Summary

As a consequence of advances in technology, order execution in financial markets has changed dramatically. Instead of trades being entered manually by brokers, orders are increasingly being conducted by computer algorithms that either seek to minimise market impact or to profit from proprietary trading opportunities. The growth in this new form of trading, with its high speed and sophistication, has generated concern on the part of regulators, exchanges, investors and journalists on the impact of ATs on market integrity and quality. As data on ATs has become available, a number of studies have begun to examine the effect of algorithmic trading on market quality. Despite this, few studies examine the impact of algorithmic trading during adverse market environments.

In this chapter, the impact of algorithmic trading on market quality is assessed over different market conditions. Over the whole sample period, results provide no evidence that AT volume has an impact on market quality. However, when the sample is split into increasing and decreasing stock returns, results show that AT is negatively associated with future market quality when prices are falling and has no relation when prices are rising. The negative impact of AT on market quality is explained by algorithmic traders engaging in positive-feedback trading, in which they reduce their buying and increase their selling of securities during periods of falling prices.

Chapter 5: Execution Costs of Option Strategy Trades

5.1 Introduction

The literature reviewed in Section 2.2 provide a number of insights into how option market makers set the bid-ask spread. Specifically, market makers adjust prices in response to information asymmetry and hedging costs (including the costs of hedging delta, vega and gamma risks). The implication is that transaction costs in option markets will be greater when hedging and adverse selection costs increase. The literature on this issue examines outright option trades; the execution costs of option strategies and its determinants are yet to be investigated. This is a result of data being unavailable to conduct this line of research. Option strategies (such as straddles and butterfly spreads) allow market participants to combine options to either speculate on future volatility, or to speculate on directional movements with greater flexibility. Despite the prominence of option strategies documented in recent empirical studies (e.g., Lakonishok et al., 2007), literature on the transaction costs of option strategies is sparse.

The objective of this essay is to bridge the gap in the literature by examining the execution costs of option strategies. More specifically, it documents the size of execution costs of option strategies relative to outright options on the Australian Options Market (AOM) and examines whether any differences can be attributed to differences in market making and adverse selection costs. The remainder of this chapter is structured as follows. Section 5.2 provides institutional details of the AOM.

Section 5.2 outlines the hypotheses on option strategies. Section 5.3 presents the data and descriptive statistics. Section 5.4 outlines the research design and presents the results. Section 5.5 summarises the chapter.

5.2 Hypotheses on Option Strategies

The two principal approaches to modeling market maker behaviour are inventory control models and adverse selection models. The level of inventory holding costs and adverse selection costs differ across financial markets. Options market makers face unique risks in managing inventory and adverse selection costs. Relative to equity market makers, they have less control over their inventory positions (Lakonishock et al., 2007). As a result of this, hedging is an integral part of the mechanics of market making in options markets (Battalio and Schulz, 2011). The literature suggests that options market makers face the following three types of hedging costs; delta cost is the cost of setting up a hedging portfolio; vega (gamma) cost is the cost incurred in maintaining a hedged portfolio as the underlying stock volatility (delta) changes over time. The presence of these dimensions of risk increases the difficulty of the market maker's hedging in options markets.

Empirical findings show that option market makers adjust prices to account for these hedging costs (Jameson and Wilhelm, 1992, Cho and Engle, 1999, Kaul et al., 2004, Patrella, 2006, Landsiedl, 2005, and Engle and Neri, 2010). For example, Wei and Zheng (2010) show that bid-ask spreads adjust to changes in a number of liquidity determinants affecting a market maker's inventory-holding costs. The authors show that over half the time series variation in the bid-ask spread is explained by changes in an option's time-to-maturity, moneyness, stock return volatility, option return volatility, option trading volume and option price.

The particular features of option markets may also attract informed investors. Options offer greater leverage relative to equity markets (Black, 1975). This greater leverage may induce investors with short-lived information to favour the use of options (Charkravarty et al. 2004). The literature shows option market makers adjust prices to account for changes in information asymmetry (Bartram et al., 2008; Ahn et al., 2008).

Option trades do not necessarily have to involve a trade in a single option series but can simultaneously involve a number of different options with different strike prices, exercise dates etc. For instance, a trader who seeks to profit from changes to the security's volatility can engage in option strategies such as straddles or strangles, which involve the simultaneous buying of a put and call option in the same option series. These present risks to the market maker that are different to trading outright options. Relative to outright option trades, the greater complexity of strategy trades means that options market makers will incur higher hedging costs for option strategy trades. This is because the market maker takes into account the cost of hedging a newly created position by trading component options separately. For example, consider a market maker who has received a quote request for a straddle. Setting the quotes, the market maker takes into account the cost of hedging a newly created position by trading component options separately. It follows that the market maker requires higher liquidity premiums for strategy-linked options than outright options. Further, a likely consequence is that strategy-linked options trade at less advantageous prices than outright options, unless option strategy traders are consistently (and considerably) superior at timing the market to traders who trade outright options.

Furthermore, the diversity of option strategies allows traders to combine options to either speculate on future volatility while eliminating exposure to directional risks, or to speculate on directional movements while eliminating the volatility of the underlying, thereby reducing risk. Informed traders may take advantage of this by engaging in option strategies over outright options. Fahlenbrach and Sandås (2010) demonstrate that volatility-based option strategies predict future realised volatility. It is therefore hypothesised that the market maker requires higher liquidity premiums for strategy trades.

Hypothesis$_{5.1}$: *Execution costs for option strategy trades are higher relative to outright option trades.*

Option strategies have different levels of complexity. For example, a straddle consists of simultaneously purchasing or selling a put and call option at the same strike price, whereas a butterfly trade consists of selling four put or call options at three different strike prices. As the market maker takes into account the cost of hedging a newly created position by trading component options separately, hedging costs for strategy trades will be higher for option strategies with greater complexity due to the greater number of option components.

The above discussion leads to the following hypothesis.

Hypothesis$_{5.2}$: *The execution costs of option strategies increase as a function of their complexity.*

As discussed, market makers' quote setting strategies are affected by information asymmetry and inventory-holding costs (e.g., Ho and Stoll, 1981, Easley and O'Hara, 1987). Furthermore, option strategies generate higher hedging costs for market makers and may contain information about future returns and volatility. This suggest that the differences in transaction costs between option strategies and outright options can be explained by differences in the level of information asymmetry and hedging costs of option strategies relative to outright options. This leads to the following hypotheses.

Hypothesis$_{5.3}$: *Market makers face higher levels of information asymmetry trading option strategies relative to outright options.*

Hypothesis$_{5.4}$: *Market makers face higher hedging costs trading option strategies relative to outright options.*

5.3 Australian Options Market

The Australian Options Market (AOM) is a quasi-limit order book market where liquidity is supplied by public limit orders and designated market makers. Limit orders and market maker quotes are ranked on a price/time priority basis. The amount of liquidity supplied by limit orders is minimal relative to market makers, meaning that the AOM can be considered to be a dealer market. The AOM offers market makers fee incentives for meeting certain benchmark quoting requirements. Each market maker, assigned two or more underlying assets, can choose to make a market on a continuous basis, in response to quote requests, or both. Market makers who choose to make a market on a continuous basis are obliged to provide orders continuously for certain percentages of time, in 18 series per underlying security, encompassing three calls and three puts in any three of the next six expiry months. Market makers who choose to make a market in response to quote requests are monitored on their provision of orders on request for certain percentages of the time for all series up to nine months maturity. Liquidity is assisted when there are multiple market makers in a class; however, as market makers are not required to provide quotes in all series, or at all times, there is no guarantee that all series will have prices displayed.

Option strategies on the AOM are referred to as combination trades. Trading of option strategies on the AOM takes place through the central limit order book using a special trade facility. Use of this facility has important advantages over the central order book for strategy trades. First, execution risk is reduced by trading all legs of the strategy simultaneously, particularly if the option legs include highly illiquid options. Second, the risk of adverse price movements, while executing each leg of the strategy, is removed.

There are two main types of combination orders ("strategy orders", hereafter) executed on the AOM; standard and tailor-made strategies. Standard strategies are limited to common strategies prescribed by the AOM. Tailor-made strategies provide the flexibility to define particular single series components of the strategy, having greater complexity than standard strategies. For each type of strategy, a trader executes a trade by entering a quote in the special trade facility for each leg of the strategy. When a particular strategy is created, it is assigned a unique strategy series identifier. The order is then assigned with all other orders with the same unique identifier, based on price/time priority against the other strategies. For a trade to occur, another trader may trade against the strategy order, matching all legs included in the strategy or the AOM matches the strategy with orders that are currently in the market for each option.

5.4 Data and Descriptive Statistics

The data are obtained from an internal database from the AOM. The sample consists of trade by trade data for all equity options listed on the AOM. For each transaction, data include the underlying stock, date, time (to the nearest millisecond), price, and volume. The sample period extends from January 1, 2007 to August 31, 2007. The sample is restricted to normal trading hours for the options market (9:30a.m. - 4:20p.m. during the sample period), and includes all options traded on a sample of 20 stocks displaying the highest option volume (including both puts and calls) over the sample period. The trade record includes a flag for trades that are part of strategies, and this is further segregated into either standard or tailor-made combinations.

The internal AOM data are combined with order book data sourced from Reuters Data Scope Tick History provided by Securities Industry Research Centre of Asia-Pacific (SIRCA). The data provide the prices of the best bid and ask quotes, time stamped to the nearest millisecond. To determine the direction of each strategy trade, Sackickas and Wilson's (2003) quote rule is used: trades are determined as buyer- or seller-initiated according to whether the trade price is above or below the bid-ask midpoint. As the quotes for strategy trades are unavailable, this study implies quotes based on the quotes given on the limit order book for the individual components. Trades that have no corresponding quotes (which may occur for strategy trades), or trade at the bid-ask mid-point, are removed.

Table 5-1 reports the average price, the average daily number of contracts traded, average moneyness, and time to maturity (TTM) for strategy-linked trades and outright trades, separately. The sample consists of a total of 775,390 transactions, of which 287,042 are strategy-linked trades: 259,134 tailor-made strategy-linked trades and 27,908 standard strategy-linked trades. This suggests that option strategies constitute a considerable proportion of option trading volume on the AOM. The moneyness of an option series is calculated as the spot (strike) price divided by the strike (spot) price for call (put) options. TTM is calculated as the difference between the current date of the option and the expiry date. Underlying volatility is calculated as the natural logarithm of the difference between the daily high and low prices of the underlying stock.

Table 5-1
Descriptive Statistics

This table reports descriptive statistics for tailor-made strategy-linked (TM), standard strategy-linked (SS), and outright options. Panel A describes the full sample. Panel B reports the descriptive statistics across three moneyness categories. The moneyness of an option series is calculated as the spot (strike) price divided by the strike (spot) price for call (put) options. Moneyness is defined as at-the-money (ATM) if it is between 0.9 and 1.1, in-the-money (ITM) if greater than 1.1, and out-of-the money (OTM) if less than 0.9. Panel C splits the sample into three time-to-maturity (TTM) categories. In Panel D, the sample is divided into volume categories: each trading day, each option series is partitioned into one of three categories based on the number of trades. *Number of Trades* is the daily average number of trades. *Trade Premium* is the average of the options premiums ($). *Moneyness* is the average moneyness. *Time to Maturity* is the average time to maturity (days). *Trade Size* is the average trade size (contracts).

