Does market depth concentration matter?
Evidence from the Australian Stock Exchange

Kristoffer Kevin Avila

305214306

Supervisors: Joel Fabre and Elvis Jarnecic
Certificate of originality

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Abstract

In considering the behaviour of market participants, this paper introduces a new variable into the model for the determinants of institutional trading costs. By using an ex-ante measure of the concentration in the opposite-side of the market, this study suggests that traders on the opposite-side of the market herd against an incoming trader looking to trade a series of orders. The new variable measures the level of broker competition prevailing on the opposite-side of the market and is found to be negatively related with price impact.

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1. Introduction

Since Schwartz and Shapiro (1990) reported that close to 70 percent of trades on the New York Stock Exchange (NYSE) originated from institutional investors, a large amount of literature has been devoted into finding the determinants of the price impact from institutional trading. Within this context, few studies consider the dynamic nature of the market participants when studying the determinants of price impact.

In a limit order book such as the Australian Stock Exchange (ASX), one can define an opposite-side broker as the patient party who controls a current standing limit order. Typically, most price impact models have assumed that the opposite-side broker has the sole purpose to provide liquidity and thus remain static on the market. In reality, the opposite-side broker has the option to place new orders, amend current orders, or withdraw orders away from the market. The current study intents to characterise the properties of the opposite-side of the market in terms of market depth, and investigate its relationship with the price movement associated with institutional trading.

The interaction of the opposite-side of the market has rarely been examined within price impact models since these models typically use ex-ante variables, such as market size and trade size, in order quantify the average gain or loss an institution will incur due to changes in that variable. The dynamic nature of the market participants ensures that the opposite-side broker will make decisions conditional and ex-post to the first trade by an institution. Since Barclay and Warner (1993) and Chakravarty (2001) show that traders looking to execute large orders may split their trades into a sequence of smaller orders,
the reactions of the opposite-side broker concerning the first trade will have a bearing on
the price impact concerning with subsequent trades. Therefore, it is necessary to identify
the impact that opposite-side brokers have on the price impact of institutional trades.
Doing so will add to the current body of literature surrounding the identification of the
determinants of price impact. Further, it may be used to assist institutional traders whose
goals are to minimise the execution costs involved in trading.

Instead of examining the ex-post actions of opposite-side brokers (which would require
the examination of an opposite-side broker’s order flow), this study adds to the current
price impact literature by introducing a new variable which captures the ex-ante state of
the market. This variable measures the nature of depth surrounding liquidity on the
opposite-side of the market in terms of the brokers competing for order flow. The current
study uses a Herfindahl-index\(^a\) to measure both the concentration and competitiveness of
broker activity within the opposite-side of the market. The nature of the index implies
that higher values will show that competition is low and depth is focused around a few
(instead of many) brokers. Using this as a proxy for the state of the opposite-side depth at
the market price, this study offers competing hypotheses which can be used to explain
possible reasons for its significance and direction of the concentration variable on the
price impact of subsequent trading.

\(^a\) Used by Chung, Chuwonganant and McCormick (2004) to measure dealer competition in NASDAQ
stocks.
Results in this study find a significant negative relationship between the index and execution costs measured by the *Open-to-Trade* and *Trade-to-Close*. This implies that lower (broker concentration) levels of the index will be associated with both a greater initial and permanent impact in the underlying stock’s price. The paper postulates that the reason for this relationship is due to the herding behaviour of brokers on the opposite-side of the market acting on the same informative signal. Their combined withdrawal from the market after the first trade induces greater price impact for the subsequent trades coming from the trade initiator.

Lastly, this research will have important implications on market design. The calculation of the index is dependant upon distinguishing between brokers on the opposite-side of the market. Evidence of a negative relationship between the depth concentration of the opposite side of the market and price impact implies that brokers and institutions will prefer a transparent market in order to minimise transactions costs.

2. Review of Literature

2.1 Market Response Behaviour

The reaction and behaviour of market participants in response to an incoming or executed trade is an issue which has been developed in the past. Studies originate from the work of Bagshot (1971) who identifies three types of traders present in the market; informed traders who trade based on superior information; liquidity-motivated traders, who trade
based on cash flow requirements; and pseudo informed traders who trade on information which has already been imbedded into a security’s price\(^b\). The presence of these traders allows a market maker to create a spread that is based on the market pressure of buyers and sellers. The ideas and insight put forth by Bagshot (1971) are later extended into theoretical models.

Garman (1976) uses a supply and demand approach for modelling the price formation of securities under various types of market structures. He postulates that the role of a market maker’s inventory must be considered in the formation of the spread. Otherwise they risk the result of market failure under a monopolistic dealer market. Amihud and Mendelson (1980) extend Garman’s (1976) work by presenting a model where a market maker’s spread is conditional upon the previous order. They find that an optimal pricing policy can be obtained for a market maker, which is based on the market maker’s levels of inventory.

The presence of traders with better information creates a problem for market participants on the opposite-side of the market who will have a higher likelihood of trading at a loss. Dupont (2000) develops a market making model that considers both spread and depth under asymmetric information conditions. He establishes that a market maker has two alternatives which are used to combat the information asymmetry problem imposed by

\(^b\) For the purposes of this study, the liquidity-motivated traders and pseudo informed traders can be placed in the same category since trading against either, in the long run, the market maker making a profit. Henceforth, we will refer to both types of traders as liquidity traders.
informed investors. First, the market maker can increase spreads, thereby lowering the probability of trading with an informed trader and trading at a loss. Consequently, this will reduce demand from liquidity traders, who are sensitive to price, and therefore potential profits. Alternatively, market makers may reduce quoted depth, allowing them to lose less against an informed trader while still maintaining the liquidity trader’s demand. This action consequently reduces the profitability of the market maker when trading against a liquidity trader. Dupont (2000) hypothesises that the trade-off between these two options is conditional upon the actual level of information asymmetry present. His model finds that changes in depth are more favoured than changes in spread as the level of information asymmetry increases.

Empirical studies examining the reaction of a single trader, in response to an incoming or executed trade, have been performed to test the theories presented by the studies cited above. Many of these studies have investigated the actions of the NYSE specialist since their actions play an important role in determining the price of a security. The studies focus on the specialist’s revision of quoted price and depth schedules in response to informative events and inventory imbalance.

Lee, Mucklow and Ready (1993) investigate the levels of spread and depth around both periods of high volume and periods of earnings announcements. Their results are consistent with the notion that both spread and depth are reduced in response to the anticipated presence of informed traders. Kavajecz (1999) extends this by using the methodology of limit order book estimation which permits the examination of order flow
from the specialist. He finds that in response to a greater likelihood of informational asymmetry, a specialist may reduce quoted depth equal to the amount of the limit order trader (who has priority) to protect themselves against adverse selection. These findings are consistent with Dupont (2000) and reveal that specialists change quoted depth schedules in response to informational events as well as to manage inventory. This is different to Kavajecz and Odders-White (2001) who use a simultaneous equation approach to investigate numerous factors which influence the revision of a specialist’s quoted price and depth schedules on the NYSE. Their analysis finds no evidence for revisions due to inventory purposes as suggested by Amihud and Mendelson (1980). However they show that the specialist is more likely to reduce posted depth (as opposed to spread) as the first form of protection against adverse selection in response to large transactions.

The above studies cited above were performed on markets with some form of market maker presence. More importantly previous studies have shown that the withdrawal of depth from a trader who controls a significant proportion of depth at the market price will have a significant impact on subsequent incoming trades against that side of the book. These studies however, do not examine the order flow from other participants present in the market such as limit order traders.

In their investigation of the Paris Bourse, Biais, Hillion and Spatt (1995) examine the role that limit order traders play in an exchange. Their analysis of order flow and the order book characteristics find that limit order traders improve the efficiency of markets with
their level of competition and speed of response in providing liquidity. This suggests that
the reaction of multiple market participants and their interaction is necessary to grasp the
nature of the opposite-side of the market. Biais et al. (1995) further generate a conditional
probability table showing the likelihood of one event taking place directly after another.
They find that in all cases, one is likely to observe the same event occurring immediately
after another event of the same kind has just occurred\(^c\). This systematic behaviour of
market participants is consistent with the notion of herding behaviour.

The herding literature originates from the notion that investors act on the same signals
and trade in the same stock and direction. Shiller (1984) argues that markets may not be
efficient due to the existence of ‘social movements’ and ‘fashion’ which cause investors
to herd in the same direction on the perception that the trading decision has been built up
to result in higher returns. Similarly, Shleifer and Summers (1990) argue that investor
sentiment and overreaction to signals provided by ‘brokers or financial gurus’ can result
in correlated shifts in demand amongst noise traders.

Herding behaviour is not limited to retail investors. Lakonishok, Shlifer and Vishny
(1992) hypothesise that institutions may herd for several reasons which may cause
markets to become more efficient. They may deduce that information is present among
another institution’s trades and follow their actions, trade on the basis on another
manager’s portfolio in order to mimic returns, or interpret the same informative signals

\(^c\) For example, they find that there is a 9.70 percent (9.24 percent) chance of observing a cancellation on the
bid (ask) side directly following a cancellation at the same side
present to the entire market in the same manner. Cont and Bouchard (2000) argue that in financial markets, decisions to trade do not need to be sequential, yet rather individual decisions based on the same sign. Further, they show how herding behaviour has the ability to affect the distribution of returns in institutional execution costs.

Much of the herding literature focuses on analysis regarding decisions to trade. Farmer (2008), on the other hand, considers the possibility that traders can cancel orders in response to the trade before. Their analysis of large price fluctuations and cancellations however yields no significant results, however, since their analysis cannot distinguish between a market order and a cancellation. This leads to the examination of the reaction of opposite-side traders and the impact they have on subsequent price changes.

2.2 Institutional Trading Costs

The second set of literature related to this study is dedicated towards identifying the factors that affect the execution costs of institutional trades. The current study intends to determine whether a variable which can proxy for the state of the opposite-side limit order depth plays a significant role in the execution costs of sequential institutional transactions due to the withdrawal of depth.

Scwartz and Shapiro (1990) found that in 1989, over 70 percent of trades originate from institutional investors and their members on the NYSE. Subsequently, much literature has focused its attention to the execution costs of institutional trades and its determinants in
order to assist a portfolio manager’s investment strategy by identifying the key factors influencing the implicit costs of trading.

The execution cost studies originate from Kraus and Stoll (1972) who identify that the cause of price impact originates from three sources. They argue that there are three explanations for price changes triggered by a transaction. Firstly, short-run liquidity costs appear when a large trader finds it difficult to attract liquidity from the opposite-side of the market. Secondly, in stocks that have imperfect substitutes to the firm’s securities, inelastic demand and supply curves lead to price concessions that lead to greater price impact depending on the size of the trade. Finally, the information content conveyed by the size of the trade may produce an impact in price that leads to new equilibrium prices.

Holthausen, Leftwich and Mayers (1987) extend this work by creating a set of variables which can be used to identify the sources of price impact as defined by Kraus and Stoll (1972). They show that short-run liquidity costs are consistent with the notion of temporary price movements where prices revert back to fundamental values. Further, they identify that the imperfect substitution and information arguments both lead to a permanent price movement where a new equilibrium price is formed. Finally they define the total price effect as the initial impact in price resulting from the institutional trade. They find that price movements are permanent for buyer-initiated institutional trades and temporary for seller-initiated institutional trades. They document price continuations for institutional purchases trades and price reversals for institutional sales suggesting purchases are more informative than sales.
2.2.1 Empirically Tested Explanatory Variables

Much of the subsequent price impact literature consistently uses these measures in order to directly isolate whether a possible variable of interest significantly affects execution costs. The following studies are based on this foundation and attempt to analyse different general explanatory factors that may better explain price impact. These factors will be used as controls for the present paper’s analysis, such that the influence of the state of the opposite-side of the market on execution costs can be measured independently.

Easley and O’Hara (1987) suggest that informed traders are likely to trade in larger quantities, and therefore should find incur greater permanent price impact. Holthausen et al. (1987) empirically verifies this and finds that increases in block size are associated with increases in price impact costs. These are found to be robust against alternative block definitions. This is consistent with the underlying theory which suggests that larger sized trades are associated with higher price impact due to the difficulty in finding liquidity providers, or because of their likelihood to convey information. Subsequent literature has found it logical to control for the complexity (difficulty) of an institutional trade when looking at execution costs. The theory that large trades convey information has been tested by Barclay and Warner (1993) and Chakravarty (2001) who find evidence

\[ \text{These studies include; Chan and Lakonishok (1993), Gemmill (1996), Bonser-Neal et al. (1999), Chiyachantana et al. (2004) and Frino et al. (2007).} \]
against, and argue that informed traders prefer to trade with medium-sized orders. By grouping a sequence of orders, studies such as Chan and Lakonishok (1995), Aitken and Frino (1996b), Comerton-Forde, Fernandez, Frino and Oetomo (2005), and Frino, Gallagher and Oetomo (2006) still provide evidence that institutional investors are likely to incur greater impact with an increasing size in the overall trade.

