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Anonymity, liquidity and fragmentation

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Abstract

We examine the effects of the removal of broker identifiers from the central limit order book of the Australian Stock Exchange. We find that spreads and order aggressiveness decline, and order book depth increases, with the introduction of anonymous trading. This is consistent with the hypothesis that limit order traders are more willing to expose their orders when they can do so anonymously. Anonymous markets attract order flow from non-anonymous substitute markets, but this effect is only seen in large stocks. Our results suggest that exchanges operating in fragmented markets should consider anonymous trading to improve price competition and liquidity, although some of these benefits may be significant only if the stocks are sufficiently large and liquid.

JEL classification: G14; G15

Keywords: Anonymity; Liquidity; Market fragmentation; Order flow

1. Introduction

Anonymity in securities trading is an issue of considerable importance to stock exchange regulators and market participants, given the global trend towards greater anonymity.[1] We

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[1]For example, Euronext Paris and the Tokyo Stock Exchange removed broker identifiers from their trading screens in 2001 and 2003, respectively. The Toronto Stock Exchange has allowed brokers the option of voluntarily making their orders anonymous since 2002. Many exchanges have completely anonymous electronic order books, such as the London Stock Exchange's SETS and Germany's XETRA, which co-exist alongside alternative trading platforms. NASDAQ also introduced post-trade anonymity on its SuperMontage platform in 2003 in response to market demand and competition from anonymous electronic communications networks (ECNs). The NYSE's recently

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examine how anonymity affects liquidity and order aggressiveness. The effects of introducing anonymity in fragmented markets where one or more substitute markets are non-anonymous are also considered. We conduct our analysis separately for large and small stocks to determine if the observed effects are symmetric across stocks with varying levels of liquidity and information asymmetry.

The main contributions of this study are three-fold. First, we document a general improvement in liquidity—as measured by quoted and effective spreads—after the Australian Stock Exchange (ASX) removed the real-time display of broker identifiers from its trading screens on 28 November 2005. This is consistent with the results of Foucault et al. (2007) for Euronext Paris stocks. We show that the reduction in trading costs is driven mainly by a reduction in the adverse selection component of the spread in large stocks, thus extending the Foucault et al. (2007) findings.

Second, in terms of order submission strategies we find that cumulative order book depth increases after anonymity is introduced, as evidenced by reductions in costs of simulated large trades executing against the book. After controlling for the determinants of order aggressiveness, we find evidence that traders are less aggressive in anonymous markets. This suggests that, at the margin, the ability to hide one's identity (and hence reduce one's order exposure risk) might cause limit orders to be more attractive than market orders for some traders. After controlling for market conditions we also find that traders are more likely to send orders to the anonymous electronic book than to the non-anonymous upstairs market. For cross-listings, we find evidence of a migration in order flow from the non-anonymous New Zealand Exchange (NZX) to the ASX.[2] These findings have important implications for exchanges that compete against other market centers for order flow.

Third, we show that larger stocks exhibit more substantial and broad-based improvements in liquidity and order flow consolidation with the introduction of anonymity, compared to smaller stocks. In contrast, smaller stocks exhibit marginally higher realized spreads and order flow in small stocks migrates away from the ASX to the NZX after the removal of broker identifiers. These differing findings for large and small stocks are consistent with the theoretical prediction of Foucault et al. (2007) relating trader anonymity to cross sectional variation in information environment. Since firm size is a reasonable indicator of the level of information asymmetry in the stock (Hasbrouck, 1991), our findings suggest anonymity has fewer benefits for stocks with lower activity levels and higher information asymmetry.

2. Previous literature

Market transparency has many dimensions, the most important being transparency of prices before (pre-) and after (post-) transactions. This paper examines another dimension of transparency, namely information on broker identities, both pre- and post-trade. We contribute to the existing literature by examining: (i) the impact of anonymity on trade

(*footnote continued*)
introduced Hybrid Market offers greater anonymity than its trading floor, which allows floor participants to observe each other's trades.

[2]NZX stocks are used here because their trading hours overlap with those of the ASX, permitting a better comparison than major centers such as New York and London with Australian cross-listings. Also, the electronic order-driven market structure of NZX is very similar to that of the ASX.

execution costs, adverse selection risk and liquidity provision; (ii) the impact of anonymity on traders' order submission strategies; (iii) the role of anonymity in attracting market share where markets are fragmented and compete for order flow; and (iv) the effect of anonymity on stocks with different levels of information asymmetry and liquidity.

2.1. Anonymity and trade execution costs

The Securities and Exchange Commission (SEC) specifically recognizes the benefits of anonymity in reducing the market impact of orders, and in assisting broker–dealers in their best execution obligations in working customer orders.[3] Anonymity facilitates the management of order exposure risk by allowing traders to conceal their intentions, thus mitigating parasitic trading or front-running by other traders (Harris, 1997). In particular, large anonymous orders are often thought to originate from informed traders who do not want to be identified (Harris, 1996). This is supported by the empirical findings of Grammig et al. (2001), Heidle and Huang (2002) and Barclay et al. (2003), who examine trader decisions when choosing between anonymous and non-anonymous trading system alternatives.

On the other hand, the academic literature on market transparency suggests that greater transparency benefits uninformed liquidity traders, albeit at a cost to informed traders. Forster and George (1992) demonstrate that greater pre-trade transparency lowers execution costs for traders who are able to signal liquidity-motivated orders.[4] Traders can reduce their adverse selection costs if the intermediating specialist, dealer or broker can price-discriminate based on the reputation of the counterparty (Benveniste et al., 1992; Battalio et al., 2007).[5]

The empirical evidence on the impact of anonymity on liquidity is mixed. For instance, Grammig et al. (2001) and Heidle and Huang (2002) find that spreads in more anonymous trading platforms tend to be wider than on the non-anonymous platforms, while Simaan et al. (2003) find that spreads are narrower in anonymous ECNs than dealer quotes posted through the more transparent NASDAQ dealer quotation system. One caveat of these studies, however, is that they compare anonymous automated market structures (e.g. ECNs, electronic limit order books) with non-anonymous market structures where liquidity suppliers can selectively participate after observing the identities of other participants (e.g. trading floors, dealer or upstairs markets). Such comparisons pose inherent problems in isolating the effects of anonymity from other market structure effects. This makes it difficult to conduct effective comparisons between such studies.

[3]For example, the SEC states in relation to the proposed introduction of a post-trade anonymity feature on NASDAQ's SuperMontage that, "The Commission believes that the SuperMontage post-trade anonymity feature should allow NASDAQ to offer some of the same benefits associated with anonymity (as other market participants such as the Pacific Stock Exchange Equities (PCXE)), such as minimizing the market impact of institutional orders. As expressed by commenters, trading information can have an impact on the price of a security". *Source*: Securities and Exchange Commission, Release No. 34-48527, Federal Register, Vol. 68, No. 189, 30 September 2003, p. 56364.

[4]Forster and George (1992) use the term "anonymity" to refer to the wider scope of trade-related information (or withholding of information), such as the direction and magnitude of a trade.

[5]In addition, Boehmer et al. (2005) examines pre-trade transparency on the NYSE, while recent studies from bond markets (e.g. Bessembinder et al., 2006; Harris and Piwowar, 2006; Edwards et al., 2007) examine post-trade transparency effects.

Natural experiments—in the form of a once-off regulatory change in the level of anonymity—more effectively control for these dissimilarities in market design. Foucault et al. (2007) use such a natural experiment on Euronext Paris. They find that quoted and effective spreads and price informativeness decline after a shift to pre-trade anonymity (with no change in post-trade anonymity). However, this is contrary to the findings of Waisburd (2003). He documents significantly wider bid-ask spreads in Paris Bourse stocks when only the transacting counterparties know each other's identities, compared to where there is full post-trade disclosure of trade counterparties' identities (with no change in pre-trade identity disclosure). He attributes this to lower inventory costs in the more transparent market, as other traders are able to identify inventory management trades and hence are more willing to participate in such trades.

We extend the prior literature by examining the natural experiment that occurred when the ASX removed the real-time display of broker identifiers from its trading screens on 28 November 2005 on both a pre- and post-trade basis. From 1987 until that date, brokers had been able to identify the broker associated with every order in the consolidated order book. The ASX replaced the real-time display of broker identifiers with aggregated market share information (for each brokerage firm) released at the end of every trading day, and the full trading history with broker identifiers three days after the trade. This means that there is post-trade anonymity on a same-day basis. Therefore, this study examines the effects of the simultaneous introduction of pre- and post-trade anonymity.

2.2. Anonymity and order submission strategies

There is relatively little empirical evidence to date on the effects of anonymity on order submission strategies in a limit order market. However, a number of prior studies suggest that reduced transparency should see traders becoming more willing to expose their orders. For example, following an increase in pre-trade transparency on the NYSE, Boehmer et al. (2005) find a decrease in order book depth, order aggressiveness, and liquidity suppliers' participation rate, as traders submit smaller orders and cancel orders faster. They attribute these results to traders' more active management of their limit order exposure in a more transparent environment. Simaan et al. (2003) find that NASDAQ dealers are more likely to quote aggressively when they can do so anonymously, and that anonymity improves price competition by discouraging collusion between dealers around quote setting.

Foucault et al. (2007) predict that a switch to anonymity generally makes informed traders more willing to trade aggressively and narrow the spread, while the behavior of uninformed dealers depends on the degree of information asymmetry between traders. If the probability of informed trading is high, uninformed traders are likely to trade less aggressively as the risk of being "picked-off" by informed traders is high. On the other hand, Foucault et al. (2007) predict that uninformed traders are more likely to post aggressive orders that narrow the spread when the probability of informed trading is low as the chances of being "picked-off" are reduced.

In general, anonymous trading means that market participants are unable to discriminate between informed and uninformed traders on the basis of their broker identifiers, to "pick-off" uninformed limit orders (Foucault et al., 2007) and free-ride or front-run informed orders (Harris, 1996). This suggests that a shift to anonymity should be associated with a decline in overall order aggressiveness, provided the risk of adverse selection—as inferred by the probability of informed trading—is low. We test this by analyzing the effect of the shift to anonymity on order aggressiveness and the use of limit orders. We also investigate if the findings of Boehmer et al. (2005) extend to the anonymity literature, by examining if order book depth increases with anonymity.

2.3. Anonymity and the consolidation of order flow

Madhavan (1995) argues that differences in trade disclosure requirements between fragmented markets should see order flow gravitate to the more liquid and efficient market. An anonymous downstairs market should therefore attract unexpressed liquidity from the non-anonymous upstairs market, if traders can better manage their order exposure risk by trading anonymously (see Grossman, 1992). Bloomfield and O'Hara (2000) find, using an experimental setting, that given a choice most dealers opt for lower transparency and consequently derive greater profits than more transparent dealers. The authors consequently question the viability of transparent markets in the face of competition from more opaque markets.

These arguments imply that an anonymous downstairs market would likely cause the upstairs market to lose an important source of information with which to identify potential counterparties and compete for order flow, leading to reduced liquidity upstairs. However, despite the significant role of the upstairs market in facilitating negotiated large trades, to date there has been relatively little empirical investigation into how anonymity affects the competition for order flow between the upstairs and downstairs markets.[6]

Similarly, it is reasonable to expect that inter-market competition for order flow will be affected by investors' preferences with regard to identity disclosure. Given increasing globalization, stock exchanges need to consider how such factors will affect their competitiveness vis-à-vis other markets. This is also relevant to exchanges that are considering introducing features that offer their users greater anonymity, such as the NYSE's Hybrid Market which allows customers the choice of routing their orders to either floor brokers or to the anonymous automated trading system. If sufficient order flow migrates to the anonymous system, the revenues and sustainability of floor brokers and specialists may come under significant pressure.