	Number of Trades	Trade Premium ($)	Moneyness	Time to Maturity (days)	Trade Size (contracts)
Panel A – Overall					
TM Options	259,134	1.38	1.00	61.81	22.06
SS Options	27,908	0.69	0.99	30.76	41.15
Outright Options	488,348	0.97	0.98	51.74	19.12
Panel B – Moneyness					
TM Options					
ATM	225,539	1.13	1.00	52.94	24.38
ITM	15,753	5.87	1.21	89.82	6.30
OTM	17,842	0.52	0.85	149.30	6.68
SS Options					
ATM	26,105	0.66	0.99	28.87	43.13
ITM	510	3.49	1.17	46.08	11.08
OTM	1,293	0.23	0.87	62.85	12.91
Outright options					
ATM	437,198	0.88	0.99	44.07	20.69
ITM	12,395	5.77	1.21	117.16	6.53
OTM	38,755	0.47	0.86	117.31	6.70
Panel C – Time to Maturity					
TM Options					
> 90 days	39,890	2.57	0.99	239.18	5.31
30 - 90 days	99,677	1.24	0.99	48.17	16.88
< 30 days	119,567	1.09	1.01	14.00	31.97
SS Options					
> 90 days	1,023	1.78	0.98	199.39	6.67
30 - 90 days	9,322	0.77	0.98	44.14	26.23
< 30 days	17,563	0.59	0.99	13.84	51.08
Outright options					
> 90 days	58,527	2.02	0.97	205.00	5.22
30 - 90 days	196,370	0.96	0.97	49.36	14.07
< 30 days	233,451	0.72	0.99	15.35	27.07

Table 1, continued

Panel D – Volume					
TM Options					
Volume Group 1 (Lowest)	22,298	2.67	1.03	135.00	1.00
Volume Group 2	38,144	2.07	1.00	102.00	2.61
Volume Group 3 (Highest)	198,692	1.10	1.00	45.85	28.16
SS Options					
Volume Group 1 (Lowest)	483	1.73	1.00	96.45	1.00
Volume Group 2	1,599	1.16	0.98	66.02	2.76
Volume Group 3 (Highest)	25,826	0.64	0.99	27.35	44.28
Outright options					
Volume Group 1 (Lowest)	35,842	1.76	0.98	125.00	1.00
Volume Group 2	67,347	1.38	0.97	89.60	2.59
Volume Group 3 (Highest)	385,159	0.83	0.98	38.30	23.82

Panel B of Table 5-1 reports the descriptive statistics along three moneyness categories: in-the-money options (ITM) where moneyness is greater than 1.1; at-the-money options (ATM) where moneyness is between 0.9 and 1.1; and out-of-the-money options (OTM) where moneyness is less than 0.9. The majority of trades are concentrated in ATM options (89% of all trades). Average moneyness ranges from 0.853 for OTM options to 1.212 for ITM options. Panel C of Table 5-1 reports summary statistics divided into three TTM categories; greater than 90 days, between 30 and 90 days, and less than 30 days to maturity. Trades that are less than 30 days to maturity make up the greatest proportion of the sample. There is a significant range in maturities between option series, with TTM for long-term options averaging over 200 days, while short-term options average less than 15 days. Panel D of Table 5-1 reports summary statistics according to volume categories based on the number of trades during a trading day.

Panel B of Table 5-1 reports the descriptive statistics along three moneyness categories: in-the-money options (ITM) where moneyness is greater than 1.1; at-the-money options (ATM) where moneyness is between 0.9 and 1.1; and out-of-the-money options (OTM) where moneyness is less than 0.9. The majority of trades are concentrated in ATM options (89% of all trades). Average moneyness ranges from 0.853 for OTM options to 1.212 for ITM options. Panel C of Table 5-1 reports summary statistics divided into three TTM categories; greater than 90 days, between 30 and 90 days, and less than 30 days to maturity. Trades that are less than 30 days to maturity make up the greatest proportion of the sample. There is a significant range in maturities between option series, with TTM for long-term options averaging over 200 days, while short-term options average less than 15 days. Panel D of Table 5-1 reports summary statistics according to volume categories based on the number of trades during a trading day.

5.5 Research Design and Empirical Results

5.5.1 Transaction Costs

This section investigates whether outright options and options that constitute strategies ("strategy-linked options", hereafter) differ in execution costs using the percentage effective spread. A standard measure of liquidity used in the literature is the bid-ask spread. The quoted bid-ask spread, which is simply the difference between the bid and ask prices, captures the ex-ante costs transaction costs of undertaking a transaction (O'Hara, 1995). Christie and Huang (1994) suggest that using the relative quoted spread is more appropriate as it takes into account the value of the security. Finally, Peterson and Fialkowski (1994) suggest that the quoted spread is not a true reflection of execution costs as a trader could place an order inside the quoted bid-ask spread, resulting in a lower execution cost. In line with Bessembinder (2003), the percentage effective spread is calculated as:

$$PerEffSpread_i = 200\% \times D_i \times \frac{(Price_i - Mid_i)}{Mid_i} \qquad (5.1)$$

where D_i is a trade direction indicator variable ($D_i = 1$ for a buy order, $D_i = -1$ for a sell order), $Price_i$ is the price of the trade, and Mid_i is the mid-quote prior to the trade. Table 4-2 reports percentage effective spreads for outright options, tailor-made strategy-linked ("TM", hereafter), and standard strategy-linked ("SS", hereafter) options by option type. The average percentage effective spread for outright options over the entire sample is 8.31%. Percentage Effective spreads for both TM (13.69%) options and SS options (10.72%) are significantly greater than those for outright options at the 1% level. Results also reveal that percentage effective spreads for TM options are significantly greater than those for SS options at the 1% level.

Table 5-2
Percentage Effective Spreads

This table reports percentage effective spreads for tailor-made strategy-linked (TM), standard strategy-linked (SS), and outright options across call and put option trades. TM – Outright is the difference in effective spreads between TM and outright options. SS – Outright is the difference in effective spreads between SS and outright options. TM – SS is the difference in effective spreads between TM and SS options. The *t*-test is used to test the deviation of the mean values from zero. ** indicates statistical significance at the 1% level. * indicates statistical significance at the 5% level.

	Call	Put	All
Panel A - Option Types			
TM Options	11.30	15.40	13.69
SS Options	8.81	12.23	10.72
Outright Options	7.61	9.17	8.31
Panel B - Difference in Percentage Effective Spreads			
TM – Outright	3.69**	6.23**	5.38**
SS – Outright	1.21**	3.06**	2.40**
TM – SS	2.49**	3.18**	2.98**

To examine whether option characteristics drive percentage effective spreads to be higher for strategy-linked options relative to outright options, the sample is partitioned into moneyness categories. Within each moneyness category, it is further separated into TTM categories. Finally, within each TTM category, the sample is categorized into three groups by trading volume. Volume categories are based on the number of trades during the day. Volume group 1 (3) includes option series with the lowest (greatest) number of trades each day.

Table 5-3 reveals that percentage effective spreads for TM options are significantly higher than those for outright options at the 1% level across all moneyness, TTM, and volume categories. Table 5-4 shows that for the majority of trades (97 per cent), SS options have higher execution costs than outright options at the 1% level. Percentage effective spreads for SS options are significantly higher for all ATM options at the 1% level, except for options in the lowest volume group with a

TTM between 30-90 days and greater than 90 days. SS options cost significantly higher for one of the ITM option categories and significantly higher for the majority of OTM options at the 1% level. Table 5-5 reveals that TM options are significantly more costly to trade than SS options at the 1% level only for a few subsets of the sample. In the ATM sample, for the majority of trades, TM options are significantly more expense to trade than SS options at the 1% level. However, differences in percentage effective spreads between the two groups are not significantly different for six of the nine ITM categories. Also, the OTM sample shows that percentage effective spreads for TM options are significantly wider than SS options at the 1% level only for a few trades.

Supporting hypotheses $H_{5,1}$ the results overall reveal that execution costs for (both TM and SS) strategy-linked options are greater than those for outright options. On the contrary to hypothesis $H_{5,2}$, between the two strategy-linked options option categories, this study does not provide strong evidence that TM options are more costly to trade than SS options. This implies that market makers require higher liquidity premiums for (both TM and SS) strategy-linked options relative to outright options regardless of option characteristics, but they do not strongly discriminate between TM and SS options in setting quotes.

Table 5-3
Percentage Effective Spreads by Volume, Moneyness, and Time to Maturity for TM and Outright Options

This table reports percentage effective spreads for tailor-made strategy-linked (TM) and outright options for volume categories within each of the moneyness and time-to-maturity categories. Volume categories are partitioned into three categories from the lowest to the highest based on the number of trades during a trading day. The moneyness of an option series is calculated as the spot (strike) price divided by the strike (spot) price for call (put) options. Moneyness is defined as (at-the-money) ATM if it is between 0.9 and 1.1, in-the-money (ITM) if greater than 1.1, and out-of-the-money (OTM) if less than 0.9. Time to Maturity is the number of days to expiry. *Number of Trades* is the average number of trades. *Difference* is the difference in percentage effective spreads between TM and outright options. The *t*-test is used to test the deviation of the mean values from zero. ** indicates statistical significance at the 1% level. * indicates statistical significance at the 5% level.

			TM Options		Outright Options		
	Moneyness	Time to Maturity (days)	Percentage Effective Spreads (%)	Number of Trades	Percentage Effective Spreads (%)	Number of Trades	Difference (TM - Outright)
Volume Group 1 (Lowest)	ATM	> 90	8.25	7090	4.30	10,458	3.95**
Volume Group 2	ATM	> 90	8.25	8410	4.22	13,032	4.03**
Volume Group 3 (Highest)	ATM	> 90	7.89	12,175	3.75	16,452	4.14**
Volume Group 1 (Lowest)	ATM	30 – 90	11.77	5,588	6.60	10,865	5.17**
Volume Group 2	ATM	30 – 90	11.46	12,906	6.21	26,540	5.25**
Volume Group 3 (Highest)	ATM	30 – 90	10.03	69,405	5.30	138,451	4.73**
Volume Group 1 (Lowest)	ATM	< 30	21.55	2,364	18.49	4,018	3.06**
Volume Group 2	ATM	< 30	19.95	7,257	15.28	13,106	4.67**
Volume Group 3 (Highest)	ATM	< 30	15.33	98,811	9.29	204,276	6.04**
Volume Group 1 (Lowest)	ITM	> 90	4.77	1,512	2.15	1,493	2.62**
Volume Group 2	ITM	> 90	5.32	1,330	2.64	1,362	2.68**
Volume Group 3 (Highest)	ITM	> 90	4.74	1,304	1.96	1,255	2.78**
Volume Group 1 (Lowest)	ITM	30 – 90	4.59	1,167	2.65	890	1.94**
Volume Group 2	ITM	30 – 90	4.95	1,395	2.53	1,077	2.42**

Volume Group 3 (Highest)	ITM	30 – 90	5.82	1,985	3.09	1,646	2.73**

Table 3, continued

Volume Group 1 (Lowest)	ITM	< 30	3.60	1,042	2.47	676	1.13**
Volume Group 2	ITM	< 30	4.58	1,760	2.73	1,108	1.85**
Volume Group 3 (Highest)	ITM	< 30	6.79	4,160	2.97	2,888	3.82**
Volume Group 1 (Lowest)	OTM	> 90	24.91	1,989	11.66	3,879	13.25**
Volume Group 2	OTM	> 90	25.44	2,292	11.62	4,756	13.82**
Volume Group 3 (Highest)	OTM	> 90	26.08	3,495	9.49	5,840	16.59**
Volume Group 1 (Lowest)	OTM	30 – 90	46.23	1,106	23.93	1,106	22.30**
Volume Group 2	OTM	30 – 90	40.79	1,810	20.82	4,821	19.97**
Volume Group 3 (Highest)	OTM	30 – 90	33.62	3,761	16.18	9,377	17.44**
Volume Group 1 (Lowest)	OTM	< 30	69.85	201	46.73	860	23.12**
Volume Group 2	OTM	< 30	63.84	486	42.63	1,545	21.21**
Volume Group 3 (Highest)	OTM	< 30	48.35	1,873	30.24	4,974	18.11**

Table 5-4

Percentage Effective Spreads by Volume, Moneyness, and Time to Maturity for SS and Outright Options

This table reports percentage effective spreads for standard strategy-linked (SS) and outright options for volume categories within each of the moneyness and time-to-maturity categories. Volume categories are partitioned into three categories from the lowest to the highest based on the number of trades during a trading day. The moneyness of an option series is calculated as the spot (strike) price divided by the strike (spot) price for call (put) options. Moneyness is defined as (at-the-money) ATM if it is between 0.9 and 1.1, in-the-money (ITM) if greater than 1.1, and out-of-the-money (OTM) if less than 0.9. Time to Maturity is the number of days to expiry. *Number of Trades* is the average number of trades. *Difference* is the difference in percentage effective spreads between TM and outright options. The *t*-test is used to test the deviation of the mean values from zero. ** indicates statistical significance at the 1% level. * indicates statistical significance at the 5% level.

