Information Endowment and Limit Order Placement

By Alex Frino, David Johnstone and Hui Zheng*

Current Version: January 2007

Very Preliminary Results; Please Don't Quote.

Abstract

This paper investigates the impact of information asymmetry on the placement of limit orders. Although the relationship between adverse selection and bid-ask spreads has been explored extensively, this is the first study to show formally how limit order traders update their quoted prices according to the adverse selection risk they face. An information-based sequential trade model is derived, which predicts that: (i) divergence in the ex-ante information endowment of investors will result in a different limit order pricing behaviour; and (ii) this difference is greater when market information asymmetry is higher. Empirical tests confirm these theoretical propositions, and demonstrate that limit order traders facing heterogeneous adverse selection risks place limit orders strategically according to their relative information endowment.

Key Words: Information Asymmetry, Limit Order Placement, Bid-ask Spread

* Finance Discipline, Faculty of Economics and Business, University of Sydney, NSW, 2006, Australia.

Mail: Finance Discipline, Faculty of Economics and Business, L4 H69, University of Sydney, NSW 2006 Australia. Phone: (61 2) 9351 39157. Fax: (61 2) 9351 6461. Email: h.zheng@econ.usyd.edu.au

This research is funded by the Capital Markets Cooperative Research Centre. The authors would like to thank the Australian Stock Exchange for the provision of data and the Securities Industry Research Centre for technical assistance.

1. Introduction

The role of limit orders in providing liquidity for security markets has stimulated increased interest in limit order trading over recent years. Not only because of the proliferation of electronic limit order book in securities exchanges (Frino, et al., 2004), but limit orders also make a significant contribution in providing market liquidity in hybrid or dealers' markets.[1] Despite the prevalence of the limit order system, the dynamic aspects of the limit order book have not been well explored. Only a handful of studies have provided theoretical descriptions of limit order book mechanics. For example, Glosten (1994) develops an equilibrium model in which limit order traders gain from liquidity driven price changes and lose from information driven price changes. Seppi (1997) demonstrates how competition between market specialists and limit order traders result in a limit order book, while Parlour (1998) presents a dynamic model of a limit order market that incorporates time priority in executing orders and interaction between traders in their order placement strategies.

The empirical work on the limit order book is scarcer due to a lack of order level data (Parlour, 1998, p. 791).[2] Among those studies, Petersen and Fialkowski (1994) examine a sample of market orders and describe intermarket differences in execution performance. Interestingly they find that the effective spread for most orders on the NYSE is only half of the posted spread, and only 10 to 22 percent of the increase in quoted spread is reflected in the effective spread. Greene (1996) develops a methodology for inferring limit order execution from transaction and quote data, and Biais et al. (1995) provide a detailed analysis of how liquidity is supplied and consumed in the market, and

[1] Harris and Hasbrouck (1996) documents that 54 percent of NYSE SuperDOT orders are limit orders, and Ross et al. (1996) report that limit orders account for 65 percent of all executed orders. In addition, Chung et al. (1999) show that the commonly observed *U*-shape intraday pattern of the bid-ask spread (McInish and Wood, 1992) largely reflects the intraday variation in spreads established by limit order traders rather than by the specialists.
[2] Harris and Hasbrouck (1996) and Bessembinder (2003) discuss the advantages of order level data relative to transaction data.

characterise the determinants of order submission.[3] This study adds to this area of market microstructure research by providing both theoretical and empirical evidence on how limit order traders place their orders under an information asymmetric trading environment.

Adverse selection costs have been widely recognised as an important component of the bid-ask spread quoted by market makers (Stoll, 1989). Glosten and Milgrom (1985) show that the existence of information asymmetry, *per se*, can lead to a non-negative spread, and Easley and O'Hara (1987) elaborate on how a market marker incorporates private information through trading with a group of potentially informed traders. Following their research, a diverse collection of market microstructure literature has focused on the optimal securities pricing behaviour of one or more dealers in an information-asymmetric trading environment;[4] however, very few studies have examined the impact of information asymmetry on the construction of limit order book. Only recently have researchers begun to empirically characterise limit order trading. For example, Ahn et al. (2001) show that a greater number of limit sell (buy) orders than market sell (buy) orders are submitted when transitory volatility arises from the ask (bid) side. Smith et al. (2000) examine the costs and determinants of order aggressiveness. Interestingly, they find that the optimal strategy for a limit order trader is to enter buy (sell) orders at the current bid (ask) price.

The lack of study of information asymmetry in limit order placement is particularly important because limit orders can contain private information. When information is short-lived, an informed trader has a higher propensity to submit market orders and to

[3] The main findings of Biais et al. (1995) about limit order placement strategies include that: (1) order flow is concentrated near the quotes, while the depth of the order book is somewhat further at nearby valuations; (2) thin books elicit orders and thick books result in trades; and (3) to gain price and time priority, investors quickly place orders within the quotes when the depth at the quotes or the spread is large.

[4] For example, see Admati and Pfleiderer (1988); Back (1992); Easley and O'Hara (1987, 1991, 1992a, 1992b, 1996a, 1996b); Foster and Viswanathan (1990); Glosten and Milgrom (1985); Kyle (1985); Subrahmanyam (1991a, 1991b).

exploit the full benefit of their information before the information leaks out (Rock, 1996; Glosten, 1994). However, when the private information is long-lived, Kaniel and Liu (2006) show that informed traders will generally prefer to use limit orders, making limit orders more informative in the market. Bloomfield et al. (2003) also find that the expected horizon of informed traders' private information is critical in the choice of limit orders versus market orders. This intuition is shared by Keim and Madhavan (1995), who show that when the order size is large, passive trading strategies is more preferred because the price impact associated with market orders will far outweigh the opportunity costs associated with non-execution. To further examine the informational impact of limit orders, this study develops a theoretical model of information asymmetry to model the behaviour of the bid-ask spread quoted by the market makers possessing different levels of ex-ante information, and subsequently test the theoretical hypotheses with a unique dataset obtained from the Australian Stock Exchange (ASX) under various market conditions.

The importance of a better understanding of information asymmetry and the limit order book is also prompted by the fact that in many financial markets, market specialists and/or dealers coexist with a limit order book, which enables researchers to examine the price impact of limit orders reflected in specialists' quotes. Madhavan and Panchapagesan (2000) find that the presence of a strategically-behaved dealer can speed price discovery in the opening process by extracting valuable information from the limit order book. Kavajecz (1999) investigates how specialists react to the presence of limit orders. He finds that specialists strategically pass off unwanted trades onto the limit order book by lowering the depth of their quotes to reflect only the interest in the limit order book. Jones and Lipson (2003) provide the first study to empirically investigate the order execution and order timing strategies of different groups of traders. After controlling for order treatment, prevailing quote conditions and intraday order flow, they find that effective spreads for retail orders are narrower than effective spreads for comparable orders originating from non-retail traders (i.e. in their study the institutions and program traders). They also find that non-retail order flow is strongly positively correlated, while retail order flow is close to random over time. Non-retail orders arrive quickly after lower spreads are posted and take advantage of these momentary changes in liquidity. Their finding is consistent with the assertion that retail order flow contains less information, and it is more profitable for liquidity providers to trade with retail traders. Their finding explains why competing security markets prefer to execute retail orders (Bessembinder and Kaufman, 1997; Huang and Stoll, 1996).

Following the previous research, this study examines how information asymmetry affects the order placement strategies of different groups of limit order traders. By differentiating investors on the basis of their likely information endowments and the impact on limit order placement, this study of relative informativeness is different from the work by Jones and Lipson (2003) that focuses on the execution of market orders by NYSE specialists. In addition, NYSE specialists and traders generally do not have information about the types of investors they are dealing with, while this study is conducted in a pure order-driven market with a high level of pre-trade transparency, (i.e. broker identities are transparent to other market participants when orders are entered into the market). This difference in market setting is especially important in understanding the trading behaviour of investors when their identities, and to some extent, the information contained in their orders, are known by the rest of market participants.

Another unique feature of our model is that it allows market makers to have different levels of information endowment. The modelling of information asymmetry in the security trading process presented in previous literature generally assumed that market markers have the same level of information endowment. For example, Easley and O'Hara (1991) assume that market makers together are better informed than uninformed traders. However, it is widely understood that many broker-dealer firms and specialist firms conduct their own research to identify miss-priced securities and predict future returns. As a result, the information endowment possessed by market markers before posting quotes differs among themselves, which in turn determines the different levels of adverse selection risk they bear individually. With a unique database, this study for the first time recognizes this difference, and provides both theoretical and empirical evidence of the relationship between liquidity providers' ex-ante information endowment and their limit order submission strategies in a pure order-driven market.

The rest of paper is organized as follows. A theoretical model of limit order placement and information asymmetry is derived in Section 2, and the empirical tests and analysis of hypotheses derived from this model are reported in Section 3. We draw our conclusions in Section 4.

