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LIFTING THE VEIL:
AN ANALYSIS OF PRE-TRADE TRANSPARENCY AT THE NYSE

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Abstract

This paper investigates an important feature of market design: pre-trade transparency, defined as the availability of information about pending trading interest in the market. We look at how the NYSE's introduction of OpenBook, which enables traders off the exchange floor to observe depth in the limit order book in real time, affects the trading strategies of investors and specialists, informational efficiency, liquidity, and returns. We find that traders attempt to manage the exposure of their limit orders: the cancellation rate of limit orders increases, time-to-cancellation of limit orders shortens, and smaller limit orders are submitted. The new information OpenBook provides seems to cause traders to prefer managing the trading process themselves, rather than delegating this task to floor brokers. We also show that specialists' participation rate in trading decreases and the depth they add to the quote goes down, consistent with a loss of their informational advantage or with being "crowded out" by active limit order strategies. We detect an improvement in the informational efficiency of prices after the introduction of OpenBook. Greater pre-trade transparency leads to some improvement in displayed liquidity in the book and a reduction in the execution costs of trades. We find that cumulative abnormal returns are positive and significant after the introduction of OpenBook, consistent with the view that improvement in liquidity affects stock returns.

1 INTRODUCTION

The proliferation of new exchanges and trading platforms in the U.S. and abroad brings to the forefront many issues in market design. Should a market have at its core an electronic limit order book? What possible role can market makers play? What information should market participants observe on order flow and prices? These issues have implications for the trading strategies employed by investors, the behavior of specialists, liquidity in the market, the informational efficiency of prices, and ultimately the valuations of listed companies and the welfare of their shareholders. In this work we investigate a key feature of market design: transparency, defined as the ability of market participants to observe the information in the trading process.

Our focus is on a particular form of transparency: the ability of market participants to observe the pending trading interests of other participants, or in other words, the content of the limit order book. Knowledge about buying and selling interest can be used both to refine one's inference about the value of a security, and to strategically plan the execution of a trading goal to minimize transaction costs. We use a natural experiment, the introduction of OpenBook by the NYSE, to investigate the impact of an exogenous increase in the level of public information about the content of the limit order book.

OpenBook, introduced in January 2002, allows traders off the NYSE floor to observe the depth in the book in real time at each price level for all securities. Before the introduction of OpenBook, only the best bid and offer that can represent both the limit order book and the specialist's own trading interest were disseminated by the NYSE. Our objective in this study is to examine how publicly revealing information about the limit order book affects the trading strategies investors employ, the manner in which prices evolve in response to order flow, the resulting state of liquidity in the market, and cumulative abnormal returns around the event.

Previous research on transparency made a distinction between pre-trade transparency, or the availability of information about quotes and trading interest, and post-trade transparency, which describes information about executed trades.[1] Even in the realm of pre-trade transparency, which is our subject of investigation, most papers looked at the influence of quote information in a multiple-dealer market (e.g., Bloomfield and O'Hara, 1999; Flood, *et al.*, 1999) or used the availability of information to characterize different market structures (e.g., Madhavan, 1992; Biais, 1993; Pagano and Röell, 1996).[2] Since, in general, detailed theoretical modeling of the interaction in a limit order book environment is a difficult task, there has been less research on the question of how much of the content of a limit order book should be revealed.

In organizing our empirical investigation, we have found it useful to think about the consequences of changes in pre-trade transparency in terms of direct effects on the trading strategies of market participants, the resulting equilibrium effects on the market in terms of informational efficiency and liquidity, and the potential welfare implications. Trading strategies of investors and market professionals, such as the use of limit orders, can differ substantially depending on whether the book is open or closed. This, in turn, affects both the adjustment of prices to new information and aggregate liquidity provision in the market (or the trading costs of investors). A change in liquidity can then result in stock prices adjusting to reflect the effects of future transactions costs on expected returns.

Harris (1996) provides a discussion of the risks associated with the exposure of limit orders. The first risk is that a trader may reveal to the market private information about the value of the security, allowing other traders to trade on it. A second risk is that exposed limit orders can be

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[1] For papers that investigate post-trade transparency see Chowhdry and Nanda (1991), Naik, Neuberger, and Viswanathan (1994), Franks and Schaefer (1995), Madhavan (1995), Lyons (1996), and Bloomfield and O'Hara (1999).

[2] Madhavan (1996) investigates the role of information about order flow, but focuses on the availability of information about traders' motives (i.e., whether liquidity traders can be identified) and therefore can be viewed more as a model of anonymity in financial markets. See also Rindi (2002).

used to construct trading strategies aimed explicitly at taking advantage of these limit orders (e.g., "pennying" or front-running the limit orders). Harris mentions strategies that limit-order traders can use to manage the exposure of their orders. Traders may break up their orders, submitting smaller limit orders. This would reduce the first risk, as market observers may be more reluctant to make an inference about the value of the security based on a small order. Traders may also increase the frequency at which they cancel and resubmit limit orders. This would reduce the second risk, as it would frustrate front-running strategies. Finally, traders may use agents closer to the trading process (floor brokers at the NYSE) to manage order exposure, rather than submitting limit orders to the book themselves.

We empirically look at the cancellation of limit orders after OpenBook is introduced, and find that the cancellation rate of limit orders increases and time-to-cancellation of limit orders in the book is shorter. We also find that the size of limit orders submitted after the change in transparency is smaller. Hence, we provide evidence that traders attempt to manage the exposure of their orders, in line with Harris' reasoning. However, we do not observe a shift from trading using limit orders in the book to trading with the help of floor brokers. In contrast, the volume executed by floor brokers declines relative to that executed against limit orders in the book. The new ability to see depth in the book may create a “visibility effect,” where traders observe information about demand and supply away from the quote and can see how their actions affect the market. This visibility effect may make self-management of orders more appealing to traders, analogously to the attraction of active traders in Nasdaq stocks to electronic communications networks. Such an effect may in fact dominate the argument made by Harris (1996) for employing agents, and explain our results.