2.4. Anonymity and cross-sectional variations in the information environment

The existence of different levels of disclosure across markets calls for a deeper understanding of how, and under what conditions, anonymity affects trading. For example, when information asymmetry is high, we would expect greater transparency to improve liquidity. Foucault et al. (2007) propose a theoretical model of limit order trading that explicitly links the effects of trader anonymity with the level of information asymmetry, and show that anonymity matters only when traders have asymmetric information. They predict that when the participation rate of informed traders in an anonymous environment is small, uninformed traders actively set the best quotes as they are aware that there is a relatively low chance that informed traders will pick off their limit orders. This leads to narrower spreads. Conversely, when informed traders' participation

[6]Upstairs trading accounts for 67% of block trading volume on the Paris Bourse (Bessembinder and Venkataraman, 2004) and 27% on the NYSE (Hasbrouck et al., 1993). In Australia, upstairs trading of block transactions accounts for about a third of total dollar volume.

rate is high in an anonymous environment, Foucault et al. (2007) predict that uninformed traders provide less liquidity as the chances of getting picked-off increase.

Smaller, less liquid stocks tend to exhibit higher information asymmetry (Hasbrouck, 1991). Therefore, the information attached to broker identifiers should be more valuable to traders in these stocks. Until now, this theory has remained largely untested (in their empirical analysis, Foucault et al. (2007) focused only on the Paris CAC40 stocks, due to data limitations). One exception is Theissen (2002) who finds that less liquid stocks tend to be more actively traded on the non-anonymous Frankfurt Stock Exchange floor than on the anonymous electronic trading platform, while the converse is true for the more liquid larger stocks.

We test the Foucault et al. (2007) prediction using the natural experiment provided by the removal of broker identifiers on the ASX. To account for different levels of liquidity and information asymmetry across stocks, we examine the effects of anonymity on three groups of stocks: first the ASX All Ordinaries (All Ords) index component stocks (“all stocks”), then for the sample subsets comprising only S&P 200 index stocks (“large stocks”) and non-S&P 200 index stocks (“small stocks”). If anonymity does affect large and small stocks differently, exchanges seeking to promote liquidity should consider non-anonymous trading arrangements for small, less active stocks while anonymity may be more favorable for large, liquid stocks.

3. Institutional background

The ASX operates a fully automated continuous auction trading system where traders may enter either market or limit orders. Limit orders are queued and traded according to price-time priority. The ASX’s market structure allows for the relatively easy comparability of our results to other markets, as the order-driven electronic trading system is the most widely used among global exchanges and is common to most European and Asian exchanges. Trading hours are between 10:00 and 16:00, with a closing single price auction occurring randomly between 16:10 and 16:12. Minimum tick sizes are based on the share price, ranging from a tick size of $0.001 for shares trading up to $0.10, to a tick size of $1 for shares trading above $999.

As in most major markets, on-exchange trading is supplemented by a parallel upstairs market (also called off-market trading) for crossings and large negotiated block trades. Negotiated block trades in Australia are typically carried out by a broker conducting the required search and syndication activity over the telephone. This is similar to block trades negotiated in the NYSE upstairs market. Upstairs trading on the ASX typically consists of single-security block trades with a minimum value of $1 million (block special crossings), or multiple-security transactions where there are at least 10 purchases and/or sales, each worth at least $200,000 and with a combined value of at least $5 million (portfolio specials).[7] Block and portfolio special crossings can occur at any price.

In addition, the ASX allows “priority crossings”, or internalized trades, with no minimum trade size requirements. These are only allowed to occur if a crossing market exists (that is, the stock has a best bid and offer of not more than one price increment apart) and the crossing price is at the market price. If a crossing market does not exist, the broker must create one by submitting an order that creates the required spread width.

[7]ASX Market Rule Procedures 18.2.1, 18.2.2 and 18.3.1. In addition, a range of “facilitated specified size block special crossings” allow for principal-facilitated single-security block transactions with a minimum value of between $2 million and $15 million, depending on the liquidity of the stock concerned.

Before executing a priority crossing, the broker must expose an order in the market at the crossing price for at least 10 seconds. Most do this by placing an order for one share. Priority crossings take precedence over other orders at the same price. However, any other orders at better prices must be filled before a priority crossing can take place.

For the purposes of this study, upstairs trades include all crossings recorded by the ASX—block and portfolio special crossings, as well as priority crossings—as they are expected to experience similar effects from the shift to anonymity. With the removal of broker identifiers from the central limit order book, traders face increased difficulty in identifying potential counterparties for private negotiation. This suggests that their capacity to arrange large negotiated trades should decrease. In addition, to the extent that traders use internalization to reduce their order exposure risk, an anonymous environment should result in reduced internalization activity.

As of end-2005, 1873 companies were listed on the ASX. The top 500 stocks by market capitalization are included in the broad-based All Ordinaries index (All Ords). The S&P/ASX 200 index (S&P 200) is a subset of the All Ords and has approximately 78% coverage of the Australian equities market. It comprises the top 200 ASX stocks based on market capitalization, liquidity and free float, and is widely regarded by institutional investors as the market's investable benchmark.

4. Data

The ASX trade and order book data for this study is obtained from the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*). NZX trade and order book data is sourced from *Reuters International plc* and made available through *SIRCA*. Both sets of data are time-stamped to the nearest second. The daily market capitalization data is obtained from *Thomson Financial Datastream*.

The initial sample consists of the 487 constituents of the All Ords as of 28 February 2006. For each stock, intraday order and trade data are analyzed over pre- and post-event windows, comprising 60 trading days before and 30 trading days after the ASX removed the display of broker identifiers from the central order book on 28 November 2005.[8]

To mitigate any short-term effects associated with the event, as well as confounding effects from the seasonally less active period around the turn of the year, the 30 trading days immediately before and after the event date are excluded from the sample. The event window is broken up into three 30-day windows: *Preperiod*1, *Preperiod*2 and *Postperiod*1. The first 30-day period evaluated before the event, from days −60 to −31 (5 September to 14 October 2005) is *Preperiod*1, and the second 30-day period evaluated before the event, from days −90 to −61 (25 July 2005 to 2 September 2005) is *Preperiod*2. The period after the event, from days +31 to +60 (12 January to 23 February 2006), is *Postperiod*1. For additional robustness, the analysis is replicated using an alternative 30-day *Postperiod*2 (24 February 2006 to 6 April 2006) instead of *Postperiod*1.[9] For brevity, only the results

[8]The longer pre-event window is used to facilitate analysis of any existing secular trends in the order book and market characteristics that are independent of the removal of broker identifiers.

[9]To verify the robustness of the results, we also evaluate alternative event windows of [−120, +120] and [−60, +60] trading days immediately before and after the event date, as well as for ±60 and ±30 trading day windows where the pre-event periods are taken from the corresponding period the previous year, to control for seasonal patterns in trading activity. These results generally indicate improved liquidity after the shift to anonymity. However, they are not reported as it is not possible to isolate these results from a possible secular decline in trading cost over that extended period of time.

relative to *Postperiod*1 are presented. Any differing results for *Postperiod*2 are discussed in the main text.

Only stocks listed continuously throughout the pre- and post-event windows are included in the final sample. This excludes 24 stocks, leaving 463 All Ords stocks for evaluation. Of this number, 187 are also constituent stocks of the S&P 200 index.

5. Descriptive statistics and univariate analysis

Univariate analysis is used to evaluate any changes in trading activity and liquidity after the introduction of anonymous trading, by comparing the pre- and post-event metrics for each security. We calculate $\Delta PrePost1$ as the difference between the *Postperiod*1 average for a particular stock less the *Preperiod*1 average for that stock, and use *t*-tests and Wilcoxon signed rank tests to evaluate if the paired means and medians of $\Delta PrePost1$ are significantly different from zero. To verify that the results are not driven by a secular trend, we also report statistics for $\Delta PrePost1-\Delta Pre(2,1)$ for every stock. This is calculated as the $\Delta PrePost1$ metric less the difference between the *Preperiod*1 and *Preperiod*2 metrics for that stock. If $\Delta PrePost1-\Delta Pre(2,1)$ is significant and in the same direction as $\Delta PrePost1$, this suggests that the $\Delta PrePost1$ results are independent of a secular trend.

Trading activity is measured using the daily dollar volume traded per stock and the daily proportion of dollar volume traded in the upstairs market per stock.[10] The proportion of upstairs trading is calculated as

$$Upstairs\ Market\ Share_{it} = \frac{Upstairs\ volume_{it}}{Upstairs\ volume_{it} + Downstairs\ volume_{it}} \times 100\%$$

where volume refers to the dollar volume of stock i traded on day t.

Table 1 reports statistically significant increases in average and median daily dollar volume in $\Delta PrePost1$ for large stocks. For large stocks' $\Delta PrePost1-\Delta Pre(2,1)$, the *t*-statistic is statistically insignificant but the Wilcoxon score of 1753 is significant, indicating a significant post-event increase in median dollar volumes that cannot be entirely explained by a secular trend.

Small stocks show no significant change in dollar volumes with the introduction of anonymity. The Wilcoxon score for their $\Delta PrePost1-\Delta Pre(2,1)$ daily dollar volume is statistically significant only because the median change from *Preperiod*2 to *Preperiod*1 (denoted as $\Delta Pre(2,1)$, not reported in Table 1) is negative and very small at only −\$469 per stock relative to the median increase of \$1831 per stock in *Postperiod*1 (denoted as $\Delta PrePost1$). Both average and median $\Delta PrePost1$ increases are statistically insignificant, indicating no significant change in small stocks' post-event volume.

We find a significant decline in the proportion of trading conducted in the upstairs market for large stocks after the removal of broker identifiers. The daily market share of upstairs (downstairs) trading shows an average decrease (increase) of 2.62% per stock for large stocks.[11] This is due to a decline in upstairs trading activity, despite an increase in the total market trading value over the same period.[12]

[10]The daily dollar volume of shares traded includes both downstairs and upstairs transactions.

[11]The *Postperiod*2 results for large stocks are consistent with those of *Postperiod*1.

[12]Concurrent with the increase in total daily dollar volume in $\Delta PrePost1$, there was a simultaneous decline in the upstairs trading volume. Average daily upstairs volume decreased by 0.46% (29.37%) per stock to \$5.38 million (\$0.09 million) per stock for large and small stocks, respectively, in $\Delta PrePost1$. This could not be

Table 1
Trading activity summary statistics

This table reports the summary statistics for changes in average and median traded volume (in Australian dollars) and the upstairs market share of total dollar volume after the removal of broker identifiers. *Post* refers to *Postperiod*1, Δ*PrePost*1 measures the change from *Preperiod*1 to *Postperiod*1 for the paired samples, and Δ*PrePost*1$-\Delta$*Pre*(2,1) refers to Δ*PrePost*1 less the difference between *Preperiod*1 and *Preperiod*2. The *t*-tests and Wilcoxon sign rank tests examine whether the difference in the paired means and medians, respectively, are equal to zero. Panels A, B and C report the results for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 index stocks), respectively. There are 16,830 observations for large stocks and 24,840 observations for small stocks.

