Upstairs, Downstairs: Does the Upstairs Market Hurt the Downstairs?[⊕]

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Abstract

We examine the price impact of block trades across three trading mechanisms: the upstairs market, a crossing network, and the limit order book. As the preponderance of liquidity and informed trades appears similar across markets, we find no evidence of filtering. Moreover, using unique exogenous measures of market access, we find no evidence that competition from these external markets has an adverse affect. Although competition is believed to be damaging, these alternative trading mechanisms benefit all market participants. Our evidence supports counterparty search instead of the informed trader filtering or risk-sharing explanations for the role of upstairs dealers.

JEL classification: G14

Keywords: Fragmentation, upstairs trading, crossing networks, liquidity, counterparty search.

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Financial markets around the world typically feature a variety of economic mechanisms to achieve trade, a reflection of the heterogeneity among investors. Many market systems embody some form of upstairs intermediation, where institutional traders can execute large-block trades through negotiated brokerage or crossing networks. The existence of such systems, whether formalized or not, raises natural questions about market efficiency and liquidity. In particular, questions arise as to whether such systems, by separating liquidity traders from others, have a significant detrimental impact on the regular ("downstairs") market.[1]

We examine competition and potential complementarities between three market systems operating on the Australia Stock Exchange (ASX): First, the "upstairs" market that occurs in the broker's office off-exchange where large institutional counterparties to a block trade negotiate over the telephone, typically with a broker/dealer who provides a search role by locating the counterparties. Second, crossing networks in which participants enter multiple anonymous orders[2], which cross at specified times at prices set in the downstairs market with typically not a high execution probability.[3] Third, the downstairs market where anonymous trading takes place. This can occur via a consolidated electronic order book.

Typically in most markets in the world where the main (downstairs) market consists of a limit order book, competition for larger orders is provided by an upstairs dealer market and, additionally, crossing networks. In some instances, restrictive access rules

[1] See Harris (2003) for an in-depth discussion of these issues.

[2] Participates typically can set price and other constraints.

[3] A possible objection to our inclusion of crossing networks in the empirical analysis is that they constitute only about one percent of our sample for the final two years of our study. Such a perspective is invalid for four reasons: First, since the matching success rate in these markets is small, placement of orders is considerably higher. The number of consummated trades understates the importance of the system (Hendershott and Mendelson (2000) and Naes and Odegaard (2002)). Second, our very large sample sizes of over 13,000 upstairs trades in just one size category alone in each of these two years provides us with over 100 ITG/POSIT network crossing observations in each year following POSIT's introduction. This is quite adequate for statistical and economic significance. Third, since introduction of the system occurred during our study period we have natural experimental evidence for the impact of crossing systems since we have data both with and without the impact of crossing systems. Finally, POSIT has been reasonably successful as a niche player since its introduction into Australia so that its impact on the ASX is similar in magnitude to other countries such as the US and UK. For example, the penetration rate for POSIT in the US is also about 1%.

limit the ability of upstairs markets to compete with and potentially eliminate the centralized limit order book market but there is typically no institutionalized protection for the dealer market preventing its elimination by the limit order book market. Glosten (1994) exemplifies the obvious advantages to pooling liquidity when he predicts that such an upstairs market would not survive. Why then do these upstairs markets not only survive but also prosper?

We discuss the literature on competition between downstairs and upstairs markets within the context of three major strands in which the upstairs dealer knows the identity of the counterparties. These include a punishment/filtering role, a search role and, finally, risk sharing. The major informational difference between upstairs dealing and the dealer in the limit order book is that the former knows the identity of both counterparties whereas in the downstairs market he knows the identity of his own client and can occasionally make an educated guess about the identity of the counterparty.[4]

In markets where the market maker knows the identity of participants, anonymity breaks down and it becomes possible for pricing to occur based on a known order size. In such non-anonymous markets, it is also possible for the dealer to punish informed traders who exploit their informational advantage to harm the dealer (see Seppi (1990), Benveniste et al. (1992), Aitken et al. (1995) and Desdranges and Foucault (2000)). The two market architectures that potentially reveal trader identity are upstairs markets in which the dealer knows the counter-parties and floor-based open-outcry systems. Aitken et al. (1995) provide evidence that dealers provide loss-making facilitating principal trades to large long-term clients who pay more for agency trades. This is contrary to the predictions of the Seppi (1990), Benveniste et al. (1992), and Desdranges and Foucault (2000) in which only uninformed trades take place with the punishing dealer while informed trades take place in the downstairs market.

A feature of both Aitken et al. (1995) and Desdranges and Foucault (2000) is that they model long-term trader reputation via an implicit contract without the need for an informative signal to the upstairs dealer. Madhavan and Cheng (1997) provide

[4] In some relatively transparent markets such as the ASX the broker ID is disclosed to other brokers (but not to investors including institutions) and this information may provide a clue as to the identity of the counterparty in the limit order book.

evidence from the NYSE upstairs market supportive of a filtering process based on a signal visible only to the upstairs dealer but Bessembinder and Venkataraman (2004) argue that special features of the NYSE may mean that counterparties can be identified downstairs, unlike an ordinary limit order book market such as the ASX or in Paris. Our findings are so similar to those of Madhavan and Cheng (1997) for the very largest NYSE stocks that they cast doubt on the Bessembinder and Venkataraman (2004) hypothesis of downstairs disclosure of counterparties on the NYSE.

Apart from these contributions, Gramming et al. (2001) show that informed traders prefer the German anonymous electronic limit order book to the less anonymous floor-trading system. They also provide evidence that spreads increase with the degree of trader information. Smith et al. (2001), in an empirical analysis of the Toronto exchange, finds evidence that the upstairs broker/dealers screen out informed trades, which they redirect downstairs. When Bessembinder and Venkataraman (2004) examine the upstairs market for the Paris Bourse, they take as evidence of a screening/certification process a relatively high temporary price impact reflecting the cost of liquidity provision to uninformed trades, and a small permanent price impact upstairs. They, nevertheless, do not attempt to specify the harm that occurs downstairs because of screening.

These models and empirical findings have the strong implication that upstairs markets filter out large relatively uninformed trades and thus benefit uninformed traders at the expense of informed traders who consequently face higher spreads and trading costs in the limit order book market. Nevertheless, is it plausible that the presence of an upstairs market consistently harms what is presumably a powerful and well-connected group of traders in the main market? By contrast, the search for counterparties upstairs hypothesis not only provides an explanation for the survival of separate upstairs market, but also their Pareto superiority to a single united market. If two markets have the same transaction cost we would expect trade to concentrate on only one of them. Reaping the benefits of trading externalities is important and fragmentation can be inefficient. Pagano (1989a) shows that the conditions for a separate upstairs market to exist for large traders are stringent unless participants can search for counterparties away from the organized market. Moreover, contrary to the pure trading case, a separate upstairs search market in which large traders look for counterparties can be Pareto improving.

In a detailed study, De Jong et al. (1995) indicate their inability to explain the migration of large orders from the limit order book on the Paris Bourse to the dealer market in London in terms of anticipated lower costs in the London market. This could be because they are unable to capture aspects of trade difficulty and because the relative ease of search for counterparties in the deep London dealer market is hard to capture in their econometric approach.

Both Burdett and O'Hara (1987) and Grossman (1992) emphasize the important search role of upstairs dealers, while Keim and Madhavan (1996) propose a very specific empirical prediction for costly upstairs search: market impact is a concave function of order size in the upstairs market but not in the downstairs market since it only captures expressed order flow. Below, we report new convincing evidence in support of their proposition. Lamoureux and Schnitzlein (1997) analyze an experimental marketplace in which traders may search bilaterally with each other for counterparties. The search alternative forces organized dealers to compete aggressively with the search alternative, lowers dealer profits and improves price discovery together with market efficiency. Arguing that screening and search are not necessarily mutually exclusive, Bessembinder and Venkataraman (2004) obtain a large overall price improvement upstairs in the Paris Bourse relative to what it would cost to execute downstairs which they take as evidence in support of Grossman's (1992) hypothesis of upstairs dealers tapping into otherwise unexpressed order flow via a search process.

Flood et al. (1999) evaluate multi-dealer experimental markets with and without quote disclosure. The market with quote disclosure is liquid with a much higher volume but price discovery is far less efficient. Costly search in the opaque market facilitates more efficient price discovery. Naik and Yadav (2003) obtain empirical findings on the effect of opacity on profitability that are supportive of Flood et al. (1999). They analyze the introduction of a limit order book for large stocks on the London Stock Exchange (LSE). Only about 25 percent of the public orders for these stocks go through the limit order book, indicating a continuing important role for voluntary market makers. Trading costs in comparable segments did not fall due to the introduction of the limit order book and dealers make higher profits from large orders due to a decline in transparency. This is because since the reform, posting of dealer quotes for large trades is not a requirement and thus opacity has increased.

Both Biais et al. (2000) and Viswanathan and Wang (2002) offer risk sharing models with contractible order sizes in which coexistence of the limit order market and upstairs market is possible. Both imply downward-sloping marginal valuations for shares by the dealer as the order size increases. They model a fundamental difference in the auction mechanism between limit order and dealer markets. Viswanathan and Wang (2002) show that a risk-adverse customer will prefer the single price auction in the dealer market to the multi-price discriminatory limit order book market for risk sharing reasons if the number of upstairs dealers is large. Large orders walking through the limit order book at multiple price steps. Moreover, in contrast to the filtering story, Bondarenko (2001) argues that competing dealers should prefer traders possessing greater information asymmetry as these are the source of the dealer's monopolistic profits that allow dealers to meet fixed entry costs. Finally, in a more general analysis of execution costs and trading activity, Swan and Westerholm (2004) find that the presence of an upstairs market lowers trading costs and improves most indicators of trading activity, regardless of whether these is a market-maker or limit order book market downstairs. Their study utilizes intraday bids and asks across 38 world exchanges covering 98 percent of the world's market capitalization while controlling for all major architectural features of world markets.

In summary, three classes of models of informed trader-dealer interaction exist which rely on knowledge of counterparties. The first are of a filtering or certification type, emphasizing the ability of dealers to punish traders in possession of asymmetric information and thus filter out informed trades in the upstairs market to the detriment of informed traders trapped in the limit order book market. The second are of a search-type, deemphasizing filtering or risk sharing in favor of the location of voluntary counterparties, but is also compatible with filtering/certification. The third, a discriminatory auction, relies on differences in the auction mechanism between the limit order book and upstairs dealer markets. Only in the first type of model is there an adverse affect on liquidity in the downstairs market.

First, we show that the upstairs and downstairs markets embody such similar liquidity and informational trades as to make the two almost indistinguishable. This finding is in stark contrast to the filtering/certification story. We then utilize a unique trading eligibility rule, which exogenously and differentially limits access to the upstairs market, to show that the upstairs market has no measurable harmful effects on the downstairs market due to non-anonymous filtering by dealers, "fragmentation"[5], or any other reason.[6] Perhaps to oversimplify, downstairs participants in stocks for which there are competing upstairs dealers do as well, if not better, than in stocks for which there is no possibility of upstairs competition. Without this unique trading rule, we would be in no better position to address this issue than our predecessors. This evidence is thus supportive of the upstairs search for counterparties approach or the differential auction mechanism approach of Viswanathan and Wang (2002), as opposed to the punishment-filtering story. Up until now, the empirical literature on upstairs trading has been silent on this issue.[7] We perform several simple tests of the Viswanathan and Wang (2002) model based on the actual number of intermediaries participating upstairs and downstairs in each stock but do not find strong support. This is because, most likely, participation is endogenous, depending on the profitability of each market. This leaves only the search approach consistent with our overall findings.

Fortunately, in terms of our study at least, the ASX restricts upstairs trading to stock trades of value at or above one million Australian dollars (hereafter AUS$1m). This eligibility rule provides an exogenous barrier to upstairs trading, and prohibits relatively large trades in smaller capitalization stocks from trading in the upstairs

[5] We note that the terms "fragmentation" and "cream skimming" are both pejorative and are typically utilized by critics of competitive processes. A more neutral term for "fragmentation" is "inter-market competition". Similarly, "cream-skimming" means treating less harmful, uninformed trades on their merits.

[6] While we have written this account as if the similarity of upstairs and downstairs trades leads to the prediction: upstairs trades do not harm to downstairs trades, the actual order of discovery is reversed. That is, having found no harm to downstairs trades we then predict (and find) the direct evidence that no filtering is taking place.

[7] In a suggestive study, Gresse (2002) finds that the relative volume placed through a crossing network has no adverse impact on spreads in the downstairs market. Since the relative placement of volumes through the two market types are purely voluntary and are thus endogenous, reflecting market conditions, she is unable to carry out the conceptual experiment of asking would the downstairs market improve if outright banning of the operation of the crossing network were to occur.

market.[8] Using this eligibility rule, we construct an upstairs market access measure to see if the large trades executed in the downstairs market in stocks with better access to the upstairs market suffer a liquidity drain, resulting in higher downstairs trading costs. Since these large eligible trades have been, according to the filtering-certification approach, priced out of the upstairs market due to information content, we deliberately introduce a bias towards finding higher permanent price impact costs in the downstairs market.