2. A Theoretical Trade Model of Information Asymmetry

An information-based model to explain the impact of information asymmetry among market makers on their quoted bid-ask spreads is derived in this section. Extending the work of Glosten and Milgrom (1985) and Easley and O'Hara (1987), this model demonstrates the role of ex-ante information possessed by market makers. The characteristics of the model described here are very similar to the model presented in the previous literature (Easley and O'Hara, 1987). Specifically, it is assumed that a market maker quotes a bid price *B* and an ask price *A* for one unit of stock. He does not know which of these prices will be taken up by the next trader and neither does he know whether the next trader is informed. Hence, in a competitive market environment, he posts quotes *B* and *A* such that his expected profit at each trade is equal to zero. That is, his quotes are ex-post 'regret free'. The market maker is assumed to be rational and risk-neutral utility maximiser: he incorporates into his price information inferred from any previous transactions in a Bayesian way. Furthermore, it is assumed that there are no transaction costs in this market and the market maker has unlimited financial resources. Consequently, he does not face any inventory risk.[5]

Two types of traders participate in this market: informed traders who trade when the stock is misspriced; and uninformed traders who trade to satisfy their exogenous liquidity needs. Trades arrive randomly and the market maker does not know which traders are informed, however part of his information is that a proportion μ of traders are perfectly informed about the stock's true value V. Although the threat of adverse selection does not make any difference to the market maker's prior belief about the probability distribution for V, it makes him revise his belief using Bayes' theorem once he knows whether the next trader wants to buy or sell. To ensure that the expected profit on each transaction is zero, he determines what B and A to post using the posterior probability distribution for V that will take effect given the direction of the ensuing trade. Hence, the prices quoted are the posterior expected values, $B = E[V \mid sell]$ and $A = E[V \mid buy]$, where *sell* indicates that the trader chooses to sell at the bid price and *buy* indicates that the trader chooses to buy at the ask price.

In this model, only informed traders know the true value of V and maximise their utility by trading on this privately possessed information. Therefore, if an informed trader were to *buy*, then the implication is that $V>A$ with certainty. Similarly, a *sell* by an informed trader would imply that $V<B$ with certainty. By contrast, an uninformed trader has no knowledge of V and his decision to either buy or sell does not convey any information about V. A further assumption for this model is that, the uninformed traders cannot observe the trading of informed traders and free ride on their private information. Although the learning process, of uninformed traders obtaining information by observing the informed traders trade, has been modelled in previous literature (Grossman, 1975, 1976, 1978; Grossman and Stiglitz, 1980), this assumption does not lose its validity

[5] This may seem to be a strong assumption for a traditional dealer's market. However, as demonstrated in Section 3, in a pure order driven market when large number of limit order traders together act as the market maker, the inventory costs for each individual are significantly reduced.

because many major financial markets are regulated in a way that trader identities are not disclosed to other market participants (Jones and Lipson, 2003).[6]

The market maker's posterior probability distribution for V conditional on observing either a *buy* or a *sell* is gauged on the assumption that informed and uninformed traders arrive randomly and independently of the stock value V. In any trade, the unconditional probability that an informed trader participates $p(I)$ is μ. Thus, the unconditional probability that an uninformed trader participates $p(U)$ is $1-\mu$. The market maker's posterior probability distribution for V conditional on observing a buy is given by:

$$p(V \mid buy) = p(U \mid buy)\,p(V \mid U, buy) + p(I \mid buy)\,p(V \mid I, buy)$$

$$= p(U \mid buy)\,p(V \mid U) + p(I \mid buy)\,p(V \mid V > A) \qquad (2.1)$$

where $p(U \mid buy) = 1 - p(I \mid buy) = \dfrac{p(U)\,p(buy \mid U)}{p(buy)}$ represents the conditional (Bayesian posterior) probability that an uninformed trader has participated. Also, $p(V \mid V > A) = 0$ for $V \le A$ and $p(V \mid V > A) = p(V)/p(V > A)$ for $V > A$.

An uninformed trader trades for reasons independent of V. Adopting the standard established in previous literature[7], it is assumed that an uninformed trader buys at random with probability η. This contrasts with the behaviour of an informed trader: by definition he only buys when $V>A$, which occurs with probability $p(V>A)$. It follows that

$$p(U \mid buy) = \frac{(1-\mu)\eta}{(1-\mu)\eta + \mu p(V > A)}.$$

[6] This assumption is important to the empirical tests in the next section. In those tests, limit order traders are partitioned into better-informed (institutional brokers) and less-informed (retail brokers) based on their ex-ante information endowments. On the Australian Stock Exchange (ASX), retail investors who typically trade through retail brokers (i.e. e-trade, etc.) are generally not able to free ride on the private information held by institutions by observing the institutions trade. Refer to Section 3 for a more detailed discussion.
[7] See Glosten and Milgrom (1985) and Easley and O'Hara (1987).

With the same set of assumptions in place, the market maker's posterior probability distribution for V conditioned on observing a *sell* is

$$p(V \mid sell) = p(U \mid sell)p(V \mid U, sell) + p(I \mid sell)p(V \mid I, sell)$$

$$= p(U \mid sell)p(V \mid U) + p(I \mid sell)p(V \mid V < B) \qquad (2.2)$$

where $p(U \mid sell) = 1 - p(I \mid sell) = \dfrac{p(U)p(sell \mid U)}{p(sell)} = \dfrac{(1-\mu)(1-\eta)}{(1-\mu)(1-\eta) + \mu p(V < B)}$ is the conditional probability that an uninformed trader has participated. Also, $p(V \mid V < B) = 0$ for $V \geq B$ and $p(V \mid V < B) = p(V) / p(V < B)$ for $V < B$.

The posterior probability distributions (2.1) and (2.2) illustrate the information updating process of the market maker on his prior expectation of the asset value V, given the next trader emerges as a buyer or seller respectively. When his prior expectation of V lies on a range of possible values, the bid and ask prices quoted by the market maker are given by

$$B = E[V \mid sell] = \int_V Vp(V \mid sell)\delta V \qquad (2.3)$$

and

$$A = E[V \mid buy] = \int_V Vp(V \mid buy)\delta V \,. \qquad (2.4)$$

These equations represent equilibrium conditions: specifying where the market maker sets his B and A quotes based on his prior expectation of the distribution of all possible values of the stock.

The actual distribution of the stock value V from the perspective of the market maker depends on many factors, such as the nature of his private information, the shape of his personal risk-averse utility function and so forth. For simplicity and without abandoning the fundamental features of his information, assume that the market maker has prior information about the unknown asset value V represented by a uniform probability distribution

$$V \sim U[E-k, E+k]$$

over the interval [E-k, E+k]. E is the market maker's prior expectation of V. In this case, the parameter k is an index of the level of the market maker's knowledge. A larger k describes a more diffuse prior distribution and reflects less information (greater ignorance) concerning V. Note that $\sigma(V) = \sqrt{3}k$. Hence the quality of the market maker's prior information is sufficiently captured in either k or σ.

To demonstrate the effect of the market maker's information on the bid-ask spread, the expectations given by equations (2.3) and (2.4) are:

$$E[V \mid sell] = \frac{E-k+B}{2} + k[\frac{E+k-B}{2k} \frac{(1-\mu)(1-\eta)}{(1-\mu)(1-\eta)+\mu p(V<B)}]$$

and

$$E[V \mid buy] = \frac{A+E-k}{2} + k[\frac{A-E+k}{2k} \frac{(1-\mu)\eta}{(1-\mu)\eta+\mu p(V>A)}]$$

where $p(V<B) = \dfrac{B-(E-k)}{2k}$ and $p(V>A) = \dfrac{E+k-A}{2k}$.

Solving (2.3) by setting $B = E[V \mid sell]$ gives the market maker's risk neutral bid price

$$B = E + k - 2k\eta - \frac{2k}{\mu}[1-\eta-\sqrt{(1-\eta)(1-\mu-\eta+2\mu\eta-\mu^2\eta)}]. \qquad (2.5)$$

Similarly, solving (2.4) by setting $A = E[V \mid buy]$ gives the ask price

$$A = E + k - 2k\eta + \frac{2k}{\mu}[\eta - \sqrt{\eta(1-\mu)(\mu+\eta-\mu\eta)}]. \qquad (2.6)$$

Both functions are linear in k, with slopes dependent on μ and η.[8] Subtracting (2.5) from (2.6) gives the size of the bid-ask spread

$$A - B = \frac{2k}{\mu}[1 - \sqrt{(1-\eta)(1-\mu-\eta+2\mu\eta-\mu^2\eta)} - \sqrt{\eta(1-\mu)(\mu+\eta-\mu\eta)}]. \quad (2.7)$$

It can easily be shown that the two polynomials under the square root functions in Equation (2.7) are symmetric around $\eta = 0.5$. Consequently the model exhibits two properties as follows.

Property 1: Given η ($0 \le \eta \le 1$) and μ ($0 \le \mu \le 1$), the bid-ask spread quoted by a market maker is a linear function of his uncertainty about the true value of the security being traded. In the particular case when $\eta = 0.5$, the bid and ask prices are affected by μ symmetrically around $B(A) = E$.