By examining the execution costs of a number of portfolios based on firm size, Stoll and Whaley (1983) find that smaller firms exhibit greater execution costs than their larger counterparts. The intuition behind this result is due to the notion that, all else being equal, smaller companies are less liquid making it more difficult to execute a trade order of the same size. Subsequent studies use a firm’s market capitalisation to control for firm size. Further, Chan and Lakonishok (1993, 1995) find that the relationship between firm size, trade complexity and execution costs is not linear such that trades with greater volume in smaller sized firms incur the greatest price impact. These studies are consistent with the underlying theory as they provide considerable evidence in showing negative correlation between firm size and price impact.

A number of studies have found it necessary to include a liquidity-based control measure in the price impact model. One such measure is the bid-ask spread (BAS), which has been used in studies including Aitken and Frino (1996b), Comerton-Forde et al. (2005), and Frino et al. (2007) and found to be significant. Lower liquidity is found to be

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Bonser-Neal et al. (1999), Chiyachantana et al. (2004), Comerton-Forde et al. (2005), and Frino et al. (2006).
associated with higher price impact as the above studies report and is due to the greater difficulty in finding a corresponding liquidity provider.

Chiyanchantana, Jain, Jiang and Wood (2004) find that the asymmetry in purchases and sales is dependant upon the state of the market. They argue that permanent price impact is more likely to be associated with purchases (sales) in a bullish (bearish) market due to a greater probability that purchases will drive prices to a higher expected equilibrium price. Consequently, institutions looking to purchase shares will find it more difficult (easy) to find willing liquidity providers in a bullish (bearish) market as opposed to a bearish (bullish) market. Further, investor sentiment will force this impact to reflect permanent costs. This notion supports the evidence presented by Aitken and Frino (1996b), and found by Frino et al. (2007) who report that market returns are positively correlated with price impact in both purchases and sales by controlling for market-wide movements using the returns of relevant market indices.

The above review suggests that trade size, firm size, stock liquidity (BAS) and market return are relevant in explaining the variation in execution costs. Subsequently, controlling for such variables is justifiable and consistent to previous price impact studies.

The theories outlining the reaction of traders on the opposite-side of the market (Section 2.1) have, to date, not been examined within the realm price impact literature. The reaction of the opposite-side trader has largely been overlooked for two reasons. First,
previous studies lack the available data to quantify the state of the opposite-side of the book. Second, studies involving the reaction of opposite-side traders are mainly concerned with ex-post order flow analysis whilst price impact literature is mainly concerned with conditions which are ex-ante to the execution of an institutional trade. Thus, by introducing an ex-ante variable into the model (and hypothesising the ex-post reaction of the market), the present study looks to identify whether the reaction of opposite-side matters.

3. Hypothesis Construction

3.1 Introduction

Analysis regarding the state of the opposite-side of the book has largely been overlooked by much of the price impact literature due to its difficulty in finding a proxy that captures the ex-ante state of the limit order book. Subsequently, the following section introduces an appropriate ex-ante instrument which has not been used in similar price impact studies. More importantly, this section provides possible reasons for the movement and variation in this instrument.

\[ \text{By no means does this study look to empirically justify the actions of the liquidity providers, rather this study intends to provide possible reasons for the significance of the instrument. These reasons are not exhaustive and only serve to theoretically support the use of such an instrument in this study.} \]
This measure will allow the present study to capture the market reaction and revision of order depth as proposed by Dupont (2000) and found by Kavajecz (1999). Further, it will capture both the concentration and competitiveness that exist between the brokers on the opposite-side of the market. By focusing on the order cancellation component of this variable, the concepts of order revision due to adverse information (Dupont 2000) can be introduced. Thus, this variable will allow one to assist institutions regarding the timing of their trades and determine the ideal conditions where trading will incur the lowest price impact.

This study incorporates the use of a Herfindahl-index which acts as an instrument for the concentration of the opposite-side of the limit order book\(^g\). It will be used to determine the sensitivity that exists between the levels of broker concentration prevailing at the time of a trade, to the overall price impact of the trade.

3.2 The Mechanics of the Herfindahl-Index

The index is used to create a numerical representation of the opposite-side of the order book that captures the concentration and competitiveness of brokers in terms of the depth posted immediately before the execution of a trade. Previous studies have used two types

\(^g\) The value at the market price is independent of the value of the second best price. Thus, to provide meaningful results, the index is only constructed at the market price and is not aggregated among the opposite-side.
of measures to analyse concentration. The Herfindahl-index increases as the number of brokers decreases or as the proportion of the leading broker increases. This index places greater weight on the leading broker’s concentration and thus allows one to identify two general market conditions (high broker concentration and low broker concentration) more readily than using the number of brokers since it takes into account the depth posted by each broker as well as the broker’s relative presence on the market.

The Herfindahl-index is calculated for stock $i$ at time $t$ using the following formula:

$$H_{it} = \sum_{j} \left[ \frac{100V_{ijt}}{\sum_{j} V_{ijt}} \right]^2$$

where $H_{it}$ represents the concentration of opposite-side limit order market depth in stock $i$ and $V_{ijt}$ represents the limit order depth posted by broker $j$ for stock $i$ immediately prior to the first trade $t$.

This formula will provide a number ranging from 0 to 10,000 for every trade event in stock $i$. Lower levels of the index imply the opposite-side of the market is highly competitive with many posted\(^h\) limit orders across many brokers, thus depth is spread and

\(^h\) The author acknowledges that there exists the presence of hidden orders and traders not visible to the market (but would trade under favourable circumstances); however, data constraints prohibit the examination of these traders.
more diluted. Higher levels of the index imply that the opposite-side of the market is less competitive in providing liquidity in terms of broker competition thus, depth is more concentrated around few brokers. It is important to establish that the index does not measure the *volume* of liquidity provided but, rather, the *broker concentration* surrounding the liquidity. This study is interested in identifying whether the broker concentration on the opposite-side of the market has the ability to affect the price impact of subsequent trades. As such, different levels of the index can be observed with the same amount of shares being provided to the trade initiator. This concept is explained in Appendix A. Further, the calculation of the index implies that the actual identity of the brokers becomes irrelevant\(^1\). The dominant broker in one index may be different to the dominant broker in another index; however they are treated the same in the calculation of their respective indices. Certain brokers may react differently to new information; however it is beyond the scope of this study to identify which brokers are more responsive to information rather it intends to identify the ideal conditions for trading - high broker concentration or low broker concentration - in the general case\(^j\).

Since the Herfindahl-index used in this study is focused on the order depth and concentration of various brokers on the opposite side of the market, it is important to

\[^{1}\text{The study only requires that depth posted by one broker can be differentiated from depth posted by another broker.}\]

\[^{j}\text{For example, if low concentration levels provide lower price impact, a trade initiator will prefer to wait for many different brokers on the opposite-side providing a similar amount of shares before executing an order.}\]
identify the factors which have the ability to influence the levels of the instrument. There are three typical events that will change the Herfindahl Index of a stock$^k$.

(1) Order Cancellations
(2) Order Additions
(3) Trade Executions

First, brokers controlling orders on the opposite-side of the market’s best prevailing price may withdraw order flow for various reasons. By cancelling an order, depth is reduced at the market price and consequently requires less executable volume (from subsequent trades) to move prices. This type of behaviour can be expected to be used to combat the risk of trading under adverse selection against larger trades, or to reflect new information that a broker receives. Unlike the models of Garman (1976) and Dupont (2000) that examine a hybrid market and focus on specialist trades, the ASX has no bodies officially providing market making duties. Thus, instead of reducing order flow to the minimum depth requirements as seen by Kavajecz (1999), this study should observe specific brokers withdraw close to all of their depth at the market price.

Second, the addition of new orders at the market price will result in a change in the level of the index. Although this is unlikely to occur against a large institutional trade, this phenomenon may exist when traders trade against a known uninformed large order, or

$^k$ Referring to one side of the bid ask spread – the opposite side of the trade initiator – for stock $i$ at time $t$. 

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illegally in the case of front running. Nevertheless, it is not the focus of this study to examine the placement of new orders against or in response to an incoming trade.

Finally, an executed trade will change the level of the index since executed orders will no longer be visible by the standing limit order book. This event will have the same effect on the index as the cancellation of identical order flow\(^1\).

Thus, by looking at changes in the Herfindahl-index, it is difficult to distinguish whether changes in the Herfindahl-index have occurred due to cancellation, addition, or execution of orders. Additionally, the change in the index will largely depend on which broker withdraws an order, which broker places new orders or which broker’s orders are executed against\(^m\). Consequently, the resulting movements in the index will provide ambiguous results. The current study avoids these problems by analysing the Herfindahl-index level immediately prior to the first trade execution of a sequence. Needless to say, this study intends to isolate the effects of the index where cancellations are present.

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\(^1\) The main difference being that trade initiators will require less subsequent shares to execute the full amount of their desired quantity.

\(^m\) If the dominant broker cancels depth, the Herfindahl-index will decrease but if a non-dominant broker cancels depth, the Herfindahl-index will increase. The same applies to whether trades are executed against the dominant broker or a non-dominant broker. This will be largely due to the time preference of the orders (which may be random in the sample). Similarly, whether a completely new broker enters the market (\(J_{t+1} = J_t +1\)), or whether the dominant or non-dominant broker enters a new order will affect the Herfindahl-index with the same ambiguity.
The aim of this study is to determine whether it is beneficial for a trade initiator to consider the nature of the opposite-side of the market when deciding upon the timing of their trades. In order to do this, several hypotheses are put forward to explain the possible significance and direction of the additional variable in its relationship with price impact. It is important to distinguish between the ex-ante instrument and its relation to the ex-post actions of liquidity providers. The present study offers possible reasons for the ex-post actions of the liquidity providers that may be more prevalent under a certain ex-ante condition. These actions are not exhaustive and only provide possible explanations for the direction of the instrument. The following sub-sections introduce the null and alternative hypotheses that will be used to determine the ideal conditions for trading.

3.3 The Null Hypothesis

Evidence of the null hypothesis occurs when the Herfindahl-index provides statistically insignificant results when measuring its sensitivity to price impact. It implies that the nature of broker competition on the opposite-side of the market has no distinguishable relationship to the price impact of subsequent trades. In essence, this means that the cancellations and withdrawal of order flow is independent of whether there are plenty of competing brokers or when there are a few dominant brokers.

Therefore, the **Null Hypothesis (H₀)** states: *the level of the Herfindahl-index prior to the first trade plays no role in the price impact of subsequent trades.*
3.4 Alternative Hypothesis 1: The Role of the Dominant Broker

Unlike the null hypothesis, the first alternative proposes that lower levels of the Herfindahl-index are ideal for traders since higher levels are associated with greater price impact of subsequent trades. To explain this, consider the following case where a large Herfindahl-index is observed prior to the first trade.

Suppose a trade initiator intends to purchase\(^n\) 2,000 shares of the stock XYZ at time \(t\), and another \(X\) amount of shares at \(t+1\) (to comply with the assumption that the trader plans to trade in a sequence). The current market ask price stands at 10.00 dollars with 11,000 available shares. Depth is shared among four (opposite-side) brokers labelled A, B, C and D (with A controlling time priority over the rest). Further, the broker competition is low on the opposite side of the market, with many smaller brokers (competition in order depth) competing against one large dominant broker (assume this is B). The Herfindahl-index associated with this event and prior to the first trade stands at 5,661. Figures 3.4.1 and 3.4.2 show the differences in the null and first alternative hypotheses respectively.

\(^n\) For brevity this example only examines a buyer-initiated trade. This example can be inverted to apply to a seller-initiated trade.
Figure 3.4.1

Trading with large concentration under the null hypothesis

\[
H(a) = \left(\frac{2,000 \times 100}{11,000}\right)^2 + \left(\frac{8,000 \times 100}{11,000}\right)^2 + \left(\frac{500 \times 100}{11,000}\right)^2 + \left(\frac{500 \times 100}{11,000}\right)^2 = 5661
\]

\[
H(b) = \left(\frac{8,000 \times 100}{9,000}\right)^2 + \left(\frac{500 \times 100}{9,000}\right)^2 + \left(\frac{500 \times 100}{9,000}\right)^2 = 7963
\]

\[
H(c) = \left(\frac{8,000 \times 100}{9,000}\right)^2 + \left(\frac{500 \times 100}{9,000}\right)^2 + \left(\frac{500 \times 100}{9,000}\right)^2 = 7963
\]
For both examples, as the timeline moves from a to b, 2,000 shares are executed against Broker A. The null hypothesis assumes that the structure of the book has no bearing on the price impact of subsequent trading. Consequently, the general reaction of the market
will be to remain the same on average and the order book arrives at 3.4.1c. A further 9,000 shares are required to be executed against the current price of 10.00 dollars in order to move the price to the next level. Thus, so long as X is less than 9,000, the trader will incur no further price impact costs. This is different to figure 3.4.2c where the dominant or leading broker in the group of opposite-side brokers (Broker B) withdraws their depth in order to protect against trading under adverse selection. Hence the limit order book arrives at 3.4.2d where only a further 1,000 shares are required to move the price to the next tick. Consequently, if X is greater than 1,000, any shares greater than the 1000th share will incur an extra 5c cost per share, adding to the price impact of the overall series of trades.