We supplement this exogenously determined upstairs market access factor, which captures the *threat* of *potential* fragmentation, with two endogenously determined upstairs trading measures of *actual* fragmentation and find no evidence that the upstairs market adversely affect the trading cost of large trades and the average bid-ask spread in the downstairs market. This is despite the bias towards finding the contrary introduced by the nature of the experiment. Thus, our findings are totally in agreement with our inability to distinguish between the two markets in terms of liquidity and informed trades, as captured by temporary and permanent price impacts.

The nature and consistency of our findings should alleviate concern that the upstairs market drains liquidity and cream skims the downstairs market. Perhaps of greater interest in terms of market design, our findings support the theoretical superiority of a hybrid market, consisting of competitive dealer market providing a search role in conjunction with the limit order book market, over a limit order book market in isolation.

The first part of our analysis cannot account for the existence of the upstairs market, only that it appears to be very similar to the downstairs market in terms of the composition of its trades and that it does no harm. In fact, our univariate analysis suggests the counter-factual proposition that costs are too high upstairs to ensure its survival. In the second part of our analysis, we estimate the price improvement offered by both the upstairs market and the crossing network. We use a new approach to compare the price impact of block trades across trading mechanisms that accounts

[8] Since trade size is to some extent endogenous it would in principle be possible for a broker to accumulate a large number of trades in a small stock that would otherwise go to the downstairs market and divert them as a single trade in excess of the minimum size limit upstairs. In practice, this is unlikely to happen because of the value of immediacy (cost of time delays) and higher execution costs for large orders.

for market selection and unbalanced data (see Section III below). We find that execution of most block trades on the ASX takes place in the upstairs market and, after controlling for market conditions such as the bid-ask spread in the downstairs market and trade difficulty, both the upstairs market and crossing system provide lower price impact for block trades than does the consolidated electronic limit order book. Moreover, there is evidence that these markets complement each other, as well as the downstairs market. Specifically, upstairs price improvement is larger for more liquid stocks, possibly reflecting the greater number and more active competition between brokers in liquid stocks. In contrast, the crossing network finds its niche and delivers larger price improvement in relatively less liquid stocks. These differences are only relative because both upstairs and crossing trades are predominantly in the larger stocks.

Our finding of a positive price improvement in the upstairs market is consistent with most previous research, e.g., Keim and Madhavan (1996), Madhavan and Cheng (1997), Smith et al. (2001), Booth et al. (2002) and Bessembinder and Venkataraman (2004), even though De Jong et al. (1995) fail to find any cost saving. Moreover, in keeping with Madhavan and Cheng (1997), but in strict contrast to Booth et al. (2002) who examine the relatively illiquid Helsinki Stock Exchange, and Bessembinder and Venkataraman (2004) who study the Paris Bourse, we find that the price improvement is economically small in the upstairs market but much greater with respect to crossing networks.[9] However, regardless of the economic magnitudes involved, block traders who go voluntarily upstairs or into crossing networks are better off. Trading upstairs or in a crossing network is not mandatory. Hence, in a rational world this result, while hardly surprising, provides comfort that our analysis is on track.

[9] Smith et al. (2001) do not explicitly address the issue of price improvement on the upstairs Toronto market and computation cannot occur without further details. On a raw basis, before taking account of trade difficulty, transaction costs are higher upstairs. Consequently, price improvement is likely to be economically small and thus similar to both the NYSE and ASX. Bessembinder and Venkataraman (2004) attribute their significant price improvement to theoretical purity in that the Paris Bourse is a limit order market downstairs whereas Madhavan and Cheng (1997) examine the largest stocks on the NYSE, the design of which they believe shares some properties in common with an upstairs market. Since the ASX is also a pure limit order market, theoretical purity cannot account for the Paris Bourse findings since our findings for the ASX are very similar to those found for the NYSE.

We structure the remainder of the paper as follows. Section I describes the institutional details and data. Section II shows the effect of upstairs trading on the downstairs price impact of large trades. Section III provides price impact comparisons of the three market types after taking account of trade difficulty. Section IV provides some simple tests of the Viswanathan and Wang (2002) model and Section V concludes with a discussion of some of the policy implications of our findings.

I. Institutional Details and Data

A. Trading on the ASX

The Australian Stock Exchange (ASX) conducts all listed equities trading in Australia. Since 1987, floor trading has given way to a fully computerized trading system called the Stock Exchange Automated Trading System (SEATS). It opens trading in a stock with a call auction between 10:00 a.m. and 10:15 a.m.[10] Continuous trading commences after the initial auction and continues until 4:00 p.m. Since May 1997 SEATS also perform a closing call auction shortly after the closure of continuous trading, currently at 4:15 p.m. SEATS allows the submission of both limit and market orders. Based on the CATS automated system, it is typical of many markets around the world (see Domowitz, 1990, 1993). Trading takes place through the intermediary services of brokers, who can trade on a voluntary basis as principal dealers to make a market or as agents in both SEATS (downstairs) and the upstairs market. The NYSE grants the specialist both privileges and obligations to make a market downstairs but generally does not allow participation upstairs. In contrast, ASX brokers are free to participate either upstairs or downstairs, and often in both, markets.[11]

As in the US, the primary market, SEATS, faces competition from a variety of off-market traders including after-hours brokers, upstairs broker-dealers, and the crossing

[10] The exact open time is random and stock-specific. The system randomly picks a stock from an ascending alphabetical group of stocks in different time intervals.

[11] Other than maintaining an orderly market (which is not explicitly defined), and not charging brokerage to customers with whom they deal as principal, market-making brokers have no special rights or obligations. There are, for example, no affirmative requirements to make a market or provide price continuity (as are NYSE specialists) if they choose not to, and they will usually only make a market for known customers.

system (e.g. POSIT Australia).[12] The introduction of POSIT took place in July 1997. While this is towards the end of our sample period, there is a sufficient period remaining to provide what amounts to a natural experiment, specifically, four and a half years without POSIT trading and 18 months with it in place.

SEATS does not execute orders outside normal trading hours which are, as noted, confined between 10:00 a.m. and 4:00 p.m. During the after-hours period, brokers manually match after-hours orders by using SEATS as a bulletin board to post orders and negotiate with each other via telephone to confirm the terms of trade. Brokers also operate an upstairs market for block trades, known as "specials" on the ASX, both during and outside the normal trading hours of SEATS. There are two types of specials: block specials and portfolio specials. Block specials are trades in one security for more than AUS$1m in value. Portfolio specials are trades with value above two hundred thousands Australian dollars and as a component of a multiple securities order with an aggregate value of more than AUS$5m.[13] Specials may execute at prices outside the quotes prevailing in SEATS even during SEATS normal trading hours and do not have to be exposed to SEATS when SEATS is operating.[14] Additionally, only specials may trade off-market during SEATS normal trading hours. This design feature of the market is crucial for our experiment.

The ASX mandates the reporting to the exchange via SEATS of all specials executed during SEATS normal trading hours as soon as possible. Hence, the trade reporting arrangements are in principle as timely and onerous in terms of transparency as in the SEATS downstairs market.[15] There are no delays allowed, as is the case on the

[12] Note that the primary (main) market SEATS is already a consolidated electronic limit order book. Therefore, there is no ECN, such as Island, that operates in Australia.

[13] This rule has been effective since October 14, 1996. Lower thresholds applied previously.

[14] This exception to price and time priority rules is contrary to the very strict rules on the NYSE that strongly discourage trades via crossing brokers. Consequently, a broker must make a public bid on both sides of the cross at one tick higher than their bid (see Smith et al., 2001, p.1729) and exposure of all upstairs trades to the floor market must occur. According to Bessembinder and Venkataraman (2004), the Paris Bourse rules require either that upstairs trades be executed at prices at or within the best bid and offer or, for certain stocks, within the weighted average spread. Hence, both exchanges have rules that are far stricter than the ASX.

[15] While in principle, reporting and time stamping is the same upstairs as downstairs, the human intervention and time required upstairs in the form of negotiations over the phone inevitably lead to small reporting delays that do not occur with the fully automated electronic limit order book. Quite

London Stock Exchange. However, the requirements outside normal trading hours are less onerous. There is still a requirement to report specials and other trades, but only at a time no later than fifteen minutes prior to the opening for trading on the following day.

B. Data

The data examined in this study consists of all trades in all ASX stocks from January 1993 to December 1998. We extract transaction data from the SEATS database of the ASX, which contains a complete record of every order and trade entered into SEATS. It also includes a record as to the identity of each broker-dealer participating in each trade or crossing. Crucial for the present study, the data contains a field that identifies whether or not a transaction was executed off-market. Direct identification of off-market trades is not possible using public data for US exchanges such as the TAQ data. Previous studies, such as Keim and Madhavan (1996), Madhavan and Cheng (1997), Booth et al. (2001) and Smith et al. (2001) focus on a very limited subsets of stocks or use indirect methods to identify trades matched outside the primary exchange. The only study that comes anywhere near our complete coverage of all trades, in all stocks for six years in terms of comprehensiveness is Bessembinder and Venkataraman (2004) who examine a limited subset (225) of Paris stocks for one year only.

Using the SEATS data, we screened every transaction record in every stock, totaling 1,702, in the sample period. Where execution of SEATS trades takes place across multiple limit orders, aggregation occurs using the corresponding order reference numbers. In addition, we make corrections for cancelled or error records, such as missing digits. The sample consists of twenty-five million aggregated trades.

The objective of this paper is to estimate the impact of upstairs trading on downstairs liquidity and to compare price impacts across different trading mechanisms. Since the ASX imposes the AUS$1m threshold criteria on upstairs trading in a single stock, we compare trading cost at a transaction level of trades valued at or above AUS$1m during SEATS trading hours. This procedure ensures that all trades used for comparison purposes are eligible for trading both upstairs and upstairs. Applying this

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recently in September 2001, after the end of our sample period, the ASX has trialed explicit reporting delays for large upstairs broker-facilitated single-stock trades.

screening criterion on the entire sample of 1,702 stocks, 69,449 trades, across 402 stocks with a total trade value of AUS$164.4 thousand million survived. Table I lists their distribution across years and annual dollar trading volume deciles. We form annual dollar trading volume deciles by ranking the total dollar trading volume across all trades in each stock in each year. Table I shows that block trades concentrate in the most heavily traded stocks. The top dollar trading volume decile stocks alone account for 92.4 percent of all block trades. None of these findings is at all surprising given the ASX definition of a block and the inability of less liquid stocks to qualify either as a block or as an upstairs trade.

PLACE TABLE I APPROXIMATELY HERE

Table II shows the proportion of these trades executed in the upstairs market and crossing network. Panel A shows that the upstairs market is the most commonly used mechanism for block trading in Australia. The upstairs market accounts for eighty percent of the total number of block trades across all stocks and years. Moreover, its use dwarfs most other upstairs markets. Adopting a far less onerous definition of a block, Bessembinder and Venkataraman (2004) find that upstairs facilitation represents 33.7 percent of block trades in Paris making up 67 percent of the volume. Madhavan and Cheng (1997) find that upstairs facilitation makes up only about 20 percent of the largest (Dow Jones) stocks on the NYSE. The distribution across volume decile indicates a higher proportion of upstairs trades in less well-traded stocks, although the number of block trades in these smaller stocks is, of course, quite small due to the size restriction. Bessembinder and Venkataraman (2004) find that the less liquid the stock, the more likely it is to be facilitated upstairs in Paris. We believe it is the minimum size restriction on the ASX that prevents smaller, less liquid stocks dominating the ranks of upstairs trading. This emphasis on less liquid stocks is consistent with the search role of the upstairs market as modeled by Burdett and O'Hara (1987) and Grossman (1992).

PLACE TABLE II APPROXIMATELY HERE

Execution occurs on the consolidated limit order book, SEATS, for those block trades not executed in the upstairs market. Panel B shows the proportion of trades matched using the ITG/POSIT crossing network, which commenced its operation in Australia in July 1997. We identify block trades executed by this crossing network using the masked broker identification number and the time of trade.[16] There are 238 actual POSIT block trades, which account for approximately one percent of the block trades in the same period.[17] Block trades via the crossing networks are almost entirely (232/238) in the top dollar trading volume decile stocks.

II. Impact of Upstairs Trading on Downstairs Liquidity

A. Univariate statistics and method

The three main price impact measures of a block trade, namely the total price impact and its division into a temporary price impact, i.e., price reversal due to the cost of liquidity provision, and the permanent price impact, reflecting price discovery, are described graphically in Figure 1. The key measure of interest to us is the total price impact (or price impact) that indicates the full information and liquidity cost of a block trade to the client or broker. Formally, the total price impact[18] of trade t, c_t, with a value of 1 indicating a 1% cost, is defined as

$$c_t = abs\,(100 \text{ x } \log\,(pr_t \,/\, pb_t)\,), \quad (1)$$

where,

pr_t is the price of the block trade t, and

pb_t is a benchmark price, which might be the mid-point of the bid and ask quote on SEATS immediately, or 10 or 20 trades prior to the block trade t, or the first trade price for the trading day of block trade t.