			SS Options		Outright Options		
	Moneyness	Time to Maturity (days)	Percentage Effective Spreads (%)	Number of Trades	Percentage Effective Spreads (%)	Number of Trades	Difference (SS – Outright)
Volume Group 1 (Lowest)	ATM	> 90	4.92	120	4.30	10,458	0.60
Volume Group 2	ATM	> 90	4.91	221	4.22	13,032	0.69*
Volume Group 3 (Highest)	ATM	> 90	5.12	417	3.75	16,452	1.37**
Volume Group1 (Lowest)	ATM	30 – 90	7.05	142	6.60	10,865	0.45
Volume Group 2	ATM	30 – 90	8.26	573	6.21	26,540	2.05**
Volume Group 3 (Highest)	ATM	30 – 90	5.92	7,924	5.30	138,451	0.62**
Volume Group 1 (Lowest)	ATM	< 30	27.97	96	18.49	4,018	9.48**
Volume Group 2	ATM	< 30	21.63	468	15.28	13,106	6.35**
Volume Group 3 (Highest)	ATM	< 30	11.91	16,060	9.29	204,276	2.62**
Volume Group 1 (Lowest)	ITM	> 90	2.97	17	2.15	1,493	0.82
Volume Group 2	ITM	> 90	4.26	20	2.64	1,362	1.62
Volume Group 3 (Highest)	ITM	> 90	2.87	19	1.96	1,255	0.91

Table 4, continued

Volume Group 1 (Lowest)	ITM	30 – 90	2.45	19	2.65	890	-0.20
Volume Group 2	ITM	30 – 90	5.10	33	2.53	1,077	2.57**
Volume Group 3 (Highest)	ITM	30 – 90	4.45	81	3.09	1,646	1.36
Volume Group 1 (Lowest)	ITM	< 30	2.01	20	2.47	676	-0.46
Volume Group 2	ITM	< 30	3.01	44	2.73	1,108	0.28
Volume Group 3 (Highest)	ITM	< 30	3.54	257	2.97	2,888	0.57
Volume Group 1 (Lowest)	OTM	> 90	15.28	25	11.66	3,879	3.62
Volume Group 2	OTM	> 90	11.17	55	11.61	4,756	-0.44
Volume Group 3 (Highest)	OTM	> 90	15.72	126	9.49	5,840	6.23**
Volume Group 1 (Lowest)	OTM	30 – 90	35.44	24	23.93	24	11.51**
Volume Group 2	OTM	30 – 90	35.21	102	20.82	4,821	14.39**
Volume Group 3 (Highest)	OTM	30 – 90	20.37	413	16.18	9,377	4.19**
Volume Group 1 (Lowest)	OTM	< 30	52.55	14	46.73	860	5.82
Volume Group 2	OTM	< 30	48.79	70	42.63	1,545	6.16
Volume Group 3 (Highest)	OTM	< 30	34.55	455	30.24	4,974	4.31**

Table 5-5

Effective Spreads by Volume, Moneyness, and Time to Maturity for TM and SS Options

This table reports percentage effective spreads for tailor-made strategy-linked (TM) and standard strategy-linked (SS) options for volume categories within each of the moneyness and time-to-maturity categories. Volume categories are partitioned into three categories from the lowest to the highest based on the number of trades during a trading day. The moneyness of an option series is calculated as the spot (strike) price divided by the strike (spot) price for call (put) options. Moneyness is defined as (at-the-money) ATM if it is between 0.9 and 1.1, in-the-money (ITM) if greater than 1.1, and out-of-the-money (OTM) if less than 0.9. Time to Maturity is the number of days to expiry. *Number of Trades* is the average number of trades. *Difference* is the difference in percentage effective spreads between TM and outright options. The *t*-test is used to test the deviation of the mean values from zero. ** indicates statistical significance at the 1% level. * indicates statistical significance at the 5% level.

			TM Options		SS Options		
	Moneyness	Time to Maturity (days)	Percentage Effective Spreads (%)	Number of Trades	Percentage Effective Spreads (%)	Number of Trades	Difference (TM- SS)
Volume Group 1 (Lowest)	ATM	> 90	8.25	7,090	4.92	10,458	3.33**
Volume Group 2	ATM	> 90	8.25	8,410	4.91	13,032	3.34**
Volume Group 3 (Highest)	ATM	> 90	7.89	12,175	5.12	417	2.77**
Volume Group 1 (Lowest)	ATM	30 – 90	11.77	5,588	7.05	142	4.72**
Volume Group 2	ATM	30 – 90	11.46	12,906	8.26	573	3.20**
Volume Group 3 (Highest)	ATM	30 – 90	10.03	69,405	5.92	7,924	4.11**
Volume Group 1 (Lowest)	ATM	< 30	21.55	2,364	27.97	96	-6.42
Volume Group 2	ATM	< 30	19.95	7,257	21.63	468	-1.63
Volume Group 3 (Highest)	ATM	< 30	15.33	98,811	11.91	16,060	3.42**
Volume Group 1 (Lowest)	ITM	> 90	4.77	1,512	2.97	17	1.80
Volume Group 2	ITM	> 90	5.32	1,330	4.26	20	1.06
Volume Group 3 (Highest)	ITM	> 90	4.74	1,304	2.87	19	1.87

Table 5, continued

Volume Group 1 (Lowest)	ITM	30 – 90	4.60	1,167	2.45	19	2.15
Volume Group 2	ITM	30 – 90	4.95	1,395	5.10	33	-0.15
Volume Group 3 (Highest)	ITM	30 – 90	5.82	1,985	4.45	81	1.37
Volume Group 1 (Lowest)	ITM	< 30	3.60	1,042	2.01	20	1.59
Volume Group 2	ITM	< 30	4.58	1,760	3.01	44	1.57
Volume Group 3 (Highest)	ITM	< 30	6.79	4,160	3.54	257	3.25**
Volume Group 1 (Lowest)	OTM	> 90	24.91	1,989	15.28	25	9.63
Volume Group 2	OTM	> 90	25.44	2,292	11.17	55	14.27**
Volume Group 3 (Highest)	OTM	> 90	26.08	3,495	15.72	126	10.36**
Volume Group 1 (Lowest)	OTM	30 – 90	46.23	1,106	35.44	1,106	10.79
Volume Group 2	OTM	30 – 90	40.79	1,810	35.21	102	5.58
Volume Group 3 (Highest)	OTM	30 – 90	33.62	3,761	20.37	413	13.25
Volume Group 1 (Lowest)	OTM	< 30	69.85	201	52.55	14	17.30
Volume Group 2	OTM	< 30	63.84	486	48.79	70	15.05**
Volume Group 3 (Highest)	OTM	< 30	48.35	1,873	34.55	455	13.80**

5.5.2 Multivariate Analysis

The literature on option bid-ask spreads suggests a number of liquidity determinants, including time to maturity, moneyness, trading volume, option volatility, and underlying stock volatility (e.g., Neal, 1987, George and Longstaff, 1993, Chong et al., 2003, Cao and Wei, 2010, and Wei and Zheng, 2010). In line with this research, the univariate analysis shows that TM and SS options have higher effective spreads relative to outright options across the following option characteristics: time to maturity, moneyness, and trading volume.

To determine if proportional effective spreads for strategy trades are higher after controlling for other option characteristics including option volatility and underlying stock volatility, the following regression is estimated for each underlying stock:

$$\begin{aligned} PES_{it} = \beta_0 + \beta_1 SS_{it} + \beta_2 TM_{it} + \beta_3 TTM_{it} + \beta_4 M_{it} \\ + \beta_5 V_{it} + \beta_6 \sigma_{o_{it}} + \beta_7 \sigma_{s_{it}} + \varepsilon_{it} \end{aligned} \tag{5.2}$$

where PES_{it} is the daily average proportional effective spread of all trades for option i on day t; $SS_{it}(TM_{it})$ is the SS (TM) traded volume as a proportion of total traded volume for option i on day t; time-to-maturity (TTM_{it}) is the difference between the current date of the option and the expiry date; moneyness (M_{it}) is the ratio of closing spot (strike) price to strike (closing spot) price of call (put) options for option i on day t; V_{it} is the logarithm of the total daily option volume for option i on day t; following Wei and Zheng (2010), option volatility ($\sigma_{o_{it}}$) is calculated as the absolute value of the option price elasticity times the underlying stock volatility for option i on day t. The stock volatility measure is given as follows:

$$\sigma_{s_{it}} = \sqrt{\frac{(\ln high_{it} - \ln low_{it})^2}{4ln2}}, i = 1, 2, \ldots, N; t = 1,2, \ldots, T \quad (5.3)$$

where volatility is calculated for stock i on day t; $high_{it}$ and low_{it} refers to the highest traded price and lowest traded price of underlying stock for each day. Each equation is estimated separately for each stock using the Generalized Method of Moments (GMM); the resulting t-statistics are robust to heteroskedasticity and autocorrelation (Newey and West, 1987).

Table 4-6 reports the cross-sectional averages of the coefficients and associated t-statistics of the estimated regressions. Consistent with prior literature, proportional effective spreads are affected by a number of option liquidity determinants. Results show that an increase in the standard strategy volume relative to total trading volume does not have an impact on proportional effective spreads, implying that market makers do not require higher compensation for providing liquidity for standard strategy-linked trades. These results hold across both put and call options. On the contrary, an increase in tailor-made strategy volume as a proportion of total trading volume is significantly associated with an increase in effective spreads at the 1% level. These results suggest that execution costs for tailor-made strategy-linked options are higher relative to outright options in line with the results of the univariate analysis. In contrast to $H_{5,1}$, execution costs are not higher for standard strategy-linked trades after option volatility and underlying stock volatility are taken into account.

Option market makers also face adverse selection costs, as the greater leverage of options and the higher investment returns they offer attract informed traders to the options market (Black, 1975, Charkravarty et al., 2004) The evidence shows that option market makers adjust prices to account for hedging and adverse selection costs. Jameson and Wilhelm (1992) report that discrete hedge rebalancing (gamma risks) and stochastic stock return volatility (vega risks) are not fully diversifiable and account for 8% and 4.5% of the option bid-ask spread, respectively. Kaul et al. (2004) report that a significant proportion of the bid-ask spread is attributable to inventory management costs; 50% attributable to setting up a delta neutral position and 6.93% associated with discrete rebalancing. Ahn et al. (2008) report that the adverse selection component of the bid-ask spread on the KOPSI 200 Index options traded on the Korean Exchange account for 34.99% of the bid-ask spread for call options and 39.14% of the bid-ask spread for put options.

Table 5-6
Multiple Regressions of Percentage Effective Spreads on Option Characteristics

This table reports the GMM estimates from the regressions estimated for each of the 20 underlying stocks. The regression model is specified as follows:

$$PES_{it} = \beta_0 + \beta_1 SS_{it} + \beta_2 TM_{it} + \beta_3 TTM_{it} + \beta_4 M_{it} + \beta_5 V_{it} + \beta_6 \sigma_{o_{it}} + \beta_7 \sigma_{s_{it}} + \varepsilon_{it}$$

where PES_{it} is the daily average proportional effective spread of all trades for option i on day t; $SS_{it}(TM_{it})$ is the SS (TM) traded volume as a proportion of total traded volume for option i on day t; time-to-maturity (TTM_{it}) is the difference between the current date of the option and the expiry date; moneyness (M_{it}) is the ratio of closing spot (strike) price to strike (closing spot) price of call (put) options for option i on day t; V_{it} is the logarithm of the total daily option volume for option i on day t; option volatility ($\sigma_{o_{it}}$) is calculated as the absolute value of the option price elasticity times the underlying stock volatility for option i on day t; stock volatility ($\sigma_{s_{it}}$) is defined in Equation (3). The regression is estimated for each underlying stock, separately for calls and puts. Regression coefficients are cross-sectional averages from the 20 stocks. Average t-statistics are in parentheses. The first (second) component in each bracket is the percentage of significantly positive (negative) coefficients at the 10% level. The R^2 is the cross-sectional average adjusted R-square.

