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Liquidity supply in electronic markets ☆

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Abstract

We examine the supply of liquidity by proprietary trading desks and hedge funds (PTDH) versus mutual funds, index funds, and insurance companies (MII) across ten bid (ask) steps of the limit order book. We document that institutional investors simultaneously supply liquidity at multiple prices in the limit order book. We also find that PTDHs are more price aggressive liquidity suppliers than MIIs, consistent with hypothesized responses to observed changes in the cost and risk of non-execution. We investigate whether these findings are robust to fast versus slow markets, the volatility of daily returns, and aggregate depth relative to daily volume.

JEL classification: G24; G25; G29

Keywords: Limit order book; Liquidity; Execution risk; Institutional orders

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1. Introduction

Screen-based order-driven automated trading is now the exclusive or predominant method of trading on most of the world's exchanges, and there is keen interest in understanding how such trading can rely on limit orders to provide the primary source of liquidity in times of market stress. In fast-paced markets, how can automated limit order trading elicit the price improvement often claimed as an advantage for dealer markets with specialists and floor traders? To address this question, this paper looks to the Australian Stock Exchange (ASX)—the second longest-running and one of the most efficient screen-based markets–to detect a likely direction of evolution of the North American markets.[1] Our findings concerning Australia should provide insights that are applicable to electronic markets worldwide, including ECNs in the US.

We show for the first time that rather than supplying liquidity at a single step in the limit order book (LOB), most institutional investors frequently display liquidity simultaneously *at multiple prices*. This multiple-price order submission practice is especially prevalent in fast-paced markets. In addition, we show for the first time that aggressiveness in placing limit orders at or near the BBO varies by type of institution. Proprietary trading desks and hedge funds are more aggressive in their supply of liquidity than mutual funds, index funds, and insurance companies, consistent with hypothesized behavior in response to differences in the cost and risk of non-execution. These findings prove to be robust to volatility, volume, and depth differences in the state of the market.

We employ a unique dataset of "snapshots" of the LOB at particular times of the trading day provided by several of the largest institutional brokers in Australia.[2] The sample comprises eighteen months of data for 35 of the most actively traded stocks. Our approach differs from previous empirical work in three ways.

First, because cooperating brokerage firms provided their schedule of clients supplying liquidity up and down the LOB, we are able to investigate multi-priced liquidity supply. Biais, Martimort, and Rochet (2000) hypothesize that a multi-price schedule of offers will emerge as an optimal execution strategy in order-driven markets with an asymmetrically informed and risk-averse liquidity demander facing competing liquidity suppliers of a common value asset. We show institutional investors in leading stocks typically do split the quantities they desire to supply across multiple price steps of the LOB. Our work on these institution-by-institution schedules of liquidity supply is also related to Handa and Schwartz (1996) who assess the profitability of a multi-price trading strategy by placing a "network" of both buy and sell limit orders simultaneously. The difference is that we document as standard practice liquidity supply at multiple prices on one side of the book only. Specifically, VWAP benchmarks necessarily entail multiple prices as institutions protect their time priority at various prices. Individual decisions to purchase at a specific price *or better* cannot achieve these better prices without a multi-price execution strategy.

Second, we are able to test hypotheses concerning the relative aggressiveness of types of institutional investors in supplying liquidity. One type of institutional client comprises those whose primary objective is to obtain superior risk-adjusted returns, including

[1] The ASX began electronic trading in 1987 and for several years has exhibited average spreads of approximately 0.01 AUD for thickly-traded stocks, which is less than 0.01 USD.

[2] An observation of the liquidity supplied by institutional clients of our cooperating brokers for AMP at 10:50 on May 13, 2002 is an example of one such snapshot.

proprietary trading desks and hedge funds—i.e., macro, market-neutral, long-short, arbitrage, event-driven, quantitative funds. We abbreviate this type of client as PTDH. Another type of institutional client includes mutual funds, insurance companies, and index funds—abbreviated as MII. Unlike PTDHs, MIIs do not actively assess the state of the market intraday in order to pursue fleeting opportunities to capture trading profits. Instead, MIIs are benchmark-focused and emphasize cost control, rather than out performance.

Third, in addition to liquidity at the BBO, we are able to study liquidity supply at individual price steps that are inferior to the best prevailing quotes, as modeled by Goettler, Parlour, and Ranjan (2004). Previous empirical work on institutional trading by Keim and Madhavan (1995) was unable to analyze liquidity supply away from the BBO because the complete LOB data were not available. Keim and Madhavan hypothesized that institutions with short-lived information or with greater deviation between their reservation prices and consensus intrinsic value prefer more aggressive order placement. While we too do not have access to the client IDs on the price steps of the complete limit order book, we are able to test this proposition with 12,064 snapshots of the institutional clients found on the individual price steps of the order books of the largest institutional trading desks.

In an electronic trading environment, demanders of liquidity place marketable limit orders that can be executed immediately against liquidity supply already standing in the book. Marketable limit orders are analogous to the market orders for immediate execution at posted prices in a specialist or dealer market such as the New York Stock Exchange. Theoretical works such as Parlour (1998), Foucault (1999), and Handa, Schwartz and Tiwari (2003) focus primarily on this choice between demanding liquidity by placing market orders (or marketable limit orders) and supplying liquidity by submitting limit orders that cannot be immediately executed. Keim and Madhavan (1995) report that institutional traders show a surprisingly strong demand for immediacy attributable either to a belief that their information is short-lived or to their high opportunity cost of failing to execute.

Because we examine the supply of liquidity on the order books of the largest trading desks *at a given point in time*, we do not address the choice of order type between market orders and limit orders. In fact, no marketable limit orders can show up in our sample because marketable limit orders execute immediately against depth standing in the ASX's electronic LOB. Therefore, we do not address overall institutional aggressiveness, but the aggressiveness of liquidity supply. This is a limitation of our study. Our paper focuses directly on the supply of liquidity offered by institutions at or away from the BBO, throughout ten steps on the ask and ten steps on the bid side of the market. In Australian equities, ten price steps at 0.01 AUD each represent seven US cents, and it is not uncommon for institutions to supply liquidity throughout most if not all of the price steps of the LOB as part of their trading strategies. We know that this multi-price behavior do not represent stale quotes because trading desk employees actively monitor the outstanding limit orders in our study.[3]

Similarly, again because our cooperating brokers agreed to a proprietary data release only at given points in time, we do not address any aspect of the *flow* of orders over time. Barclay and Warner (1993) hypothesize that informed traders break up their trades into

[3]We have direct access to the trading desks because members of our research team manage the desks.

medium-sized lots to stealth trade. Biais, Hillion, and Spatt (1995) focus on the aggressiveness of new liquidity supply relative to the supply of liquidity already in the LOB. Their least aggressive class of orders are all buy (sell) orders less (greater) than the prevailing best bid (ask), followed by orders at the BBO, then orders inside the BBO, marketable limit orders that cross the spread with depth insufficient to change the BBO, and finally marketable limit orders to buy (sell) that improve the best ask (bid). Griffiths, Smith, Turnbull, and White (2000) and Ranaldo (2004) adopt this taxonomy to study order aggressiveness, conditional on intraday market metrics. Grammig, Heinen, and Rengifo (2004) analyze a multivariate time series of count data for an expanded continuum of order types along the steps of the Xetra LOB. Lee, Liu, Roll, and Subrahmanyam (2004) investigate the persistence of order imbalance, the refresh rate, and order splitting in Taiwan's electronic market.

Although such questions about stealth trading, order placement dynamics, and the cancellation or refresh rate clearly require continuous order flow information (i.e., a "reconstruction of the book"); other microstructure research questions just as clearly do not. Specifically, the present paper employs 12,064 snapshots of the state of the limit order book at several leading institutional brokerage houses to examine cross-sectional hypotheses about liquidity supply by trader type for 35 top equities over 18 months.

Our findings about multi-price liquidity supply at particular points in time and about the relative price aggressiveness of types of institutional traders at these points in time provide insights that complement the extensive ongoing efforts to study the flow of orders over time. For example, hidden limit orders on the NYSE and Nasdaq involve dynamic order submission flow concepts like price improvement (Tuttle, 2002). Hidden limit orders do exist in Australia in the sense that partial depth in orders over 200,000 shares can be undisclosed. But in Australia hidden depth executes right along with the disclosed depth on that same price step. Moreover, even if there is only hidden depth at a given price step, the fact that there is hidden depth at that price is disclosed to the market even though the number of shares hidden is unknown.[4] Hence, in an order-driven automated trading system, no price improvement can result from the failure to disclose full depth. Since our paper is about price step aggressiveness in providing liquidity supply, hidden limit orders can not affect our results.