PLACE FIGURE 1 APPROXIMATELY HERE

Since block trades are relatively large trades, the underlying trading decision is unlikely to be made immediately. Therefore, using several lagged benchmark prices to measure the price impact of block trades enables us to find the most appropriate delay. Second, and more importantly, blocks trade prices in the upstairs market in particular, and crossing system to a lesser extent, are determined by the brokers prior to reporting

[16] The crossing network crosses orders at a random time during a five-minute interval following the official crossing time, 11 am, 12 pm and 3 pm. The orders that can be matched are reported to SEATS immediately afterwards. The trades of the crossing network operator in the fifteen minutes interval after the official crossing time are marked as crossing network trades.

[17] There are, of course, many more potential POSIT crossings which fail to gain execution.

[18] For our purposes, it is not necessary to undertake the difficult and potentially unreliable task of providing differential estimates for buyer- or seller-initiated trades.

the trade to SEATS. This reporting process is done manually; hence it is subject to inevitable delay. Consequently, the measure of price impact computed using the benchmark price immediate prior to the reported time is not directly comparable across block trades executed utilizing different trading mechanisms. All reporting downstairs is automatic and essentially instantaneous. Finally, as Keim and Madhavan (1996) point out, not only are upstairs trades typically initiated prior to the recording of the actual trade, but there is also an inevitable leakage of information to the downstairs market prior to trade completion. Hence there is a risk of understating the true price impact unless a lagged benchmark price is utilized. Our maximum window spaning one trading day is consistent with earlier block trading studies and should be sufficient to capture any leakage.[19]

Table III shows the mean and standard error of the price impact measures and the ratio of temporary to total price impact for all block trades in all three markets. In computing the temporary and permanent price impact and the ratio of temporary to total price impact, the pre-block and post-block[20] benchmark prices used are the limit order book's mid-point of the bid-ask quote (mid-quote, hereafter) sampled at specific trade lags, or the market's first and last trade prices. The table is divided into four panels based on the benchmark price establishment method. Panel A presents a zero-trade-lag, and hence only the total price impact can be meaningfully computed. Panel B utilizes a set of 10-trade-lag pre- and post- the block benchmark price, Panel C a 20-trade-lag pre- and post- the block benchmark price, while Panel D utilizes the first and the last trade for the day as the pre- and post-block benchmark price.

PLACE TABLE III APPROXIMATELY HERE

First we consider the total price impact. A crossing network, by definition, crosses orders at the mid-quote. Therefore, its trades have by definition, apart from the minimum tick, zero price impact at the time of crossing. However, using the mid-

[19] Discussions with portfolio managers suggest that completion of most block trades in Australia takes place within a day.

[20] We define the total price impact in equation (1), which requires only the block trade price and a pre-block benchmark price. The temporary price impact is defined as the return from the block trade price to a post-trade benchmark price, times –1 (a positive measure means positive cost and post-block price reversal). We define the permanent price impact as the return from a pre-block benchmark price to a post-trade benchmark price. See Figure 1 for a graphical representation.

quote immediately prior to the reported time of these trades to compute their price impact results in a mean price impact of 0.062 percent, which is significantly different from zero at 5 percent probability. Thus, based on the time of initiation, there is actually a small but significant market impact. This rises to 0.393 percent with a lag of 20 trades. The largest total price impact occurs for both downstairs and upstairs trades using the full one-day window with a value in both markets of about 1.861 percent. The price impact in the crossing network is also surprisingly high and almost of a similar order of magnitude at 1.633 percent.

We find that using lagged benchmark prices to compute the price impact results in higher price impact estimates. This is consistent with our *a priori* expectation that using lagged benchmark prices captures the true price impact more completely. While the much higher total price impact upstairs in Panel D, relative to Panel A, B, and C, could be due to informational leakage while the block is shopped, this explanation needs to be applicable downstairs as well since exactly the same impact occurs downstairs. The limit order book market might anticipate further trades in the same direction, or traders placing large orders downstairs may be being "front-run" or have their trading intention leaked to the market. An explanation which applies equally to both markets is momentum trading with traders utilizing both markets, buying as the market is rising and selling as it is falling.

The relative size of price impacts across trading mechanism is also consistent with expectations and previous research. For instance, using mid-quote 10 or 20 trades prior to the block as a benchmark, the mean price impact of block trades executed via the crossing network is the lowest, followed by those in SEATS, and lastly those in the upstairs market. The higher unadjusted mean price impact of the upstairs trades relative to downstairs trade is consistent with findings in Madhavan and Cheng (1997), Smith et al. (2001) and Booth et al. (2002). We defer further discussion of the price impact level difference between market mechanisms to a latter section where we adjust for trade difficulty.

What is most striking about Table III is the similarity of the relative importance of temporary and permanent price impacts across both the downstairs and upstairs markets. A statistical comparison is made of the ratio of temporary price impact to the total price impact in each of the panels B to D. This ratio has a lower theoretical bound of 0 (where none of the price impact is due to liquidity cost) and upper bound of 1 (where the entire price impact is due to liquidity cost). The very low Student *t* values for the comparison of the difference in the mean ratio show that the magnitude and proportion of liquidity and informed trades taking place in both markets is comparable. Hence, this is our first substantial evidence *against* the certification role of upstairs dealers postulated by Seppi (1990). Upstairs brokers do not appear to filter out or redirect informed trades downstairs.

What then explains why permanent price impacts might be so prevalent for ASX upstairs trades when nearly all the existing studies of upstairs markets led by Bessembinder and Venkataraman (2004) find no evidence of it in other upstairs markets? The most likely explanations relate to stock exchange rule differences between the ASX and other upstairs markets which have been examined. The severe and discriminatory minimum trade size for the ASX rules out smaller stocks where asymmetric information is likely to be a far more severe problem. Hence the gains from a certification role may be smaller on the ASX. Secondly, most upstairs markets either require that upstairs trades be exposed to the downstairs market, e.g., the NYSE and some stocks on the Paris Bourse, or that the upstairs price can lie outside the best bid-offer (for “eligible” stocks on the Paris Bourse) but the bounds are still tight. In contrast, the upstairs price on the ASX is not bound in any formal way by the downstairs market due to the exemption granted to “specials” from price and time priority rules. This freedom enjoyed by the ASX upstairs market relative to other markets which have been investigated may also encourage greater permanent price impact and discovery.

B. Issues and Method

What are the consequences of inter-market competition, or more pejoratively, fragmentation, on the main market? Specifically, what is the impact of upstairs trading and alternative trading systems on primary market liquidity? While the upstairs market and alternative trading system offer lower trading costs to traders in a position to participate, they divert uninformed order flows away from the downstairs market according to the filtering-certification hypothesis. This should result in increased trading cost in the downstairs market (see Grossman, 1992, and the cream-skimming literature cited above). Alternatively, based on the Pareto efficiency of hybrid markets due to either the search mechanism for counterparties upstairs or the complementary nature of the two auction mechanisms, there should be benefits to traders in both the upstairs and downstairs market. We aim to help resolve this debate by examining the issue empirically.

In this section, we use three different measures of upstairs trading to examine if the availability, and the actual level, of upstairs trading have a positive (deleterious) effect on the price impact of large trades and the average bid-ask spread in the downstairs market. The first of the three measures is upstairs market access, *uma*, exploiting the unique business rule imposed by the ASX that prohibits upstairs trading during trading hours for trades in a single stock of value less than AUS$1m. This measure of market overlap has the advantage that it depends on an exogenous rule that traders cannot control. Hence, it permits a separation between stocks in integrated hybrid markets with potentially, although not necessarily actually, overlapping markets and stocks in the stand-alone limit order market (stocks with no trades greater than the threshold). We define $uma_{j,y}$ as the proportion of the top one percent of *downstairs* trades in trade value in stock *j*, year *y* that have a trade value at or above AUS$1m. The higher is $uma_{j,y}$, the higher is the proportion of the trades having access to the upstairs market, even though the entry right remains unexercised in the case of these eligible trades. If market overlap has an adverse effect on liquidity in the downstairs market, we should observe that, all else equal, higher price impacts for larger trades and higher average bid-ask spreads for stocks with higher $uma_{j,y}$ values. Such a finding would indicate that dealers are successfully constraining the access of eligible informed traders and informed trades to the upstairs market.

The first measure of upstairs trading represents trades that could have migrated upstairs (according to the trading rule of the ASX) but actually executed downstairs. *A priori*, we would expect these to be as least as informed, if not more informed, than the block trades that pass muster with the broker/dealers monitoring access to the upstairs market if the filtering hypothesis is correct. The presence of the upstairs market is thus most likely to affect adversely these trades. The second and third measures represent the complement set of actual upstairs trades. The second measure, $utn_{j,y}$, is the ratio of the actual number of upstairs trades to the total number of upstairs and downstairs trades (no trade size restrictions) in stock *j*, year *y*. The third measure, $utv_{j,y}$, is the ratio of the dollar value of upstairs trades to the dollar value of upstairs and downstairs trades (no trade size restrictions) in stock *j*, year *y*. Again, the higher the value of these ratios, the higher is the level of upstairs trading and market fragmentation/competition. If upstairs trading adversely affects the downstairs market, these ratios should positively relate to the average downstairs price impact and average bid-ask spread.

In order to test the hypotheses, we also need to define the average downstairs price impact and bid-ask spread. Since upstairs trading during trading hours is only permitted for trades of, or above, AUS$1m, we focus on analyzing the trade-weighted average price impact, $atc_{j,y}$, of the top 1 percentile downstairs trades in trade value.[21] A relative average price impact measure, $ratc_{j,y}$, is also computed by scaling the average price impact of the top percentile trade with the average price impact of medium size trades (40-60 percentile) in order to further control stock specific trading cost differences. We formally define:

$atc_{j,y} = \frac{\sum_{i=1}^{n} c_t}{n}$, where trade i is in the top 1 percentile of trade in stock j, year y,

$amc_{j,y} = \frac{\sum_{i=1}^{m} c_t}{n}$, where trade i is in the top 40-60 percentile of trade in stock j, year y,

and $ratc_{j,y} = \frac{atc_{j,y}}{amc_{j,y}}$. (2)

The average bid-ask spread of stock j in year y, $apspd_{j,y}$, is computed as the trade-weighted average bid-ask spread across all trades.

Given we expect stock specific characteristics to affect both the price impact and the bid-ask spread, we estimate the relationship between them and the market fragmentation measures using the regression specification:

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[21] We choose the 1 percent threshold to generate the maximum variation in the variable, $uma_{j,t}$. Specifically, the AUS$1m threshold for upstairs trading is already larger than the smallest trade in the top 1 percentile of downstairs trades even for the most liquid stock on the ASX in any given year. Moving to a lower threshold would only reduce the variation in this variable. We also re-estimate all models of average price impact using the 2-5 percentile downstairs trades, the 40-60 percentile downstairs trades, and the ratio of the average price impact of the top 1 percentile downstairs trades to that of the top 40-60 percentile downstairs trades. The qualitative results are identical and the tables are available on request.

$$dep_{j,y} = \delta_1 + \delta_2 lttl_{j,y} + \delta_3 lmcap_{j,y} + \delta_4 stdrtn_{j,y} + \delta_5 indx_{j,y} + \delta_6 frag_{j,y} + e_{j,y}, \qquad (3)$$

where,

$lttl_{j,y}$	is the log of trading volume,
$lmcap_{j,y}$	is the log of market capitalization,
$dep_{j,y}$	is either $atc_{j,y}$, $ratc_{j,y}$ or $apspd_{j,y}$,
$stdrtn_{j,y}$	is 100 $\times$ the standard deviation of daily returns of stock j in year y,
$frag_{j,y}$	is either $uma_{j,y}$, $utn_{j,y}$, or $utv_{j,y}$,
$indx_{j,y}$	is an index stock, and
$e_{j,y}$	is the error term.

Since stocks that are components of a stock index, or with higher trading volume and market capitalization, are relatively liquid, we expect δ_2, δ_3 and δ_5 to be negative. Liquidity provision in stocks with a higher return standard deviation is more costly. Hence, we expect δ_4 to be positive. Finally, if upstairs trading drains liquidity from the downstairs market, we should observe positive estimates of δ_6.

C. Results

Table IV contains the summary statistics for the dependent variables consisting of the three measures of downstairs market impact and the three measures of upstairs trading access. We compute the average price impact using the immediate mid-quote prior to each trade, since all trades execute downstairs and there is no reporting time lag and no comparability issues.[22] The table shows that the average price impact for the top 1 percentile trades, $atc_{j,y}$, is 53 basis points.[23] The 1.09 percent estimate for $atc_{j,y}$ suggests that the average price impact for the top 1 percentile trade is approximately nine percent higher than that of the medium size trades. The average bid-ask spread is approximately 1.1 percent. The average level of upstairs trading or access is not very high among the top 1-percentile trades since mean values of $uma_{j,y}$, $utn_{j,y}$ and $utv_{j,y}$ are less than 0.2. The variation is the largest for $uma_{j,y}$ (0-1), followed by that of $utv_{j,y}$ (0-0.67) and $utn_{j,y}$ (0-0.11).