	Call	Put
Intercept	18.210	31.500
	(7.806)	(11.801)
	[100,0]	[100,0]
SS	1.337	1.337
	(0.279)	(1.137)
	[11,6]	[39,0]
TM	5.189	6.437
	(8.641)	(9.902)
	[100,0]	[100,0]
TTM	0.008	-0.059
	(1.884)	(-7.746)
	[44,0]	[0,100]
M	-5.020	-7.326
	(-6.934)	(-10.041)
	[0,100]	[0,100]
V	-0.515	-0.119
	(-3.347)	(-0.790)
	[0,89]	[6,22]
σ_o	0.443	0.032
	(14.209)	(7.540)
	[100,0]	[100,0]
σ_s	-5.241	-1.081
	(-7.483)	(-2.697)
	[0,100]	[6,72]
R^2 (%)	41.63	44.40

5.5.2 *Hedging and Adverse Selection*

The previous section shows that tailor-made strategy-linked options are at a disadvantage relative to outright options in terms of transaction costs. This section examines whether option hedging and adverse selection costs faced by market makers can explain this disadvantage using multivariate regression. The literature suggests that options market makers face two types of hedging costs: the initial cost of creating a delta hedged position and the cost of rebalancing the portfolio at discrete times to maintain a delta neutral portfolio (Kaul et al., 2004). Engle and Neri (2010) specify hedging costs in the option market as the percentage delta multiplied by the underlying bid-ask spread. Consequently, initial hedging costs are modeled as follows:

$$IHC_{it} = \left|\frac{\partial c_{it}}{\partial S_{it}} \times \frac{S_{it}}{P_{it}}\right| \times PBAS_{it}^{Under} \tag{5.4}$$

where $\left|\frac{\partial c_{it}}{\partial S_{it}} \times \frac{S_{it}}{P_{it}}\right|$ is the average percentage delta for option i on day t and $PBAS_{it}^{Under}$ is the average underlying percentage bid-ask spread for option i on day t. Following Patrella (2006) and Engle and Neri (2010), rebalancing costs are calculated as:

$$RHC_{it} = \Gamma_{it} \times \sigma_{s_{it}} \tag{5.5}$$

where Γ_{it} refers to the average gamma for option i on day t and $\sigma_{s_{it}}$ is measured each day using the intraday high-low price range estimator proposed by Parkinson (1980).

The degree of adverse selection is measured by the probability of informed trading (*PIN*) developed in Easley et al. (2006). The PIN is a measure which uses inferred order flow to quantify the extent information asymmetry. There are two exogenous variables in this model. One is the occurrence of an information event. The other is the value of the asset. Prior to every trading session, the occurrence of an information event is determined with probability α. If no information event occurs, the value of the asset is V^*. Otherwise, the asset value is determined to be $V^H > V^*$ with probability δ or $V^H < V^*$ with probability 1-δ. The value of the asset becomes public at the end of the trading session.

There are three types of traders: (1) informed traders, (2) uninformed traders, and (3) market makers. Informed traders observe the true value of the asset, and they know whether an information event has occurred prior to each trading session. In contrast, uninformed traders are purely liquidity motivated. Uninformed traders arrive at the trading platform according to the Poisson process at the rate ε (per minute per trading session). If an event occurs, informed traders also arrive at the rate μ. These arrival processes are independent of each other. Informed traders buy (sell) assets when the asset value is $V^H(V^L)$. Market makers set quotes such that their expected profit is zero each time. Using the model of Easley et al. (2006), the unconditional probability of informed trading is defined as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu+2\varepsilon} \tag{5.6}$$

This provides a *PIN* for each stock but constant over time. Following Engle and Neri (2010), buy and sell orders are aggregated over each minute of the trading day to provide a daily *PIN* measure. In order to ensure a sufficient number of trades in each minute interval, *PIN* is estimated for each stock for each day using transaction data in the equities market, employed as a proxy for the level of informed trading in the options market. Though the *PIN* is a proxy Engle and Neri (2010) point out that there is evidence that informed traders prefer trading in the options market (Arnold et al., 2000).

The methodology of Engle and Neri (2010) is used here to examine whether option hedging and adverse selection costs faced by market makers can explain the results in the previous section, the following regression is estimated for each underlying stock:

$$\begin{aligned} Diff\_PES_{it} = \beta_0 + \beta_1 IHC_{it} + \beta_2 RHC_{\mathrm{it}} + \beta_5 PIN_{it} + \beta_3 TTM_{it} \\ + \beta_4 M_{it} + \beta_6 V_{it} + \beta_7 \sigma_{o_{it}} + \beta_8 \sigma_{s_{it}} + \beta_9 Type_{it} + \varepsilon_{it} \end{aligned} \qquad (5.7)$$

where $Diff\_PES_{it}$ is the daily average difference in percentage effective spreads of TM (SS) trades and outright trades; initial hedging cost (IHC_{it}) is defined in Equation (3); rebalancing cost (HRC_{it}) is defined in Equation (4); PIN_{it} is defined in Equation (4), stock volatility ($\sigma_{s_{it}}$) is defined in Equation (2); $Type_{it}$ is a dummy variable that takes the value of one for call options and zero for put options. The other explanatory variables are as described for Equation (1). Each equation is estimated separately for each stock using the Generalized Method of Moments (GMM); the resulting t-statistics are robust to heteroskedasticity and autocorrelation (Newey and West, 1987).

Table 4-7 reports the results of the regression estimates. The results indicate that (both initial and rebalancing) hedging and adverse selection costs do not lead to wider proportional effective spreads for SS trades relative to outright option trades as indicated by the insignificant coefficients on the variables IHC_{it}, HRC_{it}, and PIN_{it}. All control variables included in the regressions are statistically insignificant at the 5% level. In contrast, results indicate that initial hedging costs significantly affect the difference in proportional effective spreads for TM trades relative to outright options trades, with the coefficient on IHC_{it} statistically significant at the 1% level. On the contrary, rebalancing hedging costs do no significantly affect the difference in proportional effective spreads. This is in contrast to Engle and Neri (2010) who show that both hedging and rebalancing costs are an important component of the bid-ask spread. Rebalancing costs may still be an important component of the bid-ask spread in the options market. However, the results suggest that market makers do not require compensation for rebalancing costs of strategy trades relative to outright options after the hedge has already been set up.

In contrast to $H_{5,3,}$ results show that market makers are not sensitive to adverse selection costs in setting quotes for tailor-made options relative to outright options. This is in line with other studies that show that the adverse selection component of the bid-ask spread is small (Vijh, 1990; Neal, 1992). However, given that option strategy trades in particular are likely to contain information about future realized volatility, this finding is somewhat surprising. It may be that informed traders only engage in specific types of option strategies (Fahlenbrach and Sandas, 2010). Supporting hypothesis $H_{5,4,}$ overall results indicate that the difference in proportional effective spreads for tailor-made options is affected by market making costs, which is in line with a number of studies examining the components of the bid-ask spread in the options market . The implication is that market makers require higher premiums for tailor-made options relative to outright options when initial hedging is more costly, suggesting that that informed trading is not a key component of the bid-ask spread.

Table 5-7
Percentage Effective Spreads, Hedging Costs and Probability of Informed Trading

This table reports the GMM estimates from the regressions estimated for each of the 20 underlying stocks. The regression model is specified as follows:

$$Diff_{PES_{it}} = \beta_0 + \beta_1 IHC_{it} + \beta_2 RC_{\text{it}} + \beta_5 PIN_{it} + \beta_3 TTM_{it} + \beta_4 M_{it} + \beta_6 V_{it} + \beta_7 \sigma_{o\,it} + \beta_8 \sigma_{s\,it} + \beta_9 Type_{it} + \varepsilon_i$$

where $Diff\_PES_{it}$ is the daily average difference in percentage effective spreads of TM (SS) trades and outright trades; initial hedging cost (IHC_{it}) is defined in Equation (1); rebalancing cost (HRC_{it}) is defined in Equation (2); time-to-maturity (TTM_{it}) is the difference between the current date of the option and the expiry date; moneyness (M_{it}) is the ratio of closing spot (strike) price to strike (closing spot) price of call (put) options for option i on day t; V_{it} is the logarithm of the total daily option volume for option i on day t; option volatility ($\sigma_{o_{it}}$) is calculated as the absolute value of the option price elasticity times the underlying stock volatility for option i on day t; stock volatility ($\sigma_{s_{it}}$) is defined in Equation (3); $Type_{it}$ is a dummy variable that takes the value of one for call options and zero for put options. The regression is estimated for each underlying stock. Regression coefficients are cross-sectional averages from the 20 stocks. Average t-statistics are in parentheses. The first (second) component in each bracket is the percentage of significantly positive (negative) coefficients at the 10% level. The R^2 is the cross-sectional average adjusted R-square.

	S - O	TM - O
Intercept	5.071	18.452
	(0.551)	(3.032)
	[28, 0]	[78, 0]
IHC	0.226	0.270
	(0.925)	(3.351)
	[28, 0]	[78, 0]
RHC	0.996	3.179
	(0.273)	(0.961)
	[17, 17]	[28, 0]
PIN	-0.349	0.508
	(0.042)	(0.142)
	[22, 6]	[11, 6]
TTM	-0.013	-0.010
	(-0.401)	(-0.943)
	[11,22]	[0, 22]
M	-0.938	-4.956
	(-0.372)	(-2.491)
	[17, 22]	[6, 55]
V	-0.067	-0.168
	(-0.237)	(-0.539)
	[11, 17]	[11, 25]
σ_o	-2.933	0.246
	(-0.360)	(-0.004)
	[0, 11]	[6, 11]
σ_s	-0.451	0.349
	(-0.424)	(0.421)
	[0, 17]	[17, 0]
Type	0.601	0.761
	(0.276)	(0.677)

	[0, 0]	[33, 6]
R^2 (%)	6.026	7.547

5.5 Summary

This study measures the magnitude of execution costs of outright options and options which constitute strategies ("strategy-linked options") and examines if any differences in trade prices between these two groups is attributable to differences in market making costs. The literature suggests that options market makers face the following three types of hedging costs; delta cost is the cost of setting up a hedging portfolio; vega (gamma) cost is the cost incurred in maintaining a hedged portfolio as the underlying stock volatility (delta) changes over time. Market makers may also face adverse selection costs. This study investigates whether differences in transaction costs between strategy-linked options and outright options are due to hedging cost or adverse selection costs using a proprietary data set provided by the Australian Options Market (AOM).

Results of the univariate analysis indicate that strategy-linked options exhibit wider spreads than outright options across both put and call options, and across options with different characteristics (moneyness, time to maturity, and trading activity), which are shown to be related to the liquidity of options (Wei and Zheng, 2010). Multivariate analysis shows that after directly controlling for a number of liquidity determinants, tailor-made strategy-linked trades incur higher execution costs than outright options trades. Results also indicate that the difference in execution costs between tailor-made strategy-linked options and outright options is driven by the initial costs in delta hedging the option position and not a result of higher adverse selection costs.

Chapter 6: Intraday Patterns in Quoted Depth

6.1 Introduction

A large body of empirical research has been undertaken documenting systematic patterns in bid-ask spreads different types of market exchanges, including order-driven, specialists and competitive dealer markets. However, these patterns have not yielded similar results across these market types. As a result of this, several competing theories have arisen to explain the intraday behaviour in liquidity across these markets, such as inventory, market power and information models. Furthermore, the literature reviewed in Section 2.2 reveals a number of studies examining intraday patterns in quoted depth on specialist and order-driven markets. However, no study has examined intraday patterns in quoted depth on competitive dealer markets. This essay fills the gap in the literature by investigating the intraday patterns in quoted depth on the Nasdaq.

The remainder of this chapter is structured as follows. Section 6.2 describes the data and research design employed. Section 6.3 provides the empirical results on the intraday variation in the bid-ask spread, quoted depth, volume and volatility. Section 6.4 presents additional tests. Section 6.5 summarises the chapter.