2. An overview of client data

Two of the largest institutional brokerage firms in Australia (Cooperating Broker 1 and Cooperating Broker 2, respectively) agreed to provide us with proprietary data obtained from analysis of all of their internal order records for parts of our analysis.

The firms were willing to provide these data on a one-time-only basis and aggregated in such a way that individual client identities were masked. Individual institutional clients were identified as proprietary trading desks and hedge funds (PTDH1, PTDH2, PTDH3 and so on) versus mutual funds, index funds, and insurance companies (MII1, MII2, MII3 and so on). Moreover, the brokers insisted that we collect data only on a discontinuous basis; we negotiated for 20-min intervals between trading desk order book snapshots.

In Australia institutions typically trade through a variety of brokerage firms so that each firm handles a cross-section of the order flow although the share of the order flow varies

[4]Our data sets from the institutional brokers and the ASX reveal both the disclosed and undisclosed depth.

from firm to firm. Hence, examination of the order flow of any of the top brokers provides a representative sample of the entire institutional order flow. Both of the cooperating brokers in our sample are well within the top ten institutional brokers. Together their trading represented 15% of the ASX turnover and 20% of the institutional trading volume. Each of our cooperating brokers has more than 70 MII and 150 PTDH clients.

It is also possible that institutional brokers channel their orders through retail brokers in order to disguise their order flow. While this is a limitation of our study we do not think that this limitation is serious because this type of disguising is most likely to occur in thinner stocks rather than in the thick stocks comprising our sample.

The Australian Stock Exchange (ASX) is open from 10:00 to 16:05. For each institutional client, we capture all of the liquidity supply on the LOB of our cooperating brokerage firms at twenty-minute intervals from 10:10 to 15:50 for the time period 1 January 2001–30 June 2002. We aggregated these discontinuous snapshots of the LOB by ASX-listed security and retained the 35 securities with the most snapshots. Descriptive statistics for the 35 securities in the sample are presented in Table 1. All these securities are actively traded with daily trading volume ranging from 0.25 million shares to more than 8 million shares and an average daily number of trades ranging from 45 to more than 1,000. The firms come from fourteen different industries. Note that all of the data in Table 1 come from the ASX LOB.

Again, the choice of snapshots as a data collection technique was required by our cooperating brokers. Table 2 provides an example on a particular trading day of a representative 10:50 snapshot of the order book for AMP obtained from Cooperating Broker 1.[5] One can see immediately that several institutional clients are supplying liquidity at multiple prices simultaneously. For example, on the bid side, PTDH1 demands 35,000 shares at the best bid of 6.61AUD and another 50,000 shares one step away. More significantly, client MII2 demands 1,500 shares at 6.59, two steps away from the best bid, while simultaneously demanding 20,000 shares at the still less aggressive bid of 6.56. On the sell side, MII4 offers 3,500 shares at 6.69, seven steps away from the best ask of 6.62, and simultaneously offers 10,000 shares nine steps away at 6.71. Other randomly selected snapshots reveal the same phenomenon. This discovery prompted us to investigate the simultaneous supply of liquidity at multiple prices in greater detail.

3. Liquidity supply at multiple steps of the LOB

3.1. Theoretical considerations: price schedules

Biais, Martimort, and Rochet (2000) analyze the optimal mechanism design for an oligopolistic strategic liquidity supplier who responds to the residual demand of a risk-averse and privately informed liquidity demander. The setting is a common value auction with asymmetric information (a screening problem), and the competing liquidity suppliers are modeled as multiple risk-neutral principals interacting continuously with the order flow of the risk-averse agent demanding liquidity. A unique equilibrium is derived that satisfies multiple principal-agent joint optimization with incentive compatibility and participation

[5]Cooperating Broker 1 and Cooperating Broker 2 were not willing to provide client-level data. Instead, these brokers provided aggregated data suitable for our analysis. The client-level data presented in Table 2 is an exception.

Table 1
Descriptive statistics for sample firms

For each firm in our sample, we present the average daily volume and average daily number of trades over our sample period on the ASX, the market capitalization in AUD as of 30/6/2002, and the industry. Our proprietary data represents a subset of these data.

Symbol	Daily volume	Daily number of trades	Market cap	Industry
ALL	937,580	206	$2,352,250,991	Hotels Restaurants and Leisure
AMC	1,745,671	378	$7,239,374,270	Materials
AMP	1,826,190	887	$15,904,321,926	Insurance
ANZ	3,189,261	919	$28,471,851,903	Banks
AXA	1,238,841	182	$4,564,703,778	Insurance
BHP	8,319,169	1,702	$34,429,978,064	Materials
BIL	2,383,074	681	$6,729,202,189	Commercial Services and Supplies
BPC	1,943,174	103	$513,775,574	Food Beverage and Tobacco
CCL	1,542,702	254	$4,468,494,449	Food Beverage and Tobacco
CML	2,353,500	698	$7,000,867,103	Food and Staples Retailing
CSL	264,869	320	$3,603,226,956	Pharmaceuticals and Biotechnology
CSR	2,239,586	336	$6,160,042,762	Materials
FGL	3,663,749	489	$10,134,642,533	Food Beverage and Tobacco
GAN	1,460,056	59	$1,669,709,782	Real Estate
IOF	1,063,097	69	$937,786,495	Real Estate
IPG	724,027	45	$1,464,344,031	Real Estate
JHX	539,308	98	$3,081,485,329	Materials
LLC	1,154,443	648	$4,718,976,285	Real Estate
MAY	2,961,846	699	$3,004,306,090	Health Care Equipment and Services
NAB	2,940,740	1,265	$54,056,008,486	Banks
NCP	4,777,945	1,303	$20,148,311,117	Media
NCPDP	2,830,865	502	$26,153,515,339	Media
ORI	829,575	315	$2,631,800,208	Materials
OSH	3,421,414	240	$914,280,416	Energy
OST	1,162,799	211	$878,108,131	Materials
PPX	672,944	238	$1,831,849,181	Materials
QAN	5,758,646	765	$6,521,291,017	Transportation
RIO	1,191,498	547	$16,695,376,474	Materials
SRP	1,545,816	349	$4,169,582,560	Food Beverage and Tobacco
SSX	811,155	110	$1,045,061,502	Materials
WBC	3,294,435	778	$26,639,643,318	Banks
WFT	3,017,098	147	$6,583,184,735	Real Estate
WMC	3,468,225	722	$8,509,933,769	Materials
WOW	2,278,379	632	$12,534,232,063	Food and Staples Retailing
WPL	1,723,316	478	$8,686,666,671	Energy

constraints. Biais, Martimort, and Rochet show that in such settings, liquidity suppliers do not bid the price down to the asset's expected intrinsic value (conditional on trade size) as in Betrand competition but rather compete in schedules of prices and quantities for which they earn positive expected profit. In addition, the liquidity demander splits orders across liquidity suppliers who are themselves competing by posting schedules of depths available at multiple prices.

Handa and Schwartz (1996) also analyze a "network" of multiple buy and sell limit orders simultaneously centered on actual market prices, reentering orders as others execute to maintain the network around the most recent price. They introduce real LOB data,

Table 2
Example profile of the LOB at 10:50

We present an example of the LOB for one security for one day at 10:50 obtained from Cooperating Broker 1. These client-level data are more detailed than the MII- and PTDH-level data supplied to us for our subsequent analysis. Data for nine steps on the bid side and nine steps on the ask side of the market are displayed as well as the time priority within each step. Tick sizes on the ASX are 0.01 AUD so that ten price steps represent less than ten US cents. Institutional liquidity supplied by clients of Cooperating Broker 1 is designated PTDH (proprietary trading desks and hedge funds) or MII (mutual funds, index funds, and insurance companies). PTDH1 and PTDH2 represent the masked identities of the first and second PTDH client and so forth. The remaining orders represent liquidity supplied by institutional clients of other institutional brokerage firms in the ASX LOB. Consider the bid side at 6.59 AUD. The client MII2 has the first time priority, followed by the institutional supplier of 3,100 shares, then the MII1 client with 10,200 shares, and finally the institutional supplier of 1,517 shares. If other institutional brokers have multiple limit orders at a given price standing in the LOB without an intervening MII or PTDH order, we sum their volume and report the consolidated number of orders and volume.