	Mean	Median	*t*-statistic	Wilcoxon
Panel A: *All stocks*				
Total volume (per stock)				
Post	$8,225,797	$390,808		
Δ*PrePost*1	$1,005,698	$4045	2.36**	4769*
Δ*PrePost*1$-\Delta$*Pre*(2,1)	$761,854	$24,906	1.51	8051***
% Upstairs volume (per stock)				
Post	13.11	1.38		
Δ*PrePost*1	−1.08	−0.10	−2.88***	−6689**
Δ*PrePost*1$-\Delta$*Pre*(2,1)	−0.78	0.23	−1.36	−1102
Panel B: *Large stocks*				
Total volume (per stock)				
Post	$19,757,969	$5,029,857		
Δ*PrePost*1	$2,478,637	$76,631	2.39**	1448*
Δ*PrePost*1$-\Delta$*Pre*(2,1)	$1,958,018	$291,165	1.59	1753**
% Upstairs volume (per stock)				
Post	21.82	15.85		
Δ*PrePost*1	−2.62	−2.76	−5.19***	−3673***
Δ*PrePost*1$-\Delta$*Pre*(2,1)	−2.38	−1.70	−2.93***	−1967***
Panel C: *Small stocks*				
Total volume (per stock)				
Post	$412,333	$86,170		
Δ*PrePost*1	$7729	$1831	0.09	1314
Δ*PrePost*1$-\Delta$*Pre*(2,1)	−$48,590	$17,937	−0.40	3396**
% Upstairs volume (per stock)				
Post	6.84	0.00		
Δ*PrePost*1	0.07	0.42	0.66	1643
Δ*PrePost*1$-\Delta$*Pre*(2,1)	0.47	1.94	0.67	2444*

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

These results support the argument that upstairs trading becomes more difficult if brokers are unable to easily discern interest in the order book beforehand, and downstairs trading increases when brokers are able to better manage their order exposure risk in an

(*footnote continued*)
attributed to a secular trend as there was an increase in average daily upstairs trading volume of $0.02 million per stock in *Preperiod*1 relative to *Preperiod*2.

anonymous environment. Whether this is viewed as a favorable outcome depends on who gains and who loses from upstairs trading. If anonymity leads to greater centralization of trading in the downstairs market this will promote price competition and liquidity (Simaan et al., 2003). On the other hand, anonymity will increase search costs for syndicating large trades (Flood et al., 1999) and make it harder to identify brokers with reputations for carrying out information-motivated trading in the upstairs market.[13]

It should be noted that small stocks do not experience a similar decline in the proportion of upstairs trading after the switch to anonymity. The $\Delta PrePost1-\Delta Pre(2,1)$ metric is positive and marginally significant at the 10% level, providing weak evidence of an increase in the upstairs share of trading for small stocks. When *Postperiod2* is used instead of *Postperiod1*, the average $\Delta PrePost1$ is positive and highly significant—indicating an increase in the upstairs share of trading for small stocks—although the $\Delta PrePost1-\Delta Pre(2,1)$ statistic then becomes insignificant. However, these univariate results must be interpreted cautiously as they do not consider the role of other explanatory factors that affect the decision to trade upstairs, such as order book characteristics and trade size. These factors are considered in more detail in the multivariate analysis in Section 9.1.

We also examine changes in liquidity after the removal of broker identifiers. One proxy for liquidity is the time-weighted proportional quoted spread ($TWPSPREAD_{it}$) used by McInish and Wood (1992) which is calculated every 30 minutes as follows:

$$TWPSPREAD_{it} = \frac{\sum_{t=1}^{n}\{(Ask_{it} - Bid_{it})/((Ask_{it} + Bid_{it})/2) \times T_{it}\} \times 100}{\sum_{t=1}^{n} T_{it}}$$

where T_{it} is the amount of time each proportional quoted spread of $(Ask_{it}-Bid_{it})/((Ask_{it}+Bid_{it})/2)$ spent at the inside spread in the 30 minutes up to time t for stock i. This is then averaged for every stock to obtain a daily figure.

Another measure of liquidity is the effective half-spread. It represents the cost of executing trades within the inside spread.[14] Following Bessembinder and Kaufman (1997), this is calculated as

$$Effective\ Half\text{-}Spread_{it} = 100D_{it}(P_{it} - M_{it})/M_{it}$$

where D_{it} is a dummy variable equal to $+1$ (-1) for buyer-initiated (seller-initiated) trades, P_{it} is the trade price and M_{it} is the spread midpoint immediately before the trade. The effective half-spread can be decomposed into a price impact component that measures the market's perception of the trade's informativeness, and a realized spread component that measures the post-trade price reversal net of losses to better-informed agents (see Huang and Stoll, 1996; Bessembinder and Kaufman, 1997).[15] These are defined as

$$Price\ Impact_{it} = 100D_{it}(P_{it+n} - M_{it})/M_{it}$$

$$Realized\ Spread_{it} = 100D_{it}(P_{it} - P_{it+n})/M_{it}$$

[13]In the non-anonymous upstairs market, the broking community can implicitly sanction block traders who frequently "bag the street" (submitting information-motivated trades for their clients, resulting in frequent losses by their counterparties) by refusing to participate in future block syndication activity (Seppi, 1990).

[14]For the variables using trade prices, only stocks which have observations for every day in the pre- and post-event periods are included, resulting in 166 large stocks and 78 small stocks.

[15]The realized spread component is analogous to the "temporary price impact" metric used in transaction cost literature: the transitory price movement needed to provide the liquidity to absorb the trade (Kraus and Stoll, 1972; Madhavan and Cheng, 1997).

where P_{it+n} is a proxy for the security's post-trade economic value, calculated as the first trade price recorded at least 30 minutes after the trade.

Table 2 shows that proportional quoted spreads declined across all stock groups, with an average daily decrease of 1.64 and 26.35 basis points for large and small stocks, respectively. For large stocks, both the mean and median differences for $\Delta PrePost1$ and $\Delta PrePost1-\Delta Pre(2,1)$ are significant and negative, indicating that these decreases are significant and do not arise from a secular trend. In contrast, the *t*-statistic for small stocks' $\Delta PrePost1$ decline is only marginally significant at the 10% level and insignificant for $\Delta PrePost1-\Delta Pre(2,1)$, suggesting that anonymity has little effect on liquidity in small stocks.

Interestingly, average and median effective half-spreads declined in $\Delta PrePost1$ for large stocks but increased for small stocks after the shift to anonymity.[16] The significant Wilcoxon scores for large stocks' $\Delta PrePost1-\Delta Pre(2,1)$ suggest that the post-event improvement in effective half-spreads is significant and independent of a secular trend. However, the results for small stocks are statistically insignificant, similar to the findings for proportional quoted spreads.

The decomposition of the effective spread into the price impact and realized spread components provides further insight into the asymmetric results for large and small stocks. First, it can be seen that the average and median price impact component is uniformly larger for small stocks compared to large stocks. This is consistent with prior studies that find that small stocks exhibit higher price impact costs (see, for example, Bessembinder and Kaufman, 1997).

Second, we find that large stocks exhibit a significant post-event decline in the median price impact component, as indicated by the significant Wilcoxon scores for $\Delta PrePost1$ and $\Delta PrePost1-\Delta Pre(2,1)$.[17] This suggests reduced adverse selection cost for large stocks after the introduction of anonymity, to a greater degree than may be explained by the secular decline in trading costs. However, small stocks show no significant change in the adverse selection component of the spread. Instead, they experience an increase in median realized spreads, which is marginally significant at the 10% level. This reflects an increase in the transitory price movement needed to provide the liquidity to absorb the trade, and is consistent with the findings of Theissen (2002) who finds that small stocks in the German stock market exhibit higher realized spreads on the anonymous electronic trading system compared to the non-anonymous trading floor.[18]

To check the robustness of these findings, we repeat the above analysis using the first trade price the following trading day to calculate the price impact and realized spread components, instead of the first trade price 30 minutes after the trade. The detailed results are not reported here, but they confirm our previous conclusions albeit with generally higher significance levels than those reported in Table 2. Large stocks exhibit a significant decline in the price impact component, and both large and small stocks exhibit higher

[16]It should be noted that these changes are economically small. For large (small) stocks, the average effective half-spread decline of 0.62 basis points (increase of 1.55 basis points) in $\Delta PrePost1$ translates to a \$6.20 decline (\$15.50 increase) in effective half-spreads for a \$100,000 trade in a large (small) stock.

[17]Because the price impact and realized spread components individually display much larger standard deviations than the effective spread, their *t*-statistics are generally insignificant. This explains the apparent dichotomy between the significant *t*-statistics for the effective spreads and the insignificant *t*-statistics for the price impact and realized spread components.

[18]Another interpretation of the realized spread is that it captures inventory control costs and order processing costs (Waisburd, 2003). Higher realized spreads suggest increased inventory management costs, possibly due to the difficulty in signaling inventory management trades under an anonymous environment.

Table 2
Liquidity summary statistics

This table reports the summary statistics for changes in time-weighted proportional quoted spreads, effective half-spreads, the price impact and realized spread components (measured relative to the first trade price at least 30 minutes after the trade) of the effective half-spread, average limit order size and average dollar value of orders at the best bid and ask prices for each stock each day, after the removal of broker identifiers. *Post* refers to *Postperiod*1, Δ*PrePost*1 measures the change from *Preperiod*1 to *Postperiod*1 for the paired samples, and Δ*PrePost*−Δ*Pre*(2,1) refers to Δ*PrePost*1 less the difference between *Preperiod*1 and *Preperiod*2. The *t*-tests and Wilcoxon sign rank tests examine whether the difference in the paired means and medians, respectively, are equal to zero. Panels A, B and C report the results for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 index stocks), respectively. Proportional quoted spreads utilizing order data use 16,830 observations for large stocks and 24,840 observations for small stocks, while the other metrics utilizing trade data have 14,940 observations for large stocks and 7020 observations for small stocks.

	Mean	Median	*t*-statistic	Wilcoxon
Panel A: *All stocks*				
Proportional quoted spread (%)				
Post	1.2728	0.6555		
Δ*PrePost*1	−0.1633	−0.0067	−1.75*	−5760**
Δ*PrePost*1−Δ*Pre*(2,1)	−0.1413	−0.0134	−1.09	−4757*
Effective half−spread (%)				
Post	0.2511	0.1840		
Δ*PrePost*1	0.0007	−0.0021	0.12	−1120
Δ*PrePost*1−Δ*Pre*(2,1)	0.0134	−0.0023	0.98	−0805
Price impact component (%)				
Post	0.1481	0.1050		
Δ*PrePost*1	−0.0232	−0.0046	−0.80	−2527**
Δ*PrePost*1−Δ*Pre*(2,1)	0.0088	−0.0116	0.20	−2071*
Realized spread component (%)				
Post	0.1030	0.0427		
Δ*PrePost*1	0.0240	0.0027	0.83	2479**
Δ*PrePost*1−Δ*Pre*(2,1)	0.0046	0.0091	0.11	1466
Average limit order size				
Post	$21,650	$13,387		
Δ*PrePost*1	$176	−$202	1.20	0309
Δ*PrePost*1−Δ*Pre*(2,1)	$286	−$84	1.35	1592
Ave best bid and ask value				
Post	$80,173	$27,767		
Δ*PrePost*1	$6790	$1210	1.73*	7537***
Δ*PrePost*1−Δ*Pre*(2,1)	$11,154	$2171	2.51**	8864***
Panel B: *Large stocks*				
Proportional quoted spread (%)				
Post	0.3425	0.3175		
Δ*PrePost*1	−0.0164	−0.0061	−3.25***	−2070***
Δ*PrePost*1−Δ*Pre*(2,1)	−0.0324	−0.0139	−4.00***	−2895***
Effective half-spread (%)				
Post	0.1462	0.1339		
Δ*PrePost*1	−0.0062	−0.0030	−2.76***	−1726***
Δ*PrePost*1−Δ*Pre*(2,1)	0.0134	−0.0035	−0.65	−1398**
Price impact component (%)				
Post	0.0585	0.0770		
Δ*PrePost*1	−0.0305	−0.0055	−0.72	−1965***
Δ*PrePost*1−Δ*Pre*(2,1)	0.0088	−0.0116	0.12	−1182*

Table 2 (*continued*)