6.2 Hypotheses on Intraday Patterns in Liquidity

Prior studies examining the inventory component of bid-ask spreads on a competitive dealer market suggest that inventory effects could dominate near the close of trading. In the model of Amihud and Mendelson (1982), the dealer has a preferred or target inventory position, and adjusts his/her prices to return to his/her target inventory level. If the dealer is too long, he/she lowers both the bid and ask prices to induce other traders to buy to reduce inventory towards the target level. If the market maker is below the target inventory level, he/she raises both the bid and ask prices. Chordia et al. (2002) and Bessembinder (2003b) suggest that if market makers perceive that competitive quotations will attract orders, then reductions (increases) in inventory should lead to posting of more aggressive quotations at the bid (ask) to attract sell (buy) orders and restore inventory. Inventory effects are likely to be acute at the close of trading as dealers attempt to reduce their market exposure, resulting in bid-ask spreads narrowing significantly at the market close.

The literature examining competitive dealer markets document this pattern in bid-ask spreads over the course of the trading day (see Chan et al. 1995a, Chan, Chung and Johnson, 1995, Kliedon and Werner, 1996, and Cai, Hudson and Keasey, 2004). The narrowing of spreads at the close is attributed to inventory management, with individual dealers who want to 'go home flat' post quotes that improve the inside spread in order to attract order flow away from other dealers. In addition, the dealer may remove order imbalances by increasing the depth of the quote to attract orders away from other dealers. This leads to the following hypothesis.

Hypothesis$_{6.1}$: *Quoted depth (bid-ask spreads) will be relatively large (narrow) near the close of trading.*

The Nasdaq operates as a competitive dealer market, where each individual dealer competes for investor orders by displaying quotations that represent their buy and sell interest in Nasdaq securities. In displaying their quotes, market makers post both the price (i.e., the bid and ask price) and the quantity (i.e., the bid and ask depth) of shares that they are willing to trade. In 1997, major changes were made to the way Nasdaq dealers handled customer orders following the Chrisitie and Shultz (1994) debate about price fixing by market makers on the Nasdaq. The SEC instituted new Order Handling Rules (OHR) that were designed to make the Nasdaq market more competitive and reduce dealer participation in Nasdaq trades by ensuring the dealers took public limit orders into account. The Limit Order Display Rule (LODR) requires dealers to publicly display limit orders they receive from customers, unless an exception applies. If the limit order is priced better than his or her quote or that adds size to his or her quote, the market maker must publicly display it. For example, assume a dealer is currently quoting 10,000 shares at a bid price of $10. If the dealer receives a limit order to buy 11,000 shares at a bid price of $10.50, the dealer is required to revise the quote to reflect the higher bid price and larger bid size. This rule applies to all individual dealer quotes, regardless of their quote position relative to the market inside.

The introduction of the LODR has important implications for the interrelationship between bid-ask spreads and market depth at the best quotes. Assume the dealer is currently quoting 10,000 shares at a bid price of $10 and receives a limit order to buy 10,000 shares at a bid price of $10. In this situation, the dealer does not have to change the quote as the bid price and bid size have not been improved. If the best bid happens to be at $10.50, the dealer may not wish to update the quote from 1,000 shares to 2,000 shares (which is optional), due either to the quote being too far from the inside market or decides it is in his or her interest to let the limit order replace their market making in this particular security. However, if the best bid is currently at $10, the dealer is currently quoting at the best bid, possibly wanting to buy as a result of managing his or her inventory position. In this situation, the dealer is likely to change the quote to 2,000 shares otherwise he or she may miss the opportunity to execute their order. Dealers therefore are likely to post larger depths when their quotes are at the best bid and ask prices. It follows that quoted spreads and depth are inversely related because of dealers changing their quote sizes as the move from the non-inside market to the inside market. This leads to the following hypothesis.

Hypothesis$_{6.2}$: *Quoted depth and bid-ask spreads are inversely related.*

6.3 Nasdaq

Created by the NASD in 1971, the National Association of Securities Dealers Automated Quotations (Nasdaq) was set up to enhance the efficiency of the over-the-counter (OTC) markets for stock securities, through the use of a telecommunication network linking thousands of geographically diverse participants. The Nasdaq was designed as a competitive dealer market. Within this particular market structure, prices are set by dealer quotes, where each individual dealer competes for investor orders by displaying quotations that represent their buy and sell interest in Nasdaq securities. Market makers registered to trade in listed Nasdaq securities are required to do three things. They must display their buying and selling interest by posting a two-sided quote in all stocks they choose to make a market in. They must display all quotes and orders to the Nasdaq and finally they are obligated to honour their quotes. Companies that choose to list on the Nasdaq must have at least 3 market makers (excluding ECNs).

In 1997, major changes were made to the way Nasdaq dealers handled customer orders, following the Chrisitie and Shultz (1994) debate about price fixing by market makers on the Nasdaq. The SEC instituted new Order Handling Rules (OHR) that were designed to make the Nasdaq market more competitive and reduce dealer participation in Nasdaq trades by ensuring the dealers took public limit orders into account. The new rules required dealers to handle a marketable limit order in one of three ways: (1) execute the limit order against the dealers inventory; (2) the limit order must be reflected in the dealers quote; (3) send the limit order to another dealer; (4) send the order to an Exchange Communication Network (ECN). Another important change by the SEC was to enable public access to superior prices posted by market makers in ECNs. An ECN is an electronic trading system separate to the exchange that allows investors to execute trades through an open limit order book (Fink, Fink and Weston, 2006). This enabled traders to bypass the placement of orders with dealers and instead submit orders and trade with each other directly. Prior to 1997, dealers could provide alternative pricing systems by quoting one set of prices in the public market and another better price placed on the ECN. The rule change forced dealers to publicly display their most competitive quotes, regardless of where it is placed. The effect of these reforms has been: (1) growth in limit order trades as even the small retail customers could become temporary market makers and; (2) spurred the development of ECN's, whose liquidity is based primarily on limit-order flow (McAndrews and Stefanadis, 2000).

6.4 Data and Research Design

The data is obtained from a Reuters intraday database managed by SIRCA.[7] The sample contains stocks listed on the Nasdaq-100 index and covers the period November 30, 2008 to April 23, 2009. The data is derived from one-minute intervals and consists of the best bid and ask prices and volumes at the end of each interval, the interval high and low prices, and the volume traded during the interval. Consistent with previous research (including Chung and Zhoa, 2003; Cai et al., 2004; Vo, 2007) the trading day is partitioned into 30-minute intervals, these one-minute intervals are averaged into 14 separate 30-minute trading intervals, from 09:30 hours to 16:00 hours (i.e. from the open to the close of trading).

The variables examined include the bid-ask spread, quoted depth, volume and volatility. Following Chan et al. (1995b), the bid-ask spread is defined as:

$$PBAS_t = \frac{inside\ ask_t - \ inside\ bid_t}{\left(\dfrac{inside\ ask_t\ +\ inside\ bid_t}{2} \right)} \tag{1}$$

[7] Securities Institute Research Centre of Asia-Pacific.

where $PBAS_t$ is the percentage bid-ask spread at time period *t*, the inside ask is the lowest ask price at time period *t*, and the inside bid is the highest bid price at period *t*. The midpoint is used to avoid problems associated with bid-ask bounce. Following Huang and Stoll (1996) and Chung and Zhao (2003), the following filters are applied in the calculation of the bid-ask spread: (1) bid-ask spread quotes are excluded if the spread is greater than \$5 or less than zero; (2) exclude ask quote at if $[(a_t - a_{t-1})/a_{t-1}]$ is greater than 10%; (3) exclude bid-quote if $[(b_t - b_{t-1})/b_{t-1}]$ is greater than 10%.

Quoted depth is defined as the average volume of shares available at the best bid and the best ask at the end of each interval for each stock (Harris, 1994). Volume is measured as the number of shares traded across each 30-minute interval. Volatility is measured as the natural logarithm of the difference between the interval high and interval low for each one-minute interval. To prevent cross-sectional differences across securities biasing results, all variables are standardized by subtracting the daily mean and dividing by the daily standard deviation for each stock.

In Section 6.3, it is hypothesised that bid-ask spreads and market depth are inversely related and that bid-ask spreads (quoted depth) are wide (small) at the open and tight (large) at the close of trading. To formally test for intraday patterns in bid-ask spreads, quoted depth, volume and volatility, we regress the variables upon a set of intraday dummy variables using Hansen's (1982) Generalized Methods of Moments (GMM) procedure. The GMM technique is applied in prior research examining intraday patterns in liquidity, such as Foster and Viswanathan (1993), Abhyankar et al. (1997), Cai et al. (2004). GMM estimates the coefficients through the use of orthogonality conditions and provides results that are robust to the presence of autocorrelation and heteroskedasticity. Many of the microstructure studies using the GMM technique employ the procedure of Newey and West (1987) to adjust for autocorrelation and heteroskedasticity. Autocorrelation and heteroskedasticity are controlled for using the Parzen Kernel (Gallant, 1987). Andrews (1991) shows that the Bartlett Kernel used by Newey and West (1987) exhibits greater bias and is 100 percent less efficient asymptotically than the Parzen Kernel. The lag truncation period is calculated using the formula n^(1/5) (Andrews, 1991). For each variable, the following model is estimated:

$$st(V_{i,t}) = \alpha_0 + \sum_{k=1}^{n} \alpha_k D_k + \varepsilon_t \tag{2}$$

where $st(V_{i,t})$ is the standardized variable in interval t for firm *i*, n is the number of intervals in the day, D_k a time-of-day dummy variable equal to 1 if observation *t* falls in interval *k*, otherwise zero. The 30-minute interval 12:30 to 13:00 is excluded from the regression.

6.3 Empirical Results

Foster and Viswanathan (1993) and Harris (1994) document that volume and volatility are significant determinants of both bid-ask spreads and quoted depth. As illustrated in Figure 6-1, volume on the Nasdaq follows a U-shaped pattern, being highest at the open and close of trading, and lowest during the middle of the trading day. Price volatility is highest at the start of trading, falls consistently to the middle of the trading day, and then increases for the remainder of the trading day. Regression results in Table 6-1 confirm that both volume and volatility in the first and last thirty-minute intervals of the trading day are higher than during the middle of the day. The intraday variation in trading volume and volatility is consistent with the results documented by Chan, Christie and Schultz (1995) for the Nasdaq, and is similar to the patterns in trading volume and volatility for other markets (e.g., McInish and Wood, 1992; Chan, Chung and Johnson, 1995; Ahn and Cheung, 1999).