Bid side				Ask side			
Client	Volume	Price		Price		Volume	Client ID
		AUD	Step	Step	AUD		
1 order	35,868	6.61	0	0	6.62	40,291	1 order
PTDH1	35,000	6.61	0	0	6.62	20,000	MII3
MII1	111	6.61	0	0	6.62	1,060	1 order
PTDH1	50,000	6.60	1				
10 orders		6.60	1				
MII2	1,500	6.59	2	2	6.64	30,000	PTDH2
1 order	3,100	6.59	2	2	6.64	50,000	MII3
MII1	10,200	6.59	2				
1 order	1,517	6.59	2				
4 orders	5,517	6.58	3	3	6.65	16,447	3 orders
2 orders	9,000	6.57	4	4	6.66	15,552	4 orders
5 orders	13,600	6.56	5	5	6.67	4,000	2 orders
MII2	20,000	6.56	5	6	6.68	10,818	3 orders
15 orders	24,077	6.55	6	7	6.69	3,500	MII4
5 orders	15,100	6.54	7	7	6.69	23,972	10 orders
1 order	3,000	6.53	8	8	6.70	26,818	8 orders
3 orders	13,370	6.52	9	9	6.71	8,490	3 orders
				9	6.71	10,000	MII4
				9	6.71	39,311	3 orders

allow an extended period for execution, and then close out accumulated positions at the end of the test period. Using limit orders 1%, 2%, 3% up to 5% away from the BBO, Handa and Schwartz demonstrate statistically and economically significant gains from these balanced network execution strategies. However, since few if any equity traders express buying and selling interest simultaneously, a question of the practical significance of such multi-price trading strategies remains open. Instead, we set out to document whether institutions use multi-price liquidity supply on one side of the market only as indicated by Biais, Martimort, and Rochet (2000).

Based on these considerations, we develop and investigate the following hypothesis:

Hypothesis I. Institutional clients supply liquidity simultaneously at multiple prices.

Table 3
Simultaneous occurrence of institutional liquidity supply at multiple prices
Using a proprietary data set for a leading brokerage firm, we capture the LOB every twenty minutes for five days for 35 securities. For each institutional client of Cooperating Broker 1 supplying liquidity at a given time on at least one of the first ten price steps, we sort based on whether that client is supplying liquidity at one price, two prices, three prices, and so forth, up to ten steps on one side of the LOB. We consider the bid and ask side of the market separately because instances of clients supplying liquidity on both sides of the LOB at the same time are extraordinarily rare and can be ignored.

Number of prices in LOB at same time	Institution clients of cooperating brokers			
	Bid side		Ask side	
1	709	55.96%	585	60.25%
2	277	21.86%	213	21.94%
3	116	9.16%	84	8.65%
4	62	4.89%	57	5.87%
5	34	2.68%	18	1.85%
6	25	1.97%	3	0.31%
7	12	0.95%	2	0.21%
8	11	0.87%	3	0.31%
9	11	0.87%	0	0.00%
10	10	0.79%	6	0.62%
		100%		100%

3.2. Data, methodology and tests of multi-price liquidity supply

We wish to examine the prevalence of the practice of supplying liquidity at multiple prices simultaneously, but our first dataset does not allow this because the data are aggregated by trader type. In order to study this practice in more detail, we persuaded Cooperating Broker 2 to provide additional client code data for the 18 snapshots per day for five days for the 35 securities in our sample. For each institutional client supplying liquidity at one or more prices at a given time, for the first ten price steps on one side of the LOB, we obtained a sort based on whether that client's liquidity supply is at one price, two prices, three prices, and so forth. We consider the bid and ask sides of the market separately.[6]

Table 3 displays the frequency of order splitting by institutional investors across the 35 leading equities in our sample obtained from Cooperating Broker 2. The multi-price order placement strategy is evident. Only 55.96% of institutions supplying liquidity on the bid side at a given time do so solely at one price—usually the best bid; only 60.25% supplying liquidity on the ask side at a given time do so solely at one price–usually the best ask. 21.86% (21.94%) of all institutional liquidity supply on the bid (ask) side is by clients supplying liquidity at two prices simultaneously. 22.18% (17.81%) of all institutional clients supplying liquidity at the bid (ask) do so for three or more prices simultaneously. Clearly, the strategy of supplying liquidity at several prices simultaneously is typical of

[6]Managers of the trading desks at our cooperating brokers verified that instances of clients supplying liquidity on both sides of the market at the same time are extraordinarily rare and can be ignored. Crossing the spread occurs in these markets, but not simultaneous liquidity supply on both sides of the market several steps away from the BBO.

institutional investors, confirming Hypothesis I and providing strong support for Biais, Martimort, and Rochet (2000).

Given our finding of simultaneous supply of liquidity at multiple prices, we expect to find substantial liquidity away from the BBO. Fig. 1 displays the number of shares offered for sale on each price step by individual PTDH or MII institutional traders as a percentage of that trader's total number of shares displayed for sale on that one snapshot of the limit order book. These histograms characterize the liquidity per price step averaged across all 18 times of day and across all 35 securities in our sample.

Three results stand out. First, both types of institutional traders offer substantial liquidity at price points inferior to the BBO. MIIs even offer more aggregate depth away from the best ask (100%−48% = 52%) than at the best ask. The same is true on the bid price steps where MIIs show 49% at the best bid, 14% at −1 price step below the best bid, 9% at −2 price steps, 7% at −3, 3% at −4, 5% at −5, etc. , almost identical to the sell side of the LOB. Second, both PTDHs and MIIs display 14% or 15% of their total liquidity one step away from the BBO. Finally, we see in the aggregated data of Fig. 1 a first indication that active institutional traders like the PTDHs are more aggressive in their liquidity supply than MIIs. PTDHs write a third more limit orders to sell at the best ask (66%) than MII institutional traders (48%). And PTDHs offer only 13% of their total liquidity supply at price points inferior to the best ask +1 (namely, 4% at +2, 2% at +3, +4 and +5, 3% at +6, and 1% or less thereafter) whereas MIIs offer 32% of their total liquidity supply at price points inferior to the best ask +1 (namely, 12% at +2, 4% at +3, 5% at +4, 5% at +5, and 6% at +6, etc.).

Goldstein and Kavajecz (2000) report non-negligible depth on the NYSE beyond the best quotes. Hollifield, Miller, and Sandas (2004) also find more depth away from the BBO in their detailed study of three months of the LOB for Ericsson, one of the most actively traded stocks on the Stockholm Stock Exchange. LOB information beyond the BBO is clearly critical in assessing execution strategy and testing theories of liquidity supply aggressiveness.

4. Aggressiveness of liquidity supply by type of institution

We also developed an indirect test of the Keim and Madhavan (1995) proposition that types of institutional traders with short-lived information or low reservation prices relative to consensus intrinsic value are more aggressive in their order placements. We derive a testable implication from the theory of order aggressiveness (Parlour, 1998; Foucault, 1999; Handa, Schwartz and Tiwari (2003), and Goettler, Parlour, and Ranjan (2004)) applied more narrowly to the decision by different types of institutional investors to supply liquidity.

4.1. Theoretical considerations: order aggressiveness

We assume that institutional suppliers of liquidity are uninformed but strategic traders who recognize that demanders of liquidity may have private information about intrinsic value. Following Goettler, Parlour, and Ranjan (2004), liquidity suppliers anticipate an expected profit on each transaction i of $V^{\mathrm{e}}(P_i - B - \Delta_i) * P^{\mathrm{e}}$ where P_i is the price paid, B is the liquidity supplier's reservation price (initially assumed equal to the consensus intrinsic common value of the asset), Δ_i is the price impact of the transaction, and P^{e} is the