The reasons and theoretical justification underlying the dominant broker hypothesis are implied by Garman (1976), Dupont (2000) and Kavajecz (1999) who show that market makers withdraw depth in order to protect themselves against the risk of trading under adverse selection. Although these papers differ from current study since they assume a monopolistic market making condition, similarities can be inferred since the specialist may, at times, control significant proportions of depth at the market price. This has been empirically observed by Madhavan and Sofianos (1998) who observe specialist participation rates in the NYSE and find that their activity in a stock ranges from 10

---

\(^o\) Brokers B, C or E could cancel their orders in response to the execution of Broker A’s shares however, the null hypothesis assumes that these occur randomly and in no significant pattern.

\(^p\) The broker could also have received an informational signal externally, or be withdrawing for rebalancing purposes.
percent (implying dilution in depth) to 90 percent (implying concentration in depth). On most occasions, therefore, these specialists would in fact be regarded as the ‘dominant’ broker for the purposes of the current study.

The main difference between this study and those previously mentioned, lies within the information advantage a specialist has over the general trading population. This advantage may explain the faster response to executed orders as seen by specialists. The current study postulates that brokers who control a significantly higher proportion of order depth in one stock will be more likely to monitor and readily respond to informational discrepancies as opposed to brokers who control lower proportions in the same stock.

The reasoning behind an initiating trader intending to execute multiple orders is explained by Barclay and Warner (1993) and Chakravarty (2001) who suggest that large orders can be executed with less price impact when split into sets of medium-sized trades since the information content of trades is less likely to be noticed. One could argue that initiating traders would wait for appropriate conditions such that the dominant broker cannot detect their presence, thus lowering the price impact of their trades. The present study acknowledges this possibility and postulates that price impact due to the cancellation of orders, although lower, may still be present at medium-sized orders (depending on the probability that the dominant broker can identify an informed trade), and subsequently it intends to discover whether this is indeed significant enough to alter the timing of broker trade executions.
Therefore, **Hypothesis 1 (H1)** states: *given higher levels of the Herfindahl-index prior to the first trade, subsequent trading incurs greater price impact due to the cancellation and withdrawal of order depth from the leading broker who protects against adverse selection.*

The first alternative hypothesis assumes that higher levels of the index that are associated with greater price impact which may be caused by the dominant broker withdrawing order depth. This corresponds to the previous example in which Broker B withdraws their depth order (Figure 3.4.2c). Theoretically, Broker C could cancel their order depth instead of Broker B. This would still result in fewer shares being required to move the price level (8,500) than the null (9,000), thus providing support for the first alternative hypothesis. Although both cases require fewer shares being required to move the price in subsequent trades, the former requires considerably less (1,000) and would thus provide more significant overall price impact than the latter. Therefore, the greater the number of cases where the dominant broker withdraws order depth, the more significant higher levels of the index will become.

3.5 Alternative Hypothesis 2: The Herding Effect

The second alternative hypothesis proposes that higher levels of the Herfindahl-index are ideal for traders since lower levels are associated with greater price impact of subsequent trades.
Figure 3.5.1
Trading with low concentration under the null hypothesis

\[ H(a) = 1736 \]
\[ H(b) = 2426 \]
\[ H(c) = 2426 \]

Suppose a trade initiator intends to purchase 2,000 shares of the stock XYZ at time \( t \), and another \( X \) amount of shares at \( t+1 \). The current market ask price stands at 10.00 dollars with 11,000 available shares. In this case the concentration of depth among brokers is diverse and shared among six (opposite-side) brokers labelled A, B, C, D, E and F (with
Broker A controlling time priority over the rest). Figures 3.5.1 and 3.5.2 show the differences in the null and second alternative hypotheses respectively.

**Figure 3.5.2**

*Trading with low concentration under the null hypothesis*

\[
H(a) = 1736 \\
H(b) = 2426 \\
H(c) = 4074 \\
H(d) = 5556
\]
This example works similarly to the previous where the null hypothesis results in a limit order book requiring a further 9,000 shares to increase the price of XYZ, as shown by Figure 3.5.1c. Comparing this to Figure 3.5.2c, it is assumed that one broker out of the five remaining on the opposite side of the market withdraws their depth in order to protect against trading under adverse selection\(^q\). For simplicity, assume this to Broker B. Given a herding type of behaviour exists between institutions the remaining brokers may follow the lead of Broker B and withdraw their shares. Assuming brokers C and D conform to this behaviour\(^r\), the limit order book arrives at 3.5.2d. Subsequently, only 3,000 shares\(^s\) are required to move prices to the next tick level. Similar to the previous example, the region at which X lies between the two figures \((3,000 < X < 9,000)\) reveals the amount of shares where the trade-initiator will incur greater price impact under the second alternative hypothesis.

As noted by the discussion in Section 2.1, herding behaviour is known to exist among institutions for three reasons. Firstly, they may observe the same information signal and act in the same manner as one another resulting in the correlation of their trades. Second, 

\(^q\) In this hypothesis, it does not matter which opposite-side broker firstly withdraws their depth since it is beyond the scope of this study to examine the performance of individual brokers.

\(^r\) Only two out of the remaining four brokers are used to simplify this example. In reality, any number of brokers can conform to this idea.

\(^s\) It does not matter that this amount is greater than its counterpart in the first alternative. This discrepancy is purely due to the nature of the examples and can be adjusted to equal the amount given in the first example.
they may follow the trades by competing portfolio managers in order to hedge the risk of being outperformed. Lastly, they may follow the lead of a broker who they believe to be informed. The previous example assumes this is the case. In essence, any of the above reasons can explain why the behaviour of institutions is correlated (if this is found in the results).

The correlation between the actions of brokers on the opposite-side of the book forms the basis of the second alternative hypothesis. Since brokers have the ability to both enter an exit the market freely by posting or withdrawing limit orders, the correlation in their actions drives whether price impact will be larger under more diverse concentration conditions. The actions and correlations of brokers can result in four cases;

<table>
<thead>
<tr>
<th>Broker Correlation</th>
<th>Broker Behaviour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Cancel Order</td>
</tr>
<tr>
<td></td>
<td>(a) Highest Risk</td>
</tr>
<tr>
<td>Negative</td>
<td>Do Not Cancel Order</td>
</tr>
<tr>
<td></td>
<td>(c) Lowest Risk</td>
</tr>
<tr>
<td></td>
<td>(b) Low Risk</td>
</tr>
<tr>
<td></td>
<td>(d) High Risk</td>
</tr>
</tbody>
</table>

Table 3.5 shows the different alternative correlations and actions between brokers. When actions of the brokers are positively correlated (a), the decision to cancel an order presents the highest risk to an incoming trader, whose subsequent trades will incur much more impact than the other cases. It implies that cancellation from one broker (for any of
the reasons stated above) will induce cancellations from other brokers resulting in a number of cascading cancellations occurring one after another. This is consistent with the results reported by Biais et al. (1995). Thus case (a) would suggest that more diverse the concentration is associated with greater the price impact. On the other hand, a negative correlation between brokers will be more beneficial to an incoming trader (under diverse concentration conditions) in the presence of order cancellations (b) since it will essentially hedge the risk of the trades incurring a substantial amount of price impact. This contradicts the second alternative hypothesis and may explain why diverse concentration is less significant. The final two scenarios are worth mentioning since they assume that trades are not cancelled. In essence, a positive correlation would be beneficial to an incoming trader since there is minimal risk of a cancellation among all opposite-side brokers (c). The present study, however, intends to focus on the cancellation of orders, possibly due to the risk of adverse selection.

Therefore, **Hypothesis 2 (H2)** states: *given lower levels of the Herfindahl-index prior to the first trade, subsequent trading incurs greater price impact due to positive correlation in institution behaviour in the presence of order cancellation.*

It seems logical to suggest, given the previous discussion, that the methodology involved to test the second alternative hypothesis would involve examining of the correlation

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1 This may be consistent with algorithmic trading in which orders are automatically placed (and withdrawn) based on mathematical criteria. The presence of algorithmic traders also accounts for the speed at which trades can be cancelled.
between the cancellations among brokers. This would involve the examination of the ex-post order flow directly. Instead, this study focuses on the state of the opposite-side of the order book since this is an ex-ante measure which is more useful for forecasting price impact costs.

3.6 Final Considerations

The nature of the two alternative hypotheses implies that the two are not mutually exclusive. It is possible to find instances where both the dominant broker hypothesis and herding behaviour are evident. If this is the case, then the current study will identify the alternative hypothesis that is more evident from the data and therefore more useful to traders.

A further reason behind the first alternative hypothesis involves the consideration of the risk towards an incoming trader. Under the assumption that broker behaviour is uncorrelated and that a single, random, broker may withdraw depth due to one of the previously mentioned reasons, the probability of a larger number of shares being withdrawn is higher under a high value of the Herfindahl-index. This is due to the existence of a dominant broker on higher values of the index, whereas lower index values provide a hedge against this risk.
4. Preliminaries

Having studied the structure of the ex-ante instrument used to capture opposite-side depth concentration and identifying possible reactions of liquidity providers, this study now proceeds to examine whether the phenomena exists empirically. A large body of literature has been devoted to identifying the determinants of price impact in order to assist institutional trading. These past studies have provided the foundation for the methodology used in this investigation.

4.1 Review of Institutional Trading

A significant amount of attention has been devoted in prior literature to the estimation of the execution costs for trading in equities securities. An investor faces two types of transactions costs when trading. Explicit costs are paid to the broker or exchange for providing the service to trade, whilst implicit costs are the embedded costs from execution. The present paper does not examine explicit costs since the state of the opposite-side of the market is independent of the commission costs for trading. Instead, it simply focuses on the implicit costs of trading which, by itself, have been found to be relevant and economically significant by Keim and Madhavan (1998) in their survey of equity trading costs.

Price impact literature has been developed to examine whether specific factors can influence the implicit costs of trading. Much of the literature has focused on institutional trading since it accounts for a significant amount of overall trading volume. Thus,
understanding the determinants of price impact can result in the implementation of better trading strategies from traders. As such, the study of institutional trades is important since the performance of money managers are highly sensitive in their ability to execute shares with the least amount of transactions costs. This provides sufficient motivation in understanding the nature of its determinants.

Kraus and Stoll (1972) initially examined whether large institutional trading moved markets away from an efficient market by examining the price impact following large block trades. A block trade was defined as a large number of shares that can be executed on the secondary (equities) market. Much of the early papers could not distinguish between an institutional and non-institutional transaction and subsequently used block trades to adequately infer institutional tradesu.

Using transaction data from institutional firms, many of the later studies could readily identify and distinguish an institutional trade. Chan and Lakonishok (1995) argue that institutional orders may be divided up into several trades. This is consistent with Barclay and Warner (1993) and Chakravarty (2001) whose studies suggest that informed trades are likely to be executed using medium-sized orders (as opposed to large). Thus, what appeared to be an institutional trade may not have been the actual ex-ante amount of shares desired to be traded. Consequently, it was argued that the analysis of a single institutional order provides misleading results when examining the price impact of

\[\text{\textsuperscript{u}}\text{ See for example, Holthausen et al. (1987), Keim and Madhavan (1996), Gemmill (1996), Frino et al. (2007).}\]

39
institutional trading. Instead, Chan and Lakonishok (1995) propose a method which involves the use of a trade package to substitute for the ex-ante expression of desired trade quantity of an institutional trade. This instrument involves the analysis in the collection of a sequence of executed trades executed by the same institution in the same stock and direction for a specified period of time. This period of time is determined by the time elapsed between subsequent trades (Chan and Lakonishok (1995) use a 5-day gap as the standard). Chan and Lakonishok (1995) acknowledge that this instrument, which is intended to estimate the desired ex-ante expressions of desired trade quantity, actually provides an ex-post approximation. In essence, price movements and market conditions resulting from early trades of a sequence may influence or discourage subsequent trading. However, they argue that a trade package will be a close approximation of the desired ex-ante order since the decision to trade was formed on the basis that the stock was substantially mispriced and thus a small price concession is not likely to reverse the initial trading decision. Further, using evidence provided by Kiem and Madhavan (1996), they argue that since the proportion of unexecuted orders remains small, the likelihood of discouraging later trades is minimal. Due to the nature of this approximation, subsequent studies which have not been able to determine whether a single transaction is part of a larger order have adopted this method for estimating institutional trading\textsuperscript{v}.