We also investigate the trading of one particular type of market professionals—NYSE specialists—who are both in charge of maintaining the limit order book and trade for their own account (i.e., make a market in the stocks). An open limit order book may affect specialists in a couple of ways. First, if investors become reluctant to provide liquidity with limit orders, specialists may need to step up their participation in the trading process in their capacity as liquidity providers of last resort. Second, the opening of the book may reduce the informational advantage specialists have about future price movements.[3] This may make proprietary trading riskier for the specialists, reducing their incentive to trade.

We find that the specialist participation rate in trades decreases following the introduction of OpenBook. We also find that they reduce the depth they add (together with floor brokers) to the quote beyond what is in the limit order book. These changes in trading strategies are consistent with an increase in the risk of proprietary trading on the part of specialists due to the loss of their informational advantage. Because public limit orders have priority over the specialists' proprietary trading, these changes are also consistent with a "crowding out" effect due to more active limit order strategies employed by investors. Finally, the smaller contribution of the floor to the quoted depth may be due to the shift we observe from floor trades to limit orders that are sent to the book electronically.

The changing strategies of market participants can bring about changes to characteristics of the market environment about which investors care, such as liquidity and informational efficiency. Several arguments have been made in the literature about the impact of pre-trade transparency on these market characteristics. Glosten (1999) presents an informal argument stating that increased transparency should lead to greater commonality of information, and that this tends to reduce the extent of adverse selection. His argument implies that greater transparency should result in more efficient prices (information is coming out faster) and smaller spreads (less need to protect against informed traders). Baruch (2002) examines the question of who benefits from an open limit order book in a static model where market orders are submitted by liquidity traders and a strategic informed trader, while liquidity is supplied by limit order traders and a specialist. Two

[3] On the issue of whether the limit order book contains information about future price movements see Harris and Panchapagesan (1999), Irvine, Benston, and Kandel (2000), Kaniel and Liu (2001), and Coppejans and Domowitz (2002).

implications that come out of his model are that opening the book (i) improves liquidity in the sense that the price impact of market orders is smaller, and (ii) improves the informational efficiency of prices. Therefore, both Glosten and Baruch claim that greater transparency is a "win-win" situation.

A different view is expressed by Madhavan, Porter, and Weaver (2000). They present a static model with multiple informed and uninformed traders who use market orders, and liquidity traders who use limit orders. In their model, greater transparency leads to higher spreads, smaller depth, and higher volatility. Therefore, opening the book reduces liquidity, in contrast to the predictions of Baruch (2002) and Glosten (1999). Madhavan *et al.* also conduct an empirical investigation of the decision by the Toronto Stock Exchange to publicly disseminate information about depth at the top four price levels in the book (in addition to the best bid and offer) in April of 1990. Since they do not have the detailed order-level data that we have here, they are unable to provide evidence about investor strategies or depth in the book. They do show, however, that spreads are wider after the event and that volatility is higher, both consistent with their theoretical predictions.[4]

Our results contrast with the Toronto Stock Exchange findings and provide support for the view that greater pre-trade transparency is a "win-win" situation. We examine whether greater pre-trade transparency indeed improves the commonality of information and makes prices more efficient. We use a variance decomposition methodology proposed by Hasbrouck (1993) to measure the deviations of transaction prices from the efficient (random walk) price. We find a decrease in the magnitude of the price deviations. We also document a slight decrease in the absolute value of first-order return autocorrelations calculated from quote midpoints. These

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[4] While there are no other empirical papers investigating limit order book transparency, two experimental investigations touch upon the issue. Friedman (1993) finds that showing the entire book (as opposed to only the best bid and offer) decreases the bid-ask spread in the market, but does not significantly alter the informational efficiency of prices. Gerke, Arneth, Bosch, and Syha (1997) compare open and closed book environments and find lower volatility in the transparent setting but no statistically significant differences in spreads.

findings are consistent with more efficient prices following the introduction of OpenBook that are less subject to overshooting and reversal. We examine Glosten's prediction regarding the effect of transparency on adverse selection using a different vector autoregression procedure (Hasbrouck, 1991), which enables us to estimate the normalized trade-correlated component of the efficient price variance. We find weak evidence of a decrease in the trade-correlated component, consistent with a reduction in the information content of trades.

We then examine two measures of the state of liquidity in the market: depth in the book and effective spreads. We find that displayed liquidity in the limit order book increases somewhat following the introduction of OpenBook. Results on effective spreads confirm that execution costs decline. Our analysis of the changes in liquidity around the event uses several econometric models in order to implement controls and account for potential estimation problems. Our results are robust to the different methodologies we employ.

We proceed to examine whether the change in market design influenced returns around the event. Amihud and Mendelson (1986) claim that liquidity affects expected returns in that investors require higher expected returns to compensate them for higher transactions costs. Since we document an improvement in effective spreads, a natural hypothesis is that prices increase to reflect lower future expected returns. Indeed, we provide evidence that cumulative abnormal returns are positive following the introduction of OpenBook. We also show that abnormal returns are negatively related to transactions costs (in the form of effective spreads) around the event, which is consistent with our interpretation of the price effects of the event resulting from the improved liquidity.

Overall, we find that greater transparency of the limit order book benefits investors. This finding is important for several reasons. First, the theoretical literature provides conflicting predictions on how liquidity would change when opening the book. Furthermore, our findings about liquidity contrast with those that were documented when the Toronto Stock Exchange started revealing information about demand in the book. Second, the Securities and Exchange

Commission (SEC) has repeatedly emphasized the need for increased pre-trade transparency. Our paper is the first empirical examination to provide support for such a policy. Third, our results show that market design is important for both the welfare of investors and the informational efficiency of prices. As such, research on market design can help exchanges and regulators in the direction of improving the functioning of financial markets.

The rest of this paper proceeds as follows. Section 2 provides details on the OpenBook initiative at the NYSE, describes the methodology, and presents the sample and the data sources used in the investigation. Section 3 presents the results of our tests concerning the trading strategies of investors, the participation of specialists, informational efficiency, liquidity, and returns. Section 4 is a conclusion.

2 RESEARCH DESIGN

2.1 OpenBook

Whether or not to make public the content of the limit order book maintained by specialists at the NYSE has been the subject of continuous discussion for over a decade. In 1991, the NYSE received the approval of the SEC for a program that would have provided snapshots of the book to member firms three times a day. In June of that year, the NYSE announced that it would not implement the system, citing lack of interest among member firms. In 1998, the NYSE announced that it considers providing information about the limit order book for prices that are two ticks below and above the best bid and offer. In 2001, the NYSE filed with the SEC to provide a service called OpenBook that gives information about depth in the book to subscribers, either directly from the NYSE or through data vendors such as Reuters and Bloomberg.