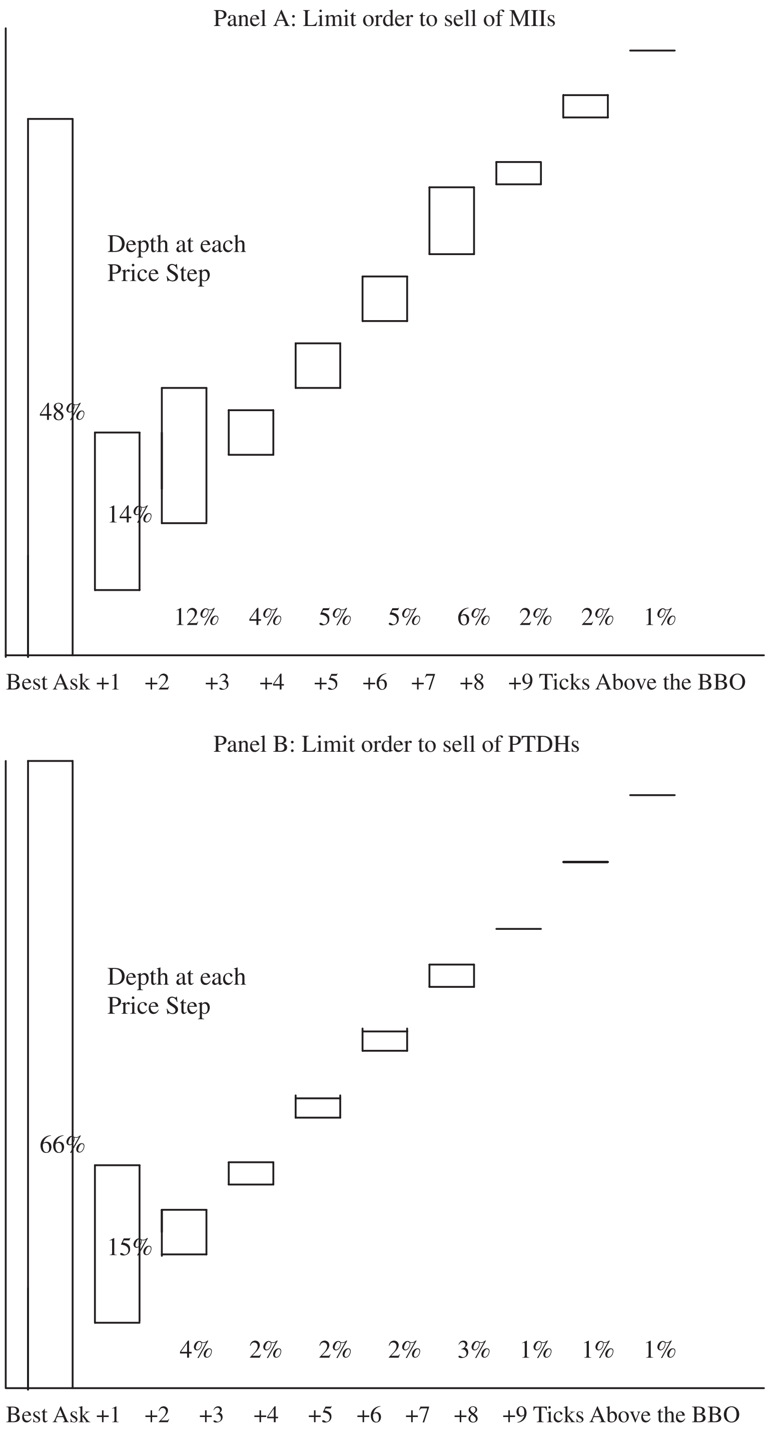

Fig. 1. Example profile of institutional liquidity supply. These figures display the number of shares offered at each price step of the LOB as a percentage of the total number of shares on that snapshot of the limit order book. Panel A shows the mean percentage for 35 securities over all 18 time slots for mutual funds, index funds, and insurance companies (MIIs), and Panel B shows the mean percentage for proprietary trading desks and hedge funds (PTDHs).

probability of execution. P^e depends on the deviation from the BBO and on the "state of the market." Given the state of the market, the more aggressive the limit price (the closer to the BBO), the lower the probability of non-execution. Optimal aggressiveness in liquidity supply therefore emerges as a tradeoff between execution risk and pickoff risk.

To illustrate, Foucault (1999) hypothesizes that volatility (perhaps from shocks to the order imbalance triggered by disparate information arrivals) is a main determinant of order aggressiveness, with higher volatility resulting in a less aggressive liquidity supply as follows. Suppose a mean-preserving spread of the distribution of intrinsic value increases the probability of losing intrinsic value greater than a reservation value equal to the ask. To reduce this probability of seller's remorse requires moving up the book, perhaps to a sell limit price at the best Ask $+2$ price steps. Moving to a sell limit price at the Ask $+2$ reduces pickoff risk at the expense of increased execution risk. However, with a mean-preserving spread, the probability of *not* executing (for any given price deviation from the BBO) has also diminished. Unambiguously then for liquidity suppliers, a mean-preserving spread resulting in less execution risk at each price point inferior to the BBO and a higher pickoff risk implies less aggressive liquidity supply (which we term "the Foucault proposition").[7]

Handa, Schwartz and Tiwari (2003)—hereinafter, HST—generalize Foucault (1999) allowing a reduction in order aggressiveness to follow not only from greater volatility, but also from differences of reservation prices (R) relative to the consensus intrinsic value (B). A trader's decision concerning limit price is determined by the execution risk faced at the time of the decision relative to the cost to that trader of non-execution. In particular, the dollar cost to the trader of seeking immediate execution against known quotes for sufficient depth by using a marketable limit order that allows the counterparty to capture the spread is compared by HST to the trader's dollar cost of non-execution. Of particular relevance to our paper, HST conjecture that the order placement difference between active and passive institutional trading reflects a difference in the acceptable level and perceived cost of non-execution. In other words, HST implies more order aggressiveness by PTDHs whether informed or not about intrinsic value B.

In Australia institutional investors pay brokerage fees based on notional value rather than per share. MIIs typically pay 2–10 basis points and PTDHs typically pay 15–35 basis points. These differences in fees reflect the differences in the level of service required by each group. MIIs are benchmark sensitive clients who usually have minimal intraday contact with the trading desk. PTDHs are high service intensity clients who require and pay for continual updates on the stocks in which they are active.

In addition to active monitoring, these clients also pay for superior access to the brokerage firm's internal book, which can be used to assess liquidity and to develop perspective concerning supply and demand imbalances at various price points. In electronic markets, some state of the market variables like thickness of the book, the spread, and the cumulative depth imbalance are observable to all market participants. But PTDHs pay to have access to order flow not disclosed to the rest of the market. This comprises internal broker flow as well as the full size of any buy/sell orders (that are known to the broker, but not to the market at large). The market sees a partial quantity (displayed in the ASX LOB), which is typically a function of liquidity conditions in the market/stock

[7]Ellul, Holden, Jain, and Jennings (2002) investigate the Foucault proposition aggregating all the price points inferior to the BBO into one category of orders.

at that time; they do not know the total demand for shares at that price. PTDHs seek trading profits by continuously monitoring the market and taking advantage of the fleeting value of knowing detailed real-time information about the state of the market including sources of liquidity, news flow, and analysts' opinions.

With real-time information about the state of the LOB, $V^e(P_i - [R - B] - \Delta_i)$ from a sell limit order transaction rises as PTDHs learn when their reservation value (R) separates below consensus intrinsic value B for short periods. The dollar value of these fleeting trading profits for PTDHs (which defines the opportunity cost of non-execution) exceeds the brokerage fees and monitoring costs associated with these active execution strategies. Since we know PTDHs pay higher brokerage fees, we can infer higher opportunity costs of non-execution. Higher opportunity costs of non-execution and lower pickoff risk based on fleeting state of the market information, in turn, implies more aggressive prices, closer to the BBO. This same implication can be derived from PTDHs monitoring more actively so that they are less exposed to pickoff risk (Foucault, Roell, and Sandas, 2003; Liu, 2005).

MIIs, on the other hand, are not in the same product space. Their customers do not substantially reward index-beating performance, but heavily penalize any inability to hit benchmarks. Hence, the expected profit from a sell limit order transaction motivated by divergence between the (impact-adjusted) transaction price $P_i - \Delta_i$ and consensus intrinsic value B alone–namely, $V^e(P_i - B - \Delta_i) * P^e$—is less likely to exceed the cost of the increased brokerage fees required to capitalize on fleeting state of the market information. So, MIIs optimally decided against securing detailed state of the market information and therefore face a lower opportunity cost of non-execution. A lower cost of non-execution immediately implies more execution risk, for any given pickoff risk, and less aggressive liquidity supply by MIIs.

4.2. Development of aggressiveness hypotheses

In an empirical study, Ranaldo (2004) confirms the Foucault proposition by showing that the execution probability and the risk of adverse selection influence limit price aggressiveness in the predicted fashion. In addition, Ranaldo finds that order aggressiveness is conditional on order size and on state of the market observables like spreads, LOB thickness, and intraday volatility, a result consistent with the findings of Griffiths, Smith, Turnbull and White (2000). Both these empirical papers analyze the placement of limit orders at the BBO or between the bid and the ask, but neither examines limit order prices inferior to the BBO.

Ellul, Holden, Jain, and Jennings (2002) also investigate the Foucault proposition with a multinomial logit model of order types on the New York Stock Exchange. Although some confirmation of theory is obtained, their results on volatility, time of day, and serial correlation of order type are inconclusive. It is unclear whether these negative results arise from the research design (i.e., order type independent of origin of the order) or from the data aggregation (i.e., all orders at price steps inferior to the BBO are collapsed into one category). To address these potential problems requires more detailed information.

Using ten price steps matching or inferior to the BBO, we compare the aggressiveness of the liquidity supply decisions of PTDHs versus MIIs by testing the following hypothesis:

Hypothesis II. Relative to MIIs, PTDHs exhibit smaller deviations from the BBO across a schedule of prices at or inferior to the BBO.