The dataset used in this study suffers from two distinct disadvantages in comparison to the datasets used in previous studies. Firstly, in order to examine the concentration of

\textsuperscript{v} See for example, Chan and Lakonishok (1997), Comerton-Forde et al. (2005), Frino et al. (2006).
broker depth, the present paper requires a dataset which permits the separate identification of broker depth on the opposite-side of the market. Therefore, the use of order level data was preferred such that the Herfindahl-index was able to be calculated. This dataset however, cannot distinguish between an institutional and non-institutional trade. Second, the dataset cannot identify whether one trade is part of a sequence of institutional orders and thus the true quantity of an institutional ex-ante order is unknown. The present paper therefore utilises a method consistent with Aitken and Frino (1996b). This method permits the analysis of data which cannot readily identify institutional trades as well as considers the notion that an institution may use multiple trades to execute a desired quantity. The remainder of this study defines a large trade event as its estimate for an institutional trade. A large buy (sell) trade event is defined as the sequence and combination of purchases (sales) executed by the same broker on a given stock on a single day where the total trading volume is greater than the stock’s average daily trading volume over the past three months. Although Chan and Lakonishok (1995) observe that only 20 percent of the value of institutional trades on NYSE and American Stock Exchange (AMEX) stocks takes place over one day, Comerton-Forde et al. (2005) find that the average life of an identically defined trade package is executed in 1.5 days on the ASX. This average is further skewed right by a heavy tail indicating that only the largest or most complicated (which may suggest trades in non-institutional illiquid stocks) trade

\[w\] A similar result is found by Frino et al. (2006) who likewise use a trade package to study execution costs on the ASX.
packages take more than 1 day to execute\textsuperscript{x}. This justifies the examination of large trade events restricted to one trading day.

There are several advantages to using this approximation in the present study. Schwartz and Shapiro (1990) estimate that institutional trades represent a larger than the average trade and thus the current proxy captures some proportion of institutional trading. This is consistent with the analysis of block trades in the past, which have been used as adequate approximations for institutional trading activity. Further, the current proxy addresses the theory that a single order may not represent the true desired ex-ante order of an institutional investor. More importantly, the examination of multiple sequential orders in the same direction directly allows the examination of the market response variable. In essence, the motivation for hypothesising the reaction of the market is only useful if a trader is intending to execute a series of trades.

Whilst combining the advantages of the two methods widely used in prior literature, the large trade event methodology also has some important considerations. Chan and Lankonishok (1993) find that institutional trading is much larger than the typical daily trading volume in small stocks, while only account for less than 40 percent in larger, more liquid stocks. This presents two problems to the large trade event methodology.

\textsuperscript{x} The 25\textsuperscript{th} and 75\textsuperscript{th} quartiles are equivalent to 1.00 trading day (see Comerton-Forde et al. (2005) Table 1 pp 36)
Firstly, this method will only capture the *largest* trade sequences which are dependant on the average daily trading volume of the stock over the prior 30 trading days. Thus it will not capture the complete activity of institutional traders and consequently will not be as clean as studies directly examining institutional data. Using trade packages, Chan and Lakonishok (1995) find that the average size of institutional trades relative to typical trading volume\(^{\text{y}}\) is 0.66 for purchases and 0.61 for sales. The current approximation will identify larger trades that have proportions which are greater than 1. Nevertheless, this study will analyse cases where institutional trading is most problematic allowing results to be relevant for larger ex-ante quantities. Further, this study can account for smaller institutional trades by the application of regression analysis. This is consistent with Aitken and Frino (1996b).

The second consideration for the use of the large trade event methodology involves the analysis of illiquid stocks. Since illiquid stocks will have a smaller amount of average daily trading volume, fewer shares are required for a sequence of orders to be classified as a large trade event. As such a single small trade in these stocks may account for over 100 percent of the average daily trading volume on a single day. Consistent with Aitken and Frino (1996b), the present study compensates for this by limiting the sample to the most liquid stocks. As such, large trade events are filtered and are restricted to trades in

---

\(^{\text{y}}\) Chan and Lakonishok (1995) use a 40-day definition instead of the 30-day definition used here. A 30-day definition was used to maintain consistency with Aitken and Frino (1996b) which the large trade event method is based upon.
stocks categorised by the S&P/ASX200\textsuperscript{z}. Constituents of this index are considered to be the largest 200 stocks based on float-adjusted market capitalisation\textsuperscript{aa}. Further, the sample is restricted to large trade events that contain more than one trade execution to complete in order to remove such cases as stated above. This is also consistent with the notion with the assumption that an initiator intends to execute a series of trades.

5. Institutional Details

In the period at which this study examines, the Australian Stock Exchange (ASX) operated on an electronic order-driven trading system known as the Stock Exchange Automated Trading System (SEATS). Trading takes place using a continuous auction between the normal trading hours; 10am and 4pm where limit and market orders can be placed with strict price and time priority. No official market-making activities are used in the exchange and orders are traded on a call auction basis for the first and last 10 minutes of normal trading.

The limit order book is restricted to registered brokers who may provide and consume liquidity to using limit and market orders. There are two available methods for a broker to withdraw depth from the book; amendments and deletions. The former involves reduction

\textsuperscript{z} This index is updated quarterly. As such, the current study uses updated constituents in its filtration process.

\textsuperscript{aa} The index covers over 80 percent of equities market capitalisation on the ASX.
of quantity without affecting an order’s time priority. The latter involves the complete removal of depth at a given price and thus loses its priority over other standing limit orders. Although amendments closely resemble the options available to a specialist in a hybrid market, the stated hypotheses assume that adverse selection and the risk of trading against an informed trader is what drives the withdrawal of order depth. Thus, in the presence of high information asymmetry between parties, deletions are more likely to be encountered as opposed to amendments. For this reason, this study only examines order deletions.

Prior to December 2005, a broker’s orders and executions were identified by all market participants using identification tags. The period of examination lies before this date and therefore brokers can readily identify and calculate the concentration of the depth regarding the opposite-side of the market. As of December 2005, broker identification tags were hidden to all market participants. Thus, if one of the competing hypotheses is supported, a broker would not be able to consistently calculate the true value of the Herfindahl-index concentration measure today. Nevertheless, a significant result in this paper will provide insight into what drives price impact. Further, it will contribute to the debate surrounding anonymity and be used to assist brokers trading under transparent conditions.
5.1 Data

The dataset used for this study extends from January 1, 2002 to December 31, 2003. Data was provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA) whose ASX Intra-day database captures records from all transactions taken from the ASX which have been captured from the Stock Exchange Automated Trading System (SEATS).

The construction of a large trade event involves the identification of a series of executed trades from the same broker. Data from the ASX Intra-day database permits the use of broker identifiers to classify such events and was performed precisely to the paper’s definition before delivery. Thus, each record conveys details regarding every large trade event residing from the examined period. The actual identity of the broker initiating a large trade event was not available for analysis which is acceptable since the investigation does not intent to postulate the actions of specific brokers. Further, in order to examine the composition of the opposite-side of the market, broker identification tags were required to construct the measure used to account for depth concentration (the Herfindahl-index). Although the actual identity of the brokers were not able to be obtained, the use of masked broker identification tags were permitted to be used for the creation of the index. Subsequently the index was able to be constructed for the best (and second best) bid or ask (depending on the direction of the trade) prices immediately prior to a large trade event.
The ASX Intra-day database can be separated into three sections: trade details, order details and index details. Each large trade event record contains details of both trade and quote data for all stocks listed on the ASX. Table 5.1.1 provides a list of fields obtained.

**Table 5.1.1**  
Data Set received

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Field Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>The date at which the large trade event has taken place</td>
</tr>
<tr>
<td>First Trade Time</td>
<td>The time at which the first trade in a large trade event was executed</td>
</tr>
<tr>
<td>Last Trade Time</td>
<td>The time at which the last trade in a large trade event was executed</td>
</tr>
<tr>
<td>Stock Code</td>
<td>The Standard and Poor's stock identifier for the stock in which the large trade event has occurred</td>
</tr>
<tr>
<td>Trade Direction</td>
<td>Identifies whether the large trade event was performed under a buyer or seller initiated sequence of transactions</td>
</tr>
<tr>
<td>Opening Price</td>
<td>The daily opening price on which the large trade event was executed</td>
</tr>
<tr>
<td>Closing Price</td>
<td>The daily closing price on which the large trade was executed</td>
</tr>
<tr>
<td>VWAP</td>
<td>The volume-weighted-average price of trades executed by the single initiating broker whose sequence of trades forms the large trade event</td>
</tr>
<tr>
<td>Market Capitalisation</td>
<td>The market capitalisation of the stock defined as the number of outstanding shares multiplied by the mid-point of the daily price</td>
</tr>
<tr>
<td>Initiating Shares</td>
<td>The total number of shares (in the same direction) executed by the single initiating broker over the period of the large trade event</td>
</tr>
<tr>
<td>Total Buy Shares</td>
<td>The total number of shares executed by all brokers at the ask price over the period of the large trade event</td>
</tr>
<tr>
<td>Total Sell Shares</td>
<td>The total number of shares executed by all brokers at the bid price over the period of the large trade event</td>
</tr>
<tr>
<td>Initiating Executions</td>
<td>The number of executed trades (in the same direction) performed by the single initiating broker over the period of the large trade event</td>
</tr>
<tr>
<td>Total Buy Initiations</td>
<td>The total number of executed trades performed by all brokers at the ask price over the period of the large trade event</td>
</tr>
<tr>
<td>Total Sell Initiations</td>
<td>The total number of executed trades performed by all brokers at the bid price over the period of the large trade event</td>
</tr>
<tr>
<td>Normal Trading Volume</td>
<td>The average daily trading volume of the stock in the prior three months</td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>The time-weighted bid-ask spread calculated over the period of the large trade event</td>
</tr>
<tr>
<td>Duration</td>
<td>Specifies the number of minutes taken to complete the large trade event (from the first trade to the last)</td>
</tr>
<tr>
<td>Volatility</td>
<td>Provides the volatility in stock returns of the previous 5, 10 and 180 days</td>
</tr>
<tr>
<td>H-index</td>
<td>Provides the Herfindahl-index at the market ask (bid) price for a purchase (sale) immediately prior (to the nearest second) to the first trade of a large trade event</td>
</tr>
<tr>
<td>Shares Ask (bid)</td>
<td>The number of standing limit order shares available for trade at the best ask (bid) price immediately prior to the first trade of the large trade event</td>
</tr>
<tr>
<td>Shares2 Ask (bid)</td>
<td>The number of standing limit order shares available for trade at the second best ask (bid) price immediately prior to the first trade of the large trade event</td>
</tr>
<tr>
<td>Av5Del Shares ask (bid)</td>
<td>The minute average number of deleted shares at the ask (bid) price calculated over the prior 5 minutes to the first trade of a large trade event</td>
</tr>
<tr>
<td>Av5Del Orders ask (bid)</td>
<td>The minute average number of deleted orders at the ask (bid) price calculated over the prior 5 minutes to the first trade of a large trade event</td>
</tr>
<tr>
<td>Del Shares ask (bid)</td>
<td>The number of deleted shares at the ask (bid) price over the next minute after the execution of the first trade of a large trade event</td>
</tr>
<tr>
<td>Del Orders ask (bid)</td>
<td>The number of deleted orders at the ask (bid) price over the next minute after the execution of the first trade of a large trade event</td>
</tr>
<tr>
<td>All Ords First</td>
<td>The level of the daily All Ordinaries Index at the start of the trading day</td>
</tr>
<tr>
<td>All Ords Last</td>
<td>The level of the daily All Ordinaries Index at the end of the trading day</td>
</tr>
</tbody>
</table>
The original dataset contains 84341 observations regarding large trade events within the sample period. There were 1222 observations containing missing values due to the unavailability of data. Such observations were deleted immediately\(^{bb}\).

The Taqtic database provided by SIRCA, was used to identify the constituents of the S&P/ASX200 in quarterly intervals. After the filtration of the dataset to include stocks comprising of the S&P/ASX200, 838 observations remained. The significant reduction in observation points highlights the sensitivity of the definition of a large trade in its ability to capture illiquid stocks. Data was used from the beginning of 2002 to the end of 2003. The growth in the ASX since the time at which Aitken and Frino (1996b) performed their study may explain the increase average daily trading volume required to be classified as a large trade. This will further increase due to the emergence of algorithmic trading.