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[22] We undertake robustness checks in this section utilizing a lag of 0, 10 and 20 trades. We show only the zero lag results since the qualitative results at all three lags are identical.

[23] This is significantly higher than the average price impact of all SEATS trades over AUS$1m in Table III (21 basis points) because Table V shows values that weight every stock equally. The price impacts of smaller and relatively illiquid stocks pull the average up. In Table III, the average is across trades in liquid stocks (since they are trades of AUS$1m or above in value) and hence the value is much lower.

PLACE TABLE IV APPROXIMATELY HERE

The regression estimates for $atc_{j,y}$ and $ratc_{j,y}$ are presented in Table V, Panels A and B respectively. We report three sets of results in each panel, representing the three different measures of upstairs trading. The coefficient estimate for the market capitalization and index composite stock dummy, δ_3 and δ_5, are of the expected sign and mostly statistical significant at the 5 percent probability level or better in both Panel A and B. However, the coefficient estimate for the trading volume variable, δ_2, is not statistically significantly different from zero. This suggests that liquid stocks, in terms of market capitalization and index inclusion, but not trading volume *per se*, have a lower percentage and relative price impact in executing large trades. The market capitalization effect may also be caused by higher public information disclosure and, hence, a lower level of adverse selection. The index inclusion effect can be a result of a higher level of institutional trading activity, creating greater frequency of large orders, which in turn lowers inventory and matching costs.

PLACE TABLE V APPROXIMATELY HERE

Generally, the coefficient estimates of all variables are of lower statistical significance in Panel B, than those in Panel A. This suggests that taking the ratio of the price impact for the top 1-percentile trades to the price impact of the 40-60 percentile trades is an effective, but not perfect, control for cross-sectional differences in average trading cost. Specifically, the coefficient estimate for the standard deviation (risk) variable, δ_4, is statistically significantly positive at 1 percent probability in the $atc_{j,y}$ regression (Panel A) but is not statistically significant in the $ratc_{j,y}$ regression. The positive coefficient estimate of δ_4 is consistent with expectations, i.e., riskier stocks are also more costly to trade.

The main coefficient of interest is δ_6. None of the estimates across Panel A and B is statistically significantly positive at the 5 percent probability level. This suggests that, neither the level of upstairs market access, nor the actual level of upstairs trading, has a statistically significant adverse consequence for the price impact of large trades in the downstairs market. It would appear that there is no negative outcome from market overlap, or fragmentation, and cream skimming, at least as far as the upstairs market is concerned. To the contrary, one of the six estimates of δ_6 is statistically significantly negative at 5 percent probability level. Specifically, the result from the second model in Panel B suggests that the higher is the number of upstairs block trades relative to the total number of trades in the upstairs and downstairs market, the lower is the price impact of the largest trades in the downstairs market relative to the price impact of medium size downstairs trades. Nevertheless, we are conscious that a one-in-six finding does not represent strong support for a negative relationship between upstairs trading and downstairs trading cost.

Our results, surprising as they may seem, are perfectly consistent with the earlier finding that the ratio of the temporary impact due to liquidity trades to the overall price impact is very similar in the two markets. They are also consistent with the finding by Aitken et al. (1995) that dealers gain the ability to charge clients more for brokerage in return for facilitating informed upstairs principal trades for large, long-term clients. This implicit contracting solution appears to be efficient in that large institutional clients trading on information gain execution upstairs when circumstances are difficult or impossible downstairs without injecting trades into the downstairs market that would further impede its efficient operation.

Table VI presents the regression estimates for the average market impact, $apspd_{j,y}$. The general finding is consistent with that of Table V. There is no statistically significant positive relationship between access to the upstairs market or the actual level of upstairs trading and the average bid-ask spread. Neither are any of the estimates of δ_6 statistically significantly positive at the 5 percent probability level. The sign and statistical significance of the coefficient estimates for the other variables are also very similar to that of $atc_{j,y}$ and $ratc_{j,y}$. The estimates of δ_3 (market capitalization) and δ_5 (index inclusion) are statistically significantly negative at the 5 percent probability level (except in one case). The estimates of δ_4 are significantly positive and the estimates of δ_2 (trading volume) are not statistically significant.

PLACE TABLE VI APPROXIMATELY HERE

III. Price Impacts

A. Trade difficulty

Although the univariate statistics presented in Tables III above provide estimates of the realized price impact of trading blocks across different trading mechanisms, they do not control for the trade difficulty or market selection bias that has been noted by several authors. Madhavan and Cheng (1997) and Bessembinder and Venkataraman (2004) find that the upstairs market is more likely to be used for more difficult trades, e.g., for larger trades and when market bid-ask spreads are higher. Conrad et al. (2003) find that easier-to-fill trades are send to ECNs and crossing networks. Comparing price impact without adjustment for trade difficult is misleading because the higher mean trading cost of upstairs trades, for instance, may simply reflect that they are more difficult trades to execute.

Madhavan and Cheng (1997) pioneered the use of an endogenous switching regression model to account for market selection bias arising from an assumed signal about the information content of the potential upstairs trade visible to the upstairs dealer but invisible to the econometrician. Conrad et al. (2003) also use this technique in studying the difference in the total execution cost between dealership market, crossing system and ECNs using US data as did Bessembinder and Venkataraman (2004) for the Paris Bourse. Such a method involves using a binary probability model to estimate the market selection decision, and then feeds the estimated probabilities into the second stage to adjust for the market selection bias. It is elegant, but involves pooling the sample of upstairs and downstairs trades. Moreover, is not well suited to cases where there are more than two choices, as in the present application. In addition, the accuracy of the trade difficulty adjustment is critically dependent on the accuracy in the first stage binary classification estimation[24], which is difficult to attain with a highly unbalanced sample with relatively few upstairs trades, as in our data set. Therefore, we use an alternative two-stage procedure to compare the price impact of block trades across trading mechanisms.

The first stage involves using block trades executed in SEATS alone to estimate the relationship between the downstairs price impact and various measures of trade difficulty, predicated only on the state of the downstairs limit order book at the time of the downstairs trade. Fortunately, section 3 above has already established that the states of the upstairs market and limit order book downstairs at the time of the upstairs

[24] We utilized our data to estimate the probit market selection model between upstairs market and SEATS, as in Madhavan and Cheng (1997). The model is statistically significant at 0 percent probability. However, the proportion of correct market classifications does not seem significantly different from that of a naïve rule, which predicts that upstairs execution should take place for all trades.

trade have no impact on the downstairs market at the time of the downstairs trade. Consequently, we can treat the limit order book variables as exogenous for all intents and purposes. In the second stage, the price impact of hypothetical SEATS block trades are generated using the trade difficulty coefficients estimated in the first stage, together with the trade difficulty characteristics of the observed upstairs and crossing network block trades, which depend on the state of the limit order book at the time of the off-market execution. The state of the limit order book is, fortunately, fully visible to us both when a block trade is executed downstairs and when the block trade is executed upstairs or on the crossing network. The price improvement provided by upstairs and crossing network trades is computed by subtracting the actual price impact of upstairs and crossing network trades from the price impact of the hypothetical SEATS block trades estimated in this way. This procedure has a two-pronged advantage. It avoids estimation using the market selection model and the need for trade matching[25], yet provides a meaningful comparison of the price impacts estimated at different times in the three markets.

B. The first stage

The first stage SEATS block trade price impact regression model depends on the state of the limit order book at the time of execution, denoted by t, and takes the form:

$$\begin{aligned} c_t \quad = \quad & \alpha_1 + \alpha_2 pspd_t + \alpha_3 pspdsq_t + \alpha_4 szrdpt_t + \alpha_5 szrsq_t + \alpha_6 time_t \\ & + \alpha_7 lmcap_t + \alpha_8 indx_t + \alpha_9 ldlyv_t + \alpha_{10} ent_t + \varepsilon_t , \end{aligned} \tag{4}$$

where,

$pspd_t$ is the percentage quoted bid-ask spread immediately prior to trade t,

$pspdsq_t$ is the square of $pspd_t$,

[25] If market selection is a real concern, observed trades can be the result of a separating equilibrium such that there would be no way to match closely the trade difficulty conditions of trades executed across different systems. For instance, if use of the upstairs market only occurs when the electronic limit order book is relatively illiquid, it would be difficult to find trades in electronic limit order book of the same size under the same market conditions. This is because such trades could not have occurred!

$szrdpt_t$	is trade size in number of shares of trade t divided by the number of shares available in the best two prices in the limit order book immediately prior to trade t,
$szdsq_t$	is the square of $szrdpt_t$,
$time_t$	is the reported time of trade t,
$lmcap_t$	is the average market capitalization of the company of trade t in the same calendar year,
$indx_t$	is a dummy that equals 1 if the company of trade t is a stock included in the All Ordinaries Index, 0 otherwise,
$ldlyv_t$	is the logarithm of the average daily dollar trading volume of the company of trade t in the same calendar year,
ent_t	is a dummy that equals 1 on or after July 2, 1997, the day that the crossing network commenced operation, and
ε_t	is the residual term.

The first five independent variables are intended to capture the market condition and trade specific characteristics that affect the price impact. The use of the bid-ask spread as a measure of adverse selection and market illiquidity is widely used, both in theoretical and empirical research. Since the price impact of a block trade is more likely to be higher when adverse selection and market illiquidity are higher, we expect the sign of α_2 to be positive. However, the effect of the bid-ask spread on price impact need not be linear because blocks trades are likely to consume limit orders at more than one price step. These multiple price steps give rise to the price discriminatory nature of the auction mechanism in the limit order book, which is modelled by Viswanathan and Wang (2002). The square of bid-ask spread is, therefore, introduced to capture any non-linear effect. We expect the sign of α_3 to be negative.

The third variable, $szrdpt_t$, is another trade difficulty measure: trade size relative to the limit order book depth. Normalizing trade size (number of shares) by the limit order book depth has the advantage of being unit free, hence controlling for cross-sectional differences across stocks. Since the larger a trade is relative to market liquidity, the more difficult it will be to execute, we expect the sign of α_4 to be positive. Keim and Madhavan (1996) find that the price impacts of block trades in the upstairs market are a concave function of trade size, but do not examine the market impact of block trades in the downstairs market. They believe this concavity to be due to search costs incurred by dealers in the upstairs market for which there is no downstairs counterpart. Hence, we introduce the variable, $szdsq_t$, to control for this potential effect in the downstairs market. If the concavity of the size effect is truly due to search costs, we should not see a statistically significantly negative estimate for α_5 utilizing downstairs trades. However, if concavity is a general aspect of the price impacts of block trades, then we should observe it in the downstairs market as well.

The fifth variable, $time_t$, is an adverse selection measure inspired by Easley and O'Hara (1992) who predict that short-lived private information is more likely to be exploited sooner than later, such that the information content of a trade of a given size is smaller when it is executed later in a trading day. We expect the sign of α_6 to be negative.

The next three variables are cross-sectional control variables. Market capitalization, $lmcap_t$, is defined over the calendar year (as opposed to the time of the trade) in order to insulate the cross-sectional differences from the effect of day-to-day changes in the price level of a stock. As larger stocks produce more public information released to the market, and have greater analyst following than do smaller stocks, the adverse selection risk in trading larger stocks is also likely to be smaller. Consequently, trading difficulty should diminish in market capitalization. Thus, we expect the sign of α_7 to be negative. Both variables, $indx_t$ and $ldlyv_t$, are cross-sectional liquidity variables, which should indicate greater ease of trade. They are thus *inverse* cross-sectional trade difficulty variables. We expect block trades in benchmark index constituent stocks, and more heavily traded stocks, to have a smaller price impact than non-indexed or less heavily traded stocks. Hence, the signs of α_8 and α_9 should both be negative.

Finally, we introduce a time series dummy to control for the entrance of the crossing network into the Australian market. If such an increase in competition improves liquidity for traders, the sign of α_{10} should be negative.

Table VII presents the estimation of the regression model specified by equation (4) using the mid-quote immediately, 10 and 20 trades prior to the block trade as the benchmark price. The model performs well. The *F*-statistic suggests that the model is statistically significant at 0 percent probability level and the adjusted *R*-squared varies from 31 percent to 71 percent. All coefficient estimates are of the expected sign. The bid-ask spread has a positive but decreasing effect on price impact. α_2 is positive and α_3 is negative, and both are statistically significant at the 1 percent probability level in five out of six cases. The positive and statistically significant estimates of α_4 suggest that larger trades relative to limit order book depth are more costly to execute on SEATS than are smaller trades. The lack of statistical significance for the estimates of α_5 indicates that the price impact is not concave in size in the downstairs market. This is consistent with concavity being due to a specific characteristic of the upstairs market such as the cost of search for counter-parties (below we see confirming evidence in the upstairs market).