Property 2: Given the quality of his information k, the bid-ask spread quoted by a market maker is a nonlinear function of the probability that he trades with an informed trader and the probability that an uninformed trader buys or sells.

Properties 1 and 2 are illustrated in Figure 1, where the bid and ask prices as well as the bid-ask spread are plotted against k, μ and η. It is clear that the bid-ask spread increases as μ increases; the market maker widens the spread when more informed traders lurk in the market. More importantly, since the factor in square brackets in Equation (2.7) is a constant given specific values of μ and η, the bid-ask spread is strictly increasing in k. It can also be seen in Figure 1 that as k increases both the bid and the ask prices diverge further from the expected value E at an *increasing* rate depending on the level of μ. The implication is that the greater the market maker's ignorance about V (reflected in higher k), the wider the spread he quotes to protect him from a potentially greater loss when

[8] There are two other solutions for B and A, neither of which has any economic meaning.

trading with informed traders.[9] Note that in Figure 1 the bid-ask spread increases as η diverges from 0.5. This is the total effect of the asymmetric impact of η on the bid and ask prices. These patterns relating the bid-ask spread to the information available to the market maker give rise to two propositions as follows.

[9] The spread is symmetric around E only when η = 0.5. For other values of η, the spread is wider on either the bid or the ask side and is affected asymmetrically by a change in either k or μ.

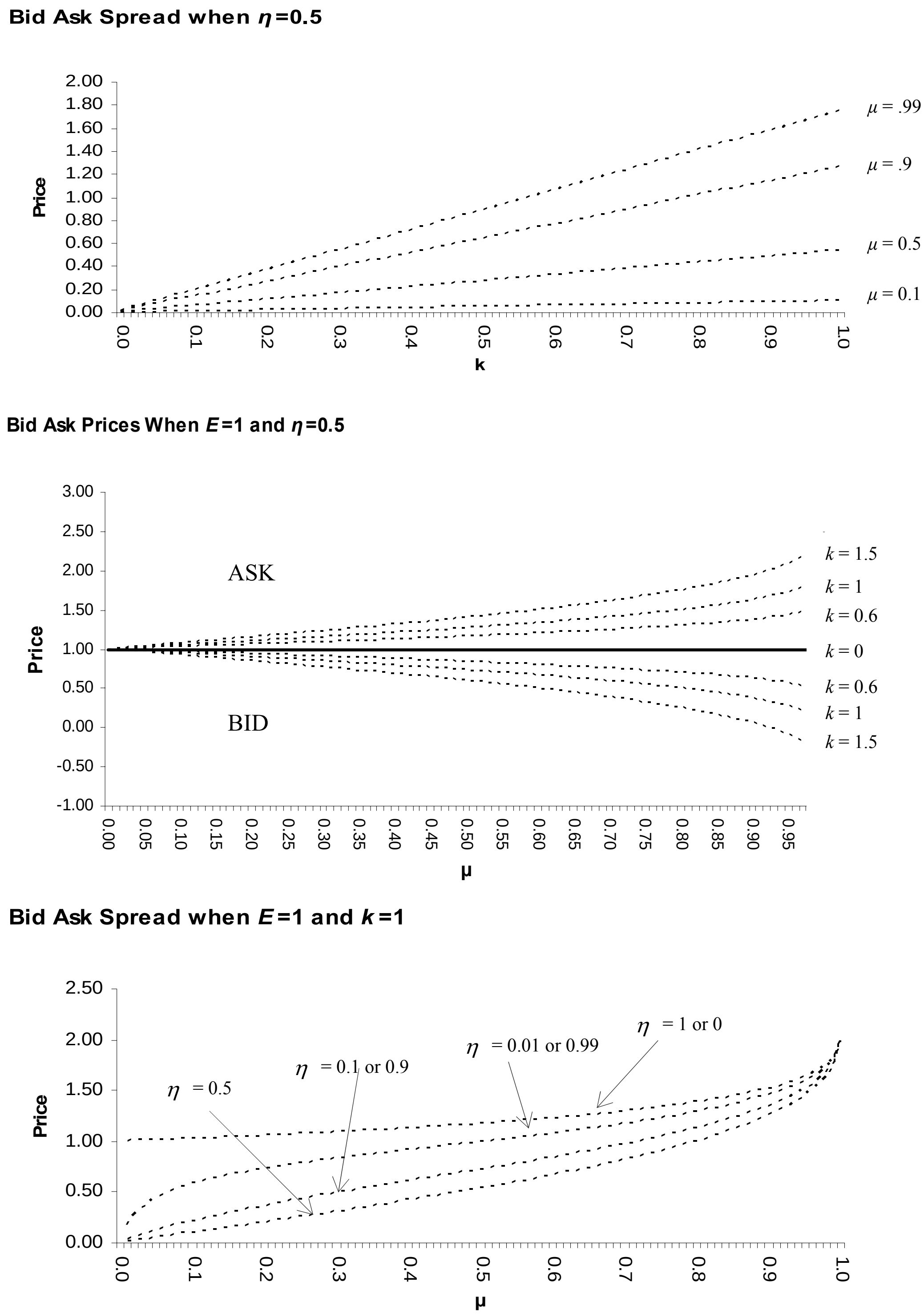

Figure 1: The Relationship between the Bid-Ask Spread and *k*, *μ* and η

This figure illustrates the properties of the relationship between the bid-ask spread and the variables k, μ, and η which are specified in Equation (2.7). E is the market maker's expected value of the asset being traded; k represents the level of uncertainty that the market marker has about the true value of the asset; μ is the probability that a trade is initiated by an informed trader; and η is the probability that an uninformed trader makes a purchase in a transaction.

Proposition 1: The market maker widens the bid-ask spread in response to his greater uncertainty about the true value of the asset being traded, that is,

$$V(BAS \mid k_1) < V(BAS \mid k_2), \forall\ k_1 < k_2,\ 0 \le \mu, \eta \le 1\,.$$

Proposition 2: The greater the difference between k_1 and k_2 *ceteris paribus*, the stronger is the inequality $V(BAS \mid k_1) < V(BAS \mid k_2)$ in Proposition 2.

In particular, Proposition 1 asserts that market makers widen the bid-ask spread when they are less knowledgeable about the true value of a stock; and Proposition 2 suggests that this influence of ex-ante information endowment on the bid-ask spread is greater when market makers' uncertainty is more pronounced.

It has been shown that an increase in the market maker's ex-ante uncertainty will compel him to quote a wider bid-ask spread. It is also conceivable that when the market maker knows less about the true value of the security in which he deals, the probability that he is less informed than other traders in the market is higher and this in turn raises the probability that he finishes up trading with an informed trader. Therefore, an increase in k is potentially associated with an increase in μ, with both of these variables acting to enlarge the bid-ask spread quoted by the market maker. In the next section, these two propositions are tested empirically using a sample of transaction data obtained from the Australian Stock Exchange (ASX).

3. Empirical Tests

This section examines empirically the bid-ask spreads quoted by institutional and retail investors, using sample data drawn from the Australian Stock Exchange (ASX). In a pure order-driven market, limit order traders may assume the role that is played in a quote-driven or hybrid market by market dealers/specialists. The fact that limit order traders provide liquidity and immediacy to the market implies that they face a similar form of adverse selection risk to that accepted by market makers.[10] Therefore, Proposition 1 and Proposition 2 can serve as theoretical hypotheses to be tested directly in an order-driven market.

In security markets, investors differ in the level of their information endowment and hence in the extent of adverse selection risk they face. It is conjectured that investors with superior knowledge about the future value of an asset have a lower chance of being adversely selected and therefore should quote narrower spreads. Conversely, less informed investors face more uncertainty about the true value of the asset and take on a higher risk of meeting informed traders. As a consequence, such investors will widen the spreads they quote to compensate for the additional risk they bear. Note that the information divide treated here does not need to occur through informed parties obtaining new information; rather, it depends on their knowledge about the uncertainty of the true value of the security. For example, an investor who is aware that there is not any new information about the value of a stock can be regarded here as an informed trader. Hence, the size of the spread quoted by an individual investor potentially reflects his ability to accurately assess the worth of the asset being traded. The better informed the investor, the more accurately he can price the asset and narrow the spread quoted, as a consequence.

It is widely believed that financial institutions are more informed on average than retail investors because they control and exploit extensive resources to discover new information (Chan and Lakonishok, 1993; Easley et al., 1996a; Jones and Lipson, 2003). On the ASX, most financial institutions have real-time access to a larger amount of market information, whereas retail investors can often only obtain pertinent information at a cost or with considerable time delay, which increases the information gap between these two types of investors accordingly.[11] Furthermore, retail investors inevitably incur

[10] This intuition is also explored by Greene (1996), where the behaviour of limit order traders is modelled as that of independent market makers.