	Mean	Median	*t*-statistic	Wilcoxon
Realized spread component (%)				
Post	0.0877	0.0338		
$\Delta PrePost1$	0.0243	0.0019	0.58	795
$\Delta PrePost1-\Delta Pre(2,1)$	0.0046	0.0023	−0.18	1
Average limit order size				
Post	\$32,523	\$23,989		
$\Delta PrePost1$	\$831	\$83	1.69*	1044
$\Delta PrePost1-\Delta Pre(2,1)$	\$1,774	\$763	1.75*	1326*
Ave best bid and ask value				
Post	\$153,728	\$70,380		
$\Delta PrePost1$	\$15,044	\$2627	1.59	1898**
$\Delta PrePost1-\Delta Pre(2,1)$	\$23,791	\$6738	2.30**	2539***
Panel C: Small stocks				
Proportional quoted spread (%)				
Post	1.9054	1.2339		
$\Delta PrePost1$	−0.2635	−0.0181	−1.68*	−1650
$\Delta PrePost1-\Delta Pre(2,1)$	−0.2159	−0.0122	−0.97	−0631
Effective half−spread (%)				
Post	0.4743	0.3662		
$\Delta PrePost1$	0.0155	0.0085	0.85	0214
$\Delta PrePost1-\Delta Pre(2,1)$	0.0134	0.0087	1.22	0219
Price impact component (%)				
Post	0.3387	0.2505		
$\Delta PrePost1$	−0.0077	0.0109	−0.49	−0129
$\Delta PrePost1-\Delta Pre(2,1)$	0.0088	−0.0157	0.27	−0214
Realized spread component (%)				
Post	0.1356	0.0891		
$\Delta PrePost1$	0.0232	0.0228	1.70*	0391*
$\Delta PrePost1-\Delta Pre(2,1)$	0.0046	0.0397	1.72*	0382*
Average limit order size				
Post	\$13,778	\$10,042		
$\Delta PrePost1$	−\$321	−\$400	0.32	−1550
$\Delta PrePost1-\Delta Pre(2,1)$	−\$893	−\$476	0.90	−1286
Ave best bid and ask value				
Post	\$30,288	\$17,922		
$\Delta PrePost1$	\$1188	\$573	0.76	1574
$\Delta PrePost1-\Delta Pre(2,1)$	\$2555	\$945	1.06	1141

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

realized spreads under anonymous trading. These results hold for both $\Delta PrePost1$ and $\Delta PrePost1-\Delta Pre(2,1)$.[19]

[19]For the price impact component, the Wilcoxon scores for large stocks' $\Delta PrePost1$ and $\Delta PrePost1-\Delta Pre(2,1)$ are both significant at the 1% level. For the realized spread component, the Wilcoxon scores for large stocks' $\Delta PrePost1$ and $\Delta PrePost1-\Delta Pre(2,1)$ are both significant at the 1% level while for small stocks they are significant at the 10% and 1% levels, respectively.

Hence, the overall evidence indicates that the price impact reduction dominates for large stocks, leading to lower post-event effective spreads. The effect of anonymity on realized spreads is mixed, with weak evidence of increased realized spreads for small stocks in particular. Higher realized spreads suggest increased inventory management costs, possibly due to the greater difficulty in signalling liquidity-motivated trades under an anonymous environment.

Finally, we examine the average limit order size and the average value of orders at the best bid and ask prices, sampled every 30 minutes and averaged per stock per day. These act as indicators of traders' willingness to expose larger orders in the central limit order book.[20] Table 2 shows a mildly significant increase in the average limit order size for large stocks in $\Delta PrePost1$. This is despite the fact that the level of Direct Market Access trading (which includes algorithmic trading) increased over this time, which likely placed downward pressure on the average order size. Large stocks also display a significant increase in the median value of orders at the best bid and ask prices in $\Delta PrePost1$, indicating improved depth at the inside spread. On the other hand, we find no significant change in the propensity of traders to expose their orders in small stocks. The evidence suggests that while traders in active stocks are more willing to disclose larger orders at the inside spread in an anonymous environment, this is not necessarily the case for traders in less liquid stocks with higher information asymmetry.

The overall evidence of improved liquidity is stronger for large stocks compared to small stocks. This suggests that the level of information asymmetry in a stock plays a role in explaining the effects of anonymity on liquidity. This issue is examined further in the following sections.

6. The effect of anonymity on liquidity

To effectively assess the impact of anonymity on liquidity, and in particular, bid-ask spreads, it is necessary to also consider other factors that may influence spreads such as trading activity, price and volatility (McInish and Wood, 1992). We control for these factors by estimating the following cross-sectional model:

$$\begin{aligned} TWPSPREAD_{it} = {} & \alpha + \beta_1 Postperiod_{it} + \beta_2 Preperiod1_{it} + \beta_3 VOLATILITY_{it} \\ & + \beta_4 \ln(VOLUME_{it}) + \beta_5 \frac{TICK_{it}}{PRICE_{it}} + \beta_6 Trend_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where $TWPSPREAD_{it}$ is the time-weighted daily proportional spread for firm i on day t. $Postperiod_{it}$ and $Preperiod1_{it}$ are dummy variables equal to 1 if the observation falls in *Postperiod*1 and *Preperiod*1, respectively, and zero otherwise. If greater anonymity gives rise to increased liquidity, β_1 should be significant and negative. If this reduction is not a continuation of a trend from *Preperiod*1, β_2 should be insignificant or positive.

Previous research also demonstrates that spreads are positively related to volatility (Copeland and Galai, 1983). In view of this, we include as an explanatory variable

[20] Depth is also measured using the volume of orders at the best bid and ask prices as a proportion of the total volume of orders in the order book. The results are generally consistent using this measure and are therefore not reported.

$VOLATILITY_{it}$, which is the daily average volatility for stock i and calculated as

$$VOLATILITY_{it} = \frac{\sum_{j=1}^{n} \ln\left(\frac{High_{ijt}}{Low_{ijt}}\right)}{n}$$

where $High_{ijt}$ and Low_{ijt} are, respectively, the highest and lowest traded prices in the jth 30-minute interval up to the final nth 30-minute interval of the trading day. This is then averaged per stock per day to yield a daily estimate of volatility. Additional explanatory variables include $\ln(VOLUME_{it})$ which is the natural logarithm of the daily traded volume, and the relative tick size $TICK_{it}/PRICE_{it}$ which is the stock's tick size relative to its daily time-weighted trade price. Volume is expected to be negatively related to spreads. As smaller relative tick sizes put downward pressure on spreads (see Harris, 1994), a positive coefficient is expected. Finally, a daily *Trend* variable taking the values of 1–30 for *Preperiod*2, 31–60 for *Preperiod*1 and 61–90 for *Postperiod*1 is included to account for any linear time trend.[21]

Eq. (1) is estimated for the event window encompassing *Preperiod*1, *Preperiod*2 and *Postperiod*1 using generalized method of moments (GMM) with White-adjusted standard errors to take into account potential autocorrelation and heteroscedasticity.

The cross-sectional results in Panel A of Table 3 show that the volatility, volume and relative tick size coefficients are all significant with the expected signs. The *PostPeriod* coefficients for large and small stocks are negative and highly significant at the 1% level with coefficients of −0.05 and −0.25, respectively. Thus, after controlling for other exogenous factors, large (small) stocks experienced average reductions in relative bid-ask spreads of 5 (25) basis points, respectively.

The *PrePeriod*1 coefficients are also negative but of smaller magnitude (−0.01 and −0.06 for large and small stocks, respectively) than for *PostPeriod*. They are also statistically insignificant for small stocks and only significant for large stocks at the 5% level. Thus, small stocks display a significant improvement in liquidity after the removal of broker identifiers in a manner that cannot be attributed to a secular trend. For large stocks, even though there is such a secular trend, a larger and more statistically significant improvement in liquidity is observed after the introduction of anonymity.

To see if the relative effects of *PrePeriod*1 and *PostPeriod* on liquidity differ significantly in magnitude, we calculate $\Delta Post$, the difference between the *PostPeriod* and *PrePeriod*1 coefficients. Wald tests are used to test the restriction that the *PostPeriod* and *PrePeriod*1 coefficients are equal; that is, $\Delta Post = 0$. $\Delta Post$ is negative and highly significant for both large and small stocks, indicating that both groups experience significantly larger declines in spreads in *PostPeriod* compared to *PrePeriod*1.

To verify the robustness of these results, Eq. (1) is re-estimated on a stock-by-stock basis. Panel B in Table 3 reports the median coefficient estimates across all stocks. The significance of the coefficients is tested using a Fisher combined probability test (Fisher, 1932), calculated by summing the $-2(\log_e)$ of the individual p-values of each coefficient's t-statistic across all stocks. The resulting statistic is chi-square distributed with twice the number of stocks as its degrees of freedom. We use this statistic to evaluate if each coefficient is significantly different from zero (see Gibbons and Shanken, 1987; Christie, 1990; Chung et al., 1999 for similar implementations of this test). It is assumed that the

[21]The analysis using *Postperiod*2 has the *Trend* variable taking the values of 91–120 over *Postperiod*2.

Table 3
Results of multivariate analysis of spreads
This table reports the estimation results of Eq. (1):

$$\begin{aligned} TWPSPREAD_{it} = \alpha + \beta_1 Postperiod_{it} + \beta_2 Preperiod1_{it} \\ + \beta_3 VOLATILITY_{it} + \beta_4 \ln(VOLUME_{it}) \\ + \beta_5 \frac{TICK_{it}}{PRICE_{it}} + \beta_6 Trend_t + \varepsilon_{it} \end{aligned}$$

Panel A displays the cross-sectional results for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 stocks). Panel B displays the median estimates from the stock-by-stock estimations of Eq. (1), with the % of estimates that are positive and negative, respectively, reported in parentheses. White's heteroscedasticity-adjusted standard errors are used. The sample covers the period spanning *Preperiod2*, *Preperiod1* and *Postperiod1*. $\Delta Post$ reports the difference (median difference) between β_1 and β_2 for the cross-sectional estimation (stock-by-stock estimations). For the cross-sectional estimates, the significance levels for $\Delta Post$ are for Wald tests of the restriction $\beta_1 - \beta_2 = 0$. The significance of the stock-by-stock coefficients and $\Delta Post$ is estimated using the Fisher combined probability test. There are 16,830 observations for large stocks and 24,840 observations for small stocks.

	Panel A: Cross-sectional estimates			Panel B: Stock-by-stock median estimates		
	All stocks	Large stocks	Small stocks	All stocks	Large stocks	Small stocks
Intercept	3.68***	0.93***	4.41***	0.62***	0.34***	1.26***
				(80%, 20%)	(88%, 12%)	(74%, 26%)
Postperiod	−0.17***	−0.05***	−0.25***	−0.03***	−0.02***	−0.10***
				(39%, 62%)	(33%, 67%)	(42%, 58%)
Preperiod1	−0.04*	−0.01**	−0.06	−4E−03***	−2E−03**	−0.01***
				(47%, 53%)	(45%, 55%)	(48%, 52%)
Volatility	57.74***	18.65***	68.62***	29.69***	16.00***	47.41***
				(97%, 3%)	(100%, 0%)	(96%, 4%)
ln(Volume)	−0.28***	−0.07***	−0.35***	−0.05***	−0.02***	−0.09***
				(10%, 90%)	(2%, 98%)	(16%, 84%)
Tick/Price	115.28***	98.92***	117.87***	94.72***	91.10***	101.05***
				(72%, 29%)	(76%, 24%)	(68%, 32%)
Trend	3E−03***	9E−04***	4E−03***	5E−04***	3E−04***	1E−03***
				(64%, 37%)	(71%, 29%)	(58%, 42%)
Adj. R^2	0.50	0.67	0.39			
$\Delta Post$	−0.13***	−0.04***	−0.19***	−0.03***	−0.02***	−0.10***
				(34%, 66%)	(26%, 74%)	(40%, 60%)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

individual t-statistics for each stock are independently distributed and the error terms are not cross-correlated.[22]

[22]For robustness, we also evaluate of the joint significance of the stock-by-stock coefficients using a Z-statistic—calculated as the sum of each stock's t-statistic for the coefficient of interest, divided by the square root of the number of stocks—as used by Dodd and Warner (1983), Warner et al. (1988), and Meulbroek (1992). This test assumes that the individual stock t-statistics are independently distributed and asymptotically unit normal. The results are identical to those of the Fisher combined test and are hence not reported separately.