PLACE TABLE VII APPROXIMATELY HERE

The negative and statistically significant coefficient, α_6, for the lagged measures of price impact suggests that this cost is decreasing over the trading day. Stocks that are benchmark index constituents and are more heavily traded have a lower price impact when measured utilizing lagged benchmark prices (significantly negative α_8 and α_9). Finally, the cross-sectional difference in market capitalization and the introduction of the crossing network, α_7 and α_{10} respectively, do not show a statistically significant effect on any price impact measures for block trades on SEATS. For the former variable, its lack of statistically significance indicates that trading volume and index inclusion are adequate for controlling the cross-sectional differences in price impact. For the latter variable, its lack of statistical significance suggests that traders utilizing the limit order book either did not see the introduction of the crossing network as a competitive threat or that quote prices cannot be improved further.

C. The second stage

In the second stage of the estimation we observe the trade difficulty variables and the state of the limit order book at the time of the upstairs and crossing network trades. The subscript *u* distinguishes these downstairs variables at the time of the upstairs trades from the corresponding downstairs variables at the time of the downstairs trades, subscripted *t* in equation (4) above. We compute the trade difficulty adjusted price improvement, $piprv_u$, for the upstairs market and crossing network trades, *u*, over the price impact of an equivalent hypothetical SEATS trade, as the difference between the computed, rather than estimated, cost of a hypothetical downstairs trade, $\hat{c}_u$, as it would have been performed under the same adverse conditions as actually pertained at the time of the upstairs trade, less the actual market impact of the upstairs trade, c_u:

$$piprv_u = \hat{c}_u - c_u, \tag{5}$$

where the hypothetical market impact downstairs,

$$\hat{c}_u = \alpha_1 + \alpha_2 pspd_u + \alpha_3 pspdsq_u + \alpha_4 szrdpt_u + \alpha_5 szdsq_u$$
$$+ \alpha_6 time_u + \alpha_7 lmcap_u + \alpha_8 indx_u + \alpha_9 ldlyv_u + \alpha_{10} ent_u,$$

α_1 to α_{10} — are the coefficients as estimated in equation (4) above,

$pspd_u$ — is the percentage quoted bid-ask spread in the downstairs market immediately prior to the upstairs or crossing network trade *u*,

$pspds_u$ — is the square of $pspd_u$,

$szrdpt_u$ — is trade size in number of shares in upstairs or crossing network trade *u* divided by the number of shares available in the best two prices in limit order book immediately prior to trade *u*,

$szdsq_u$ — is the square of $szrdpt_u$,

$time_u$ — is the reported time of upstairs or crossing network trade *u*,

$lmcap_u$ — is the average market capitalization of the company in the same calendar year in which the upstairs or crossing network trade *u* has occurred,

$indx_u$ — is a dummy that equals 1 if the company of upstairs or crossing network trade *u* is a stock included in the All Ordinaries Index, 0 otherwise,

$ldlyv_u$ — is the logarithm of the average daily dollar trading volume of the company of upstairs or crossing network trade *u* in the same calendar year,

ent_u — is a dummy that equals 1 on or after July 2, 1997, the day that the crossing network commenced operation,

ε_u — is the residual term,

and

c_u — is the price impact as computed utilizing equation (1) for upstairs or crossing network trade *u*.

The mean of $piprv_u$ should be positive if the upstairs market and crossing network provide price improvement over the equivalent downstairs SEATS trades performed at the same time and under the same trade difficulty conditions.

Table VIII contains the univariate statistics for the upstairs market and crossing network price improvement estimate, $piprv_u$. The mean estimated price improvement for the upstairs market and the crossing system over the SEATS prices are positive and statistically significantly at the 1 percent probability level, except in the case of upstairs price improvement estimated using the mid-quote immediately prior to the time of reported trade. As mentioned above, since there is reporting delay, particularly for upstairs trades, the negative price improvement estimate merely reflects this incomparability. This reporting delay bias is partially eliminated by using lagged benchmark prices. The mean estimated price improvement of the upstairs market is between two to four basis points (0.021-0.040 percent) while that of crossing network is much more substantial, thirteen to sixteen basis points (0.136-0.177).

PLACE TABLE VIII APPROXIMATELY HERE

The former estimate of upstairs price improvement is of very similar magnitude to the estimate in Madhavan and Cheng (1997) using stocks in the Dow Jones Industrial Index (no more than 2 basis points) but much smaller than the estimate in Booth et al. (2002) which uses data from the relatively illiquid Helsinki Stock Exchange (30 basis points) and Bessembinder and Venkataraman (2004) who find that Paris trades are executed upstairs at only 35 percent of the cost of downstairs execution. Our finding provides strong evidence that the upstairs market and crossing network deliver price improvement in executing block trades over the consolidated electronic limit order book after adjusting for trade difficulty. However, in conjunction with the findings from the other markets, upstairs execution provides only sizeable gains when stocks are relatively illiquid.

Does the estimated upstairs market and crossing network price improvement, $piprv_u$, vary systematically in relation to trade difficulty? In order to answer this question, we analyse the variable, $piprv_u$, using the following regression to estimate the coefficients, β_1 to β_{10}:

$$piprv_u = \beta_1 + \beta_2 pspd_u + \beta_3 pspdsq_u + \beta_4 szrdpt_u + \beta_5 szdsq_u + \beta_6 time_u + \beta_7 lmcap_u + \beta_8 indx_u + \beta_9 ldlyv_u + \beta_{10} ent_u + \varepsilon_u, \quad (6)$$

where the variables all relate to the condition of the upstairs traded stocks and the state of the limit order book at the time of the upstairs trade and are as described in equation (5) above.

Keim and Madhavan (1996) model the costly search process in the upstairs market to predict that the price impacts of upstairs trades are a concave function of trade size. Their empirical results confirm the hypothesis for the NYSE. Price impact concavity in trade size implies a positive relationship between the price improvement in upstairs market and trade size. That is, we expect β_4 to be positive. We measure the change in this concavity over trade size by β_5, which we expect to be negative; otherwise, a large enough trade will have a negative price impact.

Theoretical research by Burdett and O'Hara (1987), Pagano (1989a) and Grossman (1992), also suggests that the main role of upstairs brokers is to provide a search function within the group of prospective counterparties for large trades. Consistent with this idea, we expect that price improvement due to the upstairs market should positively relate to other trade difficult measures as well. Consequently, the sign of β_2 should be positive, while the sign of β_3, β_6, β_7, β_8, and β_9 should be negative. This assumes that the bid-ask spread downstairs is exogenous in the sense that it is not affected by the existence or otherwise of the upstairs market. Our results, which we presented in Tables IV and V above, confirm the validity of this assumption. The price improvement in the upstairs market should be higher after the introduction of the crossing network, if the introduction of the crossing network has more impact on the upstairs market than on SEATS. This would imply that β_{10} is positive.

Since the design of crossing-networks facilitates lower transaction costs via the elimination of the bid-ask spread in the downstairs market, we expect to find a positive relationship between the price improvement provided by the crossing network and the bid-ask spread. Since not a great deal is known about the properties of crossing networks, we do not have strong hypotheses concerning the relationship between the crossing network's price improvement over the limit order book and other trade difficulty variables.

Table IX presents the estimates of the regression model, equation (6) for the upstairs block trade sample. The model is statistically significant at the 1 percent probability level based on the *F*-statistic and the adjusted *R*-squared varies from 6 percent to 18 percent. Since utilizing the mid-quote price immediately prior to the reported time of an upstairs trade generates severely biased estimates of both price impact and price improvement, we only present the regression results for upstairs trades using two sets of lagged benchmark prices.

PLACE TABLE IX APPROXIMATELY HERE

The coefficients on the market condition and trade specific variables are of the expected sign and they are all statistically significant at the 1 percent probability level. The bid-ask spread has a positive but decreasing relationship with upstairs market price improvement, positive β_2 and negative β_3. Upstairs market price improvement is also increasing in trade size but at a decreasing rate, positive β_4 and negative β_5. These findings support the concavity of upstairs price impact in trade size, as both predicted and found by Keim and Madhavan (1996) for the US. The negative estimates of β_5 suggest that there is a natural limit to the upstairs price improvement as a function of trade size.

The time of day that the trade occurs has a negative effect on price improvement upstairs, *i.e.*, negative β_6. This is consistent with less informed trading, and hence a smaller benefit from search, later in the trading day.

Upstairs market price improvement, however, has an unexpected positive relationship with the cross-sectional ease of trade (inverse difficulty) variables. The coefficient estimate on the index inclusion, β_8, and average daily dollar trading volume, β_9, variables, (which are updated in each calendar year) are not statistically significant at the 1 percent probability level, while that of the market capitalization variable, β_7, is positive and statistically significant. This finding suggests that upstairs market price improvement for block trades is greater for large stocks (less difficult trades) than for small stocks (more difficult trades). This result might be due to the lack of "unexpressed orders" for smaller stocks, hence undermining the relative advantage of the upstairs market in searching for counterparties, or it could relate to the difficulty that smaller stocks have in meeting the ASX's upstairs eligibility threshold of AUS$1m. A third explanation, which is prompted by Aitken et al. (1995), is that large stocks facilitated as a principal trade by the broker's long-term clients can generate more brokerage revenue when they do trade as agents, either upstairs or downstairs. A fourth explanation is that the greater price improvement upstairs for more liquid stocks is due to the participation of more active dealers in the upstairs market for larger stocks which satisfy the tough ASX upstairs eligibility rule. Most models of dealer markets, including Viswanathan and Wang (2002), stress the role of dealer numbers and competition.

Finally, there is some weak evidence that commencement of the crossing network is associated with increased upstairs market price improvement. Specifically, β_{10} is statistically significantly positive at 1 percent probability level in the preferred model that uses mid-quote 20 trades prior to the block trade as the benchmark price. The coefficient is still positive but statistically insignificant in the other model.

We conclude that upstairs market price improvement is positive after adjusting for trade difficulty, and this price improvement is higher under more difficult market conditions. This time-varying upstairs market price improvement is stronger for the larger, higher liquidity stocks, possibly due to the large number and more active nature of block trading in these stocks and hence the greater scope to find counterparties.

Table X presents the estimate of regression model, equation (6), using the crossing network block trade sample. The variables, $indx_u$ and ent_u, are omitted in this regression because the crossing network block trade population consists of block trades in index stocks only, therefore these two variables always take the value of 1. The *F*-statistic and adjusted *R*-squared suggest the model is statistically significant. Given that Table III shows that the error in estimating the price impact of crossing trades is smallest when the benchmark price is set at the mid-point immediately prior to trade, we focus on the result presented in Panel A, which use this benchmark price to compute the price improvement.

PLACE TABLE X APPROXIMATELY HERE

Columns 1 and 2 provide the estimates for the full model. The estimates show that the overriding factor determining the price improvement due to the crossing network is the bid-ask spread. Hence, the more illiquid is the downstairs market, both cross-sectional and over time, the greater the price improvement. The estimates of β_2 are consistently positive and statistically significant at the 1 percent probability level. The significance of the bid-ask spread in this regression is an expected outcome since the purpose of a crossing network is to eliminate the bid-ask spread. However, it is surprising that the results in Panels B and C, which used lagged benchmark prices, suggest an inconsistent sign in the estimate of β_2. It is possible that we introduce noise by lagging the benchmark and thus cause this inconsistency.

In Panel A, the other variables generally do not have statistically significant coefficient estimates at the conventional probability level. This combination of high *R*-squared (59 percent) and low *t*-statistics (maximum of 2.62) across the variables suggests that multicollinearity may be a problem, particularly in this sample that contains only 238 trades. Consequently, we estimate a streamlined model that has the time of trade and market capitalization variables (whose coefficient estimates have the lowest statistical significance across all panels and where market capitalization correlates with trading volume) removed. We provide these estimates in column 3 and 4. While the problem of conflicting signs for the bid-ask spread variables in Panels B and C persists, the statistical significance of the coefficient estimates of the cross-sectional trading volume variable, $ldlyv_u$, is greatly improved. β_9 is consistently significantly negative at the 1 percent probability level. Thus, ease of trading downstairs in terms of trading volume discourages price improvement utilizing network crossings. Illiquid stocks with lower volumes gain greater price improvement. There are also clear increases in the value of the *F* statistic. All signs are indicative of a smaller multicollinearity problem.

Finally, since the inconsistency in the signs of the bid-ask spread variables are difficult to interpret, we estimate a further streamlined model that has the squared bid-ask spread term removed, in an effort to force a linear relationship. This modification, however, leads to a statistically insignificant coefficient on the bid-ask spread variable in Panels B and C. It also leads to substantially reduced adjusted *R*-squared and *F*-statistics for the lagged benchmark models. Nevertheless, the statistical significant negative sign on $ldlyv_u$ remains. Since the trading volume for a specific stock is an inverse measure of trade difficulty, this result suggests that price improvement in crossing network block trades is positively associated with relatively thinly traded stocks. This characteristic of crossing network complements the upstairs market since the upstairs market price improvement is smaller for less liquid stocks.

IV. Simple Tests of the Risk Sharing Model

Both the literature and the previous section have conclusively documented the existence of lower adjusted price impacts for upstairs and crossing network trades. While from the assumption of rational trading decisions[26], these results are expected, there is still an important issue to be addressed. The analysis so far, showing that the upstairs market does not adversely affect the downstairs market, is consistent with both upstairs search and risk sharing along the lines of Viswanathan and Wang (2002). In order to test the main implications of the risk-sharing model, which involves the impact of trade size and dealer numbers in both the limit order book and upstairs, we need to take as exogenous the number of dealers operating in each market. In Table XI we summarize the entire cross-sectional data for all stocks with eligible trades, all eligible trades over AUS$1m, and the number of participating broker-dealers for both markets. Unfortunately, however, there is no ASX rule, or similar rule on other exchanges, that requires broker-dealer numbers to be exogenous.