[11] Griffiths et al. (2000) argue that real-time information about preceding order flows as well as details disclosed through the limit order book is immensely valuable to traders. Besides, on the ASX during the

delays in implementing any response to market movements, as they have to trade through intermediates such as stock brokers, while most financial institutions are provided with more efficient trading infrastructure and services. All these elements combine to distinguish retail investors from institutional investors in terms of their relative information endowment.

Grossman (1975, 1976, 1978) shows that uninformed investors can learn form informed investors by observing informed traders' trade. However, an important market feature of the ASX is that, although information on broker identities is available to other brokers who trade in the market, this information is not apparent to retail investors, so they cannot free-ride on the information conveyed in the limit orders placed by the institutional investors. This provides an ideal experimental environment to test Proposition 1 and 2 derived in the previous section, where investors are segmented by their prior information endowment.

3.1. Data and Methodology

The data used in this study are provided by the Surveillance division of the ASX. The dataset contains every order submitted and/or amended and every trade in common shares executed on SEATS during the 2002 calendar year. For each record, fields describe the time (to the nearest one-hundredth of a second), price, volume, buy/sell identifier and a broker identity indicator that can be used to classify the order as one submitted by an institutional broker or by a retail broker. Over the sample period, there are 87 brokers registered to trade on the ASX, of whom 12 act only for institutional clients, 16 act only for retail clients, 39 act for both institutional and retail clients, 7 act for miscellaneous customers and 13 act for unidentifiable customers.[12] Given that the main objective of this study is to compare institutional and retail investors and that the exact identity of the

---

sample period examined by this study, retail investors can only observe the aggregated depth at the best bid and ask prices, while brokers are able to see the entire limit order book.

[12] See *The Participants Directory 2002*, the Australian Stock Exchange.

investor behind each order is unidentifiable in the dataset, brokers who *only* deal with either institutional clients or retail clients are selected. The dataset also specifies the best bid and ask prices that prevail immediately before each limit order is submitted to the market.

All stocks are sorted by their average daily trading frequencies during the sample period, and the top 200 most actively traded stocks are selected in order to avoid biases due to infrequent trading. There are 13.04 million orders in total, including 7.64 million limit orders. Of the limit orders, 2.27 million are submitted by institutional brokers and 0.51 million by retail brokers. Orders submitted during the opening and closing call auctions are excluded.

To test Proposition 1, the distance between the price of a limit order and the best quote price in the same direction that prevails immediately before the limit order is submitted, is defined as

$$Buy\_Dis = |Bid - Limit\ Buy\ Order| \div Bid\text{-}Ask\ Midpoint \tag{3.1}$$

for each limit buy order, and

$$Sell\_Dis = |Ask - Limit\ Sell\ Order| \div Bid\text{-}Ask\ Midpoint \tag{3.2}$$

for each limit sell order. If the limit buy (sell) order price improves upon the current best quote, the *Buy_Dis* (*Sell_Dis*) is set to zero.

Each trading day is divided into twelve 30-minute intervals and the average buy and sell distances of limit orders (i.e. Buy_Dis and Sell_Dis) submitted by institutional brokers during interval *i* are calculated as[13]

$$D^{Institutional}{}_{Buy,i} = \frac{1}{N}\sum^{N} Buy\_Dis^{Institutional} \tag{3.3}$$

and

$$D^{Institutional}{}_{Sell,i} = \frac{1}{N}\sum^{N} Sell\_Dis^{Institutional} \tag{3.4}$$

respectively, where N equals the number of limit buy (sell) orders submitted by institutional brokers during the interval. Using a similar method, $D^{\mathrm{Re}tail}{}_{Buy,i}$, and $D^{\mathrm{Re}tail}{}_{Sell,i}$ are calculated as the average buy and sell distances of limit orders submitted by retail brokers. Next, the average bid-ask spread quoted by institutional brokers in interval i is calculated as[14]

$$Spread^{Institutional}{}_{i} = D^{Institutional}{}_{Buy,i} + D^{Institutional}{}_{Sell,i}\,. \tag{3.5}$$

Analogously, for retail brokers it is calculated as

$$Spread^{\mathrm{Re}tail}{}_{i} = D^{\mathrm{Re}tail}{}_{Buy,i} + D^{\mathrm{Re}tail}{}_{Sell,i}\,. \tag{3.6}$$

The average daily bid-ask spreads posted by institutional and retail brokers are calculated as the arithmetic averages of $Spread^{Institutional}{}_{i}$ and $Spread^{\mathrm{Re}tail}{}_{i}$ over all time intervals in each trading day. If Proposition 1 holds, i.e. institutional investors possess more accurate information than retail investors, then the following will hold:

$$Spread^{Institutional}{}_{i} < Spread^{\mathrm{Re}tail}{}_{i}\,.$$

It is shown extensively in the literature that trade size carries information. Barclay and Warner (1993) show that the number of medium-sized trades has the most significant impact on stock return volatility, and their view is shared by Chan and Lakonishok (1993). Alternatively, informed traders may also be motivated to submit large orders for the sake of maximising the reward that they obtain from their information advantage. An assumption that large orders are more informative is included in several theoretical

---

[13] ASX trading hours during the sample period are from 10:00 to 16:00 Australian Eastern Standard Time (AEST).

models (Easley and O'Hara, 1987, 1992a) and is generally confirmed in empirical studies on block trades (Holthausen et al., 1990; Chan and Lakonishok, 1995). However, these empirical studies focus mainly on market orders or market transactions, and the informational effect of various sizes of limit orders is still not clear.

To ensure that the results in this study are not attributed to the influence of particular size orders, all limit orders in the sample are classified into four groups. Specifically, all limit buy orders by institutional brokers are ranked and separated into quartiles by size (the number of shares) for each stock. The quartile partition thresholds are then used to classify the retail limit buy orders into four corresponding groups. The same two-step procedure is used to classify limit sell orders by institutional brokers and then retail brokers. In theory, if a difference between the average spread charged by institutional investors and that charged by retail investors is due to their different levels of information endowment rather than different order sizes, it should be observed consistently across all the order size groups that:

$$Spread^{Institutional}{}_{i} < Spread^{\mathrm{Re}tail}{}_{i}.$$

Proposition 2 is tested by repeating the tests above across stock groups with different levels of adverse selection. Stoll's (1989) method is utilised to decompose the bid-ask spread for each stock in the sample. This involves calculation of the serial covariance of transaction price changes (Cov_t), the serial covariance of quote price changes (Cov_q) and the average bid ask spread (S) for each day and each day. These are then used to estimate the parameters of the following models for each stock:

$$COV_T = a_0 + a_1 S^2 + \mu$$
$$COV_Q = b_0 + b_1 S^2 + \upsilon$$

Stoll (1989) demonstrates that the slope coefficients a_1 and b_1 can be used to develop estimates of the probability of a transaction price reversal, π, and the size of price

[14] As described above, the term *bid-ask spread* is used here to refer to the relative percentage distance that

continuation as a fraction of the spread, α, by solving the following simultaneous equations:

$$a_1 = \alpha^2(1-2\pi) - \pi^2(1-2\alpha)$$
$$b_1 = \alpha^2(1-2\pi)$$

These parameters can then be used to estimate the proportion of the bid ask spread arising from adverse selection as follows:

$$\text{Adverse Selection Component} = 1-2(\pi-\alpha)$$

The adverse selection component is then multiplied by the average spread in order to come up with an estimate of the adverse selection cost associated with each stock. Stocks are then ranked by the magnitude of adverse selection costs and divided into quartiles for analysis. It is expected that with more pronounced information asymmetric market conditions in place, differences in levels of information endowment between institutional and retail investors will become acute. Hence, wider bid-ask spreads quoted by both types of investors to compensate for increased adverse selection risk inherent in trading particular stocks are likely to be accompanied by greater differences in spreads between institutional and retail brokers, to reflect the more commanding information advantage enjoyed by institutional investors.

In addition to the cross-sectional tests, a second set of time series tests of Proposition 2 are also conducted. It is well documented that information asymmetry levels increase during periods when company announcements are released. For example, Krinsky and Lee (1996) find that adverse selection risk is significantly higher around earnings announcements. In the time series tests conducted in this study, the average bid-ask spreads of institutional and retail brokers are modelled as interim and final earnings announcement days approach. Three observation periods are examined for each announcement: three days before the announcement, the announcement day and three days after the announcement. All other days during the year are defined as a non-

---

institutional or retail brokers place their limit orders away from the best quotes prevailing in the market.

announcement control period. Average daily bid-ask spreads during each of the announcement periods are compared with the average daily bid-ask spread during the control period. Assuming information asymmetry increases during the announcement periods, it is expected that the bid-ask spread as well as the difference between the average bid-ask spreads quoted by the two types of brokers will increase as the announcement day approaches.