4.3. Snapshot data and methodology of testing across stock-days

According to senior traders and institutional sales desks, PTDHs in our sample pay higher commissions in return for access to real-time assessments of the state of the LOB and the MIIs do not. These differential commission rates are part of a well-established client management process that permeates the institutional brokerage industry in Australia. Interviews with senior trading executives in several leading brokerages confirmed that these account distinctions are consistent across brokerage firms not just in Sydney, but across Asia. We are not able to address the extent to which institutional investors within PTDHs and MIIs behave differently.

So that we can examine differences in the way PTDHs and MIIs supply liquidity, our Cooperating Broker 1 provided the data previously described aggregated by client type by snapshot, i.e., by security, day, and time of day. Since our interest is relative price step aggressiveness in liquidity supply at selected points in time (not dynamic order placement strategy), we include only snapshots with observations for both PTDHs and MIIs. Our final sample comprises 12,064 matched snapshots. Descriptive statistics for the snapshots are provided in Table 4. Our analysis is primarily across stock-days at a given trading time. The first time of day examined, 10:10, has the smallest number of snapshots with 497 observations each for PTDHs and MIIs. Hence, there are ample observations for our analysis.

Potentially, there could be 13,608 snapshots per stock (378 trading days X 18 times each day X 2 for buy and sell side) for a total of 476,280 snapshots overall. However, to be included in our sample there must be liquidity supply from both a PTDH and MII at the same time in the same stock on the same side of the LOB. An example might be useful. We make the assumption that the probabilities are i.i.d., which is not likely, but useful, and that we have 35 identical stocks. On average there are 6,023 PTDH snapshots for each stock and 1,838 snapshots for each MII in our sample, which converts into $(6{,}023/13{,}068) = 0.44$ and $(1{,}838/13{,}608) = 0.135$. Therefore, the expected number of snapshots is $0.044 \times 0.135 \times 13{,}608 \times 35 \times 0.5 = 14{,}146$. This is close to the actual number of snapshots observed.

This snapshots approach is a research design free of systematic sampling bias for measuring the aggressiveness of PTDHs and MIIs. Undoubtedly marketable limit orders executed just prior to our snapshots do affect the aggressiveness assigned to clients with other non-marketable limit orders in the LOB. But intervening behavior between our snapshots at points in time unknown to the trader is not a plausible source of *systematic* bias. Finally, we do not perform the hypothesis tests of the ranked order aggressiveness of our trader types *intraday*. Instead, we test each intraday slice of data across the 497 stock-days of 10:10 snapshots of the LOB, and then we repeat with the 665 stock-days of 10:30 snapshots, followed by a test of the 596 stock-days of 10:50 snapshots, etc. So, we have cross-sectional tests of liquidity supply aggressiveness removed from the dynamics of order placement decisions.

We examine the aggressiveness of liquidity supply of PTDHs and MIIs by calculating a measure which we call the price of immediacy. Let B_j be the number of price steps from the market best bid to the best bid price by this trader class in price ticks. If the best bid price equals the best market bid, $B_j = 0$. Otherwise, $B_j = 1$, or 2, or 3, and so forth. We calculate B for each time of day for each day for each security and aggregate across days for PTDHs and MIIs. This measure captures the price in steps at which PTDHs and MIIs supply

Table 4
Sample observations by time of day

For each security in our sample, we examine the LOB on each side of the market at 20-min intervals (18 times per day) for the period 1 January 2001–30 June 2002. For the first security for the first day at 10:10, we first ascertain whether there exists at least one outstanding limit order to buy from both PTDHs and MIIs. If so, we record a snapshot of all ten steps of the bid side of the LOB. We then repeat this collection process for each time of day, for each security, and for the other side of the book.

Time	Number of snapshots
10:10	497
10:30	665
10:50	596
11:10	713
11:30	742
11:50	741
12:10	740
12:30	742
12:50	677
13:10	721
13:30	609
13:50	674
14:10	724
14:30	750
14:50	586
15:10	614
15:30	642
15:50	631
	12,064

liquidity or immediacy to prospective counterparties. For each time of day for each side of the market, we jointly rank the daily observations and perform a t test on the mean of the ranks. This is equivalent to a Wilcoxon rank sum test. Note that in Tables 5, 6, and 7 below the BBO data are obtained from the ASX LOB while the PTDH and MII data are from Cooperating Broker 1. Further, for Table 6 the return volatility data and for Table 7 the depth and volume data are based on all ASX trades and not just trades in our proprietary data. All of the data for Table 8 is from the ASX LOB.

4.4. Price step aggressiveness by type of institution: empirical results

The empirical results of our test of the aggressiveness of liquidity supply of PTDHs and MIIs are presented in Table 5. For each of the 18 times of day on each side of the market, the PTDHs are more aggressive (have a price closer to the BBO) than the MIIs in every case. All 36 mean-rank difference statistics are statistically significant at the 0.01 level. Hence, our evidence provides strong support for Hypothesis II. The raw values reported here in terms of price steps are relatively small because a substantial part of the liquidity supplied by most institutional clients is at the BBO.

To examine whether the relative aggressiveness of liquidity supply by institutional client type varies with market conditions, for each security in our sample, we compare price step aggressiveness for both types of clients for high and low volatility of daily returns, high and

Table 5

The price at which immediacy is supplied by PTDHs and MIIs

Let Bj be the number of price steps from the market best bid to the best bid price by this trader class in price ticks. If the best bid price equals the best market bid, $Bj = 0$. Otherwise, $Bj = 1$, or 2, or 3, and so forth. We calculate B for each time of day for each day for each security and aggregate across days for PTDHs and MIIs. Our measure captures the price in steps at which PTDHs and MIIs supply liquidity to prospective counterparties. Hence, we refer to this measure as the price of immediacy. For each time of day for each side of the market, we jointly rank the daily observations and perform a t test on the mean of the ranks. This is equivalent to a Wilcoxon rank sum test. All of the t statistics are statistically significant at the 0.01 level.

Time	Bid side			Ask side		
	PTDH	MII	t-statistic	PTDH	MII	t-statistic
10:10	0.0778	0.1124	74.77	0.0788	0.2266	74.48
10:30	0.0694	0.1055	83.43	0.0733	0.1558	83.25
10:50	0.0658	0.0872	84.63	0.0706	0.1317	84.41
11:10	0.0655	0.0879	86.10	0.0665	0.1119	86.02
11:30	0.0642	0.1002	87.03	0.0666	0.1266	86.96
11:50	0.0606	0.0931	87.29	0.0645	0.1162	87.24
12:10	0.0617	0.0952	88.21	0.0656	0.1620	88.12
12:30	0.0604	0.0931	88.93	0.0629	0.1553	88.80
12:50	0.0589	0.1099	88.31	0.0618	0.1186	88.18
13:10	0.0595	0.1038	88.41	0.0635	0.1420	88.21
13:30	0.0607	0.1011	87.93	0.0617	0.1269	87.85
13:50	0.0611	0.0916	87.61	0.0625	0.1228	87.45
14:10	0.0596	0.0905	89.35	0.0617	0.1454	89.12
14:30	0.0592	0.0898	87.79	0.0612	0.1627	87.65
14:50	0.0581	0.1052	88.97	0.0606	0.1303	88.72
15:10	0.0576	0.1019	89.06	0.0607	0.1456	88.82
15:30	0.0583	0.1238	89.42	0.0595	0.2502	89.27
15:50	0.0588	0.1040	88.96	0.0606	0.1615	88.79

low volume, and high and low depth on the limit order book relative to volume. We calculate volatility as the standard deviation of daily returns over the sample period. For each security we then classify days in quintiles according to volatility. For the top and bottom quintiles, we present in Table 6 the mean price of immediacy across firms in price steps. During low volatility days, all of the t statistics are statistically significant at the 0.01 level with the PTDHs more aggressive (closer to the BBO) than the MIIs at every twenty-minute observation window throughout the trading day on both sides of the market.

On the ask price steps, during high volatility days, the PTDHs are again more aggressive than MIIs at every 20-min observation window throughout the trading day. On the bid price steps, however, PTDHs are more aggressive than the MIIs in many 20-min snapshots, but less aggressive in others. For example, at the bid the PTDHs are much less aggressive than MIIs at 10:10, 11:30, 13:50, and 15:30. This coincides with the fact that PTDHs pay extra execution fees to be forewarned of pickoff risk in high volatility periods, especially at the start and end of the trading day.