The NYSE's request was approved by the SEC on December 7, 2001, and the OpenBook service was introduced on January 24, 2002 for all NYSE securities simultaneously. The OpenBook service operates between 7:30am and 4:30pm. It is available for all NYSE-traded securities and shows the aggregate limit order volume available in the NYSE Display Book system at each price point. The information about depth is updated every 10 seconds throughout the day. Since the NYSE charges money for the service, it is possible to have a sense of the extent to which this new information is being disseminated. OpenBook had approximately 2,700 subscribers when the service was introduced. This number grew to about 6,000 during the first four months of operation in a rather linear fashion.

2.2 Methodology

We are interested in identifying the permanent effects of the change in pre-trade transparency associated with the introduction of OpenBook. As such, we need to examine two periods in which the market is in equilibrium with respect to traders' use of order flow information, one before the event and one after the event. For the length of each period we choose two weeks (10 trading days). We believe that this choice strikes a balance between our desire to employ more data for the statistical tests on the one hand, and both the stability of the estimates and the complexity of handling NYSE order-level data on the other.

While the introduction of OpenBook is an anticipated event, altering trading strategies in response to limit order book data can only be done after the data becomes available on January 24. Therefore, there is no need to eliminate a long window before the event in order to get the steady state of the traders' strategy. Since January 24 is a Thursday, we choose the full two trading weeks prior to the introduction week as the pre-event period (January 7 through January 18).

The choice of an appropriate post-event period is more complex. While traders are able to see limit order book information beginning January 24, learning how to use this information may take time. This is true both for traders who just want to use it to optimize the execution of their orders and for traders who plan to use it to design profitable trading strategies. Furthermore, once such strategies are in place, other traders (e.g., mutual funds' trading desks) may see the execution quality of their limit orders deteriorating. This would prompt more traders to change their strategies until a new equilibrium emerges. How long it takes for such a process is hard to say. It can take days, weeks, or months, depending on the sophistication of the traders and profit opportunities. Furthermore, the number of subscribers increased in the months following the introduction of OpenBook, which could also have affected the adjustment of the market to the new pre-transparency regime.

One approach to choosing a post-event equilibrium period is therefore to take a period that is rather far from the event itself. While this may be useful in assuring that the changes are permanent, it becomes more difficult to attribute them to the event the more time has passed. Another approach is to choose a rather lengthy post-event period. This has the disadvantage that the variables of interest may not be stationary during the period of adjustment. Also, different error structures in pre- and post-event periods due to different lengths would complicate the statistical testing.

We therefore choose a third approach that we hope overcomes these problems. We use two weeks as the length of a post-event period to have a similar error structure for the pre- and post-event periods. This also enables us to capture "snapshots" of the trading environment that are not too contaminated by non-stationarity. However, to allow for an adjustment to an equilibrium state, and to examine such an adjustment, we use four post-event periods rather than one. We take the first two full weeks of trading of each month following the introduction of OpenBook: February 4-15, March 4-15, April 1-12, and May 6-17. This enables us to examine how the new equilibrium emerges over time.

For each of the periods, we compute stock-specific means for all variables. We then report the median across stocks of pair-wise differences between each of the post-event periods and the pre-event period, and the *p*-value from a Wilcoxon test for the two-sided hypothesis that the median is equal to zero. We believe that this approach is preferable to a more parametric multivariate analysis. An alternative approach is to regress the change in a variable (e.g., effective spreads) on a set of control variables (e.g., volume or volatility), and conduct tests on the intercept. There are several potential problems with such an approach. First, many of the variables we investigate do not necessarily fit the distributional assumptions needed for parametric tests. Second, the relations among many of the variables under investigation and the controls are endogenous.[5] Third, the nature of the relation (e.g., functional form) between the variables under investigation and the controls can change due to the new trading strategies of market participants who use OpenBook.[6]

Because these problems may make it difficult to interpret the results, especially in a multiple-equation regression model, we prefer to focus on non-parametric tests of each variable separately. We will therefore investigate the total effects of the introduction of OpenBook, without making an attempt to disentangle which changes represent "direct" effects of the event and which changes are "indirect" effects attributable to changes in other variables. In light of the conflicting theoretical predictions with regard to the effects of pre-trade transparency on liquidity, however, we also perform a rather extensive set of robustness tests using various econometric models when analyzing effective spreads and book depth.

2.3 Sample and Data

The universe of stocks considered for this study includes all common stocks of domestic issuers traded on the NYSE. We eliminate firms that do not trade continuously between January and May of 2002, firms with more than one class of traded shares, closed-end funds, and investment trusts. This results in a population of 1,332 stocks, which are sorted by median dollar volume in the last quarter of 2001 and divided into four quartiles. From each quartile we choose a stratified sample of 100 securities. Our final sample, therefore, consists of 400 stocks that can be

[5] For example, volume can be influenced by trading costs (e.g., effective spreads) and hence a single-equation regression of spread changes on volume changes may be inappropriate.

[6] For example, it may be the case that the entire change in spreads can be attributed to changes in volume and volatility, but the functional relation changed and so the linear regression will show a significant intercept when it should not. Similarly, spreads may actually change due to new trading strategies beyond what can be attributed to volume and volatility, but the regression may yield an insignificant intercept. This situation can arise due to a change in the level of the right-hand-side variables in conjunction with a change in the relation among the variables.

divided into four groups according to the amount of trading activity in the stocks. In the presentation of our findings, if the picture is very similar across groups we present only the results for the entire sample to simplify the exposition. Whenever the results differ for stocks with different trading intensity, we present the results for the four groups separately.

Table 1 provides summary statistics for the entire sample and for each of the four trading-intensity groups. We present summary statistics for the pre-event period and the four post-event periods. The table testifies to the heterogeneous nature of the sample, ranging from a median average daily volume of 59.43 million dollars for the most actively traded group in the pre-event period to a median of $370,000 for the least actively traded group. All variables—volume, quoted spread, depth, effective spread, and price—change in the expected manner when moving from the most active stocks to the least active stocks. For the most (least) actively traded stocks, median quoted spread is 4.4 (8.9) cents and median quoted depth (summing both the bid and ask sides) is 3,445 (1,607) shares. We also observe that prices are higher for the most actively traded stocks in the sample, $42.74, as compared with $11.15 for stocks in the least actively traded group.