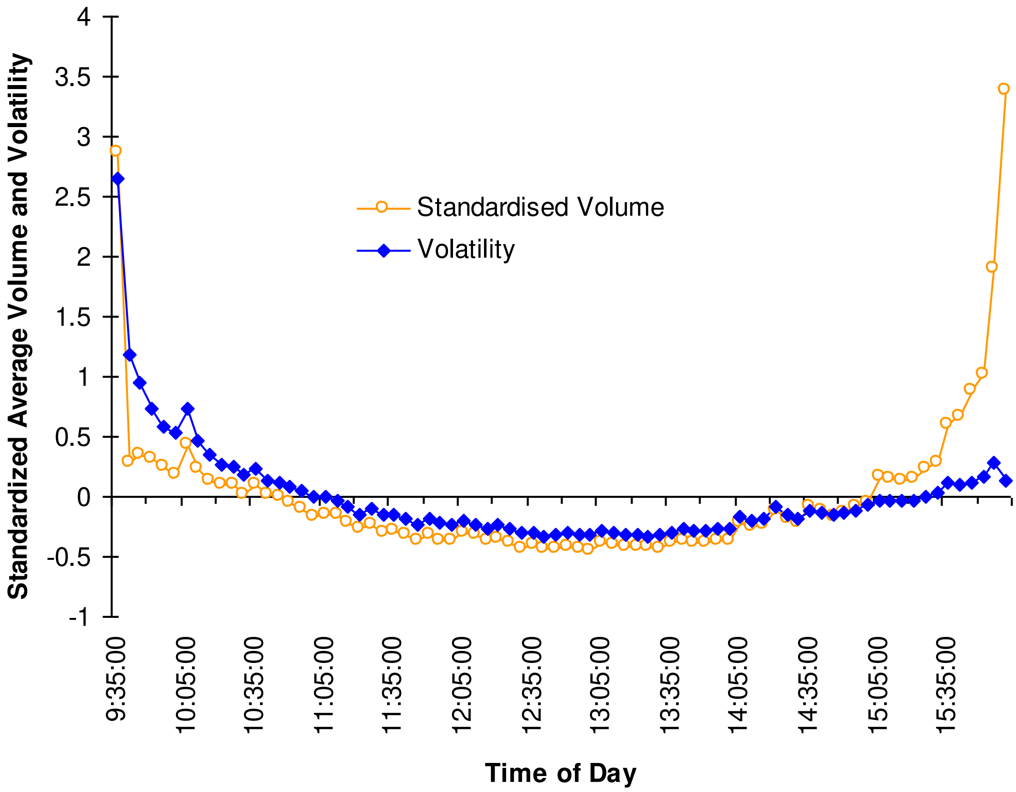

Figure 6-1
Standardized Trading Volume and Volatility

This figure depicts the intraday pattern in standardized trading volume and volatility in 5-minute intervals. The sample extends from November 30, 2008 to April 23, 2009. Traded volume is measured as the number of shares traded across each 5-minute interval. Volatility is measured as the natural logarithm of the difference between the interval high and interval low during each 1-minute interval. The two variables are then averaged across 78 equal 5-minute intervals.

Table 6-1
Mean Value of the Standardized Quoted Depth, Bid-Ask Spread, Trading Volume and Volatility

The GMM technique is used to estimate the following model:

$$st(V_{i,t}) = \alpha_0 + \sum_{k=1}^{n} \alpha_k D_k + \varepsilon_t$$

where $st(V_{i,t})$ is the standardized variable occurring in interval t for firm *i*, n is the number of intervals in the day, D_k a time-of-day dummy variable equal to 1 if observation *t* falls in interval *k*, otherwise zero. The 30 minute interval of 12:30 to 13:00 is excluded.

Time	SPREAD	DEPTH	VOLUME	VOLATILITY
9:30 - 10:00	1.0261**	-0.4451**	1.6567**	1.3851**
10:00 - 10:30	0.2542**	-0.2494**	0.7967**	0.6537**
10:30 - 11:00	0.1428**	-0.1793**	0.5042**	0.3836**
11:00 - 11:30	0.0865**	-0.1446**	0.2286**	0.1964**
11:30 - 12:00	0.0503**	-0.0946**	0.0582**	0.0806**
12:00 - 12:30	0.0163**	-0.0346**	0.0341**	0.0307**
13:00 - 13:30	0.0221**	-0.0010	-0.0770**	-0.0326**
13:30 - 14:00	-0.0052	0.0020	-0.0557**	-0.0317**
14:00 - 14:30	-0.0326**	0.0544**	0.2554**	0.1166**
14:30 - 15:00	-0.0556**	0.1230**	0.3949**	0.1573**
15:00 - 15:30	-0.1370**	0.3138**	0.8248**	0.2637**
15:30 - 16:00	-0.2664**	0.8638**	2.3065**	0.4297**
Intercept	-0.0904**	-0.0141**	-0.5329**	-0.2791**

** Indicates statistical significance at the 0.01 level
* Indicates statistical significance at the 0.05 level

Figure 6-2 plots the intraday variation of bid-ask spreads during successive 5-minute intervals. Consistent with the prediction of hypothesis $H_{6,1}$, bid-ask spreads for Nasdaq stocks are highest at the open, decline quickly over the first hour of trading, remain relatively stable until 15:00 hours, and narrow sharply towards the close. The results of the GMM estimation presented in Table 6-1 confirm this result. The coefficient of the dummy variable for the 9:30-10:00 time interval is positive and significant at the 1% level, indicating spreads in the first 30-minute interval are higher than during the middle of the day. The coefficient for the last 30-minute interval is significantly negative, indicating that spreads are narrower at the close relative to spreads in the middle of the day. The narrowing of spreads on the Nasdaq is consistent with inventory management where dealers (in the absence of market power) post competitive prices to attract orders away from competing dealers to offset inventory imbalances, thereby lowering the inside spread.

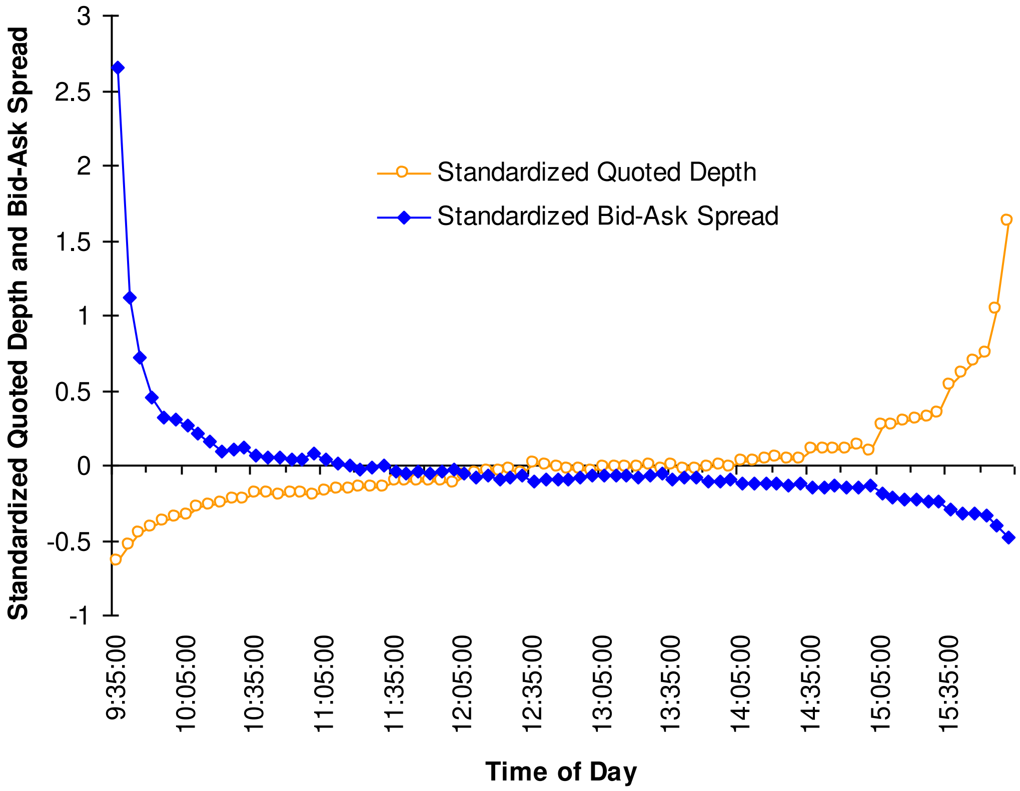

Figure 6-2
Standardized Bid-Ask Spreads and Quoted Depth

This figure depicts the intraday pattern in standardized bid-ask spreads and quoted depth in 5-minute intervals. The sample extends from November 30, 2008 to April 23, 2009. The bid-ask spread is measured as the ask quote minus the bid quote divided by the bid-ask midpoint. Quoted depth is measured as the average of the volume at the best bid and ask quotes. Both variables are calculated at the end of each 1-minute interval and then averaged across 78 equal 5-minute time-intervals.

In a study of dealer quotation behavior on the Nasdaq, Chung and Zhao (2004b) discuss how the institutional features of the Nasdaq lead to a negative correlation between the dealer's posted spread and depth. Figure 6-2 reveals the intraday variation in quoted depth is opposite to the pattern in bid-ask spreads, consistent with the second hypothesis $H_{6,2}$. Quoted depth is lowest at the open, increases over the early hours of trading and remains relatively stable until approximately 15:00 hours, when quoted depth begins to increase significantly. The results of the GMM regression in Table 6-1 document a similar pattern. The coefficient for the first 30-minute interval is significantly negative, while the coefficient for the 15:30-16:00 interval shows quoted depth reaches its highest level. This pattern in quoted depth at the close of trading differs sharply to the results of Lee et al. (1993) on the NYSE, who document significantly lower depth. However, these findings are consistent with Chung and Zhao (2004b), supporting the view that both the price and quantity of dealer's quotes are inter-dependent, and that spreads and depth are negatively correlated. The narrowing of the bid-ask spread and increase in quoted depth at the close of trading suggests that inventory management on the part of market makers results in improved liquidity at the close of trading.

6.4 Additional Tests

As a robustness test of the results presented in Table 6-2, Equation 2 is estimated using the procedure of Meulbroek (1992). Equation 2 is estimated for each stock in the sample using the GMM procedure as stated, with the dummy variable for each time interval being the average coefficient from the individual regressions. To test whether each coefficient differs statistically from zero, we calculate a Z-statistic for each coefficient. The Z-statistic is calculated as:

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} t_i \sim N(0,1), \tag{3}$$

where N is the number of stocks in the sample and t_i is the *t*-statistic for stock *i*. Table 6-2 shows that these results are robust to the estimation technique used, with the regression coefficients qualitatively similar to the results presented in Table 6-1. Trading volume and price volatility are highest at the start and end of the trading day. Bid-ask spreads (quoted depth) are highest at the opening and are lowest (highest) at the close of the trading day.

To further ensure that the intraday patterns in spreads and depth on the Nasdaq are not caused by variation in volume and volatility, we directly control for trading volume and price volatility using the method of Heflin et al. (2007). Under this approach, firm i's bid-ask spreads, quoted depth, trading volume and volatility are expressed as percent deviations from firm i's mean level for that variable computed using the 12:30 to 13:00 interval. The GMM regression is estimated separately for each time interval, with the percent deviations of volume and volatility used as 'instruments'.

Table 6-2
Regression Estimates in Variation in Standardized Bid-Ask Spread, Quoted Depth, Trading Volume and Volatility

The GMM technique is used to estimate the following model:

$$st(V_{i,t}) = \alpha_0 + \sum_{k=1}^{n} \alpha_k D_k + \varepsilon_t$$

where $st(V_{i,t})$ is the standardized variable occurring in interval t for firm *i*, n is the number of intervals in the day, D_k a time-of-day dummy variable equal to 1 if observation *t* falls in interval *k*, otherwise zero. The 30 minute interval of 12.30 to 1.00 is excluded. The coefficients are the average of the coefficients from the regression of each individual stock. Positive Coefficient (%) is the percentage of stocks in the regression with a positive coefficient. The Z-statistic to test whether the mean coefficient for each dummy variable differs from zero is given by the formula $Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} t_i \sim N(0,1),$ where N is the number of stocks in the sample and t_i is the *t*-statistic for stock *i*.