3.2. Results and Analysis

Table 1 provides descriptive statistics for the sample of limit orders. Panel I reports the average daily numbers of quotes submitted by institutional and retail brokers and Panel II reports the average order size. During the sample period, institutional brokers submit an average of 55 limit orders and retail brokers an average of 14 limit orders per day. It is clear that institutional brokers are more active in providing liquidity to the market, given that they submit more than 3 times the number of limit orders submitted by retail brokers. The mean size of institutional limit orders is 70 percent larger than the mean size of retail limit orders. The higher frequency and larger average size of institutional limit orders relative to retail limit orders are not surprising. Jones and Lipson (2003) document that, in their sample of market orders for 60 stocks traded on the NYSE, only 4 percent of the total share volume represents retail orders. Table 1 also provides a comparison of the bid-ask spreads posted by institutional and retail brokers across all the sample stocks. On average, institutional brokers place limit orders 13 basis points away from the best prevailing quotes, while retail brokers place limit orders 90 basis points away. This difference between the order placement of institutional and retail brokers is statistically highly significant, and is consistent with Proposition 1 which asserts that institutional investors endowed with more prior information about the underlying security will quote a tighter spread than retail investors. The average difference in spreads is also tested for each individual stock. The results show that retail brokers quote further away from the best prevailing quotes for all the sample stocks and the difference is significant at the

0.01 level for more than 70 percent of the sample stocks.[15] The z-statistic and ρ-value documented in Table 1 confirm that the average difference in spreads across all the stocks is highly significant, although the large differences in the order sizes placed by institutional and retail brokers make it necessary to implement controls for this systematic difference between institutional and retail limit orders.[16]

[15] It is rare to have bid and ask orders for some stocks from both institutional and retail brokers during the same time intervals. Consequently, 46 stocks are lost when examining the mean difference in spreads for individual stocks.

[16] Christie (1990, pp. 23) shows that the weighted average of t-statistics follows a z-distribution. He also suggests calculating the ρ-value that represents the hypothetical minimum correlation between the t-statistics that would have to exist to make the z-statistic insignificant. According to Christie, a $\rho>1$ indicates that the calculated z-statistic remains significant even if all the t-statistics are perfectly positively correlated.

Table 1: Descriptive Statistics for Sample Limit Orders

This table describes limit orders submitted by institutional and retail brokers for the top 200 most actively traded stocks on the ASX from January to December 2002. Brokers are classified as acting on behalf of institutional or retail clients according to the 'Participants Directory 2002' published by the ASX. For each security, the average daily number of newly submitted limit orders and the average size of orders submitted by institutional and retail brokers are calculated. The mean, median and standard deviation of these observations across all securities are shown. Each trading day is divided into twelve 30-minute intervals and the average bid-ask spreads posted by institutional and retail brokers in each interval are calculated using equations 3.1 to 3.6. The daily bid-ask spreads for each stock are the averages over the twelve time intervals in a trading day. The average daily bid-ask spreads across all the stocks are shown in Panel III. The Student's t-test is conducted of the null hypothesis that the mean difference between the bid-ask spreads posted by institutional and retail brokers is zero. Results of the same t-test conducted for each individual stock are shown in the *Significance test* section of Panel III. N<0.01 represents the number of stocks for which the mean difference is positive and significant at the 0.01 level. A z-statistic is calculated from the t-statistics for all the stocks and the ρ-value represents the hypothetical minimum covariance between the t-statistic observations that would have to exist to make the z-statistic insignificant at the 0.01 level (refer to Christie, 1990). All the numbers shown in the columns headed Mean, Median and Standard deviation are multiplied by a factor of 100.

	Mean	Median	Standard deviation
Panel I: Average daily number of quotes			
Institutional brokers	54.67	24.89	75.87
Retail brokers	14.18	7.81	17.15
Retail - Institutional	40.49	19.21	70.06
Panel II: Average order size			
Institutional brokers	25,081	10,005	40,388
Retail brokers	14,792	6,826	21,132
Retail - Institutional	10,289	2,232	30,468
Panel III: Average bid-ask spread			
Institutional brokers	0.2680	0.1538	0.3971
Retail brokers	1.8331	1.6777	1.1201
Retail - Institutional	1.5651	1.4211	0.9722 *
Significance test:			
	N<0.01	z-statistic	ρ-value
Retail - Institutional	113	81.13 *	8.13

*Note: * denotes a significant result at the 0.0001 level.*

Table 2 describes the distribution of the size (number of shares) of limit orders for each of the four different sized groups. From the frequency of orders in each category, it is apparent that retail limit orders are predominantly small and medium-sized orders, and only 16 percent of the retail orders fall into Group 4 which contains the largest size orders. This reaffirms the observation made in previous literature that retail investors are inclined to submit small orders (Jones and Lipson, 2003). For each of groups 1 to 3, the average size of institutional limit orders is similar to the average size of retail limit orders within the same group; with the difference in the mean order size between institutional and retail brokers ranging from 1 percent in Group 2 to 17 percent in Group 3. However, the difference in the mean order size in Group 4 is substantial (close to 50 percent), due to a lack of exceptionally large retail orders in this group. Note that the unequal numbers of institutional limit order observations in each group are due to the clustering of orders around the quartile partition points.

Table 2: Descriptive Statistics for Sample Limit Orders by Size Classification

This table describes the four size groups of limit orders submitted by institutional and retail brokers for the top 200 most actively traded stocks on the ASX from January to December 2002. Brokers are classified as acting on behalf of institutional or retail clients according to the 'Participants Directory 2002' published by the ASX. Independently for buy and sell orders for each stock, all limit orders submitted by institutional brokers are ranked and separated into quartiles by order size. The quartile partition points are used to divide the limit orders submitted by retail brokers into four corresponding stock groups. Statistics are reported across all sample stocks in each size group.

	Number of Observations	Mean	Median	Standard deviation
Group 1 (Smallest)				
Institutional brokers	579,906	2,100.02	508.69	7,090.02
Retail brokers	118,475	2,300.87	704.17	7,674.85
Retail - Institutional		200.85	79.96	2,729.70
Group 2				
Institutional brokers	574,267	6,257.60	2,356.89	13,513.76
Retail brokers	165,982	6,289.92	2,734.82	13,071.67
Retail - Institutional		32.32	117.30	2,363.01
Group 3				
Institutional brokers	613,964	18,281.76	7,893.62	32,293.48
Retail brokers	142,208	15,683.48	7,514.71	26,788.28
Retail - Institutional		-2,598.28	-390.68	10,443.13
Group 4 (Largest)				
Institutional brokers	504,510	83,026.57	32,009.79	139,604.20
Retail brokers	81,092	55,617.05	23,010.03	84,093.51
Retail - Institutional		-27,409.52	-6,350.27	85,137.79

Table 3 documents the bid-ask spreads posted by institutional and retail brokers in the different limit order size groups. The average spreads posted by both institutional and retail brokers widen monotonically with larger limit order sizes progressing from Group 1 to Group 4. This indicates that investors tend to place large limit orders further away from the best prevailing quotes, which is consistent with the predictions by the inventory control models. Large orders make investors vulnerable, as they bear a greater risk of carrying undue positions if the market moves against them. Even more noticeably, the average spreads posted by retail brokers are much wider than those posted by institutional brokers in all order size groups. The average spreads quoted by retail brokers are 6 to 9 times wider than those quoted by institutional brokers and the differences in average spreads are statistically significant at the 0.0001 level in all four order size groups. The average difference between retail and institutional broker spreads is statistically significant for more than 60 percent of stocks in each order size group. The *z*-statistics and hypothetical minimum *ρ*-values to accept the null hypotheses confirm that these results are highly significant.[17] The results reported in Table 1 indicate that Proposition 1 holds: limit order placement reflects the relative information endowment possessed by limit order traders, while the results reported in Table 3 suggest that Proposition 1 holds irrespective of the size of limit orders.

[17] As with the significance test reported in Table 1, large proportions of stocks are lost in each order size group due to the requirement in calculating the spread in any time interval that both retail and institutional brokers submit bid and ask orders within the range of limit order sizes applicable to the particular group.

Table 3: Bid-ask Spreads Posted by Limit Orders of Different Size

This table provides a comparison of the spreads posted by institutional and retail brokers across different limit order size groups. Limit orders submitted for the top 200 most actively traded stocks on the ASX from January to December 2002 are analysed. Brokers are classified as acting on behalf of institutional or retail investors according to the 'Participants Directory 2002' published by the ASX. The methodology used to calculate representative bid-ask spreads is outlined in Section 2 and descriptive results are reported in Table 1. Independently for buy and sell orders for each stock, all limit orders submitted by institutional brokers are ranked and separated into quartiles by order size. The quartile partition points are used to divide the limit orders submitted by retail brokers into four corresponding stock groups. For each stock, a *t*-test is conducted of the null hypothesis that the average difference in the bid-ask spreads posted by institutional and retail brokers is zero. For each order size group, $N<0.01$ represents the number of stocks for which the mean difference is positive and significant at the 0.01 level. Christie's *z*-statistic is calculated from the *t*-statistics across all the stocks and the ρ-value represents the hypothetical minimum covariance between the *t*-statistic observations that would have to exist to make the *z*-statistic insignificant at the 0.01 level (refer to Christie, 1990). All the numbers shown in the columns headed Mean, Median and Standard deviation are multiplied by a factor of 100.