The data source used for the summary statistics in Table 1 is the TAQ database distributed by the New York Stock Exchange. We use these data to analyze effective spreads, intraday volatility, and informational efficiency.[7] To study the price effects of liquidity changes, we use daily distribution- and split-adjusted returns from FactSet.

The rest of the analysis in the paper is based on NYSE order-level data contained in the System Order Data (SOD) and Consolidated Equity Audit Trail Data (CAUD) files. A reduced

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[7] The variables we analyze are calculated using NYSE trades and quotes. We apply various filters to clean the data. We only use trades for which TAQ's CORR field is equal to either zero or one, and for which the COND field is either blank or equal to B, J, K, or S. We eliminate trades with non-positive prices. We also exclude a trade if its price is greater (less) than 150% (50%) of the price of the previous trade. We eliminate quotes for which TAQ's MODE field is equal to 4, 5, 7, 8, 9, 11, 13, 14, 15, 16, 17, 19, 20, 27, 28, or 29. We exclude quotes with non-positive ask or bid prices, or where the bid is greater than the ask. We require that the difference between the bid and the ask be smaller than 25% of the quote midpoint. We also eliminate a quote if the bid or the ask satisfy the condition that they are greater (less) than 150% (50%) of the bid or ask of the previous quote. When signing trades, we employ yet an additional filter that requires the difference between the price and the prevailing quote-midpoint to be smaller than $8.

version of these files was the basis for the TORQ database organized by Joel Hasbrouck in 1991, and a description of the files can be found in Hasbrouck (1992). In general, the SOD file contains detailed information on all orders that arrive at the NYSE via the SuperDot system or are entered into the Display Book system (which powers the limit order book) by the specialist. It contains about 99% of the orders, representing 75% of NYSE volume, and follows the orders from arrival through execution or cancellation. Together with the LOFOPEN file that describes the exact state of the limit order book every day before the opening of trading, SOD allows us to precisely reconstruct the limit order book on the NYSE at any point in time. It also enables us to examine how investors change their order submission strategies, and to determine how much depth specialists and floor brokers add to the quote beyond what is in the limit order book.

The CAUD files contain detailed execution information on both electronic and manual (those handled by floor brokers) orders. It enables us to determine the participation rate of specialists in the trading process, and the portions of trading volume that originate from either floor brokers or electronic limit orders.

3 RESULTS

Our analysis of the change in pre-trade transparency induced by OpenBook closely follows the exposition of the arguments in the introduction. First, we look at how market participants change their trading strategies as a result of the event. In this context we examine both the traders' use of limit orders and the specialists' participation in trading and liquidity provision. Second, we examine how these strategies affect the informational efficiency of prices by looking at the deviations of transaction prices from the efficient price and the autocorrelations of quote-midpoint returns. Third, we look at liquidity provision in the book and execution costs for NYSE trades. Finally, we study how the changes in liquidity affect returns.

3.1 Trading Strategies

Harris (1996) conjectures that traders will react to the risk in order exposure by changing their behavior: canceling and resubmitting limit orders more frequently (shortening the time they are publicly displayed in the book), breaking down limit orders into smaller sizes, and making greater use of agents such as floor brokers.

Table 2 examines the management of order exposure by traders using data from the SOD and CAUD files. The results are presented for the entire sample, because the four groups behave in a similar fashion. The first line of Panel A shows an increase in the cancellation rate of limit orders (number of limit orders cancelled divided by the number submitted). The median differences between the post- and pre-event periods are positive, and increase monotonically with time. The median change from January to February is 0.68% (though not statistically significant), reaching 4.75% between January and May (and highly statistically significant). The second line of Panel A presents the time-to-cancellation (in seconds) of limit orders that are cancelled. It decreases following the event, and the magnitude of the changes increases with time. Compared to January, time-to-cancellation in February is 12.77 seconds shorter, and 50.58 seconds shorter in the May post-event period. On a pre-event median value of 290 seconds, the decrease in time-to-cancellation seems to be rather large (17.4%).

A limitation of the above analysis of time-to-cancellation and the cancellation rate is that it ignores censoring (i.e., limit orders that are executed or expire and therefore cannot be cancelled). We therefore use survival (or duration) analysis to estimate two models that take censoring into account (see Lo, MacKinlay, and Zhang, 2002; Hasbrouck and Saar, 2002). First, we use an accelerated failure time model where time-to-cancellation is assumed to follow a Weibull distribution. The logarithm of time-to-cancellation of limit orders is modeled as a linear function of an intercept, a dummy variable that takes the value 1 after the introduction of OpenBook, and the distance of the limit order from the relevant quote side (the bid for limit sell orders and the ask for limit buy orders) divided by the quote midpoint. The standardized distance from the quote is included as a covariate since it presumably is an important determinant of the probability of both execution and cancellation. The duration model is estimated separately for each stock using all limit orders in the 20-day pre- and post-event periods.

The first line in Panel B of Table 2 presents the cross-sectional median of the coefficients on the event dummy variable and the number of these coefficients that are statistically significant (in the 5% level). In all four post-event periods, the median of the coefficients is negative, the Wilcoxon test is highly significant, and over 394 (out of 400) of the coefficients in the individual stocks' regressions are statistically significant. To interpret the coefficients, we apply the transformation $e^{coefficient}$-1 that provides the percentage change in time-to-cancellation between the pre- and post event periods. For the February post-event period, a median coefficient of –0.1106 means that time-to-cancellation of limit orders decreased by 10.47%. By May, a median coefficient of –0.2782 means that time-to-cancellation decreased by 24.29%.