The results show that the direction and significance of all the stock-by-stock results are consistent with those of the cross-sectional results. More stocks exhibit reduced spreads after the removal of broker identifiers (62% of total stocks have negative *PostPeriod* estimates) than during a non-event period (53% have negative *PrePeriod*1 estimates). The median *PrePeriod*1 coefficient is also much smaller in magnitude at -0.004 compared to the median *PostPeriod* coefficient of -0.03. We evaluate the joint significance of the individual stocks' $\Delta Post$ using the Fisher combined probability test. We do this by aggregating the *p*-values of the individual stocks' Wald test statistics (which test the restriction $\Delta Post = 0$) in a similar manner to that described above. We find the hypothesis that $\Delta Post$ equals zero is rejected for all stock sizes.

The overall results corroborate our cross-sectional findings that after anonymity was introduced, liquidity improved to a greater degree than can be attributed to a secular trend. This is consistent with the empirical findings of Simaan et al. (2003) for anonymous ECNs and Foucault et al. (2007) for Euronext Paris stocks.

7. Anonymity and order book depth

It is important to understand how anonymity affects the depth of the book and hence the cost of trading for larger orders. We examine this by calculating the change in order book depth associated with the immediate execution of simulated orders of a certain value, based on the depth of the order book sampled at 30-minute intervals and averaged per stock per day. Boehmer et al. (2005) use a similar measure which is referred to as the "effective spreads of orders". This provides a direct measure of traders' ability to execute their orders immediately. The impact of simulated buy and sell market orders of \$1000, \$10,000, \$100,000 and \$500,000 on cumulative book depth is estimated using the following formula:

$$ESpread_{it} = \delta \frac{VWAP_{it} - SpreadMidPoint_{it}}{SpreadMidPoint_{it}} \tag{2}$$

where δ_{it} is equal to 1 for buy orders and -1 for sell orders for stock i at time t. This adjustment ensures that the $ESpread_{it}$ variable is never negative. $VWAP_{it}$ is the volume-weighted average price for a given simulated order value, while $SpreadMidPoint_{it}$ is the midpoint between the inside spread for stock i at the time of the simulated market order. A decrease (increase) in *ESpread* after the shift to anonymity indicates a decreased (increased) price impact cost associated with a trade of a specified size.

Eq. (1) is re-estimated for all orders using *ESpread* as the dependent variable. The estimation is conducted both cross-sectionally across the entire data set, as well as on a stock-by-stock basis. The results are presented in Table 4.

For large stocks, the cross-sectional *PostPeriod* and *PrePeriod*1 coefficients are significant and negative for all order sizes, indicating a decline in *ESpread* over both pre- and post-event periods. However, the magnitude of the reductions in *PostPeriod* consistently exceeds those of *PrePeriod*1 across all simulated order sizes. A \$500,000 order for a large stock would, on average, reduce order book depth on the other side of the book by 52 basis points less in *Postperiod* compared to the base period of *Preperiod*2, after controlling for other relevant factors. A similar order would create an average reduction in depth of only 14 basis points less in *Preperiod*1 compared to *Preperiod*2, assuming all other factors remain constant. We test the restriction that $\Delta Post = 0$ (that is, the restriction that

Table 4
The impact of simulated trades on order book depth

This table reports the results from the estimation of:

$$\begin{aligned} ESpread_{it} = \alpha &+ \beta_1 Postperiod_{it} + \beta_2 Preperiod1_{it} \\ &+ \beta_3 VOLATILITY_{it} + \beta_4 \ln(VOLUME_{it}) \\ &+ \beta_5 \frac{TICK_{it}}{PRICE_{it}} + \beta_6 Trend_t + \varepsilon_{it} \end{aligned}$$

for all simulated trade sizes. Panels A, B and C display the cross-sectional results for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 stocks), respectively. Panels D, E and F display the median estimates from the stock-by-stock estimations, with the % of estimates that are positive and negative, respectively, reported in parentheses. White's heteroscedasticity-adjusted standard errors are used. The sample covers the period spanning *Preperiod*2, *Preperiod*1 and *Postperiod*1. $\Delta Post$ refers to the difference (median difference) between β_1 and β_2 for the cross-sectional estimation (stock-by-stock estimations), with the % of estimates that are positive and negative, respectively, reported in parentheses. For the cross-sectional estimates, the significance levels for $\Delta Post$ are for Wald tests of the restriction $\beta_1 - \beta_2 = 0$. The significance of the stock-by-stock coefficients and $\Delta Post$ is estimated using the Fisher combined probability test. There are 16,830 observations for large stocks and 24,840 observations for small stocks.

Trade size	*Constant*	*Postperiod*	*Preperiod*1	*Volatility*	*Ln*(*Volume*)	*Tick*/*Price*	*Trend*	Adj. R^2	$\Delta Post$
Panel A: *All stocks* (*Cross-sectional estimates*)									
\$1000	0.0196***	−0.0009***	−0.0003***	0.3275***	−0.0015***	0.6085***	1.46E−05***	0.4827	−0.0007***
\$10,000	0.0292***	−0.0011***	−0.0002	0.4658***	−0.0023***	0.8856***	1.73E−05***	0.4198	−0.0009***
\$100,000	0.0880***	−0.0038***	−0.0018***	1.2734***	−0.0069***	2.6351***	5.61E−05***	0.3640	−0.0020***
\$500,000	0.1721***	−0.0056**	−0.0038***	1.7211***	−0.0120***	2.8351***	8.42E−05**	0.1804	−0.0017
Panel B: *Large stocks* (*Cross-sectional estimates*)									
\$1000	0.0049***	−0.0003***	−0.0001***	0.1129***	−0.0004***	0.5062***	4.29E−06***	0.5255	−0.0002***
\$10,000	0.0077***	−0.0004***	−0.0001***	0.1625***	−0.0006***	0.5834***	5.04E−06***	0.5132	−0.0003***
\$100,000	0.0293***	−0.0014***	−0.0004***	0.5293***	−0.0022***	1.3196***	1.48E−05***	0.4547	−0.0010***
\$500,000	0.0944***	−0.0052***	−0.0014***	1.6696***	−0.0068***	3.4774***	4.33E−05***	0.4329	−0.0037***
Panel C: *Small stocks* (*Cross-sectional estimates*)									
\$1000	0.0235***	−0.0013***	−0.0004**	0.3866***	−0.0019***	0.6227***	2.17E−05***	0.3807	−0.0010***
\$10,000	0.0363***	−0.0015***	−0.0003	0.5606***	−0.0030***	0.9291***	2.54E−05***	0.3285	−0.0012***
\$100,000	0.1100***	−0.0054***	−0.0029***	1.6310***	−0.0090***	2.7350***	8.54E−05***	0.2646	−0.0026***
\$500,000	0.2057***	−0.0041	−0.0079**	1.8631***	−0.0136***	2.2194***	1.15E−04	0.0592	0.0038

Panel D: All stocks (Stock-by-stock median estimates)									
\$1000	0.0032***	−0.0002***	−4E−05***	0.1746***	−0.0003***	0.4769***	3E−06***		−0.0001***
	(79%, 21%)	(37%, 63%)	(45%, 55%)	(97%, 3%)	(12%, 88%)	(70%, 30%)	(63%, 37%)		(37%, 63%)
\$10,000	0.0050***	−0.0002***	−5E−05***	0.2477***	−0.0005***	0.5939***	4E−06***		−0.0002***
	(81%, 19%)	(38%, 62%)	(45%, 55%)	(97%, 3%)	(8%, 92%)	(72%, 28%)	(62%, 38%)		(38%, 62%)
\$100,000	0.0108***	−0.0008***	−0.0002***	0.5167***	−0.0010***	1.4962***	4E−06***		−0.0006***
	(75%, 25%)	(36%, 64%)	(42%, 58%)	(96%, 4%)	(11%, 89%)	(70%, 30%)	(58%, 42%)		(33%, 67%)
\$500,000	0.0236***	−0.0029***	−0.0006***	0.8067***	−0.0018***	2.6222***	2E−05***		−0.0019***
	(75%, 25%)	(32%, 68%)	(41%, 59%)	(94%, 6%)	(13%, 87%)	(64%, 36%)	(61%, 39%)		(30%, 70%)
Panel E: Large stocks (Stock-by-stock median estimates)									
\$1000	0.0018***	−0.0001***	−3E−05***	0.0969***	−0.0001***	0.4228***	2E−06***		−0.0001***
	(85%, 15%)	(27%, 73%)	(43%, 57%)	(99%, 1%)	(7%, 93%)	(74%, 26%)	(70%, 30%)		(29%, 71%)
\$10,000	0.0026***	−0.0001***	−4E−05***	0.1292***	−0.0002***	0.4870***	3E−06***		−0.0001***
	(88%, 12%)	(29%, 71%)	(41%, 59%)	(99%, 1%)	(4%, 96%)	(75%, 25%)	(73%, 27%)		(29%, 71%)
\$100,000	0.0072***	−0.0005***	−0.0001***	0.3318***	−0.0007***	0.8719***	6E−06***		−0.0003***
	(89%, 11%)	(29%, 71%)	(39%, 61%)	(100%, 0%)	(1%, 99%)	(74%, 26%)	(70%, 30%)		(27%, 73%)
\$500,000	0.0213***	−0.0020***	−0.0002***	0.8064***	−0.0017***	1.6724***	2E−05***		−0.0018***
	(82%, 18%)	(28%, 72%)	(43%, 57%)	(98%, 2%)	(6%, 94%)	(63%, 37%)	(67%, 33%)		(22%, 78%)
Panel F: Small stocks (Stock-by-stock median estimates)									
\$1000	0.0074***	−0.0004***	−0.0002***	0.2596***	−0.0005***	0.5293***	9E−06***		−0.0003***
	(74%, 26%)	(44%, 56%)	(46%, 54%)	(95%, 5%)	(16%, 84%)	(68%, 32%)	(58%, 42%)		(44%, 56%)
\$10,000	0.0108***	−0.0008***	−0.0001**	0.3499***	−0.0008***	0.7455***	9E−06***		−0.0003***
	(76%, 24%)	(44%, 56%)	(48%, 52%)	(95%, 5%)	(10%, 90%)	(70%, 30%)	(55%, 45%)		(45%, 55%)
\$100,000	0.0212***	−0.0035***	−0.0010***	0.6283***	−0.0013***	2.6283***	1E−06***		−0.0029***
	(65%, 35%)	(41%, 59%)	(44%, 56%)	(93%, 7%)	(18%, 82%)	(67%, 33%)	(50%, 50%)		(39%, 61%)
\$500,000	0.0401***	−0.0085***	−0.0048***	0.8150***	−0.0021***	4.1911***	1E−05***		−0.0042***
	(63%, 37%)	(38%, 62%)	(37%, 63%)	(88%, 12%)	(24%, 76%)	(65%, 35%)	(51%, 49%)		(43%, 57%)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

the *Postperiod* and *Preperiod*1 coefficients are equal). The resulting Wald statistics are significant for all simulated order sizes for large stocks, confirming that the decline in *ESpread* in *Postperiod* is significantly larger than in *PrePeriod*1.

For small stocks, the cross-sectional results in Panel C of Table 4 indicate a similar post-event reduction in *ESpread* across all order sizes except for the largest orders of $500,000, which shows no significant change. Tests of $\Delta Post = 0$ also indicate significant reductions in *ESpread* for all order sizes except the largest simulated orders of $500,000.