	Mean	Median	Standard deviation		$N<0.01$	*z*-statistics		ρ-value
Group 1 N=96								
Institutional brokers	0.1649	0.0915	0.2385					
Retail broker	1.5061	1.4179	1.1569					
Retail - Institutional	1.3412	1.2710	1.1012	*	60	55.40	*	6.10
Group 2 N=127								
Institutional brokers	0.2688	0.1246	0.5489					
Retail brokers	1.6874	1.5435	1.1391					
Retail - Institutional	1.4186	1.3161	1.0094	*	80	66.76	*	6.68
Group 3 N=145								
Institutional brokers	0.2790	0.1437	0.5395					
Retail brokers	1.7920	1.5814	1.2694					
Retail - Institutional	1.5130	1.2891	1.1799	*	96	66.46	*	5.79
Group 4 N=142								
Institutional brokers	0.2909	0.1878	0.3526					
Retail brokers	1.8281	1.5590	1.1977					
Retail - Institutional	1.5373	1.3147	1.0536	*	94	63.60	*	5.42

*Note: * denotes a significant result at the 0.0001 level.*

Table 4 provides estimates of bid-ask spreads, adverse selection cost components and adverse selection costs associated with bid-ask spreads for all sample stocks. Panel I reports that the bid-ask spread (immediately before each trade) of all stocks sampled in this study averages 0.7 percent, while Panel II reports that the adverse selection cost component of the bid-ask spread averages 82.2 percent, which is substantially higher than observed in United States markets (Stoll, 1989; Affleck-Graves et al., 1994).[18] These results are consistent with the results reported by Frino, et al. (2004) and suggest that the risk of adverse selection represents the most significant cost faced by liquidity providers in a pure order-driven market. The reason for the higher adverse selection cost component on ASX must lie in the lower inventory holding and order processing cost components. This is likely to arise from the absence of exchange mandated dealers which could reduce inventory holding costs and the electronically traded nature of the ASX which could reduce order processing costs. Table 4 also suggests that ranking stocks according to the adverse selection costs is equivalent to ranking them on the average bid-ask spreads.

[18] This is considerably higher than estimates based on US markets. For example, Stoll (1989) estimates that the adverse selection cost component of the bid-ask spread for a sample of stocks trading on NYSE averages 43 percent, while Affleck-Graves et.al. (1994) provide estimates of 50 percent for NYSE and 36 percent for Nasdaq/NMS stocks.

Table 4: Bid-Ask Spreads, Adverse Selection Cost Components and Adverse Selection Costs for the Top 200 Most Actively Traded Stocks in 2002

This table describes bid-ask spreads, adverse selection cost components and adverse selection costs for the 200 most actively traded stocks on the ASX from January to December 2002. For each stock, the average of percentage bid-ask spreads in place immediately before all transactions in the stock is calculated. The procedure specified by Stoll (1989) is used to estimate the proportion of the spread attributable to adverse selection costs. The adverse selection cost is calculated as the product of the average percentage bid-ask spread and the adverse selection cost component of the spread. The results reported in the table are sorted into quartiles by the adverse selection costs.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Total
Panel I: Average percentage bid-ask spread					
Mean	0.0019	0.0034	0.0064	0.0164	0.0070
Median	0.0017	0.0033	0.0063	0.0148	0.0047
Maximum	0.0064	0.0068	0.0096	0.0465	0.0465
Minimum	0.0005	0.0021	0.0046	0.0080	0.0005
Standard deviation	0.0011	0.0008	0.0012	0.0077	0.0069
Panel II: Adverse selection component					
Mean	0.4454	0.8955	0.9594	0.9884	0.8222
Median	0.4812	0.9173	0.9825	0.9983	0.9604
Maximum	0.9921	1	1	1	1
Minimum	0	0.6055	0.4760	0.8328	0
Standard deviation	0.3787	0.0994	0.0852	0.0277	0.2974
Panel III: Total adverse selection cost					
Mean	0.0008	0.0030	0.0061	0.0162	0.0065
Median	0.0008	0.0030	0.0061	0.0144	0.0045
Maximum	0.0020	0.0044	0.0080	0.0465	0.0465
Minimum	0	0.0020	0.0046	0.0080	0
Standard deviation	0.0007	0.0007	0.0011	0.0077	0.0071

The first (cross-sectional) test of Proposition 2 is reported in Table 5. In this table, estimated bid-ask spreads posted by institutional and retail brokers for stocks with different levels of adverse selection risk are documented. Panels I and II give the estimated spreads posted by institutional and retail brokers and Panel III gives the differences in the spreads. It is clear that the average bid-ask spreads of both institutional and retail brokers widen appreciably for stocks with higher adverse selection costs. Investors evidently quote wider spreads to compensate for higher adverse selection risk. It is also clear that the average spreads placed by retail brokers are wider than the average spreads placed by institutional brokers in all stock groups. Moreover, the difference between the average institutional and retail spreads increases monotonically with the level of information asymmetry.[19] Student *t* tests are conducted to compare, between consecutive quartiles, the mean spreads quoted by institutional investors (Panel I) and by retail investors (Panel II), as well as the differences between institutional and retail spreads (Panel III). The results confirm that the monotonic increases are all statistically significant. These results provide strong support for Proposition 2: investors with superior information endowments place their limit orders closer to the best prevailing quotes, whereas investors with less reliable information react more drastically than informed investors in moving their limit orders further away from best quotes when faced with higher adverse selection risk.

[19] The pairwise correlation between the mean differences of spreads and the adverse selection cost across all stocks is 0.37.

Table 5: Comparative Spreads Posted by Institutional and Retail Brokers Partitioned on Adverse Selection Costs of Underlying Stocks

This table provides a comparison of average bid-ask spreads posted by institutional and retail brokers across different stock groups. The procedure specified by Stoll (1989) is used to estimate the proportion of the spread attributable to adverse selection costs. Stocks are ranked and separated into quartiles by their adverse selection costs, calculated as the product of the average percentage bid-ask spread and the adverse selection cost components of the spreads. All the figures shown in the columns headed Mean, Median and Standard deviation are multiplied by a factor of 100. Student *t* tests are conducted of hypotheses that the mean differences in the bid-ask spreads between adjacent stock groups and between institutional and retail brokers are zero in each case.

	Statistics			Equality *t*-test		
	Mean	Median	Standard deviation	Null hypothesis	Mean difference	Standard deviation
Panel I: Institutional broker spread						
Quartile 1	0.1485	0.0851	0.2512			
Quartile 2	0.1601	0.0855	0.2639	H_0: Q1 = Q2*	-0.0115	0.26
Quartile 3	0.2454	0.1205	0.3725	H_0: Q2 = Q3	-0.0853	0.30
Quartile 4	0.4863	0.0505	0.7852	H_0: Q3 = Q4	-0.2410	0.55
Panel II: Retail broker spread						
Quartile 1	1.4040	1.0304	1.3978			
Quartile 2	1.7053	1.3201	1.6359	H_0: Q1 = Q2	-0.3013	1.48
Quartile 3	2.0359	1.5706	1.8454	H_0: Q2 = Q3	-0.3306	1.70
Quartile 4	2.5660	2.1396	2.0425	H_0: Q3 = Q4	-0.5301	1.91
Panel III: Retail - Institutional						
Quartile 1	1.2555	0.8987	1.3952			
Quartile 2	1.5453	1.1812	1.6270	H_0: Q1 = Q2	-0.2898	1.47
Quartile 3	1.7906	1.3127	1.8172	H_0: Q2 = Q3	-0.2453	1.69
Quartile 4	2.0797	1.6794	2.0268	H_0: Q3 = Q4**	-0.2891	1.89

*Note: * and ** denote significant results at the 0.1 and 0.01 levels, respectively; whereas all other tests provide significant results at the 0.0001 level.*

The second sets of (time series) tests of Proposition 2 are reported in Table 6, and are focused on adjustments to bid-ask spreads surrounding corporate interim and final profit announcements. Three experimental periods are chosen: three days preceding announcements, announcement days and three days following announcements; and the remaining days over the sample period are regarded as the non-announcement (control) period. Panel I reports the average bid-ask spread posted by retail and institutional brokers together with differences between spreads as time approaches and moves beyond announcement days. Panel II reports the results of statistical tests on the mean differences. The table shows that institutional limit orders are placed closer on average to the best prevailing quotes during all three sets of experimental periods and during the control periods. Although the average bid-ask spreads quoted by both institutional and retail brokers during the three days preceding announcement days are slightly smaller than during the announcement free periods, these differences are not statistically significant. More substantial differences are seen in relation to the announcement days: both retail and institutional brokers widen the spreads they quote as time progresses from three day periods preceding announcement days to announcement days. The degree of widening which occurs is greater for retail brokers than for institutional brokers. During the three days following announcements, both retail and institutional spreads are narrowed to some extent from the peak on announcement days, although they remain substantially wider than during the control periods. The mean difference between retail and institutional broker spreads remains larger than the mean difference during the control periods. The results shown here are consistent with those shown in Table 5 in providing additional support for Proposition 2: limit order traders provide liquidity strategically, taking account of their relative levels of information endowment.