We also report the results of semiparametric Cox regressions (see Cox, 1972), where the logarithm of the hazard rate is modeled as a linear function of an intercept, a dummy variable for the event, and the distance from the quote. While both the Cox model and the Weibull model belong to the class of proportional Hazard models, the Cox model does not require that we choose a particular probability distribution for time-to-cancellation. The second line of Panel B presents the cross-sectional median of the coefficients on the dummy variable and the number of significant coefficients. These coefficients can be interpreted as the ratio of the estimated cancellation rate of limit orders in the post-event period to the estimated cancellation rate in the pre-event period (controlling for the distance from the quote). The results indicate that the cancellation rate increases in a gradual manner: from 6.36% in February to 15.90% in May. The increase in cancellation rate is highly statistically significant in all four periods.

Panel C of Table 2 continues our investigation of changes to the trading strategies of investors following the introduction of OpenBook. The first line shows median pair-wise differences in the size of limit orders between the post- and pre-event periods. For all four post-event periods, the median changes are negative and statistically different from zero. The magnitude of the changes seems to increase with time after the event. The difference in the size of a typical limit order of the same stock between February and January is -29.5 shares. This difference increases in magnitude to -68.4 in May. On a pre-event median limit order size of 543 shares, this represents a decrease of 12.6%.

The second line in Panel C presents the changes in floor-broker activity relative to electronic limit-order activity. The ratio we compute is the sum of the number of shares bought and sold by floor brokers divided by the sum of the number of shares bought and sold by limit orders in the book. We document a decline in floor activity relative to limit orders in the book, ranging from -0.014 in February to -0.05 in May (with the differences in the last three post-event periods statistically different from zero).

The results are consistent with heightened limit-order exposure management: smaller limit orders are submitted, limit orders are cancelled more often, and limit orders are left for a shorter time in the book. The new ability to see depth in the book seems to make self-management of the trading process more attractive. The shift we document from floor trading to electronic limit orders may indicate that the benefit associated with active trading strategies employed by the traders themselves using OpenBook outweighs the cost of displaying trading interests. The trend in median differences for the four post-event periods that we observe in the variables describing trading strategies is consistent with traders learning over time about the new service, learning how to use the information in OpenBook, and adjusting their trading strategies accordingly.[8]

The change in pre-trade transparency and the change in the behavior of traders can cause NYSE specialists, who make a market in the stocks, to alter their behavior. We use the CAUD files to examine the specialists' participation rate in the trading process. The participation rate is defined

[8] The adjustment takes time because not all traders learn at the same speed, and also because predatory trading strategies based on the information in OpenBook take time to develop. Time may be further required for institutional traders to learn about the risks in leaving their limit orders on the book in the new environment.

as the number of shares bought and sold by the specialist over the total number of shares bought and sold. The first line in Panel D of Table 2 shows that the specialists' participation rate decrease in the post-event periods. While the median difference between the first post-event period and the pre-event period is not statistically distinguishable from zero, the median differences of the three other post-event periods are negative and highly statistically significant.[9]

The second line in Panel D describes the dollar value that the specialists (potentially reflecting floor brokers' trading interest) add to the quoted depth beyond what is in the limit order book. To create this variable, we use the LOFOPEN and SOD files to reconstruct the book and compare the best prices in the book to the quote disseminated by the exchange every five minutes throughout the trading day. Then we average the specialist's contribution over all five-minute snapshots and compute the differences between the post- and pre-event periods for each stock. The specialists' contribution decreases monotonically over the four post-event periods, from a median difference of -\$1,164.76 to -\$2,599.81 (with three out of the four differences statistically different from zero).

These results—less participation by the specialists in trading and committing to a smaller quoted depth—are consistent with an increase in the risk associated with the specialists' proprietary trading due the loss of their informational advantage. They are also consistent with a "crowding out" effect, where more active management of public limit orders (that have priority over the proprietary trading of specialists) is limiting the ability of specialists to participate in the trading process. Finally, the smaller depth added by the specialists and floor brokers is also consistent with the shift from floor to electronic limit orders that we have documented above.

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[9] Similar results are obtained when defining the participation rate in terms of number of orders rather than number of shares.

3.2 Information and Prices

Both Glosten (1999) and Baruch (2002) predict that improved transparency would lead to increased informational efficiency of prices. We implement two methodologies to test this hypothesis. The first test is based on the variance decomposition procedure from Hasbrouck (1993). Using information about transaction prices and trade size, Hasbrouck proposes a vector autoregression model to separate the efficient (random walk) price from deviations introduced by the trading process (e.g., short-term fluctuations in prices due to inventory control or order imbalances in the market). More specifically, the variance of log transaction prices, V(p), is decomposed into the variance of the efficient price and the variance of the deviations induced by the trading process, V(s). Because the expected value of the deviations is assumed by the procedure to be zero, the variance is a measure of their magnitude.

To control for possible changes in the overall variability of prices around the event that can cause a change in the magnitude of the deviations, we divide V(s) by V(p) to normalize the measure. This ratio, VR(s/p), reflects the proportion of deviations from the efficient prices in the total variability of prices. If OpenBook allows traders to better time their trading activity to both take advantage of displayed liquidity and provide liquidity in periods of market stress, the proportion of deviations from the efficient price should be smaller after the event. Similarly, such an effect will take place if greater "commonality of information," as Glosten (1999) puts it, leads to faster adjustment to the efficient price with fewer orders executing during the adjustment process. The first line of Table 3 shows median changes between the pre- and post-event periods for VR(s/p) (where the ratio is expressed in percentage terms). While they are not significantly different from zero in the February and March post-event periods, they become negative and highly significant in the April and May post-event periods.

Conceptually it is possible that even if the deviations of transaction prices from the efficient price remain the same, increased pre-trade transparency brings about faster revelation of information and therefore a quote-midpoint process that more closely follows the efficient price. A more efficient quote-midpoint process would be closer to a random walk and therefore exhibit less autocorrelation (both positive and negative).

The second and third lines of Table 3 show changes in the absolute value of the 30-minute and 60-minute first-order quote-midpoint return autocorrelation. For the 30-minute process, we divide the trading day into half-hour intervals and compute the returns from the prevailing quote midpoints at the beginning and end of each interval (a similar construction is used for the 60-minute process). We examine the absolute value of the correlation coefficients because we would like to test how close the return process is to a random walk, which is characterized by zero autocorrelations.