Similarly, for each security in our sample we calculate average depth on the LOB as a proportion of volume of daily trades over the sample period and report the results in Table 7. When the limit order book is relatively thin on heavier volume days, one would expect less aggressive order placement by less informed MIIs than by PTDHs, who pay fees to the trading desks to keep them better informed about the intraday state of the

Table 6
The price at which immediacy is supplied by PTDHs and MIIs, high and low volatility days

We again calculate the price of immediacy for each time of day for each day for each security and aggregate across days for PTDHs and MIIs (see Table 5). We calculate volatility as the standard deviation of daily returns over the sample period. For each firm for each day, we divide the observations into quintiles and present the mean across firms for the bottom and top volatility quintiles. For each time of day for each side of the market, we jointly rank the daily observations and perform a t test on the mean of the ranks. This is equivalent to a Wilcoxon rank sum test. All of the t statistics are statistically significant at the 0.01 level.

Time	Bid side			Ask side		
	PTDH	MII	t-statistic	PTDH	MII	t-statistic
Bottom quintile of daily volatility						
10:10	0.0802	0.1187	52.00	0.0794	0.3040	51.89
10:30	0.0730	0.1239	57.71	0.0725	0.1448	57.57
10:50	0.0731	0.1033	57.87	0.0682	0.1483	57.77
11:10	0.0700	0.1140	58.79	0.0642	0.1178	58.77
11:30	0.0707	0.1119	60.05	0.0656	0.1520	59.92
11:50	0.0651	0.0897	59.77	0.0621	0.1409	59.71
12:10	0.0666	0.1069	60.95	0.0635	0.1955	60.76
12:30	0.0645	0.0853	60.91	0.0631	0.1784	60.78
12:50	0.0646	0.1227	60.63	0.0625	0.1179	60.58
13:10	0.0645	0.1174	60.78	0.0649	0.1358	60.67
13:30	0.0654	0.1051	60.62	0.0643	0.1307	60.55
13:50	0.0664	0.0879	60.07	0.0645	0.1279	60.02
14:10	0.0659	0.0887	61.63	0.0644	0.1398	61.51
14:30	0.0635	0.0936	60.91	0.0644	0.1610	60.77
14:50	0.0645	0.1039	61.56	0.0628	0.1221	61.41
15:10	0.0602	0.0915	61.17	0.0621	0.1543	60.90
15:30	0.0644	0.1130	61.38	0.0602	0.2942	61.33
15:50	0.0642	0.0908	60.99	0.0617	0.1702	60.85
Top quintile of daily volatility						
10:10	0.1160	0.0600	20.05	0.1620	0.6437	19.94
10:30	0.0967	0.1247	20.53	0.1196	0.6020	20.50
10:50	0.0880	0.0843	21.34	0.1186	0.6493	21.28
11:10	0.0907	0.0960	22.21	0.1090	0.3860	22.15
11:30	0.0898	0.0592	21.49	0.1178	0.6608	21.47
11:50	0.0846	0.0907	21.32	0.1275	0.3413	21.25
12:10	0.0967	0.0944	21.69	0.1169	0.5756	21.70
12:30	0.0825	0.1417	22.36	0.1065	0.5783	22.31
12:50	0.0751	0.1088	21.08	0.1048	0.7281	21.04
13:10	0.0879	0.0971	21.78	0.1088	0.7200	21.77
13:30	0.0862	0.0913	21.43	0.0985	0.7638	21.42
13:50	0.0839	0.0541	21.23	0.1064	0.7206	21.20
14:10	0.0838	0.0909	21.90	0.1098	0.7791	21.84
14:30	0.0913	0.1096	21.19	0.1073	0.8383	21.20
14:50	0.0726	0.0709	21.55	0.1063	0.6695	21.47
15:10	0.0797	0.0967	21.49	0.1111	0.5644	21.52
15:30	0.0670	0.0387	22.13	0.1206	0.7735	22.03
15:50	0.0786	0.1341	22.68	0.1099	0.5064	22.62

market. As in prior splits of the sample, the PTDHs are more price step aggressive in supplying liquidity than MIIs at every 20-min observation window throughout the trading day on both sides of the market. In addition, however, when the market is stressed by low

Table 7
The price at which immediacy is supplied by PTDHs and MIIs, high and low depth days and high and low volume days

We examine the price of immediacy for high and low depth days. For Panel A, we calculate the market depth available on the bid side of the limit order book for each firm and time of day. This is then averaged across the day and divided by daily volume, with the resulting observations then divided into quintiles. For the bid side of the market, columns 3–5 present the mean across firms for the bottom quintile (low depth days) and columns 5–7 the equivalent results for the top quintile. For each time of day for each type of institution, we jointly rank the daily observations and perform a t test on the mean of the ranks. This is equivalent to a Wilcoxon rank sum test. All of the t statistics for Panel A are statistically significant at the 0.01 level. The results for ask side depth are not displayed as they are qualitatively the same. Panel B presents a similar analysis across low and high volume days for each type of institution, with the t statistics again all significant at the 0.01 level. We replicated the analysis for quintiles of ask side depth, and those results are also qualitatively the same.

Time	Bottom quintile			Top quintile		
	PTDH	MII	t-statistic	PTDH	MII	t-statistic
Panel A: Low and high depth days, bid side						
10:10	0.01	0.04	24.56	0.02	0.05	23.70
10:30	0.01	0.05	27.14	0.01	0.04	26.78
10:50	0.02	0.04	27.98	0.01	0.04	28.18
11:10	0.01	0.04	28.36	0.01	0.04	29.91
11:30	0.01	0.04	28.71	0.01	0.04	30.93
11:50	0.02	0.04	28.54	0.01	0.04	30.26
12:10	0.02	0.04	29.11	0.01	0.04	31.34
12:30	0.02	0.05	27.84	0.01	0.04	31.81
12:50	0.02	0.05	27.61	0.01	0.04	31.94
13:10	0.02	0.05	27.20	0.01	0.04	31.19
13:30	0.01	0.05	26.68	0.01	0.04	31.35
13:50	0.01	0.05	27.19	0.02	0.04	31.45
14:10	0.01	0.05	28.37	0.02	0.04	32.28
14:30	0.01	0.04	26.25	0.02	0.04	32.78
14:50	0.01	0.04	27.49	0.01	0.04	32.66
15:10	0.02	0.04	26.74	0.02	0.04	33.12
15:30	0.02	0.04	27.73	0.02	0.04	32.81
15:50	0.02	0.04	28.70	0.03	0.04	33.81
Panel B: Low and high volume days, bid side						
10:10	0.01	0.03	13.23	0.03	0.05	28.97
10:30	0.01	0.04	15.04	0.02	0.05	32.75
10:50	0.01	0.03	16.68	0.03	0.04	34.49
11:10	0.02	0.03	17.81	0.03	0.04	36.72
11:30	0.00	0.03	18.30	0.02	0.04	38.34
11:50	0.01	0.03	18.44	0.03	0.04	38.10
12:10	0.02	0.04	17.92	0.03	0.04	38.70
12:30	0.02	0.04	18.60	0.02	0.04	38.89
12:50	0.02	0.04	18.75	0.02	0.04	39.12
13:10	0.02	0.04	18.35	0.02	0.04	38.62
13:30	0.02	0.04	18.35	0.03	0.04	37.59
13:50	0.03	0.04	18.51	0.03	0.04	38.32
14:10	0.02	0.04	19.33	0.02	0.04	39.98
14:30	0.02	0.04	18.96	0.03	0.04	39.68
14:50	0.01	0.04	19.40	0.02	0.04	39.88
15:10	0.01	0.04	19.01	0.03	0.04	40.62
15:30	0.01	0.04	18.67	0.02	0.05	40.61
15:50	0.01	0.04	19.43	0.03	0.04	40.78

Table 8
The price at which immediacy is supplied by institutional and retail clients

Let Bj be the number of price steps from the market best bid to the best bid price by this trader class in price ticks. If the best bid price equals the best market bid, $Bj = 0$. Otherwise, $Bj = 1$, or 2, or 3, and so forth. We weight by volume to create a VWAP in price steps for each time of day for each day for each firm and aggregate across days for institutional and retail market participants. Our measure captures the price in steps at which institutions and the public supply liquidity or immediacy to prospective counterparties. Hence, we refer to this measure as the price of immediacy. For each time of day for each side of the market, we jointly rank the daily observations and perform a t test on the mean of the ranks. This is equivalent to a Wilcoxon rank sum test. All of the t statistics are statistically significant at the 0.01 level.