Additional filters were placed on the dataset. Observations where the number of executions required in completing a large event was equal to one were deleted, allowing hypothesised ex-post actions of the liquidity provider to be relevant. Further observations were deleted in cases where the initiator was the only trader in a stock on a given day since this was not representative of a liquid stock. Finally, since the sample was small,

\(^{bb}\) Missing observations was mainly due to the unavailability of values of the All Ordinaries Index. Further missing observations was due unavailability of data to calculate the bid-ask spread, however, after filtering for the constituents of the S&P/ASX200, it was seen that these observations would have been omitted anyway.
inferences were highly sensitive to large influential data points. Therefore the inter-quartile range test was used to filter extreme data points cc. These data points were viewed before deletion and 84.33 percent of observations were constituents of the bottom half of the S&P/ASX200 dd. The final data sample consisted of 593 large trade events covering 1.59 billion dollars in principal.

5.2 Preliminary Analysis

In order to understand the nature of the sample dataset, standard descriptive statistics are used to evaluate how closely the data resembles analysis in prior studies. Since a large trade event is used to infer an institutional trade, it is useful to examine how quickly they can be executed.

The duration of a package is defined as the number of minutes required to execute all trades making up a large trade event. Table 5.2.1 reports the frequency distribution of large trade events by length. Each panel shows the proportion of the number large trade events that were executed within the specified time frame. Further, the principal total is shown to standardise the number of packages against the dollar value of its shares. The difficulty in executing large trade events is evident. For the most part, only 25.13 percent of the value of all large trade events is completed within three trading hours.

cc $Q_i - 1.5*(Q_3 - Q_i), Q_3 + 1.5*(Q_3 - Q_i)$

dd This was done by comparing outliers to the S&P/ASX100.
Table 5.2.1

Frequency Distribution of Large Trade Events against Duration

<table>
<thead>
<tr>
<th>Duration (min)</th>
<th>90</th>
<th>91-180</th>
<th>181-270</th>
<th>271-360</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Events</td>
<td>13.66</td>
<td>11.47</td>
<td>21.42</td>
<td>53.46</td>
</tr>
<tr>
<td>Principal</td>
<td>18.42</td>
<td>5.33</td>
<td>9.06</td>
<td>67.18</td>
</tr>
</tbody>
</table>

Panel A: All Trades (593 Large Trade Events, $1589 Million Principal)

| Trade Events (35.58%) | 12.80 | 8.06 | 20.85 | 58.29 |
| Principal (24.86%)    | 12.69 | 6.50 | 13.91 | 66.91 |

Panel B: Purchases (211 Large Trade Events, $395 Million Principal)

| Trade Events (64.42%) | 14.14 | 13.35 | 21.73 | 50.79 |
| Principal (75.14%)    | 20.32 | 4.95  | 7.46  | 67.27 |

Panel C: Sales (382 Large Trade Events, $1194 Million Principal)

Each number in this table represents the percentage of large trade events executed within the indicated number of minutes. Principal amounts represent the percentage of large trades weighted by the dollar principal (VWAP). Trade events are reported for large purchases (sales) which comprise of a sequence of trades by the same broker in the same direction where the total volume of the large trade exceeds the 30-day average normal trading volume of the underlying stock.

This suggests that the treating block trades, as used by other studies, as institutional trades can be misleading since the majority of trades take more than 3 hours to complete. Further, since 67.18 percent of the value of trades requires greater than four and a half hours to execute, some large trades may require more than one day to complete. This is consistent with Chan and Lakonishok (1995) who find that approximately 20 percent of institutional trading occurs within one day. Nevertheless, both Comerton-Forde et al. (2005) and Frino et al. (2006) report a one day average to complete a trade package.
Comparing Panels B and C, a greater number of sales were witnessed over the period. Further, 20.32 percent of the value of sales can be executed within 90 minutes as compared with 12.80 percent for purchases. This suggests that a large sale can be completed faster than an identical large purchase.

Table 5.2.2 provides other relevant statistics regarding the sample of large trade events used in this study. Panels A and B report the average shares and dollar value observed in each large event. It shows that the average large buy (sale) event is composed of 893,000 (1,571,000) shares worth 1,873,000 Australian dollars (3,126,000 Australian dollars). These observations are at odds when compared to Australian trade package studies such as Comerton-Forde et al. (2005) and Frino et al. (2006) who observe institutional trades containing between 245,000 Australian dollars and 365,000 Australian dollars in dollar value. The difference between the current study and the previous can be attributed to the different instruments used to measure institutional trading costs since the values presented in this study resemble Aitken and Frino (1996b), who report larger average dollar values for institutional trading (1.123 million Australian dollars for purchases and 1.163 million Australian dollars for sales). Consequently, both this study and Aitken and Frino (1996b) examine only the largest proportion of institutional trading.
### Table 5.2.2

Other Characteristics of Large Trade Events

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Purchases</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Shares Traded (Thousands)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1,330</td>
<td>893</td>
<td>1,571</td>
</tr>
<tr>
<td>10th percentile</td>
<td>122</td>
<td>122</td>
<td>122</td>
</tr>
<tr>
<td>25th percentile</td>
<td>195</td>
<td>181</td>
<td>417</td>
</tr>
<tr>
<td>Median</td>
<td>405</td>
<td>368</td>
<td>417</td>
</tr>
<tr>
<td>75th percentile</td>
<td>885</td>
<td>852</td>
<td>896</td>
</tr>
<tr>
<td>90th percentile</td>
<td>1,988</td>
<td>2,100</td>
<td>1,970</td>
</tr>
<tr>
<td>Sum</td>
<td>788,432</td>
<td>188,318</td>
<td>600,114</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Panel B: Dollar Value of Large Trade Event (Thousand $AUD)</strong></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2,680</td>
<td>1,873</td>
<td>3,126</td>
</tr>
<tr>
<td>10th percentile</td>
<td>145</td>
<td>191</td>
<td>125</td>
</tr>
<tr>
<td>25th percentile</td>
<td>276</td>
<td>333</td>
<td>518</td>
</tr>
<tr>
<td>Median</td>
<td>585</td>
<td>711</td>
<td>518</td>
</tr>
<tr>
<td>75th percentile</td>
<td>1,486</td>
<td>1,871</td>
<td>1,259</td>
</tr>
<tr>
<td>90th percentile</td>
<td>3,677</td>
<td>3,511</td>
<td>3,857</td>
</tr>
<tr>
<td>Sum</td>
<td>1,589,310</td>
<td>395,105</td>
<td>1,194,205</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Panel C: Large Trade Event Size Relative to Normal Trading Volume</strong></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.62</td>
<td>1.47</td>
<td>1.71</td>
</tr>
<tr>
<td>10th percentile</td>
<td>1.04</td>
<td>1.05</td>
<td>1.04</td>
</tr>
<tr>
<td>25th percentile</td>
<td>1.11</td>
<td>1.11</td>
<td>1.30</td>
</tr>
<tr>
<td>Median</td>
<td>1.27</td>
<td>1.25</td>
<td>1.30</td>
</tr>
<tr>
<td>75th percentile</td>
<td>1.62</td>
<td>1.55</td>
<td>1.70</td>
</tr>
<tr>
<td>90th percentile</td>
<td>2.19</td>
<td>1.95</td>
<td>2.43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Panel D: Large Trade Event Size Relative to 95th Percentile of Trading Volume</strong></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.59</td>
<td>0.37</td>
<td>0.87</td>
</tr>
<tr>
<td>10th percentile</td>
<td>0.05</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>25th percentile</td>
<td>0.09</td>
<td>0.07</td>
<td>0.23</td>
</tr>
<tr>
<td>Median</td>
<td>0.18</td>
<td>0.15</td>
<td>0.23</td>
</tr>
<tr>
<td>75th percentile</td>
<td>0.40</td>
<td>0.35</td>
<td>0.50</td>
</tr>
<tr>
<td>90th percentile</td>
<td>0.89</td>
<td>0.86</td>
<td>1.10</td>
</tr>
</tbody>
</table>

This table provides a description of the large trade events. Trade events are reported for large purchases (sales) which comprise of a sequence of trades by the same broker in the same direction where the total volume of the large trade exceeds the 30-day average normal trading volume of the underlying stock. Descriptive statistics are shown for both purchases and sales. In Panel C, relative normal trading volume is calculated as the 30-day average normal trading day volume for the underlying stock. In Panel D, large trade event size is divided by the 95th percentile of the distribution of trading volume over the average 30-day period.
However, this is not a limitation since both Comerton-Forde et al. (2006) and Chan and Lakonishok (1995) observe the distribution of institutional trades (both the number of shares and dollar value) to be highly skewed to the right. As such, the sample used will still provide useful results and regression analysis can be used to make inferences for smaller institutional trades.

Panel C reports the relative size for every trade event standardised against the 30-day average trading volume for a given stock. The average large trade event is 62 percent larger than the typical trading volume of a given stock. By definition, all trades examined in this study must be larger than the average daily trading volume of a stock in order to be classified as a large trade. The relative size of a large event follows closely to Chan and Lakonishok’s (1995) classification of the third quintile group for firm size (with a mean of 1.75 for purchases and 1.57 for sales). Further, they report that institutional trades occur in the largest firms sometimes at three times the normal trading volume (the top 1 percent of packages). The largest (90th) percentile documented in this study reports an average of close to 2.48 times normal trading volume, suggesting the sample is composed with relatively large firms which justifies the use for the filtration of the initial sample with the S&P/ASX200 index.

Panel D accounts for the variability in a stock’s daily trading volume by measuring the size of a large trade event against the average daily trading volume of the 95th
percentile\textsuperscript{ee}. The present study finds similar results to Panel C as the variation in trade size is large with the largest trades contributing significantly to the mean.

6. Methodology

6.1 Execution Costs

This paper follows methodology consistent with prior literature. This study separately captures the different components of the implicit costs of trading using the following measures;

\[
\text{Open-to-Trade (Total Impact)} = \frac{\text{VWAP} - \text{Opening Price}}{\text{Opening Price}} \quad (1)
\]

\[
\text{Trade-to-Close (Temporary Impact)} = \frac{\text{Closing Price} - \text{VWAP}}{\text{VWAP}} \quad (2)
\]

\[
\text{Open-to-Close (Permanent Impact)} = \frac{\text{Closing Price} - \text{Opening Price}}{\text{Opening Price}} \quad (3)
\]

A large trade event is constructed by identifying a series of aggregated trades from a single broker in one stock. To examine the effects of each, purchases and sales are separated. The volume-weighted-average-price, \textit{VWAP}, is used to represent the overall price paid (received) by a buyer (seller) initiated trade. \textit{Opening Price} and \textit{Closing Price} is used as the pre and post benchmark measures to determine the implicit costs of trading.

\textsuperscript{ee} The 95\textsuperscript{th} was chosen to be consistent with Chan and Lakonishok (1995).
These are defined as the opening and closing share prices for a given stock on the same trading day. These measures are consistent with those used by Chan and Lakonishok (1993) and Aitken and Frino (1996b).

Kraus and Stoll (1972) and Holthausen et al. (1987) provide theoretical justification for the separate analysis of the price impact components. Holthausen et al. (1987) show that short-run liquidity costs can be measured by temporary impact (2). They argue that insufficient substitutes, inelastic demand curves and information effects can be used to explain the permanent movement in a stock’s price (3). Finally, they state that overall movement in the stock resulting from the trade can be measured through total impact (1). Further, this measure is used to identify the initial impact of a trade. At first glance, one would expect to find opposite-side depth concentration to be most prevalent under the Open-to-Trade and Open-to-Close measures. Cancellations of immediate order flow will directly affect the initial impact of a trade event, and assuming these cancellations were forced due to adverse selection, a permanent impact would be observed by the Open-to-Close measure.