We find that the direction of changes in autocorrelation is consistent with more efficient prices, but the results are rather weak. While the median changes are negative in all post-event periods, only two of the numbers are statistically different from zero. One of the two statistically significant changes, however, is in the March post-event period that did not have a statistically significant change in VR(s/p). The results of these two tests together point to some improvement in informational efficiency under the new pre-trade transparency regime.

The argument made by Glosten (1999) about the commonality of information can also be interpreted to mean that improved transparency would reduce the extent of the adverse selection problem. If this is indeed the case, we should observe that trades cause smaller permanent price changes. To test this hypothesis we use the variance decomposition procedure developed in Hasbrouck (1991). A vector autoregression of quote midpoint returns, a signed trade indicator variable, and log volume is used to identify both the efficient price variance, V(w), and the trade-correlated component of the efficient price variance, V(x).[10]

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[10] The trade indicator variable is identified using the quote midpoint rule. This rule assigns the value –1 to the trade indicator variable if the trade price is less than the prevailing quote midpoint, 0 if the trade price is equal to the midpoint, and +1 if the trade price is greater than the quote midpoint. The log volume variable is constructed by adding 1.00 to the number of shares in order to accommodate a change to the quotes without an intervening trade.

We use the ratio of the two (in percentage terms), VR(x/w), as a measure of the normalized trade-correlated component of the efficient price variance, or the fraction of the efficient price variance that is due to information in trades. The last line of Table 3 shows the cross-sectional medians of differences in VR(x/w) between the post- and pre-event periods. The results suggest a gradual decrease in VR(x/w), and the median is negative and statistically significant in the April and May post-event period. This evidence is consistent with a (weak) decrease in the extent of the adverse selection problem.

Theoretical models such as Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987) show how adverse selection hurts liquidity. The VR(x/w) results can therefore indicate a slight improvement in liquidity. On the other hand, the shorter duration and smaller size of limit orders reported in Section 3.1 may indicate worsened liquidity, but this is not necessarily so. Limit orders may be submitted more often, and limit order traders may seize opportunities to trade cheaply against temporary order imbalances that are created in the market. We therefore turn to a more explicit investigation of liquidity by examining both displayed trading interest in the book and execution costs.

3.3 Liquidity

What we would like to examine in this section is how the changing strategies of investors and specialists aggregate to create the new state of liquidity provision in the market. This analysis has special significance since the theoretical arguments surveyed in the introduction disagree on this point: Glosten (1999) and Baruch (2002) claim that greater transparency would improve liquidity; in contrast, Madhavan, Porter, and Weaver (2000) claim that it would cause liquidity to deteriorate.

For each 5-minute snapshot of the limit-order book, we compare displayed liquidity in the book at several distances from the relevant side of the quote (the ask for limit sell orders and the bid for limit buy orders) to spot potential differences between liquidity that is closer to current prices and away from the market. To better compare the liquidity of stocks with different share prices, we define the distance from the relevant side of the quote as a percentage of the stock's price. We choose several cutoffs in dollar terms (5 cents, 25 cents, 1 dollar, and 5 dollars) and divide them by $30, the average share price in the pre-event period, to get the percentage bounds.[11] These bounds are then applied to each stock individually to create five categories of cumulative number of shares in the book between the relevant side of the quote and (i) 0.166% of the price, (ii) 0.833% of the price, (iii) 3.333% of the price, (iv) 16.667% of the price, and (v) the end of the book.

Panel A of Table 4 presents the median change in cumulative depth in the book for each category. Out of the twenty numbers in the table (five categories, four post-event periods), only five are statistically significant at the 5% level. All of these numbers are positive. The rest of the numbers (positive and negative) are not statistically distinguishable from zero. This means that displayed liquidity changed relatively little, and the change we can detect is that liquidity increased (more depth is available in the book). This finding is consistent with the shift we document in Table 2 from using floor brokers to using electronic limit orders.

But even if liquidity in the book improves, a decrease in specialist participation may cause execution costs of trades to increase. To judge "ex-post" liquidity, or how much is paid to execute trades, we examine changes in the effective spreads (defined as the distance between the transaction price and the prevailing quote midpoint). Panel B of Table 4 presents the effective spreads in dollar terms for the entire sample and for the four trading-intensity groups. It is interesting to note that there is an increase in effective spreads in February, but a decrease in the March, April, and May post-event periods (relative to the January pre-event period). A closer look shows that the significant increase in effective spreads in February is only for the most actively traded stocks. It is possible that predatory strategies (presumably more profitable in active stocks)

[11] The results are qualitatively similar when we use the dollar bounds.

initially cause liquidity to worsen. However, once investors adjust their trading strategies sufficiently, this reverses and liquidity improves.

The table also shows a trend in improved liquidity. The magnitude of the median change in effective spreads increases from -0.143 cents in March to -0.330 in April and -0.454 in May. Overall, it seems that the permanent effect of the change in transparency is to improve liquidity for all stocks. We obtain similar results using percentage effective spreads and effective spreads computed separately for five trade-size categories.

Since the theoretical models conflict on the issue of liquidity, and because there is much evidence that liquidity is affected by attributes that we do not test here (like volume), we also use several parametric approaches to examine the change in liquidity conditional on three control variables. The controls are the average daily dollar volume, intra-day volatility expressed as the average daily range of transaction prices (high minus low), and the average transaction price of the stock (to control for price level effects).

The first econometric specification assumes that the liquidity measure for stock *i* in period τ (where $\tau \in$ {pre, post}), $L_{i,\tau}$, can be expressed as the sum of a stock-specific mean (m_i), an event effect (a), a set of control variables, and an error term (h):

$$L_{it} = m_i + a d_t + b_1 AvgVol_{it} + b_2 HiLow_{it} + b_3 AvgPrc_{it} + h_{it}$$

where d_t is an indicator variable that takes the value zero in the pre-event period and one in the post-event period, *AvgVol* represents dollar volume, *HiLow* is intra-day volatility, and *AvgPrc* is the price. By assuming that the errors are uncorrelated across securities and over the two periods (though we do not require them to be identically distributed), we can examine differences between the post- and pre-event periods and eliminate the firm specific mean:

$$DL_i = a + b_1 DAvgVol_i + b_2 DHiLow_i + b_3 DAvgPrc_i + e_i$$

where *D* denotes a difference between the post- and pre-event periods.