The stock-by-stock results corroborate the cross-sectional evidence of a decline in *ESpread* for large stocks (Panel E of Table 4). All median coefficients for *Postperiod*, *Preperiod*1 and $\Delta Post$ are significant and negative. Additionally, the proportion of large stocks with negative *Postperiod* coefficients (71–73% of large stocks) is consistently higher than those with negative *Preperiod*1 coefficients (57–61% of large stocks). This indicates a more broad-based decline in *ESpread* for large stocks in the post-event period compared with the pre-event period. For small stocks, the stock-by-stock results are consistent with the cross-sectional results with one exception. Panel F of Table 4 shows that the *Postperiod* and $\Delta Post$ estimates for small stocks point towards a significant post-event decline in *ESpread* across all simulated order sizes, including for the largest orders of $500,000 which showed no significant change in the cross-sectional results. However, the proportion of stocks exhibiting negative *Postperiod* coefficients (56–62% of small stocks) is similar to those with negative *Preperiod*1 coefficients (52–63% of small stocks). In addition, a smaller proportion of small stocks have negative $\Delta Post$ (55–61% of small stocks) compared to large stocks with negative $\Delta Post$ (71–78% of large stocks). These results suggest that relatively fewer small stocks (as a proportion of the small-stock universe) experienced a post-event decline in *ESpread* compared to large stocks.[23]

Overall, the results suggest that the introduction of anonymity has enhanced liquidity and reduced the cost of executing trades through increased book depth, particularly for the larger and more active stocks. Our findings are consistent with those of Foucault et al. (2007), who document a significant improvement in quoted depth for Euronext Paris stocks after the introduction of pre-trade anonymity. However, we find that the results for small stocks are less robust with respect to larger trade sizes. Also, a smaller cross-section of small stocks exhibit a post-event decline in *ESpread* compared to large stocks.[24] This evidence of a weaker improvement in liquidity for small stocks is consistent with the univariate findings in Section 5 and provides weak support for the Foucault et al. (2007) prediction linking the effects of a switch to anonymity to the information environment.

8. The effect of anonymity on order aggressiveness

To analyze the role of anonymity in traders' aggressiveness in placing orders, we estimate an ordered probit model (see Ranaldo, 2004 for a similar implementation). The

[23]For robustness, we also evaluate of the joint significance of the stock-by-stock coefficients using a Z-statistic as described in footnote 22. The results are identical to those of the Fisher combined test except for the *Trend* variable for simulated trades of $100,000 and $500,000 in small stocks, which are insignificant.

[24]Additional cross-sectional analysis using *Postperiod*2 results negative $Postperiod_{it}$ estimates and the rejection of $\Delta Post = 0$ for all simulated order sizes in large stocks and $1000 orders in small stocks. All larger simulated order sizes in small stocks have statistically insignificant $\Delta Post$. For the stock-by-stock results, none of the $\Delta Post$ is significant except for $10,000 and $100,000 orders in large stocks, which are significant at the 10% and 1% levels, respectively.

dependent discrete variable takes on a value of 1–7 denoting increasing levels of order aggressiveness from, progressively: cancelled orders, limit orders outside the prevailing best quote, limit orders at the best quote, limit orders at a price better than the best quote, market orders that are fully executed immediately at the prevailing best quote, market orders with volumes greater than that available at the prevailing best quote but which do not walk up the book, and market orders which consume all available volume at the best quote and subsequently walk up the book.

The independent variables are volumes at the best bid and ask prices at the time of the order submission, the average time between the last three order arrivals on the same side of the book as the order submitted, the proportional bid-ask spread, the standard deviation of the previous 20 midquote percentage returns, and *Preperiod*1 and *Postperiod* dummy variables as defined previously.

The cross-sectional and median stock-by-stock results are presented in Table 5. For the stock-by-stock estimations, significance tests for the variables are conducted using the Fisher combined probability test explained in Section 6.[25]

The cross-sectional results show that *Postperiod* is negative and highly significant for both large and small stocks, at −0.0465 and −0.0202, respectively. These results are consistent across all pre-post event windows, and are supported by the negative stock-by-stock median *Postperiod* estimates of −0.0382 and −0.0076 for large and small stocks, respectively. This reduction in order aggressiveness reverses the general trend of increasing order aggressiveness in *Preperiod*1, which is significantly positive in the cross-sectional results for large stocks and in the median stock-by-stock results for both large and small stocks. The significant $\Delta Post$ for large and small stocks—in both cross-sectional and stock-by-stock results—also confirms that the post-event decline in order aggressiveness cannot be attributed to a secular trend.

These findings are consistent with our expectation of reduced order aggressiveness in an anonymous trading environment. Without broker identifiers, traders' ability to determine which orders are informed is reduced. Uninformed traders are more willing to expose their orders due to the reduced risk that informed traders will pick off their orders. At the same time, informed traders are also willing to expose their orders as the risk of being identified and front-run by other traders is reduced.

However, small stocks appear to experience a less broad-based reduction in order aggressiveness compared to large stocks. For example, 68% of large stocks experienced a decline in *Postperiod*, compared to 52% of small stocks (Panel B of Table 5). The median $\Delta Post$ is −0.06 for large stocks compared to −0.02 for small stocks, indicating that large stocks exhibit a higher likelihood of reduced post-event order aggressiveness compared to small stocks. These results may be due to the higher information asymmetry and shallower liquidity in small stocks, which discourage the placement of passive limit orders by uninformed traders as they offer a "free option" to informed traders.

The remaining results in Table 5 show that order aggressiveness is positively (negatively) related to the depth on the same (opposite) side as the order, as expected (Handa et al., 2000).

[25]For robustness, we also evaluate the statistical significance of the stock-by-stock coefficients across k stocks using the sum test (see, for example, Koziol and Perlman, 1978 for a more detailed discussion). The test statistic is calculated by summing the variable of interest's chi-square test statistics across all stocks to form an omnibus chi-square, which has χ^2 critical value with k degrees of freedom. The results are identical to those of the Fisher combined test and hence not reported here.

Table 5
Results of probit analysis on order aggressiveness

This table reports the results from the probit regressions where the dependent variable is order aggressiveness ranked from the least to most aggressive order type. Panel A reports the cross-sectional results. Panel B reports the median coefficients from the stock-by-stock estimations, with the % of estimates that are positive and negative, respectively, reported in parentheses. The explanatory variables are the prevailing volume at the best price on the same side as the submitted order (*samedepth*), the prevailing volume at the best price on the same side as the submitted order (*oppdepth*), the average time between the last three order arrivals on the same side as the submitted order (*orderwait*), the proportional bid–ask spread (*pspread*), the standard deviation of the previous 20 midquote percentage returns (*volatility*) and the dummy variables *Preperiod*1 and *Postperiod*. The sample covers the period spanning *Preperiod*2, *Preperiod*1 and *Postperiod*1. $\Delta Post$ is the difference (median difference) between the *Postperiod* and *Preperiod*1 coefficients for the cross-sectional estimation (stock-by-stock estimations), with the % of estimates that are positive and negative, respectively, reported in parentheses. For the cross-sectional estimates, the significance levels for $\Delta Post$ are for Wald tests of the restriction $\Delta Post = 0$. The significance of the stock-by-stock coefficients and $\Delta Post$ is estimated using the Fisher combined probability test. The results for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 stocks) are reported separately, with the significance of the individual chi-square statistics reported as indicated. There are 23,043,225 observations for large stocks and 2,407,229 observations for small stocks.

Variable	All stocks	Large stocks	Small stocks
Panel A: Cross-sectional estimates			
Samedepth	0.0606***	0.3068***	0.0082***
Oppdepth	−0.0169***	−0.1538***	−0.0229***
Orderwait	0.0122***	0.0261***	0.0058***
Pspread	−0.1158***	−0.2308***	−0.0157***
Volatility	1.7909***	0.9050***	0.3175***
*Preperiod*1	0.0122***	0.0160***	−0.0160***
Postperiod	−0.0477***	−0.0465***	−0.0202***
$\Delta Post$	−0.0599***	−0.0625***	−0.0042**
Panel B: Stock-by-stock median estimates			
Samedepth	3.2442***	5.3936***	2.1640***
	(89%, 11%)	(99%, 1%)	(83%, 17%)
Oppdepth	−1.0102***	−1.8828***	−0.5198***
	(22%, 78%)	(6%, 94%)	(32%, 68%)
Orderwait	0.0052***	0.0515***	0.0021***
	(89%, 11%)	(96%, 4%)	(84%, 16%)
Pspread	−0.1097***	−0.3142***	−0.0556***
	(8%, 92%)	(1%, 99%)	(13%, 87%)
Volatility	2.6554***	6.5456***	1.7927***
	(65%, 35%)	(66%, 34%)	(64%, 36%)
*Preperiod*1	0.0100***	0.0095***	0.0105***
	(54%, 46%)	(55%, 45%)	(53%, 47%)
Postperiod	−0.0249***	−0.0382***	−0.0076***
	(42%, 58%)	(32%, 68%)	(48%, 52%)
$\Delta Post$	−0.04***	−0.06***	−0.02***
	(36%, 64%)	(24%, 76%)	(44%, 56%)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

This is also consistent with Biais et al. (1995) who find that limit order traders tend to undercut each other in quick succession when providing liquidity, and place more aggressive orders within the quotes when competition for execution is high, in order to gain priority for execution.

We also find that spreads are negatively related to order aggressiveness, consistent with the findings of Ranaldo (2004) for the Swiss market. The positive coefficients for *orderwait* imply an inverse association between the order submission rate and order aggressiveness. In other words, a faster order submission rate is associated with more passive orders. This may be due to liquidity providers clustering their limit orders, due to factors such as time priority and tick sizes (see Ranaldo, 2004 for a more detailed explanation). Episodic events such as periods of low information asymmetry may also result in the clustering of passive orders.

Contrary to the view that higher volatility induces traders to reduce their exposure to being picked off by placing less aggressive limit orders (see Ranaldo, 2004 and Foucault et al., 2007), we find that volatility is positively related to order aggressiveness. Our results are, however, consistent with the empirical findings of Hasbrouck and Saar (2002) and Hall and Hautsch (2006). These results reflect the view that higher volatility increases the free option value of mispriced limit orders, thus making limit orders less desirable and market orders more attractive. Bloomfield et al. (2005) also argue that informed traders supply liquidity and price the limit orders more aggressively during periods of higher volatility because they do not face the same uncertainty over the true value of the security as uninformed traders do.

9. The effect of anonymity on market selection

9.1. Upstairs vs downstairs trading

The univariate results in Section 5 show a decline in the average proportion of upstairs trading in large stocks after the removal of broker identifiers. We extend the investigation into the choice between the upstairs and downstairs markets further by controlling for market conditions using a probit model (Barclay et al., 2003; Bessembinder and Venkataraman, 2004).[26] For estimation purposes, only stocks with at least 10 upstairs and 10 downstairs trades in each pre- and post-period are included in our analysis. To facilitate comparison between upstairs and downstairs trades, only block trades are considered. Block trades are identified here as all trades of *Max*[$100,000, 1% of mean traded value in the stock over the sample period].[27] This results in 171,341 trades in 182 S&P 200 stocks and 7140 trades in 74 non-S&P 200 stocks in the final sample. Of these, 53% (50%) of the trades in the S&P 200 (non-S&P 200) stocks are upstairs trades.

[26]The model is also estimated on a stock-by-stock basis to account for any stock-specific effects. The results are consistent with the cross-sectional regressions and hence not reported. Bessembinder and Venkataraman (2004) estimate a two-stage model involving the estimation of the probit in the first stage and an endogenous switching model in the second stage to account for any self-selection bias due to different execution costs in the upstairs and downstairs markets. We do not consider the endogenous switching model as the ASX's eligibility criteria for upstairs trades mean that the decision of whether to trade upstairs or downstairs will not be purely based on execution cost, but also on the exchange's minimum upstairs trading requirements.

[27]The block is required to be at least $100,000, an economically significant amount, to prevent the inclusion of block trades of low economic value in the lowest-priced stocks.

The dependent variable of the probit model is equal to 1 if the trade is conducted upstairs and zero otherwise. The explanatory variables are the proportional bid-ask spread (*pspread*), trade imbalance (*imb*), a dummy variable equal to 1 if the trading is buyer-initiated and zero otherwise (*buyer*), block size standardized by the mean traded value in the stock (*size*), volatility (*volatility*), the inverse of the trade price (*invprice*) and *Preperiod*1 and *Postperiod* dummy variables as defined previously.[28]

The cross-sectional results for large stocks show that *Postperiod* is significant and negative at −0.15, and significant and positive at 0.05 for the non-event *Preperiod*1 window (Table 6). This shows that, relative to the base period of *Preperiod*2, traders became more likely to trade upstairs in *Preperiod*1 but subsequently less likely to do so in *Postperiod*1. This supports the univariate findings of reduced upstairs trading after the introduction of anonymity.