6.2 Multiple Regression Analysis

To ensure consistency with previous price impact studies, regression analysis is used to test the joint relationship that exists between execution costs, opposite-side depth concentration, and a set of relevant control variables. As identified in Section 2, studies have shown that trade size, firm size, market return, length of the trade and size of the
spread have significant explanatory power in determining execution costs. Hence the following regression is estimated using Ordinary Least Squares for both purchases and sales:

\[ PI_{p,j} = \beta_0 + \beta_1 H_j + \sum_{j=2}^{4} \gamma_j D_{ij} + \sum_{j=2}^{4} \delta_j S_{ij} + \beta_2 BAS_i + \beta_3 \ln(Duration_i) + \beta_4 R_i + \epsilon_i \]

\( PI_{p,j} \) represent one of the three variations (\( p \)) in the measurement of price impact costs: Open-to-Trade Trade-to-Close and Open-to-Close for large trade event \( i \). \( H_j \) is used to estimate the opposite-side depth concentration and thus takes the value of the Herfindahl-index\( ^{ff} \) prevalent on the market ask (bid) price immediately prior to the first executed trade of a large purchase (sale). The variables \( D_{ij} \) and \( S_{ij} \) are a set of dummy variables which control for the impact of both the size of the trade and size of the firm. A trade’s complexity measures the difficulty in the execution of a large trade event. This paper defines complexity as the proportion of shares traded by the initiating broker relative to the total amount of shares traded on the same side of the market over the duration of the large trade event\( ^{gg} \). Firm size is defined as the underlying stock’s current market

\[ ^{ff} \text{The same adjustment is made in this section where any large purchase (sale) which had less than 1000 shares available at the market ask (bid) price used the Herfindahl-index at the second best price instead.} \]

\[ ^{gg} \text{Complexity has been measured using other proxies such as share volume, the number of relative broker executions, the dollar value of shares traded, or trading volume relative to normal trading day volume. The current definition used in this study is consistent with literature and was chosen since it provided the best fit.} \]
capitalisation at the time of the first trade. Both complexity and market capitalisation are classified into four groups: <25th percentile, 25th-50th percentile, 50th-75th percentile, and >75th percentile. Using the smallest percentile <25th as a base for both measures, a dummy variable is assigned for each category in each trade event, \( i \). This type of classification is consistent with Chan and Lakonishok (1995) who argue that trade size, firm size and execution costs are not linearly related. \( BAS_i \) is defined as the time-weighted bid-ask spread of the underlying stock over the duration of large trade event, \( t^{hh} \). It is used to control for the liquidity of the underlying stock. \( Duration_i \) is measured as the number of minutes taken to execute a large trade event\(^{ii} \). Finally, \( R_i \) represents the arithmetic returns of the All Ordinaries Index calculated on the day of the trade and controls for market-wide movements in price.

### 6.3 Description and Direction of Explanatory Variables

Section 3 identifies the possible alternative hypotheses regarding the correlation of the opposite-side depth concentration variable with execution costs. A positive relationship between in relation to execution costs suggests that the risk of cancellation and subsequent price impact is higher when fewer brokers dominate the opposite-side of the market. Alternatively one may find a negative relationship exists, where lower

\(^{hh}\) This study also considered the intensity ratio as used by Aitken and Frino (1996b) but found no significance.

\(^{ii}\) The natural logarithmic transformation of duration is used to provide a better fit.
concentration levels suggest a correlation between broker actions in terms of the
cancellation of order flow. Although these two events may not be mutually exclusive,
regression analysis will show which effect is more dominant and whether it is
consistently affecting execution costs (found through significance).

Chan and Lakonishok (1993) argue that both firm size and trade size are significantly
related to execution costs. They find that larger sized trades represent trades with greater
difficulty to execute since the task of finding short-run liquidity becomes difficult as the
size gets larger. Thus a positive (negative) relationship is expected to be observed
between the variable for complexity and execution costs for purchases (sales). Further,
Chan and Lakonishok (1993) argue that institutional trades executed on larger stocks will
incur the least amount of execution costs since liquidity is expected to be higher and
more readily available as compared to smaller stocks. Consequently, a negative (positive)
relationship is expected to be observed between the variable for firm size and execution
costs for purchases (sales). Finally, using the grouping approach, as defined above,
provides a better fit to the model by allowing the non-linearity of the variables to be
modelled as Chan and Lakonishok (1995) have suggested.

Studies such as Aitken and Frino (1996b) and Frino et al. (2007) find it necessary to
control for the bid-ask spread of the underlying stock such that tighter spreads are
associated with higher liquidity and lower price impact. Thus, one would expect a
positive (negative) relationship between the time-weighted bid-ask spread and execution
costs for purchases (sales).
Duration is a variable which has been used to control for institutional trades that take more than one execution to complete. Consequently, this variable has only been used by the recent studies using trade packages and large trade events. Nevertheless, this variable can represent the difficulty in executing the large trade (represented by permanent price impact), or it can show the patience of the initiator to obtain lower costs (represented by temporary price impact). Such mixed results are found by Comerton-Forde et al. (2005).

Finally, the market return variable controls for systematic movements involving stocks in the exchange. Thus if the market is growing, purchases (sales) will be more likely to incur permanent price impact and less subsequent price reversal.

7. Results

7.1 Average Execution Costs

Table 7.1.1 examines the trading costs measured across purchases and sales. Results from this data show a 0.86 percent (0.95 percent) average price increase (decrease) relative to the opening price on the day at which a large purchase (sale) was executed. Further, the average price impact does not revert after the trade. The absence of price reversal from the Trade-to-Close measure results in a higher overall permanent price impact for all large trade events. The lack of price reversal is at odds with price impact literature, which generally finds an asymmetry in price reversal following an institutional trade. The
Table 7.1.1

**Execution Costs**

<table>
<thead>
<tr>
<th>Execution Costs</th>
<th>Open-to-Trade (%)</th>
<th>Trade-to-Close (%)</th>
<th>Open-to-Close (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.86</td>
<td>0.27</td>
<td>1.14</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.61</td>
<td>1.78</td>
<td>2.62</td>
</tr>
<tr>
<td>t-statistic</td>
<td>7.81</td>
<td>2.19</td>
<td>6.31</td>
</tr>
<tr>
<td>Proportion&gt;0</td>
<td>0.65</td>
<td>0.57</td>
<td>0.60</td>
</tr>
<tr>
<td>10th percentile</td>
<td>-0.78</td>
<td>-1.16</td>
<td>-1.64</td>
</tr>
<tr>
<td>25th percentile</td>
<td>-0.01</td>
<td>-0.38</td>
<td>0.00</td>
</tr>
<tr>
<td>Median</td>
<td>0.55</td>
<td>0.05</td>
<td>0.72</td>
</tr>
<tr>
<td>75th percentile</td>
<td>1.69</td>
<td>1.00</td>
<td>2.30</td>
</tr>
<tr>
<td>90th percentile</td>
<td>3.25</td>
<td>2.30</td>
<td>4.82</td>
</tr>
</tbody>
</table>

**Panel A: Purchases (n = 211)**

- Mean: 0.86, 0.27, 1.14
- Standard Deviation: 1.61, 1.78, 2.62
- t-statistic: 7.81, 2.19, 6.31
- Proportion>0: 0.65, 0.57, 0.60
- 10th percentile: -0.78, -1.16, -1.64
- 25th percentile: -0.01, -0.38, 0.00
- Median: 0.55, 0.05, 0.72
- 75th percentile: 1.69, 1.00, 2.30
- 90th percentile: 3.25, 2.30, 4.82

**Panel B: Sales (n = 382)**

- Mean: -0.95, -0.55, -1.48
- Standard Deviation: 1.86, 2.29, 3.35
- t-statistic: -10.01, -4.70, -8.63
- Proportion<0: 0.62, 0.54, 0.59
- 10th percentile: -3.61, -2.34, -5.08
- 25th percentile: -1.69, -0.95, -2.37
- Median: -0.55, -0.02, -0.69
- 75th percentile: 0.00, 0.32, 0.00
- 90th percentile: 1.09, 1.17, 1.37

This table shows the descriptive statistics of each of the three different execution costs that are reported for each large trade event: **Open-to-Trade** measures the pre-execution benchmark and initial price impact, **Trade-to-Close** measures the post-execution benchmark and **Open-to-Close** measures the total price impact. Execution costs are reported in percentage returns. Panel A represents large purchases and Panel B represents large sales.

The results suggest otherwise and a large trade event is likely to be associated with subsequent price permanent impact. A number of implications can be drawn from this result. First, large trade events may be more likely to be associated with information.
Second, due to their size, large trade events may be traded more patiently. This is consistent with Table 5.2.1, showing 67.18 percent of the dollar value of all large trade events being executed over 4.5 hours. Finally, large trade events may be more likely to be executed in stocks with imperfect substitutes or inelasticity in its supply and demand schedules.

Notably, the total execution costs are generally higher than previous studies have reported. Aitken and Frino (1996b) report the average execution costs measured from the Open-to-Close at -0.01 percent (-0.08 percent) for purchases (sales) which suggests that the institutional trading definition is not the cause for the greater execution costs. The findings are however, similar to Bonser-Neal et al. (1999) who measure the Open-to-Close at 1.82 percent and -0.37 percent for purchases and sales. They attribute this to the bid-ask bounce associated with taking pre and post trade benchmarks at the open and close of the day.

7.2 Price Impact of High and Low Opposite-Side Depth Concentration

Table 7.2.1 reports execution costs relative to opposite-side market concentration. The Herfindahl-index is measured at the market price. Since the study’s analysis focuses on market depth, there exists the possibility that insignificant small depth is posted within the quotes making the new market price (and the Herfindahl-index attached) unrepresentative of the true concentration of depth.
This table reports the descriptive statistics of the execution costs; Open-to-Trade, Trade-to-Close and Open-to-Close measured in percentage returns. Large trades are separated as into two classes defined through the Herfindahl-index level being greater (less) than the medium for high (low) concentration. The Herfindahl-index is calculated by:

\[ H_s = \frac{100^2}{\sum V_{ij}^2} \]

where and \( V_{ij} \) represents the limit order depth posted by broker \( j \) for stock \( i \) immediately prior to the first trade \( t \). The index at the second best market price is used when the number of shares posted on the best price on the opposite-side is less than 1000. Trade events are reported for large purchases in Panel A and large sales in Panel B which comprise of a sequence of trades by the same broker in the same direction where the total volume of the large trade exceeds the 30-day average normal trading volume of the underlying stock.

To account for this, any Herfindahl-index that was calculated with a total volume of shares less than 1000 was replaced with the Herfindahl-index at the second best price.
Panel A describes the behaviour of execution costs that involve the purchasing of shares. Lower concentrations of depth are associated with 1.14 percent, 0.40 percent and 1.55 percent increases in price for Open-to-Trade, Trade-to-Close and Open-to-Close measures respectively. This is comparatively higher than events associated with higher concentrations of depth, which result in 0.59 percent, 0.14 percent and 0.73 percent increases in price for the respective measures. Clearly one can see that higher concentration of depth is associated with lower comparative impact. Similar behaviour can be found in Panel B, which reports the same measures under large sales. The consistency of the execution costs in both Panel A and B provide support for the second alternative hypothesis.

To further examine the second alternative hypothesis, one may compare the opposite-side concentration with the frequency of cancellations at each respective market price. Cancellations are calculated as the total amount of shares removed at the market ask (bid) within 1 minute after a large purchase (sale) has executed the first of a sequence of trades,\textsuperscript{ij} to the total shares executed in the same direction (for all brokers) over the duration of the trade event.

Thus it measures the size of orders withdrawn relative to the total shares executed over a large trade event. Table 7.2.2 provides tentative support for the second alternative hypothesis.

\textsuperscript{ij} One does not assume causality between the initiating order an the cancellation. There may be multiple reasons for the withdrawal of depth.
hypothesis. It shows that a lower concentration of opposite-side order depth has a higher likelihood of attracting withdrawal of depth as compared with higher concentrations.

### Table 7.2.2

<table>
<thead>
<tr>
<th></th>
<th>Low Concentration</th>
<th>High Concentration</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Purchases (n = 198)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cancellation (%)</td>
<td>0.56</td>
<td>0.05</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>3.04</td>
<td>0.33</td>
</tr>
<tr>
<td>t-statistic</td>
<td>1.89</td>
<td>1.65</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Low Concentration</th>
<th>High Concentration</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel B: Sales (n = 356)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cancellation (%)</td>
<td>0.34</td>
<td>0.28</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.24</td>
<td>2.01</td>
</tr>
<tr>
<td>t-statistic</td>
<td>2.13</td>
<td>1.91</td>
</tr>
</tbody>
</table>

Cancellations are calculated as the number of orders deleted at the market ask (bid), observed one minute after the first executed trade of a large trade event, relative to the number of shares executed at the ask (bid) for large purchases (sales). Large trades are separated as into two classes defined through the Herfindahl-index level being greater (less) than the median for high (low) concentration. The Herfindahl-index is calculated by:

\[
H_i = \frac{100 \sum_{j} V_{ijt}^2}{\sum_{j} \sum_{i} V_{ijt}^2}
\]

where and \(V_{ijt}\) represents the limit order depth posted by broker \(j\) for stock \(i\) immediately prior to the first trade \(t\). The index at the second best market price is used when the number of shares posted on the best price on the opposite-side is less than 1000.