We estimate the equation above using OLS and compute test statistics based on White's heteroskedasticity-consistent standard errors. The first line in Panel A of Table 5 presents the intercepts and *p*-values from the regressions using the change to total depth in the book (in round lots) as the liquidity variable. The intercepts for all four post-event periods are positive and two out of the four are statistically significant in the 5% level, indicating some increase in book depth in the post event period. The second line in Panel A presents the results using effective spreads (in cents) as the dependent variable. All coefficients are negative, and they increase in magnitude with time from –0.1046 in February to –0.8001 in May (where the last three post-event periods are statistically significant). It appears that after controlling for changes in volume, volatility, and price level, the unconditional result of an increase in effective spreads in February disappears, and we observe a stronger indication of an improvement in liquidity.[12]

Since the event happens to all stocks at the same time, it is possible that the error terms are correlated across stocks. This would cause the standard errors of the intercepts to be biased, but the OLS coefficients would still be consistent. To examine the robustness of our results to this potential problem we use two specifications. For the first specification, we compute daily values of

[12] Since effective spreads measure the cost of trading and volume measures the quantity of trading, it can be argued that a single-equation specification where volume is regressed on effective spreads suffers from an endogeneity problem. One way to overcome this potential problem is to run a simultaneous-equation model of spreads and volume. We ran the following model:

$$DESpread¢_i = a + b_1 DAvgVol_i + b_2 DHiLow_i + b_3 DAvgPrc_i + b_4 DStdInv_i + e_i$$

$$DAvgVol_i = b_5 + b_6 DESpread¢_i + b_7 DHiLow_i + b_8 DAvgPrc_i + b_9 DSysVol_i + n_i$$

where *DStdInv* is the standard deviation of daily inventory closing positions of specialists (from the NYSE's SPETS file), and *DSysVol* is the systematic component of dollar volume. The systematic component is obtained from a market model of dollar volume using one year of daily data ending before the beginning of the pre-event period, with an equal-weighted portfolio of all common-domestic NYSE stocks as a proxy for the market (see Lo and Wang, 2001, and Llorente, Michaely, Saar, and Wang, 2002, on the issue of a market model for volume). The simultaneous-equation model was estimated both using two-stage least squares and three-stage least squares. For all post-event periods, the magnitudes of the intercepts from the effective spreads equation and their statistical significance were almost identical to those obtained using the single-equation specification reported in Table 5 (and are therefore omitted for brevity).

the variables (e.g., ten daily averages of effective spreads indexed by t rather than an average over the entire period) and estimate the following equation:

$$L_{it} = Intercept + \Sigma_{k=1}^{n} (\beta_k D_{itk}) + ?_1 Vol_{it} + ?_2 HL_{it} + ?_3 Prc_{it} + \varepsilon_{it}$$

where the dummy variables D_{itk} (k=1, …, n) take the value one for the k-th day in the n-day post-event period and zero otherwise, *Vol* is the daily dollar volume, *HL* is the daily range of transaction prices, and *Prc* is the daily average transaction price of the stock. We estimate the model in two ways: (i) for the pre-event period combined with each of the post-event periods (resulting in 10 coefficients of the daily post-event dummy variables), and (ii) pooling together all 50 pre-event and post-event days (resulting in 40 coefficients of the daily post-event dummy variables).

Panel B of Table 5 reports the median of the coefficients on the post-event dummy variables and the p-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. Three out of the four post-event periods show a significant increase in book depth after the introduction of OpenBook, and so does the pooled regression over all periods. Similarly, there is a highly significant decrease in effective spreads in three out of the four post-event periods, and the same goes for the pooled regression.

The second specification that attempts to overcome the potential problem of cross-correlated errors relies on computing cross-sectional daily averages of each variable and using OLS to estimate the following time-series model:

$$CSL_t = Intercept + \Sigma_{k=1}^{4} (\beta_k D_k) + ?_1 CSVol_t + ?_2 CSHL_t + ?_3 CSPrc_t + \varepsilon_t$$

where the dummy variables D_k (k=1, 2, 3, 4) take the value of one for the k-th post-event period and zero otherwise, *CSVol* is the cross-sectional average of daily dollar volume, *CSHL* is the cross-sectional average of intra-day volatility, and *CSPrc* is the daily mean transaction price averaged across stocks.

In Panel C of table 5 we report the coefficients of the dummy variables for the four post-event periods and their associated *p*-values calculated using White's heteroskedasticity-consistent standard errors. All four coefficients are positive and statistically significant in the depth regression, and two out of the four are negative and significant in the effective spreads regression. The fact that the results are qualitatively similar using all the econometric specifications above indicates that our findings are rather robust. We conclude that both “ex-ante” liquidity (displayed trading interest in the book) and “ex-post” liquidity (effective spreads) increase following the introduction of OpenBook.[13]

3.4 Price Effects of Changes in Pre-trade Transparency

It is usually difficult to examine the welfare effects of changes in regulation or the structure of markets. We do not claim that our analysis will be able to come up with unequivocal statements about the optimality of the change in pre-trade transparency. Rather, we will provide some evidence about one aspect of welfare: the impact of OpenBook on the wealth of investors.

It has long been claimed that liquidity affects required returns (e.g., Amihud and Mendelson, 1986). The argument usually made is that investors require higher expected returns to compensate them for higher execution costs. If liquidity improves following the introduction of OpenBook, prices of stocks should increase to reflect the lower future expected returns that investors will require of the stocks. An increase in prices due to a more efficient market mechanism makes investors better off, and this is the welfare aspect we examine here.

[13] Note that both displayed liquidity and effective spreads provide information about the potential or actual execution costs for individual trades. As part of the trading strategy of an investor, an order may be broken down and traded over the course of a day to achieve better execution. Large intra-day fluctuations in prices may decrease the ex-ante willingness of institutions to hold large positions in the stock (due to potential difficulties in obtaining and liquidating a position), which may have a detrimental effect on liquidity. On the other hand, intra-day volatility may also work to the benefit of traders by making limit orders more profitable as they benefit from increased transitory volatility. The median post-event changes in intra-day volatility (*HiLow*) are \$0.035, \$0.0275, \$0.033, and \$0.039 for February, March, April, and May, respectively. All of them are statistically different from zero. On a pre-event value of \$0.6035, this increase in intra-day volatility seems to be modest.