The remaining results for large stocks indicate that the likelihood of an upstairs trade is positively related to *size* and negatively related to *buyer* and *invprice*, which is consistent with Bessembinder and Venkataraman (2004). The positive sign on *size* may be driven at least in part by the minimum size requirements for block special and portfolio special crossings. The coefficients for *pspread* are negative, possibly due in part to the exchange's rules requiring the order book spread to be at least one tick wide or less before a priority crossing can occur. *Imb* is also negatively related to the likelihood of an upstairs trade. This is perhaps due to reduced trade execution costs in the downstairs market when trade imbalance is high on the side of the initiating order, as the market is likely to interpret these trades as uninformed. Upstairs trades in large stocks are more likely when *volatility* is high, indicating traders are less willing to post in the limit order book when uncertainty is high.

For small stocks, only the *pspread*, *imb* and *size* variables are significant. The insignificant *Postperiod* parameter suggests that small stocks' upstairs trading is unaffected following the removal of broker identifiers. Wald tests of $\Delta Post = 0$ are highly significant for large stocks but not for small stocks, supporting this conclusion. However, it should be noted that the lower liquidity in these stocks, coupled with the exchange's minimum size requirements for block special and portfolio special crossings, mean that it is inherently more difficult to conduct upstairs trades in small stocks compared to large stocks.[29] Thus, our results may be affected by the relatively small sample size for these stocks.

Overall, we find evidence of some migration of trading in large stocks from the upstairs to the downstairs market after the introduction of anonymous trading in the downstairs market. This suggests that: (i) participants are indeed taking advantage of the anonymity offered by the downstairs market to conduct block trades; and (ii) upstairs trades may be more difficult to facilitate in the absence of broker identifiers in the order book, preventing brokers from identifying potential liquidity suppliers for block trades. These effects may not be as relevant for small stocks if order book depth in these stocks is too thin to offset the benefits of upstairs negotiation in facilitating block trades.

[28] *Imb* is calculated as: *Own side trading volume in last* 10 *trades*/*Total trading volume in last* 10 *trades* (see Handa et al., 2004). The Lee and Ready (1991) algorithm is used to identify buyer- and seller-initiated trades. All opening-initiated trades are excluded from the sample.

[29] We also estimate the model after taking these size restrictions into account. However, this truncates the sample of small stocks to the extent that we are unable to obtain valid results.

Table 6
Results of probit analysis on the choice of upstairs vs. downstairs trading

This table reports the results from the cross-sectional probit estimations evaluating the choice of upstairs vs. downstairs trading for all trades of max[$100,000, 1% of mean traded value over the sample period]. The dependent variable is equal to 1 if the trade is conducted upstairs and zero otherwise. The explanatory variables are the proportional bid–ask spread (*pspread*), trade imbalance (*imb*), a dummy variable equal to 1 if the trading is buyer-initiated and zero otherwise (*buyer*), standardized block size (*size*), volatility (*volatility*), the inverse of the trade price (*invprice*) and the dummy variables *Preperiod*1 and *Postperiod*. The probit is estimated for the period encompassing *Preperiod*2, *Preperiod*1 and *Postperiod*1. The results are reported separately for all stocks (All Ords stocks), large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 stocks), with the significance of the individual chi-square statistics reported as indicated. $\Delta Post$ is the difference between the *Postperiod* and *Preperiod*1 coefficients, and the significance levels for $\Delta Post$ are for Wald tests of the restriction $\Delta Post = 0$. There are 91,378 (3595) upstairs trades in large (small) stocks and 79,963 (3545) downstairs trades in large (small) stocks.

	All stocks	Large stocks	Small stocks
Intercept	0.35***	0.32***	0.10
Pspread	−0.40***	−0.34***	−0.43***
Imb	−0.29***	−0.29***	−0.40***
Buyer	−0.06***	−0.06***	0.06
Size	3.47***	4.67***	1.32***
Volatility	0.21***	0.24***	−0.11
Invprice	−0.45***	−0.60***	0.04
*Preperiod*1	0.05***	0.05***	−0.05
Postperiod	−0.15***	−0.15***	−0.03
$\Delta Post$	498.00***	499.51***	0.17

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

9.2. ASX vs NZX trading

As a further test of whether anonymity represents an important factor in determining the direction of order flow in competitive fragmented markets, we compare the trading activity of stocks cross-listed on the ASX and the (non-anonymous) NZX before and after the removal of broker identifiers on the ASX. To do this, we replicate the analysis in Sections 5 and 9.1 using trade and order book data during overlapping trading hours for a sub-sample of 35 stocks that have cross-listings on the ASX and NZX.[30] First, we examine the post-event change in the market share of both exchanges to determine if the removal of broker identifiers has encouraged the migration of trading activity to substitute markets with the preferred level of anonymity. ASX market share is calculated as follows:

$$ASX\ market\ share_i = \frac{ASX\ \$volume_i}{ASX\ \$volume_i + NZX\ \$volume_i} \times 100\%$$

[30]To be included in the sub-sample, stocks had to be cross-listed throughout the sample period and had to have data available for the entire sample period. The time overlap is delayed by an hour for a small proportion of the sample due to non-synchronous daylight savings changes in Australia and New Zealand.

All dollar amounts are expressed in Australian dollars. We find that the average ASX market share for large (small) ASX-listed stocks increased by 0.76% (3.03%) in *Preperiod*1 to 91.32% (59.02%) in *Postperiod*1. However, this change is significant at the 0.05% level only for small stocks. The results for $\Delta PrePost1 - \Delta Pre(2,1)$ as defined in Section 5 are statistically insignificant for large stocks and only marginally significant at the 10% level small stocks, indicating that the increase in average ASX market share over time may have been at least partly due to a secular trend. This is confirmed by the results obtained when *Postperiod*2 is used instead of *Postperiod*1, where neither $\Delta PrePost1$ nor $\Delta PrePost1 - \Delta Pre(2,1)$ are significant.

To determine the effects of anonymity after controlling for other factors influencing traders' market selection decision, we estimate the following cross-sectional probit for the sample of cross-listed stock pairs:

$$\begin{aligned} ASX\ Dummy_{it} = {} & \alpha + \beta_1 RPspread_{it} + \beta_2 RImb_{it} + \beta_3 RDepth_{it} + \beta_4 RVolatility_{it} \\ & + \beta_5 RMktCap_{it} + \beta_6 Buyer_{it} + \beta_7 AUDSize_{it} + \beta_8 AusIncorp_{it} \\ & + \beta_9 preperiod1_{it} + \beta_{10} Postperiod_{it} + \beta_{11} AUDPost_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

The dependent variable $ASX\ Dummy_{it}$ is equal to 1 if the trade is conducted on the ASX and zero otherwise. The explanatory variables are the relative proportional bid-ask spread *RPspread* (calculated as the ratio of the proportional spread on the ASX to the proportional spread for the same stock on NZX at the same point in time), relative order imbalance (*RImb*), relative market depth (*RDepth*), relative volatility (*RVolatility*) and relative market capitalization (*RMktCap*).[31] Additional explanatory variables are a dummy variable equal to 1 if the trade is buyer-initiated and zero otherwise (*Buyer*), the value of the trade in AUD terms (*AUDSize*), a dummy variable that is equal to 1 if the stock is incorporated in Australia and zero otherwise (*AusIncorp*), dummy variables for *Preperiod*1 and *Postperiod*, and an interaction variable *AUDPost* which is the product of *AUDSize* and *Postperiod*.

Eq. (3) is estimated separately for large and small stocks. Only stocks with at least 10 ASX and 10 NZX trades in each pre- and post-period are considered. The resulting sample has 20 pairs of stocks with a total of 343,326 trades. Eighty-six per cent of these trades are conducted on the ASX. Of the nine large stocks in the sample which are components of the S&P 200 index, eight are Australian-incorporated. Of the 11 small stocks which are not included in the S&P 200 index, nine are New Zealand-incorporated, one is Australian-incorporated and one UK-incorporated.

The cross-sectional estimation results in Table 7 show that traders are significantly more likely to trade large stocks on the ASX rather than on the NZX after the introduction of

[31]Imbalance is calculated as the ratio of the volume-weighted average price at the 10 best price levels on the side of the trade initiator to the combined volume-weighted average price at the 10 best price levels on both sides of the order book. If there is no volume on either side of the book, the imbalance is set to 0.5 by default. Depth is calculated as the combined volume at the 10 best bid and ask prices in the order book (denoted in millions of units). Volatility is calculated as the natural logarithm of the highest traded price to the lowest traded price in the half-hour block in which the trade occurs. Market capitalization is the stock's price multiplied by the number of shares outstanding, and is denoted in billions of Australian dollars. All relative ratios are calculated as the ASX metric divided by the corresponding NZX metric for the same stock at the same time, except where otherwise indicated.

Table 7
Results of probit analysis on the choice of ASX vs. NZX trading

This table reports the results from the cross-sectional probit estimations evaluating the choice of ASX vs. NZX trading for all trades in 20 cross-listed stock pairs. The dependent variable is equal to 1 if the trade is conducted on the ASX and zero otherwise. The explanatory variables are the ratio of the proportional bid–ask spread on the ASX to the NZX (*RPspread*), ratio of the order imbalance on the side of the initiating order on the ASX to the NZX (*RImb*), ratio of the order depth at the time of the trade on the ASX to the NZX (*RDepth*), ratio of the volatility on the ASX to the NZX (*RVolatility*), a dummy variable equal to 1 if the trading is buyer-initiated and zero otherwise (*Buyer*), trade size in AUD (*AUDSize*), the interaction variable between *AUDSize* and *Postperiod* (*AUDPost*), the ratio of the stock's market capitalization on the ASX to the NZX in AUD (*RMktCap*), a dummy variable which is equal to 1 if the stock is incorporated in Australia and 0 otherwise (*AusIncorp*), and the dummy variables *Preperiod*1 and *Postperiod*. The probit is estimated for the period encompassing *Preperiod*2, *Preperiod*1 and *Postperiod*1. The results are reported separately for large stocks (S&P 200 index stocks) and small stocks (non-S&P 200 stocks), with the significance of the individual chi-square statistics reported as indicated. $\Delta Post$ is the difference between the *Postperiod* and *Preperiod*1 coefficients and the significance levels for $\Delta Post$ are for Wald tests of the restriction $\Delta Post = 0$. There are 276,349 (18,846) ASX trades in large (small) stocks and 26,521 (21,610) NZX trades in large (small) stocks.

	Large stocks	Small stocks
Intercept	−2.3749***	1.8656***
RPspread	−0.7775***	−0.2133***
RImb	0.0906***	−0.0281
RDepth	0.0016***	0.7229***
RVolatility	0.0815***	0.2776***
Buyer	−0.0430***	−0.0246
AUDSize	−0.1516***	−0.2783***
AUDPost	−0.1419***	0.1873
RMktCap	3.3074***	−2.0524***
AusIncorp	0.8428***	0.7085***
*Preperiod*1	−0.0396**	−0.0176
Postperiod	0.0614***	−0.3468***
$\Delta Post$	0.1010***	−0.3291***

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

anonymity.[32] This is seen by the positive and significant *Postperiod* estimate of 0.0614 for large stocks. The *Preperiod*1 estimate is −0.0396, indicating traders were less likely to trade on the ASX during the pre-event period where anonymity was not available.