### 7.3 Multiple Regression Analysis

The results of the regression analysis are provided in Table 7.3.1. It provides some evidence supporting the validity of the variables predefined by prior literature and their ability to explain execution costs. This study finds the following:
Table 7.3.1
Results of Regression Analysis

<table>
<thead>
<tr>
<th></th>
<th>Open-to-Trade</th>
<th></th>
<th>Trade-to-Close</th>
<th></th>
<th>Open-to-Close</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Purchases</td>
<td>Sales</td>
<td>Purchases</td>
<td>Sales</td>
<td>Purchases</td>
<td>Sales</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td>Coefficient</td>
<td>p</td>
<td>Coefficient</td>
<td>Coefficient</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.20</td>
<td>-0.74</td>
<td>0.68</td>
<td>-2.00 **</td>
<td>1.86</td>
<td>-2.66 **</td>
</tr>
<tr>
<td>Concentration</td>
<td>-0.000143 ***</td>
<td>0.000116 ***</td>
<td>-0.000051</td>
<td>0.000068 *</td>
<td>-0.000199 ***</td>
<td>0.000182 ***</td>
</tr>
<tr>
<td>Complexity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (least)</td>
<td>0.08</td>
<td>-0.45 *</td>
<td>0.01</td>
<td>-0.09</td>
<td>0.08</td>
<td>-0.53</td>
</tr>
<tr>
<td>2</td>
<td>0.11</td>
<td>-0.93 ***</td>
<td>0.07</td>
<td>-0.14</td>
<td>0.18</td>
<td>-1.05 **</td>
</tr>
<tr>
<td>3 (most)</td>
<td>0.59 **</td>
<td>-0.60 **</td>
<td>0.14</td>
<td>-0.29</td>
<td>0.73</td>
<td>-0.86 *</td>
</tr>
<tr>
<td>Market Capitalisation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (smallest)</td>
<td>-0.62 **</td>
<td>0.94 ***</td>
<td>0.37</td>
<td>0.96 ***</td>
<td>-0.24</td>
<td>1.87 ***</td>
</tr>
<tr>
<td>2</td>
<td>-0.88 ***</td>
<td>1.17 ***</td>
<td>0.35</td>
<td>1.28 ***</td>
<td>-0.53</td>
<td>2.40 ***</td>
</tr>
<tr>
<td>3 (largest)</td>
<td>-1.02 ***</td>
<td>1.35 ***</td>
<td>-0.17</td>
<td>1.25 ***</td>
<td>-1.18 **</td>
<td>2.56 ***</td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>0.35 ***</td>
<td>-0.01</td>
<td>0.14</td>
<td>0.01</td>
<td>0.50 ***</td>
<td>0.00</td>
</tr>
<tr>
<td>Duration</td>
<td>0.13</td>
<td>-0.26 **</td>
<td>-0.08</td>
<td>0.04</td>
<td>0.05</td>
<td>-0.23</td>
</tr>
<tr>
<td>Market Return</td>
<td>0.60 **</td>
<td>0.38</td>
<td>0.33</td>
<td>0.66 **</td>
<td>0.93 *</td>
<td>1.04 **</td>
</tr>
<tr>
<td>Adj Rsquared</td>
<td>10.92%</td>
<td>14.32%</td>
<td>-1.34%</td>
<td>5.02%</td>
<td>6.13%</td>
<td>12.97%</td>
</tr>
</tbody>
</table>

This table reports the results from the following regressions:

\[ P_{i,j} = \beta_0 + \beta_1 H_i + \sum_{j=2}^{4} \gamma_j D_{ij} + \sum_{j=2}^{4} \delta_j S_{ij} + \beta_2 BAS_i + \beta_3 \ln(Duration_i) + \beta_4 R_i + \epsilon_i \]

where \( P_{i,j} \) represent one of the execution costs measures; Open-to-Trade, Trade-to-Close and Open-to-Close. \( H_i \) represents opposite-side depth concentration, \( D_i \) captures trade complexity, \( S_i \) captures market capitalisation, \( BAS_i \) measures the time-weighted bid-ask spread from the first to the last trade of a large trade event, \( Duration_i \) captures minutes required to complete the large trade event. \( R_i \) is calculated as the return on the All Ordinaries Index on the day of the large trade event, \( i \).

*Denotes 10 percent significance
** Denotes 5 percent significance
*** Denotes 1 percent significance

A distinct relationship can be inferred between opposite-side concentration and execution costs due to the significance in the Open-to-Trade measure. The negative (positive) coefficient on purchases (sales) indicates that lower index values are more likely to be associated with larger price impact. Thus the concentration variable accounts for a 0.14 (0.12) percent decrease in the total impact for purchases (sales) for every 1,000 added.

The direction and correlation are more important than this interpretation since it is difficult to quantify the specific volume and number of brokers needed on the opposite-side of the market that are required to reduce costs. Nevertheless, correlation is clearly
negative and evidence of a continuation in price reduction is found by the Trade-to-Close measure. In fact, a higher index is significantly associated with less price impact suggesting that large traders believe there is less risk in the loss of order flow (via withdrawal of depth) when trading against few brokers with high proportions of depth on the opposite-side of the market.

Due to a small sample size, not all the variables were found to be significant. As such, mixed results are found. For the most part, variables are qualitatively consistent with prior literature. Execution costs incrementally increase from the smallest sized trades to the largest and are consistent with literature. The coefficients for the trade complexity move from 0.08 to 0.59, 0.01 to 0.14 and 0.08 to 0.73 for Open-to-Trade, Trade-to-Close and Open-to-Close measures for purchases and -0.45 to -0.60, -0.09 to -0.29 and -0.53 to -0.86 for sales. These imply that in moving from the smallest (base case) sized trades to the largest (1, 2 and 3), prices generally rise for purchases and falls for sales reflecting the difficulty of executing a larger trade. This is consistent with the idea that larger sized trades convey more information. Mixed results, however are seen for sales since the middle group is shown to have a larger price impact than the largest group. This is significant in our sample and inconsistent with literature.

Coefficients for firm size move from -0.62 to -1.02, and -0.24 to -1.18 for Open-to-Trade and Open-to-Close measures for purchases and 0.94 to 1.35, and 1.87 to 2.56 for sales. This is consistent with the notion that smaller sized firms incur greater overall price impact due to their illiquidity when compared to larger firms. It also suggests that larger
stocks have less permanent impact due to their ability in having elastic supply and demand curves. These results are not consistent when measured by Trade-to-Close. It shows a price reversal for purchases in the first and second groups of stocks when compared to the base. For sales, the results suggest that trading in medium sized firms incurs the least amount of impact. This is not consistent with the notion that liquidity is greater in larger stocks.

The coefficients for the bid-ask spread, are all positively (negatively) correlated for purchases and sales. Consistent with literature and illustrates that wider spreads are associated with greater price impact.

The duration of a trade may be influenced by more than one factor. The difficulty in execution, as large trades move to a longer duration, is evident from the Open-to-Close measure, reporting a 0.05 percent increase and -0.23 percent decrease in the price for the average stock in purchases and sales respectively. This is may be due to the greater complexity of the trade and also implies a more informed trade. Further, price reversal is illustrated by the Trade-to-Close measure (-0.08 percent for purchases and 0.04 percent for sales) suggesting that patient traders are able to obtain lower costs. This is consistent with the findings of Comerton-Forde et al. (2005).
Table 7.3.2
Contribution to R-Squared

<table>
<thead>
<tr>
<th></th>
<th>Open-to-Trade</th>
<th></th>
<th>Trade-to-Close</th>
<th></th>
<th>Open-to-Close</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Purchases</td>
<td>Sales</td>
<td>Purchases</td>
<td>Sales</td>
<td>Purchases</td>
<td>Sales</td>
</tr>
<tr>
<td>Full Model</td>
<td>10.92% ***</td>
<td>14.32% ***</td>
<td>-1.34%</td>
<td>5.02% ***</td>
<td>6.13% ***</td>
<td>12.97% ***</td>
</tr>
<tr>
<td>Excluding Concentration</td>
<td>5.98% ***</td>
<td>11.39% ***</td>
<td>-1.40%</td>
<td>4.55% ***</td>
<td>2.70% *</td>
<td>10.79% ***</td>
</tr>
<tr>
<td>Excluding Complexity</td>
<td>10.15% ***</td>
<td>11.72% ***</td>
<td>0.05%</td>
<td>5.58% ***</td>
<td>6.32% ***</td>
<td>12.25% ***</td>
</tr>
<tr>
<td>Excluding Market Capitalisation</td>
<td>6.69% ***</td>
<td>7.58% ***</td>
<td>-1.51%</td>
<td>0.87%</td>
<td>4.76% ***</td>
<td>4.91% ***</td>
</tr>
<tr>
<td>Excluding Bid-Ask Spread</td>
<td>7.39% ***</td>
<td>14.54% ***</td>
<td>-1.38%</td>
<td>5.27% ***</td>
<td>3.57% **</td>
<td>13.20% ***</td>
</tr>
<tr>
<td>Excluding Duration</td>
<td>10.96% ***</td>
<td>13.23% ***</td>
<td>-0.98%</td>
<td>5.36% ***</td>
<td>6.56% ***</td>
<td>13.00% ***</td>
</tr>
<tr>
<td>Excluding Market Return</td>
<td>9.59% ***</td>
<td>14.05% ***</td>
<td>-1.27%</td>
<td>4.30% ***</td>
<td>5.00% **</td>
<td>12.09% ***</td>
</tr>
</tbody>
</table>

This table represents the adjusted R-squared values of the full model:

\[ P_{l,i,j} = \beta_0 + \beta_1 H_i + \sum_{j=2}^{4} \gamma_j D_j + \sum_{j=2}^{4} \delta_j S_j + \beta_5 BAS_i + \beta_6 \ln(Duration_i) + \beta_7 R_i + \epsilon_i \]

where \( P_{l,i,j} \) represent one of the execution costs measures; \( Open-to-Trade, Trade-to-Close \) and \( Open-to-Close \). \( H_i \) represents opposite-side depth concentration, \( D_i \) captures trade complexity, \( S_i \) captures market capitalisation, \( BAS_i \) measures the time-weighted bid-ask spread from the first to the last trade of a large trade event, \( Duration_i \) captures minutes required to complete the large trade event. \( R_i \) is calculated as the return on the All Ordinaries Index on the day of the large trade event, \( i \). From the full model, one variable at a time is removed, the regression re-estimated and the R-squared recalculated.

*Denotes 10 percent significance
** Denotes 5 percent significance
*** Denotes 1 percent significance

Finally, market return is consistently positive across all measures suggesting that market-wide movements in stock prices play a major role in investor sentiment. Thus, purchases are more likely to exhibit greater impact than sales. This is consistent with Chiyachantana et al. (2004).

Following the standard set by Chan and Lakonishok (1993), Table 7.3.2 is useful for outlining the contribution of each variable to the total variation in execution costs. This is done by removing one variable at a time (with replacement) from the full model. Significance tests are performed using the F-test identified in Greene (2003). The models examined in this model obtain adjusted R-squared statistics ranging from -1.34 percent to 14.32 percent. This value is difficult to compare to other studies since different amounts
and types of variables are used. Nevertheless, Aitken and Frino (1996b) report R-squared statistics between 2.15 percent to 8.50 percent whilst using variables to control for order type and broker type. This result is an improvement in most areas of the model apart from purchases measured at the Trade-to-Close. The opposite-side concentration variable explains 4.94 (2.93) percent, 0.05 (0.47) percent and 3.43 (2.18) percent of the variation in Open-to-Trade, Trade-to-Close and Open-to-Close measures respectively. Comparing these values to the total amount explained by each model, the opposite-side concentration provides a large proportion of the variation. This is particularly evident in Open-to-Trade and Open-to-Close measures. This result is compelling since the benchmark used to calculate the previous two measures was the opening price on the day of the large trade event. Thus, the concentration prior to the first trade plays a major role in determining the impact of subsequent trades. This is also evident in sales, and its contribution in variation is only second to market capitalisation.