Table 6: Information Announcements and Comparative Spreads Posted by Institutional and Retail Brokers

This table provides a comparison of average bid-ask spreads posted by institutional and retail brokers during control periods (distant by greater than three days from information announcements) and experimental periods (three days preceding information announcements, announcement days and three days following announcements). Information announcements include the release of company semi-annual and annual reports during the 2002 calendar year. Student *t*-tests are conducted of null hypotheses that the mean differences in the bid-ask spreads between experimental periods and control periods are zero. All the figures shown in the columns headed Mean and Standard deviation are multiplied by a factor of 100.

	Time distant from announcements (Control Period)		Three days preceding announcements		Announcement days		Three days following announcements	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Panel I: Statistics								
Institutional brokers	0.1765	0.3202	0.1507	0.3224	0.2457	0.3389	0.2203	0.3776
Retail brokers	1.5928	1.5753	1.5042	1.4294	2.0985	1.7768	1.9807	1.7448
Retail - Institutional	1.4163	1.5576	1.3535	1.4270	1.8528	1.7099	1.7603	1.7186
Panel II: Student t-tests			Mean difference	*t*-statistics	Mean difference	*t*-statistics	Mean difference	*t*-statistics
Institutional brokers			-0.0258	-1.05	0.0692	2.51 *	0.0438	2.37 *
Retail brokers			-0.0886	-0.73	0.5057	3.72 ***	0.3878	4.27 ***
Retail - Institutional			-0.0628	-0.52	0.4365	3.25 **	0.3440	3.84 ***

*Note: *, ** and *** denote significant results at the 0.05, 0.01 and 0.001 levels, respectively.*

3.3. Robustness Tests

In the cross sectional tests, stocks were partitioned based on methods developed by Stoll (1989). It is necessary, however, to examine the robustness of these results by using alternative measures of information asymmetry levels in trading stocks.[20] In this section, the methodology established by Easley, et al. (1996b) that relies on calculating the probability of information-based trading (PIN) is adopted to estimate the level of adverse selection risk for each sample stock.[21] The PIN methodology supplements the serial covariance models developed by Stoll (1989) and is widely used in recent studies to estimate information asymmetry levels among securities and between exchanges (Easley et al., 1997a, 1997b; Grammig et al., 2001). Tests of Proposition 2 discussed in this study rely on the internal validity of the measurement device used to assess adverse selection risks. It is important to show that the results are robust to alternative methodologies.

Table 7 provides the results of the comparison between retail and institutional spreads for two stock groups ranked on the estimated PIN value of each stock.[22] Specifically, all the sample stocks are ranked and sorted by their PIN values: the top 50 percent of stocks are categorised as 'High PIN' and the lower 50 percent as 'Low PIN'. In this table, the average spreads quoted by institutional brokers for the two groups of stocks are significantly narrower than those quoted by retail brokers. Both institutional and retail brokers quote wider spreads on average for high PIN stocks than for low PIN stocks. Furthermore, the difference between the average spreads quoted by retail and institutional brokers is larger for high PIN stocks than for low PIN stocks. The results corroborate those presented in Table 5.

[20] We thank the participants at the seminar held at the University Of Sydney for pointing out this robustness test.
[21] Refer to the Appendix for a brief explanation of the PIN calculation.
[22] The results of the PIN estimation for sample stocks are not reported here, but are available upon request.

Table 7: Probabilities of Information-Based Trading (PIN) and Comparative Spreads Posted by Institutional and Retail Brokers

This table provides a comparison of average bid-ask spreads posted by institutional and retail brokers across two different stock groups. The probability of information-based trading (PIN) (Easley et al., 1996b) is calculated for each sample stock. Stocks are then ranked by their PIN values; and categorised as 'Low PIN' if they are among the lower 50 percent of the distribution or as 'High PIN' if they are among the upper 50 percent. All the figures shown in the columns headed Mean, Median and Standard deviation are multiplied by a factor of 100.

	Statistics			
	Mean	Median	Standard deviation	
Panel I: Institutional broker spread				
Low PIN	0.1689	0.0815	0.3022	
High PIN	0.2107	0.0968	0.3951	
Equality test	Mean = -0.042		0.00	
Panel II: Retail broker spread				
Low PIN	1.5712	1.1166	1.5993	
High PIN	1.7261	1.3693	1.5527	
Equality test	Mean = -0.2		0.02	
Panel III: Retail - Institutional				
Low PIN	1.4022	0.9594	1.5828	
High PIN	1.5154	1.1836	1.5236	
Equality test	Mean = -0.1		0.02	*

*Note: * denotes a significant result at the 0.001 level; and both of the other tests yield significant results at the 0.0001 level.*

4. Conclusion

This paper examines the consequences of information asymmetry for limit order placement strategies. A theoretical trading model is derived to portray the effect of information asymmetry on the relationship between the ex-ante information endowment possessed by market makers and the bid-ask spreads they quote. It was shown that uncertainty about the true value of the asset being traded affects how market makers place their quotes. In particular, two propositions have been derived from this model. Proposition 1 asserts that market makers widen the bid-ask spread when they are less knowledgeable about the true value of a stock; and Proposition 2 suggests that this influence of ex-ante information endowment on the bid-ask spread is greater when market makers' uncertainty is more pronounced.

These theoretical propositions are tested empirically using a sample of limit order data obtained from the Australian Stock Exchange, and it is found that institutional brokers place substantially tighter spreads in the order book than retail brokers. It is also verified that these differences in limit order placement strategies cannot readily be attributed to disparities in the relative order sizes pursued by these two groups of brokers. Given that most financial institutions trading in security markets are believed to be better informed through their access to extensive information resources, this finding provides evidence that is consistent with Proposition 1, i.e. bid-ask spreads are positively related to the level of information endowment possessed by market makers (or limit order traders in a pure order driven market). This relationship is further tested in periods when investors face different levels of adverse selection risk. It is found that: (i) investors typically widen the spreads they quote when facing higher adverse selection risk; and (ii) the difference in the spreads quoted by retail and institutional brokers is increasing in the extent of information asymmetry in the market. These findings are predicted by Proposition 2 and confirm that uninformed traders respond to the increased probability of information-asymmetric trading by widening the spreads they quote to a greater extent than better-informed traders possibly because they are more vulnerable to adverse selection.

The purpose often ascribed to the limit order book is to meet the demands of liquidity traders in return for the payment of a liquidity premium (Handa and Schwartz, 1996). By placing orders away from the market, limit order traders will receive a premium for providing liquidity to the market when their orders are hit during short-term market fluctuations (Chung et al., 1999). Investors with superior long-term information also use limit orders to exploit their advantage (Kaniel and Liu, 2006). This study provides empirical evidence to support another explanation of investors' motivation in placing limit orders. Risk-adverse limit order traders who are uncertain about future security values place orders further away from the best prevailing quotes to protect themselves from adverse selection risk. This evidence extends the evidence provided in previous studies of the effect of information asymmetry on bid-ask spreads, and consequently, the results described in this study extend the insights pioneered by Glosten and Milgrom (1985) and Easley and O'Hara (1987), demonstrating empirically how information asymmetry affects the dynamic process by which limit order traders post bid-ask quotes.

The results provided in this paper are important for understanding the composition of a limit order book. As shown, the market bid-ask spread indicated by best prevailing quotes is composed primarily of institutional limit orders, and market liquidity is also predominantly led by institutional investors. Clearly there is a rationale for policy makers to facilitate the participation of institutional investors in the market design whenever liquidity is a major concern. Future research can extend our study by looking at how this information asymmetry reflected in the limit order book affects the price discovery process and its implications for the market regulators and participants.

Appendix: The Estimation of Probability of Information-based Trading (PIN) (Easley, et al., 1996b)

In a similar market setting to those specified in Section 2, Easley et al. (1996b) show that, given that an order to sell arrives at time *t*, the market maker's posterior probability of no information event at time *t* is:

$$P_n(t \mid S_t) = \frac{P_n(t)\varepsilon}{P_n(t)\varepsilon + P_b(t)(\varepsilon+\mu) + P_g(t)\varepsilon} = \frac{P_n(t)\varepsilon}{\varepsilon + P_b(t)\mu}$$

$$(\because P_n(t) + P_b(t) + P_g(t) = 1).$$

Similar,

$$P_b(t \mid S_t) = \frac{P_b(t)(\varepsilon+\mu)}{\varepsilon + P_b(t)\mu}$$

and

$$P_g(t \mid S_t) = \frac{P_g(t)\varepsilon}{\varepsilon + P_b(t)\mu}.$$

In these equations, S_t denotes the event that a sell order arrives at time *t*; $P(t) = (P_n(t), P_b(t), P_g(t))$ reflects the market maker's prior belief about there being no information, a bad information event or a good information event, respectively, at time *t*; ε is the arrival rate of uninformed traders in the market and μ is the arrival rate of informed traders.