Time	Bid side			Ask side		
	Institutions	Retail	t-statistic	Institutions	Retail	t-statistic
10:10	0.0148	0.0215	227.1	0.0220	0.0182	227.9
10:30	0.0126	0.0194	231.5	0.0199	0.0184	231.3
10:50	0.0128	0.0188	233.3	0.0144	0.0167	233.9
11:10	0.0131	0.0176	234.5	0.0148	0.0156	234.8
11:30	0.0120	0.0172	236.0	0.0136	0.0161	236.7
11:50	0.0121	0.0175	237.0	0.0135	0.0162	237.6
12:10	0.0119	0.0173	237.0	0.0135	0.0159	238.1
12:30	0.0125	0.0168	237.0	0.0128	0.0152	238.8
12:50	0.0122	0.0172	238.2	0.0131	0.0150	240.1
13:10	0.0119	0.0165	239.2	0.0136	0.0143	240.4
13:30	0.0122	0.0160	240.1	0.0130	0.0141	240.7
13:50	0.0113	0.0165	239.8	0.0130	0.0146	240.8
14:10	0.0104	0.0166	240.9	0.0126	0.0153	241.6
14:30	0.0107	0.0177	239.1	0.0127	0.0162	239.0
14:50	0.0110	0.0179	239.2	0.0168	0.0164	240.3
15:10	0.0107	0.0179	240.2	0.0123	0.0162	240.8
15:30	0.0108	0.0185	239.3	0.0163	0.0168	239.5
15:50	0.0120	0.0194	238.3	0.0126	0.0176	238.9

depth combined with high volume, PTDHs are relatively more aggressive than at identical trading times on high depth/volume days. For example, at 13:50, 14:10, 14:30 and 15:50, the PTDHs are one or two steps more aggressive relative to MIIs than they are at the identical time periods on high depth days.

For each security in our sample we calculate volume of daily trades over the sample period. We also report these results in Table 7. In slow and fast markets, the PTDHs are more price step aggressive in supplying liquidity than MIIs at every twenty-minute observation window throughout the trading day on both sides of the market. When daily volume is in the lowest quintile, PTDHs are relatively more aggressive than at identical trading times in fast markets (i.e., high daily volume). For example, at 10:50, 11:30, 11:50, 12:10, 13:30, 14:30, and 14:50 in slow markets, PTDHs are one price step more aggressive relative to MIIs than at the identical time periods in fast markets. At 15:10 and 15:30 in slow markets, PTDHs are *two* price steps more aggressive relative to MIIs than they are at the identical time periods in fast markets.

We attempt to match our proprietary data to orders in the ASX LOB. We are not able to obtain a complete match due to several factors, the most important of which is that if two or more PTDH clients or MII clients place orders for the same stock on the same side of the market at the same time, these two orders are aggregated in our data but disaggregated in the ASX LOB. Nevertheless, we obtain about 46,000 matches, which represent more than 75% of the observations available for matching. We are able to obtain matches for 38,792 PTDH observations and 7,712 MII observations, reflecting the much more active trading of the PTDHs. After obtaining a match, we calculate statistics to the end of the trading day.

Our data shows the PTDHs are more aggressive and monitor their orders more actively than MIIs. For PTDHs, 28,666 (73.9%) of the orders were at least partially filled and the mean time to first fill was 2,057 s. MIIs obtained at least partial fills for 6,048 orders (78.4%), but the mean time to first fill was 3,456 s, undoubtedly because of their less aggressive prices. Time to last fill was 2,976 s for PTDHs and 4,343 s for MIIs. PTDHs monitor their orders more actively. While PTDHs amended 38.3% (14,872) of their orders compared to 42.7% for MIIs, the time to first amend is 2,041 s for PTDHs and 2,480 s for MIIs. For PTDHs 28.5% (11,052) of the orders were ultimately at least partially canceled by the end of the trading day with a mean time until cancellation of 6,239 s. For MIIs 13.5% (1,047) of orders were ultimately canceled by the end of the day with a mean time of 8,852 s until cancellation. A substantial number of MII orders were carried over to the next day. Virtually none of the PTDH orders are carried overnight.

5. Retail price step aggressiveness

In order to shed additional light on liquidity supply aggressiveness, we also incorporate a comparative examination of retail liquidity supply. Retail order flow data is somewhat more problematic than our institutional trading desk data because it is fragmented. That is, limit orders on the ASX exchange-posted LOB are often subsets of larger order submission strategies. And with retail orders there is no client ID information to assist in consolidating order instructions by client. Hence, our findings on retail price aggressiveness in liquidity supply are necessarily less conclusive than the findings above based on trading desk instructions from the individual institutional clients.

We chose to examine order placement only when all three investor types (PTDHs, MIIs, and retail) were present in the market. Clearly a rational agent's liquidity supply aggressiveness would be conditioned on what types of other clients are present in the order flow. Our purpose in looking at all three was to try to employ the retail broker ID codes disclosed by the ASX LOB to match up points in time (and therefore, states of the market) captured by our 20-min interval trading desk data. Again, without complete LOB data for a continuous window of time, we are unable to examine dynamic order submission strategy. However, with the above caveats about retail order splitting and omnipresent trader types, we can characterize the relative aggressiveness in liquidity supply across these three types of traders at 20-min intervals.

5.1. *Theoretical considerations for retail client hypothesis*

Unlike the two types of institutional investors, retail investors have a relatively small amount of capital and high fixed costs, preventing them from adopting sophisticated liquidity supply strategies. By comparison with institutional investors, we conjecture that retail investors have less access to real-time information about the changing state of the LOB, both with respect to its timeliness and its quality. As a result, their cost of non-execution falls well below either PTDHs or MIIs. We would expect therefore retail investors to be still less aggressive in their liquidity supply than either PTDHs or MIIs.

We recognize that retail investors do not continuously monitor the market. If it were costless to update frequently one's limit order submission strategy, retail investors would prefer not to be picked off regularly as counterparties to institutional traders that are better informed about the state of the market. However, we conjecture that ''lingering'' or ''stale'' retail limit orders are not an artifact of data collection but rather reflect an endogenous consequence of optimal liquidity supply behavior by retail market participants.

Therefore, we hypothesize

Hypothesis III. PTDHs are the most aggressive suppliers of liquidity followed by MIIs and then retail market participants.

5.2. *Retail data and ordered hypothesis tests*

The ASX has a high level of pre-trade as well as post-trade transparency, including the ability to identify separately all 76 retail brokers of the 95 total brokers.[8] For a particular snapshot, we identify retail liquidity supply as the shares placed in the LOB by these 76 retail brokers. The results in this section are based on VWAPs in price steps from the BBO.

A first indication of the aggressiveness of liquidity supply by institutions versus retail market participants comes from the ASX LOB itself. All of the results reported in Table 8 are based on data from the ASX LOB and not on our proprietary data. For each of the 18 times of day on each side of the market, we display in Table 8 the mean difference from the BBO of the VWAP in price steps for retail and non-retail orders over 350 trading days. These data cannot be directly compared to the data reported in Tables 5 and 6, which are not VWAPs in price steps. Institutional orders are more aggressive (have a VWAP closer to the BBO) than the retail orders. The mean-rank difference is statistically significant in all 36 cases.

Note that the aggressiveness statistic is much smaller in Table 8 than in Table 6. This is because as more and more brokers are added to the dataset, it becomes more and more likely that there will be orders on each price step for each security. However, as long as the clients of Cooperating Broker 1 are representative, which we believe to be the case, this does not affect the relative aggressiveness of MIIs vis-à-vis PTDHs, which is the focus of our analysis. Hence, we do not expect the relative sizes of the aggressiveness statistic to affect our results.

To test the ordered Hypothesis III involving the three trader types, PTDH and MII from our proprietary data set and retail participants from our ASX data, we examine the volume-weighted average price of liquidity supply as a measure of the relative aggressiveness of PTDHs, MIIs, and retail market participants.

Again, we calculate the deviation of price from the BBO in price steps, which captures the relative price at which PTDHs, MIIs, and retail market participants supply liquidity or immediacy to prospective counterparties. For this analysis we weight each price by the proportion of shares at each price at which that investor class is supplying liquidity, creating a volume weighted average price (VWAP) in price steps. This VWAP approach is used with the ASX LOB data because when the data are obtained from many brokers (the

[8]Several of the largest brokerage houses like ABN AMRO, Macquarie, BNP, Merrill Lynch, Salomon Smith Barney, and UBS maintain separate institutional and retail brokerages, identified as such in the ASX database.

retail data are from 76 brokers) there are orders on the book in each of our 12,604 snapshots.

We use Page's (1963) L-statistic to test the null Hypothesis III of equal aggressiveness in supply of liquidity, H_0: $P_{PTDH} = P_{MII} = P_{Retail}$, against its ordered alternative—for the bid side, HA1: $P_{PTDH} > P_{MII} > P_{Retail}$, and for the ask side,

HA1: $P_{PTDH} < P_{MII} < P_{Retail}$. Page's L-statistic for three ordered variables is computed as follows:

$$L = \sum_{j=1}^{3} \left(Y_i \sum_{i=1}^{m} X_{ij} \right),$$

where m is the number of observations at each time period, X_{ij} the observed rank of the i'th observation of order flow category j and Y_j the hypothesized rank of category j. The critical value of L (for a given level of confidence and three ordered variables) is computed as follows:

$$L_{critical} = 2m\left[\frac{Z_{critical}}{\sqrt{2m}} + 6\right].$$

This testing procedure for ordered hypotheses has been employed previously in both asset pricing (Levhari and Levy, 1977) and in financial market microstructure (Wood and McInish, 1984). Rejection of H_0 and in favor of HA1 supports Hypothesis III.