PLACE TABLE XI APPROXIMATELY HERE

The cross-sectional regression equations, which we use to explain market impact, c_t, and to test the main predictions of the model, take the very simple interactive form:

$$c_t = \alpha_0 + \alpha_1 stdrtn_t.szrdpt_t + \alpha_2 stdrtn_t.szrdpt_t.nd + \alpha_3 nd + \varepsilon\,, \tag{7}$$

where, as before, c_t, $stdrtn_t$ and $szrdpt_t$ are the market impact, daily standard deviation of stock return, and trade size deflated by the depth of the limit order book at the time of the downstairs or upstairs block trade, respectively. *nd* is the number of participating broker-dealers in that stock, depending on whether the trade takes place in the limit order book or upstairs market. Note that our trade size measure is directly risk-adjusted, as in the Viswanathan and Wang (2002) model.

There are four very specific implications of the Viswanathan and Wang model. Denoting downstairs variables by the subscript, *d*, and upstairs by the subscript, *u*, these are, first, that conditional on trade size, market impact is falling in the number of

[26] Upstairs market and crossing systems offer an alternative to trading downstairs. Since there are no laws compelling investor to trade in these markets, it must be to their own benefit. However, as Viswanathan and Wang (2002) note, risk-averse traders could still trade upstairs for efficient risk-sharing reasons even if the expected market impact is higher.

broker-dealers in each market, $\frac{\partial c_d}{\partial nd_d} < 0; \frac{\partial c_u}{\partial nd_u} < 0$, as competition and the ability to risk-share improves. Second, that the upward-sloping linear market impact-trade size schedule is flatter in the limit order book than in the upstairs market, $\frac{\partial c_d}{\partial szrdpt_d} < \frac{\partial c_u}{\partial szrdpt_u}$, for a given number of broker-dealers. Third, that the linear market impact-trade size schedule is rising in the number of broker-dealers in the downstairs market, $\frac{\partial^2 c_d}{\partial szrdpt_d \partial nd_d} > 0$ and, finally, is falling in the number of broker-dealers in the upstairs market, $\frac{\partial^2 c_u}{\partial szrdpt_u \partial nd_u} < 0$. The third and fourth implications arise from the way the dealer demand schedule rotates at a point, given by a large trade size in the limit order book and at a zero trade size in the upstairs market, as the number of broker-dealers in a particular stock rises.

We can easily see from the coefficient estimates presented in Table XII that, while the first implication of the impact of competition is correct, the remaining three predictions are not satisfied. The trade size schedule is steeper in the limit order book than in the upstairs market and also falls rather than rises as broker competition intensifies. These results are robust to adding in the variety of controls employed the earlier regression models.

PLACE TABLE XII APPROXIMATELY HERE

V. Conclusion

Using by far the most comprehensive dataset for this type of analysis obtained from the ASX, this paper studies the price impact of block trades across three trading mechanisms, the upstairs market, an electronic crossing network system and a consolidated electronic limit order book. We estimate both the temporary and permanent price impact effects of block trades downstairs and upstairs, as well the total price impact in downstairs, upstairs and crossing networks. Contrary to nearly all exiting studies of upstairs markets, we find that upstairs markets appear remarkably similar to downstairs markets with a similar preponderance of liquidity and informed trades with very similar market impact costs. This is direct evidence against the Seppi

(1990) certification-screening model of upstairs markets in a context in which upstairs markets are exceedingly active in terms of the dollar value of shares traded.

We conjecture that the very rule denying upstairs market access to smaller stocks with greater information asymmetry could help to account for the failure to find any sign of filtering-certification, and the small price improvement upstairs on the ASX, since the inability to trade small stocks with severe informational asymmetry reduces the benefits of filtering. Moreover, ASX rules, which differ from most upstairs markets in that they provide an unfettered ability for price discovery to occur upstairs without reference to the downstairs market, might also encourage retention of informed trades in the upstairs market as does the ability of long-term clients to reward upstairs facililitating broker-dealers by providing them with profitable agency business. We then exploit a unique trading rule imposed by the ASX to address the central issue of market fragmentation: whether upstairs intermediation adversely affects downstairs market liquidity due to the utilization of punishment-filtering mechanisms or for any other reason.

Using three measures of upstairs market access, of which one is exogenously determined and two are endogenous, we find no evidence that upstairs market activity increases either market impact or the bid-ask spread in the downstairs market. Migration of trades to the upstairs market does not cause the high asymmetric information problems (high bid-ask spread and price impact) in the downstairs market that makes the upstairs market so valuable for investors at such times. Fortunately, our findings as to the lack of certification-screening, which is apparent in the market impact costs themselves and in the absence of any harm imposed by the upstairs market on the downstairs, are highly consistent.

Our results show that execution of most block trades on the ASX occurs in the upstairs market and, after controlling for market conditions and trade difficulty, both the upstairs market and crossing system provide lower price impact for block trades than the consolidated electronic limit order book. Following further analysis, the results show that upstairs market price improvement relates positively to downstairs time-varying market-condition related trade difficulty measures, such as the bid-ask spread. Surprisingly, it also relates positively to the cross-sectional ease of trade measure, stock size, but we would also expect there to be more upstairs dealers in larger stocks.[27] By contrast, all block trades utilizing the crossing system in our sample are trades of indexed stocks and their price improvement relates positively to the bid-ask spread and only to one cross-sectional trade difficulty measure, namely, stocks with lower trading volumes.

There is also evidence that the introduction of the crossing system in Australia is associated with a statistically significant increase in price improvement upstairs. This is consistent with complementarities between the two markets. One way of thinking about crossing networks is that they provide an exceptionally cheap form of counterparty search mechanism for traders for whom immediacy is not an issue. In recent times, the IRESS terminals used by the institutions now provide an expression of interest in terms of future upstairs and SEATS participation. Because of the improved efficiency of the upstairs market, it is becoming harder for the crossing network to succeed in the Australian environment, although it has achieved about the same market share as on the LSE and NYSE.

The demonstrated lack of harm to downstairs market participants, as well as the similarity in price discovery upstairs and downstairs, seem to deny any certification-filtering explanation for the role of upstairs markets but do not rule out an important search role for counterparties when conditions are tough downstairs. Nor does it rule out a risk-sharing role based on a single price auction upstairs and a discriminatory auction in the limit order book, according to Viswanathan and Wang (2002). However, several simple tests fail to support many of the very specific implications of the risk-sharing model, leaving us with the search model as the most promising explanation. We find additional support for the search model by showing that the market impact schedule is concave in trade upstairs but is not downstairs, as Keim and Madhavan (1996) predict.

Our results clearly support the assertion that the introduction and functioning of an upstairs market is Pareto improving, since harm to any market or set of market participants does not occur while investors who utilize the market gain. Our results

[27] An alternative explanation is that "shares outstanding" is increasing in market capitalization and the probability of finding a natural counterparty for a position increases in shares outstanding. While on the ASX larger stocks are typically larger by virtue of a higher price per share, there is no reason to think that ease of execution relates directly to the number of shares on issue since small investors are free to trade smaller parcels of larger stocks or larger parcels of smaller stocks.

also provide empirical support Pagano (1989a) who shows theoretically that a search role for the upstairs market can be Pareto-efficient and thus helps to explain its survival when, on the face of it, fragmentation would appear harmful.

What might these results imply for the design of all three markets: upstairs, crossing networks and downstairs markets? Perhaps the most important is that there may be scope for relaxing many of the severe controls, if not outright bans, on upstairs and crossing activity that are still the norm in markets worldwide. For example, the ASX could replace the minimum block trade size of AUS$1m across all stocks by a relative size measure for "specials" which does not discriminate so heavily against smaller, lower market capitalization, stocks trading upstairs during the period that the downstairs market is operating, or even abolish size limitations altogether. Simple simulations based on our estimates show considerable gains to participants from the relaxation of controls. Our results downplay the role of upstairs filtering, although implicit contracts based on order size and long-term institutional-broker relationships are likely to enhance the search role of upstairs dealers.

Our results confirm the intuition that diverse trading mechanisms arise endogenously to serve the needs of heterogeneous clienteles. Provided there is a level playing field that prevents off-market trades from free riding off the downstairs quotes, the forces of competition lead to the evolution of complex market structures that add value to all investors.

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Table I
Distribution of Block Trades

The table lists the distribution of block trades across the years of our sample and annual dollar trading volume deciles. The Exchange defines a block trade as a trade of over AUS$1m in value. According to the Business Rules of the Australia Stock Exchange, execution of these trades may take place on SEATS, off-market (upstairs), or on a crossing network. Our sample is the entire population of block trades over the investigation period. We rank the total dollar trading volume across all trades in each stock in each year to construct the annual dollar trading volume deciles. It shows that block trades concentrate in the most heavily traded stocks. The top dollar trading volume decile stocks alone account for 92.4% of all block trades.

Volume Decile	1993	1994	1995	1996	1997	1998	Total Across Years	
								% Grand Ttl
10 (Highest)	6,860	8,797	9,657	11,755	13,827	13,261	64,157	92.4%
9	313	542	535	1,061	1,012	932	4,395	6.3%
8	77	84	79	255	180	133	808	1.2%
7	6	14	11	25	14	6	76	0.1%
6	3	1	1	4	1	-	10	0.0%
5	-	-	-	-	2	-	2	0.0%
4	-	-	-	1	-	-	1	0.0%
Grand Total							69,449	

Table II
Proportion of Block Trades Executed Upstairs and in Crossing Network

Panel A: Upstairs Market

This panel shows the proportion of all block trades (AUS$1m and above) executed in the upstairs market by dealers.

Volume Decile	1993	1994	1995	1996	1997	1998	Across Years
10 (Highest)	85%	81%	75%	80%	82%	76%	80%
9	87%	87%	85%	82%	82%	88%	85%
8	81%	90%	94%	83%	77%	81%	83%
7	67%	93%	73%	96%	71%	83%	84%
6	100%	0%	0%	50%	0%		50%
5					100%		100%
4				100%			100%
Across all Deciles							80%

Panel B: Crossing Network

This panel shows the proportion of trades matched using the ITG/POSIT crossing network, which did not commence its operation in Australia until July 1997. We identify block trades executed by this crossing network using the masked broker identification number and the time of trade. The crossing network crosses orders at a random time during a five-minute interval following the official crossing time, 11 am, 12 pm and 3 pm. The orders that can be matched are reported to SEATS immediately afterwards. The trades of the crossing network operator in the fifteen minutes interval after the official crossing time are marked as crossing network trades. 238 crossing trades account for approximately one percent of the block trades in the same period. Block trades via the crossing networks are almost entirely (232/238) in the top dollar trading volume decile stocks.

10 (Highest)					1%	1%	
9					0%	0%	
8						1%	
7							
6							
5							
4							
Across all Deciles					1%	1%	

Table III
Summary Statistics of Price Impact Measures*

This table shows the mean and standard error of the price impact measures of all block trades. We define the price impact (total price impact) as *abs*(100 x log (pr_t/pb_t)), where pr_t is the price of the block trade and pb_t is a pre-block benchmark price, which might be the mid-quote on SEATS immediately, 10 or 20 trades prior to the block trade, or the opening trade price on the same trading day. Figure 1 shows graphically how the temporary and permanent price impacts are measured.

	SEATS LOB		Upstairs			Crossing Network		
N	12,022		47,628			238		
Variable	Mean	Std err	Mean	Std err	*t*-test for diff. fr. SEATS	Mean	Std err	*t*-test for diff. fr. SEATS
Panel A: Mid quote immediate prior to block								
Total price impact	0.210	(0.005)	0.392	(0.003)		0.062	(0.025)	
Panel B: Mid quote 10 trades pre- and post-block								
Total price impact	0.386	(0.008)	0.557	(0.004)		0.270	(0.038)	
Temporary price impact	0.021	(0.019)	0.134	(0.011)		0.040	(0.043)	
Permanent price impact	0.608	(0.020)	0.745	(0.011)		0.488	(0.040)	
Ratio of temporary to total price impact	0.113	(0.072)	0.158	(0.036)	0.554	0.055	(0.169)	-0.113
Panel C: Mid quote 20 trades pre- and post-block								
Total price impact	0.512	(0.009)	0.713	(0.005)		0.393	(0.047)	
Tempor. price impact	-0.038	(0.017)	0.082	(0.011)		-0.028	(0.042)	
Perman. price impact	0.806	(0.019)	1.041	(0.012)		0.584	(0.048)	
Ratio of temporary to total price impact	0.084	(0.264)	0.031	(0.030)	-0.362	-0.292	(0.219)	-0.200
Panal D: Opening and closing trade price								
Total price impact	1.861	(0.017)	1.873	(0.008)		1.663	(0.109)	
Tempor. price impact	0.993	(0.013)	0.969	(0.006)		0.672	(0.078)	
Perman. price impact	1.091	(0.013)	1.126	(0.005)		1.229	(0.077)	
Ratio of temporary to total price impact	0.483	(0.117)	0.508	(0.008)	0.390	0.575	(0.258)	0.110

Table IV
Summary Statistics of the Top 1% of Trades by Dollar Value

This table presents summary statistics for the trade-weighted average price impact, $atc_{j,y}$, of the top 1% of downstairs trades by trade value. A relative average price impact measure, $ratc_{j,y}$, is computed by scaling the average price impact of the top percentile trade with the average price impact of medium size trades (40-60 percentile). A third measure, the average bid-ask spread of stock j in year y, $apspd_{j,y}$, is computed as the trade-weighted average bid-ask spread across all trades. We compute three measures of potential upstairs trading cost. $uma_{j,y}$ is the proportion of the top 1 percentile downstairs trades in trade value in stock j, year y that have a trade value at or above AUS$1m. The higher is $uma_{j,y}$, the higher is the proportion of trades having access to the upstairs market. Additional measures are $utn_{j,y}$, the ratio of the actual number of upstairs trades to the total number of upstairs and downstairs trades in stock j, year y, and $utv_{j,y}$ the ratio of the dollar value of upstairs trades to the dollar value of upstairs and downstairs trades (no trade size restrictions) in stock j, year y.