However, traders become less likely to trade small stocks on the ASX rather than the NZX during the post-event period, as indicated by the significantly negative *Postperiod* estimate of −0.3468 for small stocks. Wald tests of $\Delta Post = 0$ are highly significant for both large and small stocks, indicating that these changes are not merely a continuation of a trend from *Preperiod*1. This asymmetry between the effects for large and small stocks suggests that brokers are more willing to transfer their order flow from more transparent

[32]The stock pair-by-stock pair probit results are not reported as they are biased with the omission of the *AusIncorp* variable, which is constant for each stock pair. In addition, the reporting of any aggregated or median results may not be an accurate representation of the true population parameter as the small number of stocks used in the sample means the aggregate and median significant coefficients are very sensitive to extreme values.

regimes to obtain anonymity, provided that adverse selection risk is low (with stock size being a reasonable proxy for this risk).

The analysis is repeated using *Postperiod*2 instead of *Postperiod*1 as the post-event period. The conclusions remain the same for small stocks, but for large stocks the post-event change becomes insignificant, indicating that the shift in trader preference towards the ASX is not consistent over different post-event intervals.

The results for the other variables in Eq. (3) are as expected. The *RPspread* estimate is negative, indicating that a trade is more likely to occur on the ASX when the proportional bid-ask spread for a stock is narrower on the ASX than on the NZX. Similarly, a trade is more likely to occur on ASX if market depth and volatility are higher on the ASX than on the NZX at the time of the trade, and if the ASX is the ‘‘home’’ exchange (that is, the stock is incorporated in Australia). These effects are consistent across both large and small stocks. The *RMktCap* estimate is positive (negative) and significant for large (small) stocks, indicating that traders generally prefer to trade large (small) stocks on the exchange where the stock's market value is higher (lower).

Buyer-initiated and large trades are less likely to occur on the ASX than the NZX, as seen by the negative coefficient for *Buyer* for large stocks, and negative coefficients for *AUDSize* for both large and small stocks. Liquidity traders may prefer not to send large orders to an anonymous market where they cannot easily disclose their identities to signal that their trades are liquidity-motivated. This is possibly even more of a concern for large liquidity-motivated buy orders, which can be misconstrued by other participants as being informed (see, for example, Chan and Lakonishok, 1993; Gemmill, 1996; Saar, 2001; Reiss and Werner, 2005). The significantly negative interaction variable *AUDPost* for large stocks supports the idea that liquidity traders prefer not to send large orders to an anonymous market. *AUDPost* is insignificant for small stocks, suggesting that for these stocks the preferred trading venue for trades of different sizes is unaffected by the removal of broker identifiers.

Finally, the estimate for *RImb* is positive and significant for large stocks and insignificant for small stocks. This suggests that it is only for larger stocks that traders consider a larger order imbalance on the ASX relative to the NZX in their decision to trade on the ASX.

The overall evidence indicates that the removal of broker identifiers has resulted in an increase (decrease) in ASX market share for large (small) stocks which are cross-listed on the NZX. This is not unexpected given large stocks' strongly improved liquidity and cumulative depth on a broader-based level compared to small stocks, as documented in Sections 5–8. However, this increase in market share is not consistent over different post-event intervals. This suggests that anonymity is an important factor of market selection by traders of cross-listed stocks, but is not by itself a primary determinant in traders' choice of trading venue. Other factors such as spreads, order book depth, volatility, order size, market capitalization and the country of incorporation continue to play significant roles in traders' order submission decisions.

10. Summary and conclusions

The removal of broker identifiers from the ASX limit order book has generally had a positive impact on liquidity. We find that anonymity leads to reduced spreads and increased order book depth, after controlling for other explanatory factors. We also find that anonymity leads to reduced order aggressiveness. This is consistent with our expectation that (limit) order exposure becomes more attractive in an anonymous market because market participants cannot identify informed and uninformed traders, thus reducing the risk of both uninformed and informed orders being "picked-off", piggybacked or front-run by other traders, and supports empirical findings of Foucault et al. (2007) for Euronext Paris stocks.

Larger and more active stocks appear to benefit the most from anonymity, particularly in the form of a significant reduction in the price impact component of the spread, and a broader-based improvement in order book depth compared to small stocks. Marginally higher post-event realized spreads in small stocks suggest increased inventory management costs with the introduction of anonymous trading. These differences may be due to the lower liquidity and higher information asymmetry levels present in small stocks. Traders may find it more difficult to signal liquidity-motivated trades in stocks with already high levels of information asymmetry under an anonymous trading environment. Uninformed traders in these stocks may also be reluctant to trade aggressively if there is a high risk of being "picked-off" by informed investors, particularly when they cannot identify other traders and the order book is already thin, indicating few liquidity providers.

These differences in the results for large and small stocks provide some support for the Foucault et al. (2007) prediction that trader anonymity is related to cross-sectional variation in the information environment. This has important implications for market design: if smaller stocks are less responsive to public policy measures which entail some reduction in transparency, exchanges may wish to carefully consider if an anonymous order-driven trading environment is really optimal for these stocks.

Finally, we find evidence of liquidity consolidation following the removal of broker identifiers, with order flow gravitating to the trading venue offering anonymity. This is shown by an increase in the proportion of trading in the downstairs market compared to the non-anonymous upstairs market. It is also shown in the significant shift in trading activity in large stocks from the NZX to the ASX, although this effect does not appear to be permanent. This suggests that brokers are more inclined to expose their orders downstairs when they can do so anonymously, and that they are willing to transfer their order flow from more transparent regimes to obtain anonymity, provided that adverse selection risk is low.

Our overall results support the Simaan et al. (2003) proposition that exchanges operating in fragmented markets should allow anonymity to improve price competition and narrow bid-ask spreads further. However, we also find evidence that some of these benefits may be significant only if the stocks are sufficiently large and liquid.

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References

Barclay, M.J., Hendershott, T., McCormick, D.T., 2003. Competition among trading venues: information and trading on electronic communications networks. Journal of Finance 58, 2637–2665.

Battalio, R., Ellul, A., Jennings, R., 2007. Reputation effects in trading on the New York Stock Exchange. Journal of Finance 62, 1243–1271.

Benveniste, L., Marcus, A., Wilhelm, W., 1992. What's special about the specialist? Journal of Financial Economics 32, 61–86.

Bessembinder, H., Kaufman, H.M., 1997. A comparison of trade execution costs for NYSE and NASDAQ-listed stocks. The Journal of Financial and Quantitative Analysis 32, 287–310.

Bessembinder, H., Venkataraman, K., 2004. Does an electronic stock exchange need an upstairs market? Journal of Financial Economics 73, 3–36.

Bessembinder, H., Maxwell, W., Venkataraman, K., 2006. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. Journal of Financial Economics 82, 251–288.

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

Bloomfield, R., O'Hara, M., 2000. Can transparent markets survive? Journal of Financial Economics 55, 259–425.

Bloomfield, R., O'Hara, M., Saar, G., 2005. The "make or take" decision in an electronic market: evidence on the evolution of liquidity. Journal of Financial Economics 75, 165–199.

Boehmer, E., Saar, G., Yu, L., 2005. Lifting the veil: an analysis of pre-trade transparency at the NYSE. Journal of Finance 60, 783–815.

Chan, L.K.C., Lakonishok, J., 1993. Institutional trades and intraday stock price behavior. Journal of Financial Economics 33, 173–199.

Christie, A.A., 1990. Aggregation of test statistics: an evaluation of the evidence on contracting and size hypotheses. Journal of Accounting and Economics 12, 15–36.

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

Copeland, T.E., Galai, D., 1983. Information effects on the bid–ask spread. Journal of Finance 38, 1457–1469.

Dodd, P., Warner, J.B., 1983. On corporate governance: a study of proxy contests. Journal of Financial Economics 11, 401–438.

Edwards, A.K., Harris, L.E., Piwowar, M.S., 2007. Corporate bond market transaction costs and transparency. The Journal of Finance 62, 1421–1451.

Flood, M.D., Huisman, R., Koedijk, K.G., Mahieu, R.J., 1999. Quote disclosure and price discovery in multiple-dealer financial markets. Review of Financial Studies 12, 37–59.

Forster, M.M., George, T.J., 1992. Anonymity in securities markets. Journal of Financial Intermediation 2, 168–206.

Foucault, T., Moinas, S., Theissen, E., 2007. Does anonymity matter in electronic limit order markets? Review of Financial Studies 20, 1707–1747.

Gemmill, G., 1996. Transparency and liquidity: a study of block trades on the London Stock Exchange under different publication rules. Journal of Finance 51, 1765–1786.

Gibbons, M.R., Shanken, J., 1987. Subperiod aggregation and the power of multivariate tests of portfolio efficiency. Journal of Financial Economics 19, 389–394.

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

Grossman, S., 1992. The informational role of upstairs and downstairs markets. Journal of Business 65, 509–529.

Hall, A., Hautsch, N., 2006. Order aggressiveness and order book dynamics. Empirical Economics 30, 973–1005.

Handa, P., Schwartz, R.A., Tiwari, A., 2000. Quote setting and price formation in an order driven market. Journal of Financial Markets 6, 461–489.

Handa, P., Schwartz, R.A., Tiwari, A., 2004. The economic value of a trading floor: evidence from the American Stock Exchange. Journal of Business 77, 331–355.

Harris, L., 1994. Minimum price variations, discrete bid–ask spreads, and quotations sizes. Review of Financial Studies 7, 149–178.

Harris, L., 1996. Does a large minimum price variation encourage order exposure? Working Paper, University of Southern California

Harris, L., 1997. Order exposure and parasitic traders. Paper presented at the Deusche Bourse AG Symposium "Equity Market Structure for Large- and Mid-Cap Stocks," Frankfurt, 12 December 1997.

Harris, L.E., Piwowar, M.S., 2006. Secondary trading costs in the municipal bond market. The Journal of Finance 61, 1361–1397.

Hasbrouck, J., 1991. Measuring the information content of stock trades. Journal of Finance 46, 179–207.

Hasbrouck, J., Saar, G., 2002. Limit Orders and Volatility in a Hybrid Market: The Island ECN. Working Paper, NYU

Hasbrouck, J., Sofianos, G., Sosebee, D., 1993. New York stock exchange systems and trading procedures. NYSE Working Paper 93-01.

Heidle, H.G., Huang, R.D., 2002. Information-based trading in dealer and auction markets: an analysis of exchange listings. Journal of Financial and Quantitative Analysis 37, 391–424.

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

Koziol, J.A., Perlman, M.D., 1978. Combining independent chi-squared tests. Journal of the American Statistical Association 73, 753–763.

Kraus, A., Stoll, H.R., 1972. Price impacts of block trading on the New York Stock Exchange. The Journal of Finance 27, 569–588.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733–746.

Madhavan, A., 1995. Consolidation, fragmentation, and the disclosure of trading information. Review of Financial Studies 8, 579–603.

Madhavan, A., Cheng, M., 1997. In search of liquidity: block trades in the upstairs and downstairs market. Review of Financial Studies 10, 175–203.

McInish, T.H., Wood, R.A., 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks. Journal of Finance 47, 753–764.

Meulbroek, L.K., 1992. An empirical analysis of illegal insider trading. The Journal of Finance 47, 1661–1699.

Ranaldo, A., 2004. Order aggressiveness in limit order book markets. Journal of Financial Markets 7, 53–74.

Reiss, P.C., Werner, I.M., 2005. Anonymity, adverse selection, and the sorting of interdealer trades. Review of Financial Studies 18, 599–636.

Saar, G., 2001. Price impact asymmetry of block trades: an institutional trading explanation. Review of Financial Studies 14, 1153–1181.

Seppi, D., 1990. Equilibrium block trading and asymmetric information. Journal of Finance 45, 73–94.

Simaan, Y., Weaver, D., Whitcomb, D., 2003. Market maker quotation behavior and pre trade transparency. Journal of Finance 58, 1247–1268.

Theissen, E., 2002. Floor versus screen trading: evidence from the German stock market. Journal of Institutional and Theoretical Economics 158, 32–54.

Waisburd, A., 2003. Anonymity and Liquidity: evidence from the Paris Bourse. mimeo, Texas Christian University.

Warner, J.B., Watts, R.L., Wruck, K.H., 1988. Stock prices and top management changes. Journal of Financial Economics 20, 461–492.