7.4 Tests for Robustness

The crucial aspect driving the value in its results lies in whether the relationship between opposite-side depth concentration and execution costs is robust throughout the sample. Additional tests were implemented to quantify reinforce a negative relationship, and support for the second alternative hypothesis, observed by the initial regression.
Table 7.4.1
Concentration against Execution Costs

Panel A: Purchases (n = 251)

<table>
<thead>
<tr>
<th></th>
<th>Low Concentration (Bottom 50%) H &lt; 8557</th>
<th>High Concentration (Top 50%) H &gt; 8557</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Execution Costs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Open-to-Trade (%)</strong></td>
<td>Mean: 1.41</td>
<td>-0.735</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation: 4.82</td>
<td>3.10</td>
</tr>
<tr>
<td></td>
<td>t-statistic: 3.28</td>
<td>1.106</td>
</tr>
<tr>
<td></td>
<td>Proportion &gt; 0: 0.72</td>
<td>0.544</td>
</tr>
<tr>
<td></td>
<td>10th percentile: -0.92</td>
<td>-5.537</td>
</tr>
<tr>
<td></td>
<td>25th percentile: 0.00</td>
<td>-0.578</td>
</tr>
<tr>
<td></td>
<td>Median: 1.00</td>
<td>0.1399</td>
</tr>
<tr>
<td></td>
<td>75th percentile: 2.57</td>
<td>1.4741</td>
</tr>
<tr>
<td></td>
<td>90th percentile: 5.12</td>
<td>3.9534</td>
</tr>
<tr>
<td><strong>Trade-to-Close (%)</strong></td>
<td>Mean: 0.2535</td>
<td>-0.242</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation: 2.5276</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>t-statistic: 1.1257</td>
<td>0.584</td>
</tr>
<tr>
<td></td>
<td>Proportion &gt; 0: 0.5476</td>
<td>-2.814</td>
</tr>
<tr>
<td></td>
<td>10th percentile: -1.649</td>
<td>-0.374</td>
</tr>
<tr>
<td></td>
<td>25th percentile: 0.00</td>
<td>-1.205</td>
</tr>
<tr>
<td></td>
<td>Median: 0.1179</td>
<td>0.0256</td>
</tr>
<tr>
<td></td>
<td>75th percentile: 1.1746</td>
<td>2.069</td>
</tr>
<tr>
<td></td>
<td>90th percentile: 7.32</td>
<td>5.3299</td>
</tr>
</tbody>
</table>

Panel B: Sales (n = 445)

<table>
<thead>
<tr>
<th></th>
<th>Low Concentration (Bottom 50%) H &lt; 8513</th>
<th>High Concentration (Top 50%) H &gt; 8513</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Execution Costs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Open-to-Trade (%)</strong></td>
<td>Mean: -1.935</td>
<td>-2.457</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation: 6.056</td>
<td>6.5874</td>
</tr>
<tr>
<td></td>
<td>t-statistic: -6.196</td>
<td>-5.558</td>
</tr>
<tr>
<td></td>
<td>Proportion &lt; 0: 0.713</td>
<td>0.5766</td>
</tr>
<tr>
<td></td>
<td>10th percentile: -3.827</td>
<td>-10.05</td>
</tr>
<tr>
<td></td>
<td>25th percentile: -2.791</td>
<td>-2.724</td>
</tr>
<tr>
<td></td>
<td>Median: -0.912</td>
<td>-0.457</td>
</tr>
<tr>
<td></td>
<td>75th percentile: 0.0</td>
<td>0.2584</td>
</tr>
<tr>
<td></td>
<td>90th percentile: 0.4394</td>
<td>1.605</td>
</tr>
<tr>
<td><strong>Trade-to-Close (%)</strong></td>
<td>Mean: -0.914</td>
<td>-1.121</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation: 4.6646</td>
<td>3.8614</td>
</tr>
<tr>
<td></td>
<td>t-statistic: -6.196</td>
<td>-4.327</td>
</tr>
<tr>
<td></td>
<td>Proportion &lt; 0: 0.713</td>
<td>0.5721</td>
</tr>
<tr>
<td></td>
<td>10th percentile: -3.827</td>
<td>-3.187</td>
</tr>
<tr>
<td></td>
<td>25th percentile: -2.791</td>
<td>-1.176</td>
</tr>
<tr>
<td></td>
<td>Median: -0.912</td>
<td>-0.078</td>
</tr>
<tr>
<td></td>
<td>75th percentile: 0.0</td>
<td>0.2601</td>
</tr>
<tr>
<td></td>
<td>90th percentile: 0.4394</td>
<td>1.1298</td>
</tr>
</tbody>
</table>

This table reports the descriptive statistics of the execution costs; Open-to-Trade, Trade-to-Close and Open-to-Close measured in percentage returns. Large trades are separated as into two classes defined through the Herfindahl-index level being greater (less) than the median for high (low) concentration. The Herfindahl-index is calculated by:

\[
H_s = \frac{1}{\sum_j 100V_{ijt}^2} \left( \sum_j V_{ijt} \right)^2
\]

where and \( V_{ijt} \) represents the limit order depth posted by broker \( j \) for stock \( i \) immediately prior to the first trade \( t \). The index at the second best market price is used when the number of shares posted on the best price on the opposite-side is less than 1000. Trade events are reported for large purchases in Panel A and large sales in Panel B which comprise of a sequence of trades by the same broker in the same direction where the total volume of the large trade exceeds the 30-day average normal trading volume of the underlying stock. Large trade events are not initially filtered for outliers.

To examine whether the relationship between the opposite-side depth concentration and execution costs exists is sensitive to the data filtration techniques, Table 7.4.1 provides
the average costs associated with high and low values of the index using the unfiltered sample.

Results for Table 7.4.1, Panel A show negative execution costs across all measures for purchases. Notably, these are all not significantly different from zero suggesting the presence of highly influential observations. Nevertheless, the general direction of the relationship between execution costs and the opposite-side depth concentration measure is negative for all purchases which can be seen by taking the difference between equivalent measures\(^{kk}\). This is consistent with the result obtained in Table 7.2.1, Panel A.

Results for Table 7.4.1, Panel B are at odds with the initial relationship, hence further investigation was required. Regression analysis was performed and finds that the relationship holds over purchases, whilst sales produce positive coefficients that are statistically insignificant. Nevertheless, due to the insignificance of sales under all execution cost measures, this robust test still provides weak support for the second alternative hypothesis.

\(^{kk}\) For example, for the Open-to-Trade measure, the difference between high and low index values is - 0.73 - 1.41 = - 2.14. This indicates a reduction of 2.14 percent in the Open-to-Trade costs when moving from a low index value to a high index value.
7.5 Implications of Results

The results from both descriptive statistic and regression analysis provide evidence for the second alternative hypothesis. Table 7.2.1 provides evidence that lower opposite-side depth concentration is associated with greater impact for both purchases and sales. Further, regression analysis shows a distinct negative relationship between the opposite-side depth concentration measure and Open-to-Close and Trade-to-Close measures which is indicative of a permanent affect on stock price. This suggests actions taken by brokers on the opposite-side of the market are related to the informative nature of the trade being executed. Further, lower opposite-side depth concentration is associated with higher withdrawal of depth as shown by Table 7.2.2. This indicates that herding behaviour may exist among opposite-side brokers. Finally, the combination of these results is consistent with the notion that herding between brokers is present.

8. Conclusion

The behaviour of liquidity providers has been examined in the past by analysing the price changes of the order flow associated with their actions. The reaction of the liquidly provider is important since a withdrawal of depth will cause greater price impact for subsequent trades on that side of the book. This study introduces a Herfindahl-index to measure the concentration of posted depth on the opposite-side of the market prevailing at the time before an institutional trade. This is used within the context of price impact literature to determine the associated costs related to changes in the nature of the
opposite-side of the market. The general ex-post reactions of liquidity providers can then be approximated from this variable’s significance and direction.

This study finds evidence that a significant negative relationship exists between opposite-side depth concentration and the price impact measures for *Open-to-Trade* and *Trade-to-Close*. This implies that the costs of executing a sequence of large trades is greater under a lower opposite-side depth concentration where depth is spread across different brokers holding relatively equal amounts of depth. This study also finds support for the notion of herding behaviour which can be used to explain the relationship empirically identified in the above analysis. A large proportion of this herding behaviour can be attributed to information due to the permanent price effects associated with withdrawal in order depth.

This study contributes to price impact literature examining the variables causing the most variation in price impact. The opposite-side depth concentration explains 2.70 percent and 5.98 percent of the total variation in *Open-to-Close* and *Open-to-Trade* measures respectively. Further implications of this research suggest that institutional traders can manage trading costs by trading in stocks that have depth concentrated around fewer amounts of brokers. This however, can only be used in markets with pre-trade transparency.

Finally, extensions of this study may involve the use of a cleaner proxy for opposite-side depth concentration that is not affected by the other actions of liquidity providers (such as order placement and order execution).
Consider a stock XYZ traded on and electronic limit order book. A trade-initiating broker wishes to go long on the stock by purchasing shares from the market. Assuming there are 10,000 available shares outstanding at the market *ask price* of stock XYZ with five *different* brokers posting order depth, the limit order book may be depicted in an infinite amount of ways. For brevity, this study presents two different possible scenarios.

**Figure A**

\[ H = 2000 \]
The first scenario, depicted by Figure A, presents the case where the five brokers share the volume of posted depth equally. This scenario is considered the most competitive and diluted in terms of posted broker depth since no broker controls more depth than another and results in a Herfindahl index equal to 2,000.

The second scenario, depicted by Figure B, shows a different case where one broker (Broker A) controls a significant proportion of posted depth in comparison to the rest. This would be considered as a less competitive scenario compared to the previous, since one broker controls most of the posted order depth and results in a Herfindahl index equal to 4,000.
Appendix B

<table>
<thead>
<tr>
<th></th>
<th>Open-to-Trade</th>
<th></th>
<th>Trade-to-Close</th>
<th></th>
<th>Open-to-Close</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Purchases Coefficient</td>
<td>Sales Coefficient</td>
<td>p</td>
<td>Purchases Coefficient</td>
<td>Sales Coefficient</td>
<td>Purchases Coefficient</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.20</td>
<td>2.83</td>
<td>1.08</td>
<td>-1.79</td>
<td>3.11</td>
<td>1.05</td>
</tr>
<tr>
<td>Concentration Coefficient</td>
<td>-0.000375 **</td>
<td>0.000043</td>
<td>-0.000067</td>
<td>0.000003</td>
<td>-0.000434 **</td>
<td>0.000053</td>
</tr>
<tr>
<td>Complexity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (least)</td>
<td>0.61</td>
<td>-1.34 *</td>
<td>0.33</td>
<td>0.24</td>
<td>0.80</td>
<td>-1.09</td>
</tr>
<tr>
<td>2</td>
<td>-0.61</td>
<td>-1.67 **</td>
<td>-0.78</td>
<td>0.37</td>
<td>-1.27</td>
<td>-1.32</td>
</tr>
<tr>
<td>3 (most)</td>
<td>-0.07</td>
<td>-1.67 **</td>
<td>0.09</td>
<td>0.23</td>
<td>0.02</td>
<td>-1.44</td>
</tr>
<tr>
<td>Market Capitalisation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (smallest)</td>
<td>3.67 ***</td>
<td>0.43</td>
<td>2.24 ***</td>
<td>1.40 ***</td>
<td>5.52 **</td>
<td>1.65</td>
</tr>
<tr>
<td>2</td>
<td>2.81 ***</td>
<td>1.97 ***</td>
<td>1.60 ***</td>
<td>2.13 ***</td>
<td>3.97 **</td>
<td>3.85 ***</td>
</tr>
<tr>
<td>3 (largest)</td>
<td>2.54 **</td>
<td>3.12 ***</td>
<td>1.46 ***</td>
<td>2.22 ***</td>
<td>3.55 *** ***</td>
<td>5.04 ***</td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>0.00</td>
<td>-0.35 **</td>
<td>0.11</td>
<td>-0.08</td>
<td>0.11</td>
<td>-0.40 *</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.23</td>
<td>-0.94 ***</td>
<td>-0.36</td>
<td>-0.14</td>
<td>-0.50</td>
<td>-1.04 **</td>
</tr>
<tr>
<td>Market Return</td>
<td>3.45 ***</td>
<td>2.24 ***</td>
<td>1.67 ***</td>
<td>1.12 **</td>
<td>4.75 *** ***</td>
<td>3.16 ***</td>
</tr>
<tr>
<td>Adj Rsquared</td>
<td>6.61%</td>
<td>7.45%</td>
<td>6.84%</td>
<td>6.38%</td>
<td>8.42%</td>
<td>8.80%</td>
</tr>
</tbody>
</table>

This table uses unfiltered data points and reports the results from the following regressions:

\[ P_{i,t} = \beta_0 + \beta_1 H_i + \sum_{j=2} \gamma_j D_{ij} + \sum_{j=2} \delta_j S_{ij} + \beta_2 BAS_i + \beta_3 \ln(\text{Duration}_i) + \beta_4 R_i + \epsilon_i \]

where \( P_{i,t} \) represent one of the execution costs measures; Open-to-Trade, Trade-to-Close and Open-to-Close. \( H_i \) represents opposite-side depth concentration, \( D_i \) captures trade complexity, \( S_i \) captures market capitalisation, \( BAS_i \) measures the time-weighted bid-ask spread from the first to the last trade of a large trade event, \( \text{Duration}_i \) captures minutes required to complete the large trade event. \( R_i \) is calculated as the return on the All Ordinaries Index on the day of the large trade event, \( i \).

*Denotes 10 percent significance
** Denotes 5 percent significance
*** Denotes 1 percent significance
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