Number of observations N=839

Variable	Mean	Std Dev	Min	Max
Average price impact, $atc_{j,y}$	0.53	0.57	0.05	7.87
Relative average price impact, $ratc_{j,y}$	1.09	0.34	0.42	5.35
Average bid-ask spread, $apspd_{j,y}$	1.10	1.22	0.08	20.28
Prop. top 1% dstairs trades > *$1*, $uma_{j,y}$	0.07	0.12	0.00	1.00
Act. # upstairs trades to total, $utn_{j,y}$	0.01	0.01	0.00	0.11
$ value upstairs to total, $utv_{j,y}$	0.16	0.13	0.00	0.67

Table V
Panel Regression of the Average Price Impact of the Top 1% of Trades by Dollar Value

The regression estimates for two measure of downstairs market impact, $atc_{j,y}$ and $ratc_{j,y}$ are presented in Panels A and B respectively. Three sets of results are reported in each panel, representing the three different measures of upstairs trading for the regression: $dep_{j,y} = \delta_1 + \delta_2 lttl_{j,y} + \delta_3 lmcap_{j,y} + \delta_4 stdrtn_{j,y} + \delta_5 indx_{j,y} + \delta_6 frag_{j,y} + e_{j,y}$, where, across all trades in stock j in year y, $dep_{j,y}$ is either $atc_{j,y}$ or $ratc_{j,y}$, $lttl_{j,y}$ denotes log of dollar volume, $lmcap_{j,y}$ denotes market capitalization, $stdrtn_{j,y}$ denotes standard deviation of daily returns, $indx_{j,y}$ indicates index inclusion, $frag_{j,y}$ is one of three upstairs market measures, $uma_{j,y}$, $utn_{j,y}$, and $utv_{j,y}$. $uma_{j,y}$ is the proportion of the top 1% downstairs trades in trade value in stock j, year y that have a trade value at or above one million Australia dollars. $utn_{j,y}$ is the ratio of the actual number of upstairs trades to the total number of upstairs and downstairs trades in stock j, year y, and $utv_{j,y}$ is the ratio of the dollar value of upstairs trades to the dollar value of upstairs and downstairs trades in stock j, year y.

		Upstrs Mkt Measure 1		Upstrs Mkt Measure 2		Upstrs Mkt Measure 3	
Variable	Coef.	Est.	*t*-stat.	Est.	*t*-stat.	Est.	*t*-stat.
Panel A: Average Price Impact (mid-quote immediately prior)							
Constant	δ_1	3.83	(19.47)	3.86	(19.59)	3.79	(20.68)
Log of \$ volume, $lttl_{j,y}$	δ_2	-0.01	(-0.48)	-0.01	(-0.52)	-0.01	(-0.43)
Log of market cap, $lmcap_{j,y}$	δ_3	-0.15	(-6.63)	-0.15	(-6.59)	-0.15	(-6.48)
Std dev of daily returns, $stdrtn_{j,y}$	δ_4	0.05	(4.89)	0.05	(4.88)	0.05	(4.84)
Index stock, $indx_{j,y}$	δ_5	-0.25	(-4.26)	-0.25	(-4.32)	-0.24	(-4.06)
Prp. top 1% dstairs trds > \$1m, $uma_{j,y}$	δ_6	-0.02	(-0.16)				
Act. # upstairs trades to total, $utn_{j,y}$	δ_6			0.72	(0.52)		
\$ value upstairs to total, $utv_{j,y}$	δ_6					-0.18	(-1.83)
Adjusted R-squared			0.58		0.58		0.58
F-statistic			232.39		232.42		233.50
N			839		839		839
Panel B: Average Relative Price Impact (mid-quote immediately prior)							
Constant	δ_1	1.59	(8.08)	1.49	(8.39)	1.56	(9.24)
Log of \$ volume, $lttl_{j,y}$	δ_2	0.01	(0.91)	0.02	(1.10)	0.01	(0.99)
Log of market cap, $lmcap_{j,y}$	δ_3	-0.03	(-2.09)	-0.03	(-1.86)	-0.03	(-2.05)
Std dev of daily returns, $stdrtn_{j,y}$	δ_4	0.01	(1.46)	0.01	(1.44)	0.01	(1.40)
Index stock, $indx_{j,y}$	δ_5	-0.19	(-4.33)	-0.19	(-4.40)	-0.18	(-4.16)
Prp. top 1% dstairs trds > \$1m, $uma_{j,y}$	δ_6	0.01	(0.06)				
Act. # upstairs trades to total, $utn_{j,y}$	δ_6			-3.90	(-1.97)		
\$ value upstairs to total, $utv_{j,y}$	δ_6					-0.07	(-0.71)
Adjusted R-squared			0.12		0.12		0.12
F-statistic			22.97		23.75		23.08
N			839		839		839

Table VI

Panel Regression explaining the Average Percentage Bid-Ask Spread

This table presents the regression estimates for $apspd_{j,y}$, the average trade weighted bid-ask spread in the downstairs market. Three sets of results are reported in each column, representing the three different measures of upstairs trading for the regression: $apspd_{j,y} = \delta_1 + \delta_2 lttl_{j,y} + \delta_3 lmcap_{j,y} + \delta_4 stdrtn_{j,y} + \delta_5 indx_{j,y} + \delta_6 frag_{j,y} + e_{j,y}$, where across all trades in stock j in year y, $lttl_{j,y}$ denotes log of dollar volume, $lmcap_{j,y}$ denotes market capitalization, $stdrtn_{j,y}$ denotes standard deviation of daily returns, $frag_{j,y}$ is one of three upstairs market measures, $uma_{j,y}$, $utn_{j,y}$, and $utv_{j,y}$. $uma_{j,y}$ is the proportion of the top 1% downstairs trades in trade value in stock j, year y that have a trade value at or above one million Australia dollars. $utn_{j,y}$ is the ratio of the actual number of upstairs trades to the total number of upstairs and downstairs trades in stock j, year y, and $utv_{j,y}$ is the ratio of the dollar value of upstairs trades to the dollar value of upstairs and downstairs trades in stock j, year y.

		Upstrs Mkt Measure 1		Upstrs Mkt Measure 2		Upstrs Mkt Measure 3	
Variable	Coef.	Est.	*t*-stat.	Est.	*t*-stat.	Est.	*t*-stat.
Constant	δ_1	7.41	(11.11)	7.50	(11.08)	7.22	(11.32)
Log of \$ volume, $lttl_{j,y}$	δ_2	0.02	(0.28)	0.02	(0.34)	0.03	(0.44)
Log of market cap, $lmcap_{j,y}$	δ_3	-0.34	(-4.92)	-0.35	(-4.92)	-0.34	(-4.86)
Std dev of daily returns, $stdrtn_{j,y}$	δ_4	0.19	(2.60)	0.19	(2.60)	0.19	(2.55)
Index stock, $indx_{j,y}$	δ_5	-0.30	(-1.87)	-0.32	(-2.01)	-0.30	(-2.04)
Prp. top 1% dstairs trds > \$1m, $uma_{j,y}$	δ_6	0.26	(1.77)				
Act. # upstairs trades to total, $utn_{j,y}$	δ_6			8.67	(1.39)		
\$ value upstairs to total, $utv_{j,y}$	δ_6					-0.20	(-0.93)
Adjusted R-squared			0.70		0.70		0.70
F-statistic			390.72		392.22		390.24
N			839		839		839

Table VII
Price Impact Regression for Downstairs SEATS Block Trades

This table presents the estimation of the first stage SEATS block trade price impact regression model: $c_t = \alpha_1 + \alpha_2 pspd_t + \alpha_3 pspdsq_t + \alpha_4 szrdpt_t + \alpha_5 szrsq_t + \alpha_6 time_t + \alpha_7 lmcap_t + \alpha_8 indx_t + \alpha_9 ldlyv_t + \alpha_{10} ent_t + \varepsilon_t$, where $pspd_t$ is the percentage quoted bid-ask spread immediately prior to trade *t*, $pspdsq_t$ is the square of $pspd_t$, $szrdpt_t$ is trade size in number of shares in trade *t* divided by the number of shares available in the best two prices in limit order book immediately prior to trade *t*, $szdsq_t$ is the square of $szrdpt_t$, $time_t$ is the reported time of trade *t*, $lmcap_t$ is the logarithm of average market capitalization of the company of trade *t* in the same calendar year, $indx_t$ is a dummy that equals 1 if the company of trade *t* is a stock included in the All Ordinaries Index and 0 otherwise, $ldlyv_t$ is the logarithm of the average daily dollar trading volume of the company of trade *t* in the same calendar year, ent_t is a dummy that equals 1 on or after July 2, 1997, the day that the crossing network commenced operation, and ε_t is the residual error term using the mid-quote immediately, 10 and 20 trades prior to the block trade as benchmark price.

		Immed. prior		10 trades prior		20 trades prior	
Variable	Coef.	Est.	*t*-stat.	Est.	*t*-stat.	Est.	*t*-stat.
Constant	α_1	0.20	(3.49)	2.06	(8.53)	3.00	(10.29)
% bid-ask spread, $pspd_t$	α_2	0.50	(30.02)	0.62	(10.77)	0.74	(11.33)
Sqre % bid-ask sprd, $pspdsq_t$	α_3	0.00	(-1.30)	-0.05	(-4.10)	-0.07	(-5.52)
Trade size/mkt depth, $szrdpt_t$*	α_4	0.10	(3.11)	0.47	(3.97)	0.63	(4.48)
Square rel. trade size, $szdsq_t$**	α_5	-0.01	(-1.53)	-0.03	(-0.78)	-0.05	(-1.26)
Reported trade time, $time_t$**	α_6	0.00	(0.40)	-0.02	(-7.26)	-0.04	(-10.27)
Log market cap., $lmcap_t$	α_7	-0.01	(-1.51)	0.01	(1.00)	0.03	(1.60)
Index inclusion, $lndx_t$	α_8	0.02	(0.44)	-0.25	(-1.99)	-0.33	(-2.21)
Log av. daily trad. vol., $ldlyv_t$	α_9	0.00	(-0.63)	-0.11	(-6.68)	-0.16	(-8.14)
Intro. crossing network, ent_t	α_{10}	-0.01	(-1.83)	-0.02	(-1.72)	0.01	(0.51)
Adj. R-squared			0.71		0.33		0.31
F-statistic			3,251.20		647.23		590.26
Number			12,022		12,022		12,022

*Coefficient estimates × 100

**Coefficient estimates × 10,000

Table VIII

Summary Statistics for Upstairs Price Improvement

This table contains the univariate statistics of the upstairs price improvement estimate, $piprv_u = \hat{c}_u - c_u$, with $\hat{c}_u = \alpha_1 + \alpha_2 pspd_u + \alpha_3 pspdsq_u + \alpha_4 szrdpt_u + \alpha_5 szdsq_u + \alpha_6 time_u + \alpha_7\, lmcap_u + \alpha_8 indx_u + \alpha_9 ldlyv_u + \alpha_{10} ent_u$, where $pspd_u$ is the percentage quoted bid-ask spread immediately prior to upstairs trade *u*, $pspdsq_u$ is the square of $pspd_u$, $szrdpt_u$ is trade size in number of shares in upstairs trade *u* divided by the number of shares available in the best two prices in limit order book immediately prior to upstairs trade *u*, $szdsq_u$ is the square of $szrdpt_u$, $time_u$ is the reported time of upstairs trade *u*, $lmcap_u$ is the average market capitalization of the company of upstairs trade *u* in the same calendar year, $indx_u$ is a dummy that equals 1 if the company of upstairs trade *u* is a stock included in the All Ordinaries Index, 0 otherwise, $ldlyv_u$ is the logarithm of the average daily dollar trading volume of the company of upstairs trade *u* in the same calendar year, ent_u is a dummy that equals 1 on or after July 2, 1997, the day that the crossing network commenced operation, and ε_u is the residual term using the mid-quote immediately, 10 and 20 trades prior to the upstairs trade *u* as benchmark price. c_u is the actual price impact cost upstairs. $\hat{c}_u$ is computed using the coefficients estimated from the downstairs market but utilizing values corresponding to the time of the upstairs trade.