Time	SPREAD	DEPTH	VOLUME	VOLATILITY
9:30 - 10:00	1.0267	-0.4533	1.7291	1.4195
Positive Coefficient (%)	93.75	5.21	100	100
Z-statistics	181.855	-88.925	157.193	282.444
p-value	0.0000	0.0000	0.0000	0.0000
10:00 - 10:30	0.2514	-0.2554	0.8704	0.6844
Positive Coefficient (%)	83.33	6.25	100	100
Z-statistics	55.03	-49.13	96.72	154.43
p-value	0.0000	0.0000	0.0000	0.0000
10:30 - 11:00	0.1410	-0.1822	0.5773	0.4142
Positive Coefficient (%)	80.21	7.29	100	100
Z-statistics	32.60	-35.95	67.94	105.59
p-value	0.0000	0.0000	0.0000	0.0000
11:00 - 11:30	0.0859	-0.1505	0.3047	0.2296
Positive Coefficient (%)	80.21	6.25	100	100
Z-statistics	21.20	-28.90	38.31	63.19
p-value	0.0000	0.0000	0.0000	0.0000
11:30 - 12:00	0.0498	-0.1000	0.1361	0.1131
Positive Coefficient (%)	83.33	8.33	90.72	100
Z-statistics	13.00	-18.99	17.42	32.21
p-value	0.0000	0.0000	0.0000	0.0000
12:00 - 12:30	0.0164	-0.0392	0.1091	0.0628
Positive Coefficient (%)	67.71	22.92	94.85	98.97
Z-statistics	4.51	-8.18	14.90	19.85
p-value	0.000	0.000	0.000	0.000
13:00 - 13:30	0.0221	-0.0064	0.0245	0.0018
Positive Coefficient (%)	80.21	47.92	61.86	52.58
Z-statistics	6.25	-0.25	3.31	0.50
p-value	0.0000	0.8034	0.0008	0.6202
13:30 -14:00	-0.0045	-0.0010	0.0783	0.0320
Positive Coefficient (%)	48.96	51.04	89.69	86.60
Z-statistics	0.66	-0.36	10.30	9.96
p-value	0.5090	0.7117	0.0000	0.0000
14:00 - 14:30	-0.0318	0.0510	0.3314	0.1482

Positive Coefficient (%)	22.92	71.88	100.00	98.97
Z-statistics	7.60	8.94	39.71	36.82
p-value	0.0000	0.0000	0.0000	0.0000
14:30 - 15:00	-0.0554	0.1175	0.4734	0.1892
Positive Coefficient (%)	18.75	87.5	100	100
Z-statistics	13.96	22.25	57.00	48.84
p-value	0.0000	0.0000	0.0000	0.0000
15:00 - 15:30	-0.1348	0.3109	0.9080	0.2973
Positive Coefficient (%)	8.33	92.71	100	100
Z-statistics	35.40	54.91	102.72	78.62
p-value	0.0000	0.0000	0.0000	0.0000
15:30 - 16:00	-0.2628	0.8595	2.3863	0.4637
Positive Coefficient (%)	5.21	100	100	100
Z-statistics	67.36	125.46	228.42	112.16
p-value	0.0000	0.0000	0.0000	0.0000

** Indicates statistical significance at the 0.01 level
* Indicates statistical significance at the 0.05 level

For each half hour interval, the following equation is estimated:

$$dst(V_{i,t}) = \alpha_0 + \alpha_1 DVOLATILITY_{i,t} + \alpha_2 DVOLUME_{i,t} + e_{i,t} \tag{4}$$

where $dst(V_{i,t})$, $DVOLATILITY_{i,t}$ and $DVOLUME_{i,t}$ are per cent deviations of $st(V_{i,t})$ (spread and depth), $VOLATILITY_{i,t}$, $VOLUME_{i,t}$ for interval *t* from firm *i*'s mean of each of these variables computed from the 12:30-13:00 interval.

Table 6-3
Regression Estimates of Variations in the Standardized Bid-Ask Spread

The GMM method is used to estimate the following model:

$$dst(V_{i,t}) = \alpha_0 + \alpha_1 DVOLATILITY_{i,t} + \alpha_2 DVOLUME_{i,t} + e_{i,t}$$

where $dst(V_{i,t})$, $DVOLATILITY_{i,t}$ and $DVOLUME_{i,t}$ are per cent deviations of $st(V_{i,t})$, $VOLATILITY_{i,t}$, $VOLUME_{i,t}$ for interval *t* from firm *i*'s mean of each of these variables computed from the 12:30-1:00 interval. The model is estimated separately for each 30-minute trading interval.

Time	a0	t-statistic	a1	t-statistic	a2	t-statistic
9:30 - 10:00	0.4898	27.23**	-0.0353	-7.91**	0.0817	10.85**
10:00 - 10:30	0.1577	15.84**	-0.0758	-5.7**	0.0822	10.75**
10:30 - 11:00	0.1108	19.78**	-0.0775	-15.68**	0.0829	11.47**
11:00 - 11:30	0.0709	15.97**	-0.0896	-15.27**	0.1001	10.12**
11:30 - 12:00	0.0555	11.92**	-0.0655	-4.64**	0.0608	2.47**
12:00 - 12:30	0.0244	10.63**	-0.0775	-8.82**	0.0819	5.19**
13:00 - 13:30	0.0129	5.26**	-0.0753	-6.37**	0.1152	7.89**
13:30 -14:00	0.0014	0.56	-0.0815	-13.8**	0.0973	8.88**
14:00 - 14:30	-0.0174	-5.72**	-0.0351	-3.82**	0.0408	2.43*
14:30 - 15:00	-0.0258	-8.05**	-0.0438	-5.22**	0.0581	3.98**
15:00 - 15:30	-0.0649	9.90**	-0.0427	-12.76**	0.0627	-18.84**
15:30 - 16:00	-0.0881	-19.84**	-0.0170	-12.03**	0.0257	5.64**

** Indicates statistical significance at the 0.01 level
 * Indicates statistical significance at the 0.05 level

The GMM regression results are presented in Tables 6-3 and 6-4, with the coefficients on the control variables consistent with Foster and Viswanathan (1993) and Harris (1994). An increase in the deviation of trading volume and price volatility from their midday mean levels are negatively related to bid-ask spreads and positively related to quoted depth. Controlling for these variables, the trend in bid-ask spreads and quoted depth are qualitatively similar to the results presented in Table 6-1.

Table 6-4
Regression Estimates of Variations in Standardized Quoted Depth

The GMM is used to estimate the following model:

$$dst(V_{i,t}) = \alpha_0 + \alpha_1 DVOLATILITY_{i,t} + \alpha_2 DVOLUME_{i,t} + e_{i,t}$$

where $dst(V_{i,t})$, $DVOLATILITY_{i,t}$ and $DVOLUME_{i,t}$ are per cent deviations of $st(V_{i,t})$ (depth), $VOLATILITY_{i,t}$, $VOLUME_{i,t}$ for interval *t* from firm *i*'s mean of each of these variables computed from the 12:30-1:00 interval. The model is estimated separately for each 30-minute trading interval.

Time	a0	t-statistic	a1	t-statistic	a2	t-statistic
9:30 - 10:00	-0.2106	-22.23**	0.0148	5.8**	-0.0286	-9.96**
10:00 - 10:30	-0.0899	-10.07**	0.0716	7.43**	-0.0830	-10.15**
10:30 - 11:00	-0.0497	-6.56**	0.1096	14.28**	-0.1252	-12.3**
11:00 - 11:30	-0.0331	-5.19**	0.1537	13.2**	-0.1608	-11.62**
11:30 - 12:00	-0.0050	-0.58	0.1029	3.91**	-0.0965	-2.07*
12:00 - 12:30	0.0224	4.84**	0.1278	7.48**	-0.1456	-5.04**
13:00 - 13:30	0.0498	13.35**	0.1246	9.11**	-0.1798	-9.90**
13:30 -14:00	0.0687	14.07**	0.1680	11.11**	-0.2265	-9.00**
14:00 - 14:30	0.1272	20.24**	0.0537	3.16**	-0.0713	-2.51*
14:30 - 15:00	0.1917	23.85**	0.0689	2.92**	-0.1020	-2.58**
15:00 - 15:30	0.3548	31.86**	0.1194	11.19**	-0.2342	-9.00**
15:30 - 16:00	0.7655	34.02**	0.0988	9.06**	-0.1739	-3.88**

** Indicates statistical significance at the 0.01 level
 * Indicates statistical significance at the 0.05 level

Re-estimating equation (4) using the procedure of Meulbroek (1992), as shown in Tables 6-5 and 6-6 reveal no qualitative difference in the results. Traded volume and volatility cannot explain differences in the variation in spreads and depth between the competitive dealer market and other market structures.

Table 6-5
Regression Estimates of Variations in the Standardized Bid-Ask Spread

The GMM method is used to estimate the following model:

$$dst(V_{i,t}) = \alpha_0 + \alpha_1 DVOLATILITY_{i,t} + \alpha_2 DVOLUME_{i,t} + e_{i,t}$$

where $dst(V_{i,t})$, $DVOLATILITY_{i,t}$ and $DVOLUME_{i,t}$ are per cent deviations of $st(V_{i,t})$ (spread), $VOLATILITY_{i,t}$, $VOLUME_{i,t}$ for interval *t* from firm *i*'s mean of each of these variables computed from the 12:30-1:00 interval. The model is estimated separately for each stock for each 30-minute trading interval. The coefficients are an average of the coefficients from the regression of each individual stock. Positive Coefficient (%) is the percentage of stocks in the regression with a positive coefficient. The Z-statistic to test whether the mean coefficient for each time interval differs from zero is given by the formula $Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} t_i \sim N(0,1)$, where N is the number of stocks in the sample and t_i is the *t*-statistic for stock *i*.

Time	a0	a1	a2
9:30 - 10:00	0.0689	-0.0402	0.5292
Positive Coefficient %	95.79	4.21	86.32
Z-statistics	55.71	-19.41	17.81
p-value	0.0000	0.0000	0.0000
10:00 - 10:30	0.1562	-0.0885	0.0902
Positive Coefficient %	91.58	4.21	84.21
Z-statistics	27.52	-25.82	23.52
p-value	0.0000	0.0000	0.0000
10:30 - 11:00	0.1044	-0.0815	0.0962
Positive Coefficient %	85.26	14.74	88.42
Z-statistics	21.50	-20.45	19.58
p-value	0.0000	0.0000	0.0000
11:00 - 11:30	0.0678	-0.0939	0.1115
Positive Coefficient %	83.16	16.84	88.42
Z-statistics	17.92	-19.83	18.36
p-value	0.0000	0.0000	0.0000
11:30 - 12:00	0.0486	-0.0981	0.1144
Positive Coefficient %	96.84	10.53	81.05
Z-statistics	15.76	-20.58	19.73
p-value	0.0000	0.0000	0.0000
12:00 - 12:30	0.0231	-0.0914	0.1078
Positive Coefficient %	81.05	11.58	83.16
Z-statistics	10.30	-22.97	20.54
p-value	0.0000	0.0000	0.0000
13:00 - 13:30	0.0142	-0.0969	0.1266
Positive Coefficient %	72.63	11.58	84.21
Z-statistics	6.32	-19.36	19.18
p-value	0.0000	0.0000	0.0000
13:30 -14:00	0.0009	-0.0949	0.1187
Positive Coefficient %	49.47	11.58	87.37
Z-statistics	0.1142	-24.8195	21.1243
p-value	0.9091	0.0000	0.0000
14:00 - 14:30	-0.0244	-0.0713	0.1067
Positive Coefficient %	25.26	17.90	84.21
Z-statistics	-11.04	-21.89	31.21

p-value	0.0000	0.0000	0.0000
14:30 - 15:00	-0.0314	-0.0684	0.1044
Positive Coefficient %	22.11	17.90	84.21
Z-statistics	-13.49	-24.59	30.12
p-value	0.0000	0.0000	0.0000
15:00 - 15:30	-0.0727	-0.0507	0.0861
Positive Coefficient %	5.26	16.84	83.16
Z-statistics	-29.16	-24.01	26.62
p-value	0.0000	0.0000	0.0000
15:30 - 16:00	-0.1005	-0.0236	0.0580
Positive Coefficient %	23.16	11.58	86.32
Z-statistics	-27.98	-21.88	22.95
p-value	0.0000	0.0000	0.0000

Table 6-6
Regression Estimates of Variations in Standardized Quoted Depth

The GMM method is used to estimate the following model:

$$dst(V_{i,t}) = \alpha_0 + \alpha_1 DVOLATILITY_{i,t} + \alpha_2 DVOLUME_{i,t} + e_{i,t}$$

where $dst(V_{i,t})$, $DVOLATILITY_{i,t}$ and $DVOLUME_{i,t}$ are per cent deviations of $st(V_{i,t})$ (depth), $VOLATILITY_{i,t}$, $VOLUME_{i,t}$ for interval *t* from firm *i*'s mean of each of these variables computed from the 12:30-1:00 interval. The coefficients are an average of the coefficients from the regression of each individual stock. Positive Coefficient (%) is the percentage of stocks in the regression with a positive coefficient. The Z-statistic to test whether the mean coefficient for each time interval differs from zero is given by the formula $Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} t_i \sim N(0,1),$ where N is the number of stocks in the sample and t_i is the *t*-statistic for stock *i*.