5.3. Cross-sectional tests of retail aggressiveness

Table 9 presents the results of Page's L-test under the null hypothesis of equal rankings in aggressiveness across trader types. This no-difference null hypothesis is rejected in 70% of the cases (227 out of 324 stock-timestamp combinations) in favor of the ranked alternative (Alternative Hypothesis A1 in Table 9) in which PTDHs are more aggressive suppliers of liquidity than MIIs, who are, in turn, more aggressive than their retail counterparts. The remaining 97 cases are tested to establish whether any alternate ranking is significant. For 40 of the 97 stock-timestamps, or 12% of the total sample of 324, MIIs are found to be more aggressive in their order submission than PTDHs, with retail investors continuing to be the least aggressive.

To check the robustness of the Page L test procedure, we perform two additional sets of cross-sectional tests. First, we retest the null hypothesis of no difference in the VWAP price deviations against the alternative that had characterized 12% (40) of the stock time-stamps.

HA2: $P_{MII} > P_{PTDH} > P_{Retail}$ for the buy side and HA2: $P_{MII} < P_{PTDH} < P_{Retail}$ for the sell side (i.e., Alternative Hypothesis A2 in Table 9). In the last column, we show that for each of the 18 time stamps, we are *unable* to reject the null hypothesis in favor of this alternative ordering of investor types. Hence, our evidence clearly supports Hypothesis III.

Second, both market-wide and stock-specific price trends have the potential to change the liquidity supply strategy of all types of investors. A rising (falling) stock market may result in increased (decreased) retail participation. A strong stock price trend may also increase or decrease institutional participation as a result of liquidity constraints. That is, a sufficient decline in market capitalization may result in MIIs exiting a stock that no longer meets their portfolio's investment criteria, with a significant rise having the opposite effect.

Table 9

A Page (1963) L-statistic test of aggressiveness of liquidity supply

Page's L-statistic is used to accept/reject the null hypothesis of equal aggressiveness of liquidity supply across PTDHs, MIIs, and retail investors vis-à-vis its ordered alternate ($P_{PTDH}>P_{MII}>P_{Retail}$ for the buy side and $P_{PTDH}<P_{MII}<P_{Retail}$ for the sell side). The L-statistic for three ordered variables is computed as follows:

$$L=\sum_{j=1}^{3}\left(Y_i\sum_{i=1}^{m}X_{ij}\right),$$

where m is the number of observations at each time period, X_{ij} the observed rank of the ith observation of order flow category j and Y_j the hypothesized rank of category j. The critical value for L at the 10% level of significance is computed as follows:

$$L_{10\%}=2m\left[\frac{1.645}{\sqrt{2m}}+6\right].$$

For each of the 18 times of the day, column 2 presents the number of stocks for which the null hypothesis is rejected at the 10% level of significance (before the "/") and the total number of stocks in that timestamp (after the "/"). Column 3 reports the same test against a second alternative hypothesis that ordered the MIIs as most aggressive, the PTDHs as less aggressive, and the retail market participants as least aggressive.

Time of day	Cases where L-statistic rejects null /total cases	
	Alternative Hypothesis A1	Alternative Hypothesis A2
	$P_{PTDH}>P_{MII}>P_{Retail}$ for the buy side and $P_{PTDH}<P_{MII}<P_{Retail}$ for the sell side	$P_{MII}>P_{PTDH}>P_{Retail}$ for the buy side and $P_{MII}<P_{PTDH}<P_{Retail}$ for the sell side
10:10	11/14	0/14
10:30	12/20	5/20
10:50	12/16	2/16
11:10	16/21	3/21
11:30	14/22	4/22
11:50	16/22	3/22
12:10	15/20	1/20
12:30	13/19	2/19
12:50	12/18	2/18
13:10	14/20	1/20
13:30	12/16	2/16
13:50	14/18	2/18
14:10	14/19	3/19
14:30	14/20	1/20
14:50	13/15	2/15
15:10	12/16	1/16
15:30	11/17	4/17
15:50	12/17	2/17

Consequently, we split the sample to test the robustness of the ordered hypothesis across the eighteen month sample period. Using a Wilcoxon sign rank test of the first and second half of the sample period (not shown), we find no significant difference in the liquidity-supply aggressiveness by trader type in the before and after periods for any stock.[9] Therefore, based on all three robustness checks, we can conclude that PTDH institutional investors are more aggressive suppliers of liquidity than MIIs, who, in turn, are more aggressive suppliers of liquidity retail market participants. Again, the retail orders arise from exchange-reported order flow data that may be misleading because of order splitting, and other conclusions about relative price aggressiveness in liquidity supply might arise if only two of the three types of investors we investigated were present in the market. Nevertheless, with those two caveats, our findings strongly support Hypothesis III.

6. Summary and conclusions

Using data for 35 thickly-traded Australian equities, we examine the liquidity supply of proprietary trading desks and hedge funds (PTDHs) versus mutual funds, index funds, and insurance companies (MIIs) across ten price steps on the bid side and ten price steps on the ask side of the LOB. PTDHs seek trading profits from the fleeting value of detailed assessments concerning the state of the market, while MIIs emphasize execution cost control and benchmark matching.

We show that both PTDHs and MIIs simultaneously supply liquidity at multiple prices. This is the behavior that Biais, Martimort, and Rochet (2000) hypothesize will result from an optimal execution strategy in order-driven markets with an asymmetrically-informed and risk-averse liquidity demander facing competing liquidity suppliers of a common value asset. Both previous empirical (Keim and Madhavan, 1995; Griffiths, Smith, Turnbull, and White, 2000; and Ranaldo, 2004) and theoretical (e.g., Goettler, Parlour, and Ranjan, 2004) work generally focused on liquidity supply at the BBO. Our analysis, which extends to nine price steps beyond the BBO, shows that inclusion of liquidity supply at prices inferior to the BBO may be needed to capture traders' behavior adequately.In cross-sectional testing across 12,064 stock-timestamps, we show that PTDH institutions are more price step aggressive in their supply of liquidity than MII institutions. Retail clients are less aggressive still, subject to the qualification that, unlike our institutional trading desk data, our retail order flow data arises from exchange-posted LOBs that may reflect order splitting. Hence, our retail price aggressiveness findings are less conclusive than our findings about the two types of institutional clients. Recall that our institutional data are based on client trading instructions prior to any trading desk decisions about how the order would actually be worked into the execution flow.

Price step aggressiveness in supplying liquidity should be influenced by the state of the market. Therefore, we split our sample three ways to investigate days with high and low return volatility, thick and thin books relative to traded volume, and fast and slow markets. During low volatility days on both sides of the market and high volatility days on the ask side, PTDHs are again more aggressive than MIIs at every twenty-minute observation window throughout the trading day. On the bid price steps during high volatility days, however, PTDHs are more aggressive than the MIIs in many twenty-minute snapshots, but less aggressive than MIIs at 10:10, 15:30 and two points in between. We interpret this finding in light of the extra execution fees PTDHs pay to be forewarned of pickoff risk at the start and end of what may prove to be a high volatility trading day.

Similarly, since PTDHs pay additional fees to the trading desks to keep them better informed about the intraday state of the market relative to MIIs, we find PTDHs are more

[9]These Wilcoxon test results are available from the authors.

price step aggressive at every 20-min observation window on both sides of the market during both thick and thin depth days. In addition, however, we find that when the market is stressed by low depth combined with high volume, PTDHs are still more aggressive relative to MIIs than at identical trading times on high depth/volume days. Finally, during slow and fast trading days, the PTDHs are more price step aggressive in supplying liquidity than MIIs at every 20-min observation window on both sides of the market. When daily volume is in the lowest quintile, PTDHs are still more aggressive relative to MIIs than at identical trading times in fast markets (i.e., high daily volume).

Several directions are available for future research using our approach to modeling price step aggressiveness of liquidity supply in automated order-driven markets. These include alternatives to our definition of the price of immediacy as the deviation (in price steps) of the VWAP of a client's order instructions from the BBO, about which there can certainly be further debate. Beyond our investigations of the volatility of daily returns, aggregate depth relative to daily volume, and fast versus slow markets, subsequent research can pursue additional effects of market conditions on the relative price step aggressiveness of liquidity supply.

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