Assuming the underlying asset market value is $\underline{V}$ when the outcome is a bad information event, $\overline{V}$ when it is a good information event and V^* (unconditional prior expected value) when there is no information event, Easley et al. (1996b) show that the spread at time *t* on day *i* is given by:

$$\sum(t) = b(t) - a(t) = \frac{\mu P_g(t)}{\varepsilon + \mu P_g(t)}(\overline{V}_i - E[V_i \mid t]) + \frac{\mu P_b(t)}{\varepsilon + \mu P_b(t)}(E[V_i \mid t] - \underline{V}_i),$$

and the probability that any trade that occurs at time t is information-based is:

$$PI(t) = \frac{\mu(1-P_n(t))}{\mu(1-P_n(t))+2\varepsilon}.$$

In this model, the initial probability that an information event occurs is α and this event is bad news with probability δ. The likelihood function for the joint probability of observing B number of buys and S number of sells on a day of unknown type is the weighted average of the probability of observing B buys and S sells on a bad event day, on a no-event day and on a good event day. The weights are the probabilities of each type of day occurring: $(1-\alpha)$, $\alpha\delta$ and $(1-\alpha)\delta$ respectively. Thus the likelihood function has the form:

$$L((B,S)\,|\,\theta) = (1-\alpha)^{*} e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta^{*} e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{[(\varepsilon+\mu)T]^S}{S!}$$
$$+\alpha(1-\delta)^{*} e^{-(\mu+\varepsilon)T}\frac{[(\varepsilon+\mu)T]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}$$

and

$$PI = \frac{\alpha\mu}{\alpha\mu+2\varepsilon}.$$

Reference:

Admati, A., P. Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, *Review of Financial Studies* 1, pp. 3-40.

Affleck-Graves, J., S. Hegde and R. Miller, 1994, Trading mechanisms and the components of the bid-ask spread, *Journal of Finance* 49, pp. 17-34.

Ahn, H.J., K.H. Bae and K. Chan, 2001, Limit orders, depth, and volatility: evidence from the stock exchange of Hong Kong, *Journal of Finance* 56, pp. 767-788.

Back, K., 1992, Insider trading in Continuous time, *Review of Financial Studies* 5, pp. 387-409.

Barclay, M. and J. Warner, 1993, Stealth trading and volatility, *Journal of Financial Economics* 34, pp. 28-305.

Bessembinder, H., 2003, Issues in assessing trade execution costs, *Journal of Financial Markets* 6, pp. 233-257.

Bessembinder, H. and H.M., Kaufman, 1997, A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks, *Journal of Financial Economics* 46, pp. 293-319.

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

Bloomfield, R., M. O'Hara and G. Saar, 2003, The make or take decision in an electronic market: evidence on the evolution of liquidity, Working paper, Johnson Graduate School of Management, Cornell University.

Chan, L.K.C. and J. Lakonishok, 1993, Institutional trades and stock price behaviour, *Journal of Financial Economics* 33, pp. 173-190.

Chan, L.K.C. and J. Lakonishok, 1995, The behaviour of stock prices around institutional trades, *Journal of Finance 50*, pp. 1147-1174.

Christie, A., 1990, Aggregation of Test Statistics, *Journal of Accounting and Economics* 12, pp. 15-36.

Chung, K.H., B.F. Van Ness and R.A. Van Ness, 1999, Limit orders and the bid-ask spread, *Journal of Financial Economics* 53, pp. 255-287.

Easley, D. and M. O'Hara, 1987, Price, trade size and information in securities markets, *Journal of Financial Economics* 19, pp. 69–90.

Easley, D. and M. O'Hara, 1991, Order form and information in securities markets, *Journal of Finance* 46, pp. 905-927.

Easley, D. and M. O'Hara, 1992a, Adverse selection and large trade volume: the implications for market efficiency, *Journal of Finance* 27, pp. 185-208.

Easley, D. and M. O'Hara, 1992b, Time and the process of security price adjustment, *Journal of Finance* 47, pp. 577-605.

Easley, D., N.M. Kiefer and M. O'Hara, 1996a, Cream skimming or profit sharing? The curious role of purchased order flow, *Journal of Finance* 51, pp. 811-833.

Easley, D., N.M. Kiefer and M. O'Hara, 1997a, One day in the life of a very common stock, *Review of Financial Studies* 10, pp. 805-835.

Easley, D., N.M. Kiefer and M. O'Hara, 1997b, The information content of the trading process, *Journal of Empirical Finance* 4, pp. 159-186.

Easley, D., N.M. Kiefer, M. O'Hara and J. Paperman, 1996b, Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, pp. 1405-1436.

Foster, F.D. and S. Viswanathan, 1990, A theory of the interday variation in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, pp. 593-624.

Frino, A., D. Johnstone and H. Zheng, 2004, The information content of trader identity, *Working Paper*, The University Of Sydney.

Frino A, A. Hill, E. Jarnecic and M. Aitken, 2004, The impact of electronic trading on bid-ask spreads: Evidence from futures markets in Hong Kong, London and Sydney, *Journal of Futures Markets* 24, pp. 675-696.

Glosten, L.R. and P.R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, pp. 71-101.

Glosten, L.R., 1994, Is the electronic open limit order book inevitable, *Journal of Finance* 49, pp. 1127-1161.

Grammig, J., D. Schiereck and E. Theissen, 2001, Knowing me, knowing you: trader anonymity and informed trading in parallel markets, *Journal of Financial Markets* 4, pp. 385-412.

Greene, J., 1996, The Impact of Limit Order Executions of Trading Costs in NYSE Stocks, dissertation, Indiana University.

Griffiths, M., B. Smith, A. Turnbull and R. White, 2000, The costs and determinants of order aggressiveness, *Journal of Financial Economics 56*, pp. 65-88.

Grossman, S., 1976, On the efficiency of competitive stock markets were trades have diverse information*, Journal of Finance* 31, pp. 573-585.

Grossman, S., 1978, Further results on the informational efficiency of competitive stock markets, Special Studies Papers 114, Board of Governors of the Federal Reserve System (U.S.).

Grossman, S. and J.E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, pp. 393-408.

Grossman, S., 1975, The existence of futures markets, noisy rationale expectations and information externalities, Ph.D. Dissertation Chapter 2, University of Chicago.

Handa, P. and R.A. Schwartz, 1996, Limit order trading, *Journal of Finance* 51, pp. 1835-1861.

Harris, L. and J. Hasbrouck, 1996, Market vs. limit orders: the SuperDot evidence on order submission strategy, *Journal of Financial and Quantitative Analysis* 31, pp. 213-231.

Holthausen, R., R. Leftwich and D. Mayers, 1990, Large-block transactions, the speed of response, and temporary and permanent stock-price effects, *Journal of Financial Economics* 26, pp. 71-95.

Huang, R.D., and H.R. Stoll, 1996, Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE, *Journal of Financial Economics* 41, pp. 313-357.

Jones C.M. and M.L. Lipson, 2003, Are retail orders different, Working paper, Columbia University.

Kaniel, R., and H. Liu, 2006, So what orders do informed traders use, *Journal of Business 79*, pp. 1867 – 1913.

Kavajecz, K.A., 1999, A specialist's quoted depth and the limit order book, *Journal of Finance* 54, pp. 747-771.

Keim, D.B. and A. Madhavan, 1995, Anatomy of the trading process, empirical evidence on the behaviour of institutional traders, *Journal of Financial Economics* 37, pp. 371-398.

Krinsky, I. and J. Lee, 1996, Earnings announcements and the components of the bid-ask spread, *Journal of Finance* 51, pp. 1523-1535.

Kyle, A., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, pp. 1315–1335.

Madhavan, A., and V. Panchapagesan, 2000, Price discovery in auction markets: a look inside the black box, *Review of Financial Studies* 13, pp. 627-58.

McInish, T, and R. Wood, 1992, An analysis of intraday patterns in bid/ask spreads for NYSE Stocks, *Journal of Finance* 47, pp. 753–764.

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

Petersen, M. and D. Fialkowski, 1994, Posted versus effective spreads: good prices or bad quotes, *Journal of Financial Economics* 35, pp. 269-292.

Rock, K., 1996, The specialist's order book and price anomalies, working paper, Harvard University.

Ross, K., J. Shapiro and K. Smith, 1996, Price improvement of SuperDot market orders on the NYSE, Working paper 96-02, New York Stock Exchange.

Seppi, D.J., 1997, Liquidity provision with limit orders and strategic specialist, *Review of Financial Studies* 10, pp. 103-150.

Smith, B., M. Griffiths, A. Turnbull and R. White, 2000, The costs and determinants of aggressiveness, *Journal of Financial Economics*, pp. 65-88.

Stoll, H., 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance* 44, pp115 – 134.

Subrahmanyam, A., 1991a, A theory of trading in stock index futures, *Review of Financial Studies* 4, pp. 17-51.

Subrahmanyam, A., 1991b, Risk aversion, market liquidity and price efficiency, *Review of Financial Studies* 4, pp. 417-441.