Time	a0	a1	a2
9:30 - 10:00	-0.1680	0.0184	-0.0556
Positive Coefficient %	15.79	88.42	4.21
Z-statistics	-40.05	18.00	-25.68
p-value	0.0000	0.0000	0.0000
10:00 - 10:30	-0.0575	0.1008	-0.1421
Positive Coefficient %	29.47	96.84	4.21
Z-statistics	-13.08	23.44	-31.55
p-value	0.0000	0.0000	0.0000
10:30 - 11:00	-0.0192	0.1238	-0.1912
Positive Coefficient %	42.11	98.95	2.11
Z-statistics	-6.14	23.94	-33.50
p-value	0.0000	0.0000	0.0000
11:00 - 11:30	-0.0086	0.1688	-0.2414
Positive Coefficient %	40.00	97.90	1.05
Z-statistics	-5.16	23.20	-31.15
p-value	0.0000	0.0000	0.0000
11:30 - 12:00	0.0204	0.1909	-0.2859
Positive Coefficient %	56.84	96.84	3.16
Z-statistics	1.24	22.75	-30.75
p-value	0.2166	0.0000	0.0000
12:00 - 12:30	0.0285	0.1707	-0.2648
Positive Coefficient %	73.68	90.53	2.11
Z-statistics	6.06	19.18	-25.75
p-value	0.0000	0.0000	0.0000
13:00 - 13:30	0.0500	0.1680	-0.2712
Positive Coefficient %	72.63	11.58	84.21
Z-statistics	14.17	19.12	-25.01
p-value	0.0000	0.0000	0.0000
13:30 -14:00	0.072	0.198	-0.332
Positive Coefficient %	91.58	94.74	2.11
Z-statistics	16.27	24.36	-30.20
p-value	0.0000	0.0000	0.0000
14:00 - 14:30	0.1313	0.1514	-0.2492
Positive Coefficient %	90.53	95.79	2.11
Z-statistics	26.09	20.53	-30.85
p-value	0.0000	0.0000	0.0000
14:30 - 15:00	-0.2721	0.1572	0.1924

Positive Coefficient %	98.95	95.79	2.11
Z-statistics	32.08	23.72	-34.90
p-value	0.0000	0.0000	0.0000
15:00 - 15:30	0.3553	0.1536	-0.3533
Positive Coefficient %	1.05	97.90	100
Z-statistics	44.81	27.67	-36.21
p-value	0.000	0.000	0.000
15:30 - 16:00	0.8339	0.1294	-0.4500
Positive Coefficient %	100	96.84	2.11
Z-statistics	58.14	26.42	-35.61
p-value	0.0000	0.0000	0.0000

6.5 Summary

This chapter analyses the behavior of quoted depth in addition to the bid-ask spread on the Nasdaq, a competitive dealer market. Results show that the intraday pattern in quoted depth is negatively associated with the bid-ask spread. Nasdaq stocks experience wide spreads at the open and narrow spreads at the close, while depth is low at the open and high at the close. The general pattern in quoted depth on the Nasdaq differs to that observed on the NYSE, where depth declines at the close of trading.

The negative correlation between spreads and depth for Nasdaq stocks supports the contention of Chung and Zhao (2004b) that both the price and quantity of dealer quotes are inter-dependent, with both used by dealers to manage their inventory. As patterns in the determinants of spreads and depth, namely trading volume and volatility, are similar across dealer, specialist and order-driven markets, it is concluded that the higher depth at the end of the trading day results from inventory management by Nasdaq dealers and that this results in improved liquidity.

Chapter 7: Conclusions

This dissertation examines order submission strategies across different trading platforms. Liquidity and transaction costs depend upon both the characteristics of individual securities and the structure of the market and subsequent order submission strategies of market participants. The market structure of an exchange is multidimensional, consisting of various factors affecting the trading behaviour of market participants. As market design affects trading strategies and hence liquidity, exchanges are continually adjusting their trading platforms in order to maximise liquidity and cater to market participants. It is therefore important for exchanges, regulators, market participants and academics to understand how market design affects investors order submission strategies in order to further understanding of what constitutes optimal market structure.

This dissertation focusing on two areas, namely order submission strategies in (1) limit order markets where market makers are not present and (2) markets that employ designated market makers. Limit order markets depend on endogenous liquidity creation based on investors agreeing to trade with each other. It examines a number of issues yet to be investigated in the literature in relation to order submission strategies across limit order markets and markets with designated market makers. This includes the impact of a tick increase on market quality in a futures market setting, the relation between algorithmic trading volume and future market quality the execution costs of option strategies and their determinants and, intraday patterns in quoted depth on the Nasdaq, a competitive dealer market.

7.1 Summary of Findings

Chapter 3 examines the impact of a tick size increase on market quality in a futures market setting. Exchanges worldwide have lowered the minimum price increment with the aim of improving liquidity and lowering transaction costs. A number of studies analyse the impact of tick size reductions on market quality, with results showing that the tick size reduction is associated with lower bid-ask spreads and quoted depth. This literature provides conflicting evidence on whether the change is indicative of an overall improvement or reduction in liquidity. In 2009, the Sydney Futures Exchange (SFE) and the Eurex increased the minimum tick size for the 3-Year Treasury Bond Futures ("3Y T-bond") and the 5-Year Euro Bobl Futures ("5Y Bob1") to facilitate increased liquidity during the Global Financial Crisis (GFC). This natural experiment provides an opportunity to re-examine this issue.

Consistent with prior studies, results show that an increase in the tick size is associated with an improvement in depth at the best quotes and depth throughout the limit order-book for both contracts. The evidence also suggests that the increase in the tick size resulted in an increase in the bid-ask spread. The price impact analysis, used as a comprehensive measure of the change in liquidity after the increase in minimum tick, suggests that the tick size resulted in an increase in execution costs for the event contracts. These results indicate that the increase in the bid-ask spread more than offset the increase in quoted depth.

Chapter 4 examines the relation between algorithmic trading volume and future market quality. Although prior literature examines the effect of algorithmic trading on market quality, few papers assess the impact of algorithmic trading over different market conditions. Using a proprietary data set provided by the Australian Securities Exchange (ASX), the results over the whole sample provide no evidence that market quality is associated with algorithmic trading volume. This conclusion changes however, when the sample is split into intraday intervals of increasing and decreasing stock returns. Results show that algorithmic trading volume is significantly associated with future spreads, depth and volatility when prices are falling, and has no relation when prices are rising. This may imply that during price declines, ATs increase their demand for liquidity. Finally, results reveal that algorithmic trading's negative association with market quality can be explained by ATs engaging in positive feedback trading, where they systematically decrease their purchases of stocks during periods of falling prices, while increasing their level of selling.

Chapter 5 examines the execution costs of option strategies and outright options on the Australian Options Market. This essay builds on prior studies examining transaction costs in the options market, which do not distinguish between outright options and options that constitute strategies. This is a significant omission, as option strategies may have higher transaction costs given their greater complexity. This chapter adds to the literature by being the first study to measure the execution costs of option strategies relative to outright options and investigates if any differences in the execution costs of strategy-linked options and outright options are attributable to differences in market making costs.

The analysis reveals three key findings. First, execution costs for strategy-linked options are greater relative to outright options. Second, the execution costs of option strategies are dependent upon the complexity of option strategies, with tailor-made strategy-linked options being more costly to trade than standard strategy-linked options. These findings are supported by a range of empirical measures. Strategy-linked options display wider effective spreads across put and call options and across a number of different option characteristics. Multivariate analysis shows that after directly controlling for a number of liquidity determinants, tailor-made strategy-linked trades incur higher execution costs than outright options trades. The third key finding is that the greater execution costs of option strategies are caused by the higher inventory-holding costs of the market maker and not higher adverse selection costs. Results indicate that the difference in execution costs between tailor-made strategy-linked options and outright options is driven by the initial costs in delta hedging the option position.

Chapter 6 examines the intraday pattern in quoted depth on the Nasdaq, a competitive dealer market. The empirical evidence from prior literature suggests that market design plays an important role in the observed pattern in bid-ask spreads and quoted depth over the course of the trading day. The literature examining markets with designated market makers shows that bid-ask spreads tighten near the close of trading, as market makers improve their prices to attract order flow from other liquidity suppliers in order to manage their inventory levels. Using similar arguments, it is hypothesised that quoted depth increases near the close of trading.

Consistent with prior studies on competitive dealer markets, results show bid-ask spreads are widest at the open of trading and tightest near the close of trading. Furthermore, quoted depth is shown to be inversely related to bid-ask spreads, increasing over the trading day and increasing most significantly near the close of trading. Results show that the pattern in quoted depth is a result of the market structure of the Nasdaq and not a result of patterns in the determinants of spreads and depth. Controlling for two important determinants of bid-ask spreads and quoted depth, trading volume and price volatility, results show that the patterns in quote depth and bid-ask spreads are unaffected. The results support the hypothesis that the price and quantity quotes of dealers are interdependent and that dealers use both spreads and depth to manage their inventory near the close of trading.

7.2 Contributions to the Literature, Limitations and Areas for Future Research

The findings from this dissertation provide a number of insights into the factors affecting liquidity in limit order markets and markets with designated market makers and their impact on market quality.

The results in Chapter 3 suggest that increasing the tick size encourages more limit orders to be posted throughout the limit order book. Despite this, it still leads to a higher execution costs, as futures markets already have sufficient depth to meet traded volume (Alampieski and Lepone, 2009). This confirms the results of other studies that show a reduction in tick size primarily benefits small trades and liquid securities (Bollen and Whaley, 1998). One avenue to explore is whether there are other benefits to a tick size increase is to examine its impact on the resiliency of the order book, which is a key aspect of liquidity (Kyle, 1985). Resiliency is a temporal dimension of liquidity and reflects the speed at which the limit order book is replenished after being subject to a liquidity shock, such as a market order. The increase in the tick size may have led to an improvement in the resiliency of the limit order book, resulting in an improvement in overall market liquidity.

The results in Chapter 4 indicate algorithmic trading destablises markets during all price declines, rather than during extreme market movements (Kirilenko et al, 2011). Analysis suggests that it results from algorithmic traders withdrawing liquidity from the market, in line with studies examining the behaviour of algorithmic traders (ASIC, 2012). An issue of concern however is the accuracy of classifying trades as algorithmic trades. The algorithmic trading measure will encompass both liquidity supply likely comes both from high frequency traders that are making markets algorithmically and from buy-side institutions that are submitting limit orders as part of "slice and dice" algorithms. As the concern with algorithmic trading rests with the potential behavior of high frequency traders, being able to specifically identify high frequency traders in the data would provide a more robust analysis of the impact of HFTs on market quality during price declines. A further issue is the use of lagged algorithmic trading as an instrumental variable when assessing the impact of algorithmic trading on market quality. This may not overcome all endogeneity issues however if the liquidity variables are serially correlated. A more robust approach is to identify a structural change that resulted in higher algorithmic trading for a sample of stocks on an exchange. This natural experiment can be used to provide more robust causal estimates of the impact of algorithmic trading on market quality during price declines.

Chapter 5 provide the first empirical evidence measuring the transaction costs of option strategies and its determinants. It indicates that market makers do not adjust bid-ask spreads in response to adverse selection costs. Further evidence is needed to validate and extend these findings. Two approaches could be used. Partitioning option strategy trades according to institutional and retails investors could be used to test whether certain option strategy trades are informative and whether these trades are driving the higher observed transaction costs, under the assumption that institutional investors are proxies for informed traders. An alternative is to examine whether there are certain types of strategy trades that are predictive of future returns and assess whether market makers are likely to adjust the bid-ask spread in response to these strategy trades.

Chapter 6 shows that market makers narrow bid-ask spreads and increase quoted depth in response to inventory imbalances, in order to end the day 'flat'. This indicates that market makers improve liquidity at the end of the trading day. As a further test of whether market makers adjust for inventory imbalances, the behaviour of market makers can be compared for liquid and illiquid stocks. Under the inventory-based model, the decrease (increase) in spreads (depth) should be greater for illiquid stocks, as it is more difficult to unwind inventory positions in illiquid securities.

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