Benchmark Price		Upstairs Market	Crossing Network
Mid-quote immediately prior	Mean	-0.078	0.139
	Std err	0.002	0.015
Mid-quote 10 trades prior	Mean	0.021	0.136
	Std err	0.003	0.021
Mid-quote 20 trades prior	Mean	0.040	0.177
	Std err	0.004	0.027
Number of observations, *N*		47,628	238

Table IX
Upstairs Block Trades Price Improvement and Trade Difficulty

In this table we estimate the regression equation explaining the upstairs price improvement: $piprv_u = \beta_1 + \beta_2 pspd_u + \beta_3 pspdsq_u + \beta_4 szrdpt_u + \beta_5 szdsq_u + \beta_6 time_u + \beta_7 lmcap_u + \beta_8 indx_u + \beta_9 ldlyv_u + \beta_{10} ent_u + \varepsilon_u$, where $pspd_u$ is the percentage quoted bid-ask spread immediately prior to upstairs trade u, $pspdsq_u$ is the square of $pspd_u$, $szrdpt_u$ is trade size in number of shares in upstairs trade, u, divided by the number of shares available in the best two prices in the limit order book immediately prior to upstairs trade u, $szdsq_u$ is the square of $szrdpt_u$, $time_u$ is the reported time of upstairs trade u, $lmcap_u$ is the average market capitalization of the company of upstairs trade u in the same calendar year, $indx_u$ is a dummy that equals 1 if the upstairs trade u is in a stock included in the All Ordinaries Index, 0 otherwise, $ldlyv_u$ is the logarithm of the average daily dollar trading volume for the upstairs trade's u , stock in the same calendar year, ent_u is a dummy that equals 1 on or after July 2, 1997, the day that the crossing network commenced operation, and ε_u is the residual term using the mid-quote immediately, 10 and 20 trades prior to the upstairs trade u as benchmark price.

		Mid-quote 10 trades prior		Mid-quote 20 trades prior	
Downstairs variables corresponding to upstairs trades	Coef.	Est.	*t*-stat.	Est.	*t*-stat.
Constant	β_1	-0.99	(-7.83)	-0.97	(-6.59)
% bid-ask spread, $pspd_u$	β_2	0.15	(6.59)	0.14	(4.49)
Square % bid-ask sprd, $pspdsq_u$	β_3	-0.02	(-5.47)	-0.03	(-5.78)
Trade size / mkt depth, $szrdpt_u$*	β_4	0.20	(5.26)	0.35	(8.65)
Square rel. trade size, $szds_u$**	β_5	-0.02	(-4.23)	-0.04	(-8.92)
Reported trade time, $time_u$**	β_6	-0.01	(-6.80)	-0.02	(-9.80)
Log market cap., $lmcap_u$	β_7	0.04	(4.85)	0.06	(5.47)
Index inclusion, $indx_u$	β_8	-0.03	(-0.46)	-0.16	(-2.04)
Log av. daily trad. vol., $ldlyv_u$	β_9	0.01	(1.03)	0.01	(0.49)
Intro. crossing network, ent_u	β_{10}	0.00	(0.59)	0.04	(5.07)
Adj. *R*-squared				0.18	
F-statistic				218.40	
Number				47,628	

*Coefficient estimates $\times 100$
**Coefficient estimates $\times 10{,}000$

Table X

Crossing Network Price Improvement and Trade Difficulty

In this table we estimate the regression equation explaining the crossing network price improvement: $piprv_u = \beta_1 + \beta_2 pspd_u + \beta_3 pspdsq_u + \beta_4 szrdpt_u + \beta_5 szdsq_u + \beta_6 time_u + \beta_7 lmcap_u + \beta_9 ldlyv_u + \varepsilon_u$, where $pspd_u$ is the percentage quoted bid-ask spread immediately prior to crossing network trade *u*, $pspdsq_u$ is the square of $pspd_u$, $szrdpt_u$ is trade size in number of shares in the crossing network trade *u* divided by the number of shares available in the best two prices in limit order book immediately prior to crossing network trade *u*, $szdsq_u$ is the square of $szrdpt_u$, $time_u$ is the reported time of upstairs trade *u*, $lmcap_u$ is the average market capitalization for the crossing network trade's *u* company in the same calendar year, $ldlyv_u$ is the logarithm of the average daily dollar trading volume for the crossing network trade's *u* company in the same calendar year, and ε_u is the residual term using the mid-quote immediately, 10 and 20 trades prior to the crossing network trade *u* as benchmark price.

Downstairs variables corresponding to the timing of crossing trades		Full Model		Stremld Mdl 1		Stremld Mdl 2	
Panel A: Mid-quote immediately prior							
Variable	Coef.	Est.	*t*-stat.	Est.	*t*-stat.	Coef..	*t*-stat.
Constant	β_1	0.65	(2.08)	0.49	(3.15)	0.36	(2.33)
% bid-ask spread, $pspd_u$	β_2	0.26	(2.62)	0.27	(2.60)	0.37	(5.55)
Square % bid-ask, $pspdsq_u$	β_3	0.04	(0.90)	0.04	(0.86)		
Trde size/mkt depth, $szrdpt_u$*	β_4	0.36	(1.60)	0.36	(1.64)	0.37	(1.68)
Square rel. trade size, $szdsq_u$*	β_5	-0.51	(-1.04)	-0.51	(-1.04)	-0.56	(-1.11)
Reported trade time, $time_u$**	β_6	0.00	(-0.53)				
Log market cap., $lmcap_u$	β_7	-0.01	(-0.37)				
Log av. daily trad. vol., $ldlyv_u$	β_9	-0.02	(-0.56)	-0.03	(-3.49)	-0.02	(-2.77)
Adj. *R*-squared		0.59		0.59		0.59	
F-statistic			48.99		68.94		84.46
N			238		238		238
Panel B: Mid-quote 10 trades prior							
Constant	β_1	1.63	(2.04)	1.91	(4.84)	1.11	(2.50)
% bid-ask spread, $pspd_u$	β_2	-0.43	(-2.50)	-0.44	(-2.65)	0.16	(1.01)
Square % bid-ask, $pspdsq_u$	β_3	0.21	(4.06)	0.21	(4.50)		
Trde size/mkt depth, $szrdpt_u$*	β_4	-0.51	(-1.54)	-0.52	(-1.57)	-0.45	(-1.28)
Square rel. trade size, $szdsq_u$*	β_5	1.81	(3.81)	1.80	(3.84)	1.52	(3.15)
Reported trade time, $time_u$**	β_6	0.00	(0.08)				
Log market cap., $lmcap_u$	β_7	0.03	(0.42)				
Log av. daily trad. vol., $ldlyv_u$	β_9	-0.13	(-1.94)	-0.10	(-4.64)	-0.06	(-2.53)
Adj. *R*-squared			0.29		0.30		0.20
F-statistic			15.01		21.11		15.87
N			238		238		238

Panel C: Mid-quote 20 trades prior

Constant	β_1	0.96	(0.98)	1.26	(2.65)	2.48	(4.17)
% bid-ask spread, $pspd_u$	β_2	0.71	(3.28)	0.68	(3.28)	-0.23	(-0.95)
Square % bid-ask, $pspdsq_u$	β_3	-0.34	(-6.07)	-0.33	(-6.35)		
Trde size/mkt depth, $szrdpt_u$*	β_4	-0.01	(-1.63)	-0.01	(-1.62)	-0.01	(-1.79)
Square rel. trade size, $szdsq_u$*	β_5	0.00	(2.27)	0.00	(2.22)	0.00	(2.59)
Reported trade time, $time_u$**	β_6	0.00	(-0.90)				
Log market cap., $lmcap_u$	β_7	0.05	(0.56)				
Log av. daily trad. vol., $ldlyv_u$	β_9	-0.12	(-1.43)	-0.07	(-2.70)	-0.13	(-4.06)
Adj. R-squared			0.23		0.23		0.10
F-statistic			10.94		15.17		7.85
N			238		238		238

*Coefficient estimates × 100
**Coefficient estimates ×10,000

Table XI
Summary Statistics of All Eligible Block Trades, 1993-1998, for Simple Tests of the Risk-Sharing Model

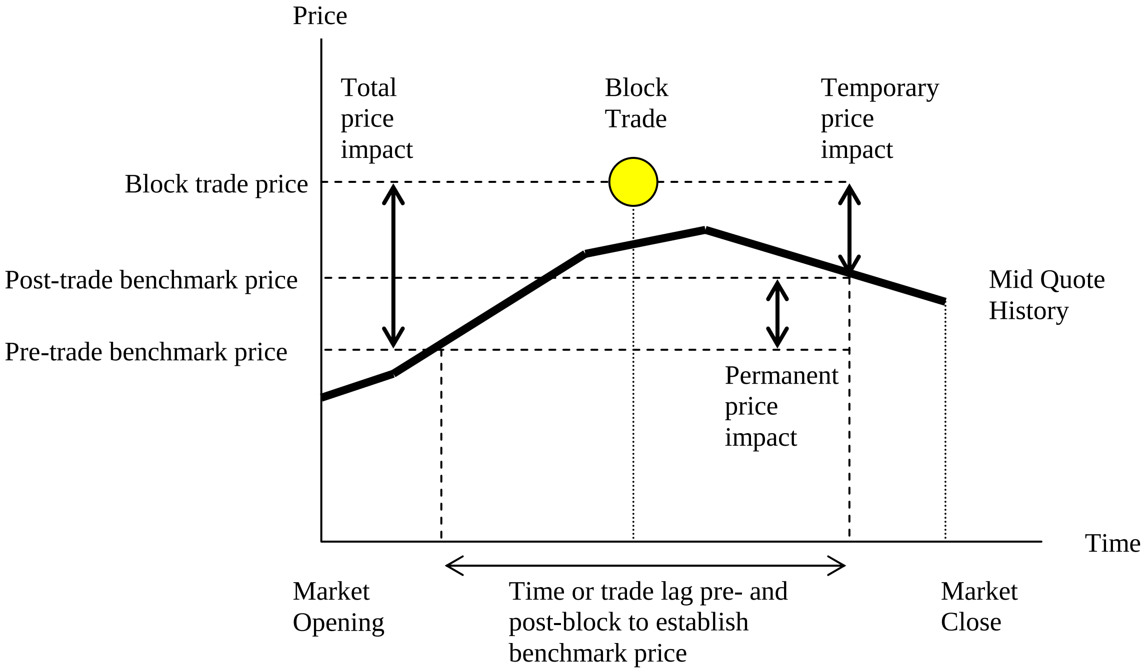
	Limit Order Book	Upstairs Market
Market Impact, c_t	0.511759	0.716483
Number of Broker-Dealers, *nd*	16.02	15.82792
Daily Std. Dev. of Stock Returns, $stdrtn_t$	0.0043437	0.0045894
Trade Size defl. by LOB Depth, $szrdpt_t$	6.62321	17.35995
Product, $stdrtn_t \times szrdpt_t$	0.031975	0.085079
Product, $stdrtn_t \times szrdpt_t \times nd$	0.27119	1.02727
Number of Observations, N	12,022	47,403

Table XII
Simple Explanation for Market Impacts in the Limit Order Book and Upstairs based on the Viswanathan and Wang Risk-Sharing Model

The model is $c_t = \alpha_0 + \alpha_1 stdrtn_t.szrdpt_t + \alpha_2 stdrtn_t.szrdpt_t.nd + \alpha_3 nd$, where the variables are as described in Table XI.

	Limit Order Book		Upstairs Market	
	Est.	t-val	Est.	t-val
Constant	1.0511	(42.97)	1.89963	(62.48)
$std_t \times szrdpt_t$	1.6962	(7.35)	0.53260	(3.23)
$std_t \times szrdpt_t \times nd$	-0.0943	(5.44)	-0.01163	(1.1)
Number of broker-dealers, *nd*	-0.0355	(32.3)	-0.07686	(50.3)
Adj.R-squared	0.202982		0.217811	
F_Statistic	1,021.49		4,400.91	

Figure 1. Graphical presentation of price impact measures



We define the total price impact of a block trade as the return from a pre-trade benchmark price to the block trade price. The benchmark price is either the mid-point of the bid-ask quote sampled at 10 or 20 trade pre- or post block, or the trade price of the first or last trade on the same trading day. We define the temporary price impact as the return from the block trade price to a post-trade benchmark price, time –1 (such that we interpret a positive value as a positive reversal and liquidity cost). We define the permanent price impact of a trade as the return from the pre-block benchmark price to the post-block benchmark price. Figure 1 depicts a block trade executing at above the mid quote at the time of the block. Consider this block as a buyer initiated block, with positive price impact (total price impact), positive price reversal and positive permanent price impact.