We study the changes in prices around the introduction of OpenBook using standard event-study methodology. We compute a Cumulative Abnormal Return (CAR) measure by summing daily abnormal returns from January 24 (the introduction of OpenBook) to the end of each post-event period. The daily abnormal returns are the residuals of a market model using all trading days in 2001 with the Standard and Poor's 500 Index as a proxy for the market.[14]

Panel A of Table 6 shows the cross-sectional median CAR and the *p*-value for a Wilcoxon test against the hypothesis of a zero median. The medians reported for all periods are positive and highly statistically significant. The magnitudes of the medians, ranging from 1.68% in February to 8.4% in April, seem to be rather substantial from an economic standpoint.

While we attribute the increase in prices to the event, one always wonders whether eliminating the systematic component measured relative to a market proxy is sufficient to warrant such a conclusion. A priori, we do have a reason to expect increased prices, as we have shown in Section 3.3 that liquidity improves. Next we examine the relationship between effective spreads and cumulative abnormal returns to see if indeed a decrease in effective spreads is likely to show up as higher CAR. We estimate the following cross-sectional relation between changes in relative effective spreads between the pre- and post-event periods and cumulative abnormal returns from the beginning of the pre-event period to the end of each post-event period:

$$CAR_i = a + bDESpread_i + e_i$$

If b is negative and significant, stocks that experience greater changes in effective spreads around the event also exhibit greater changes in prices in the appropriate direction.

[14] We have also used January 2, 2000 to November 30, 2001 as the interval over which to estimate the market model to exclude the period after December 7, 2001 (the date when the SEC approved the NYSE petition). Conceptually, the changes in liquidity might have been anticipated after the approval of OpenBook on December 7, but it is hard to imagine a significant effect since there was no consensus on how, if at all, liquidity would change as a result of the change in pre-trade transparency. Whatever the case may be, any adjustment of prices between December 7, 2001 and January 24, 2002 would bias us against finding a significant CAR following the introduction of OpenBook.

Panel B of Table 6 presents the results of the cross-sectional OLS regressions for each of the post-event periods. We present the results for each trading-intensity group separately because the magnitude of the slope coefficients seems to be rather different for the four groups. It is clear from the table that the negative relation between changes in effective spreads and cumulative abnormal returns holds around the event. All 16 slope coefficients (four groups, four post-event periods) are negative and statistically different from zero. The coefficients are monotonically decreasing across trading-intensity groups. We believe that this is due to the systematic difference in magnitudes of the effective spreads of the groups (as evident in Table 1). These negative and significant slope coefficients provide some confidence in the existence of a relationship between effective spreads and CAR that could generate the positive abnormal returns we document following the introduction of OpenBook.[15]

4 CONCLUSIONS

The structure of securities markets in the U.S. and around the world is undergoing many changes. Various competing market structures were introduced into U.S. equity trading by Alternative Trading Systems, and the SEC has been instrumental in providing the conditions that helped these new trading platforms to flourish. In particular, the SEC has been pushing for greater pre-trade transparency mandating certain display requirements for limit orders (affecting both market makers and Alternative Trading Systems organized as electronic limit order books). The insistence of the SEC on pre-trade transparency stems from its conviction that transparency improves not just price discovery, but also the fairness, competitiveness, and attractiveness of U.S. markets.

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[15] Madhavan, Porter, and Weaver (2000) estimate a similar relation between returns and effective spreads except that they use buy-and-hold returns rather than cumulative abnormal returns (i.e., they do not eliminate the systematic component). They also document a significant negative cross-sectional relation between changes in effective spreads and returns in their sample.

So far, however, there has not been a consensus in the academic literature on whether greater pre-trade transparency in the sense of disclosing more information about limit orders in the book is beneficial to the market. As previously mentioned, the theoretical model in Madhavan, Porter, and Weaver (2000) implies that greater pre-trade transparency harms liquidity, and they find support for this claim when investigating an increase in pre-trade transparency implemented by the Toronto Stock Exchange in 1990. Against this context, the results presented in this paper have important implications in that they provide empirical support, for the first time, to the view that improved pre-trade transparency of a limit order book is beneficial. Our focus on the largest market in the world and the quality of the order-level data we use make our findings even more significant in the debate among academics and policy makers.

We find that investors do change their strategies in response to the change in market design: they submit smaller limit orders and cancel limit orders in the book faster and more often. These findings are consistent with a more active management of trading strategies in the face of greater risk of order exposure. Additionally, we find that traders shift activity away from floor brokers toward electronically submitted limit orders. This may indicate that OpenBook enables traders to implement more complex strategies themselves, and therefore reduces their need to delegate that responsibility to floor brokers. We also find that NYSE specialists change their behavior in that they trade less and, together with floor brokers, add less depth to the quote. These changes can reflect the increased risk in proprietary trading without the help of privileged information about the book, a crowding out effect that results from increased competition provided by active limit order trading, and a shift in investor strategies from using floor brokers to limit orders submitted electronically via SuperDot.

The equilibrium effects on the state of the market, both in terms of liquidity and informational efficiency, seem to suggest that increased transparency is a "win-win" situation. We find some improvement in informational efficiency following the event, consistent with the view that greater pre-trade transparency is beneficial for the price discovery process. Displayed liquidity in the book increases and execution costs decline. Beyond providing support to current SEC beliefs about the importance of transparency for the quality of U.S. markets, our paper provides evidence that market structure has implications for the welfare of investors. This natural experiment in market design shows how providing additional information to investors can help them manage their trading needs, and our analysis suggests that the improvement in liquidity resulted in higher stock prices.

The introduction of OpenBook provides hope that even markets that are considered highly liquid and active, such as the NYSE, can improve by changing features of market design to meet investor and regulator demands. NYSE material stresses that OpenBook was designed to increase transparency in a decimal trading environment. Because the idea of publicly distributing information about the book has been around for many years, the implementation at this point in time indeed seems to have been in response to the change in the tick size. In a sense, one regulatory change in market design (the decreased tick size) caused the NYSE to implement another change in market design (improved pre-trade transparency).

The current securities trading environment is characterized by both frequent regulatory interventions and competitive pressures. The experience with OpenBook suggests that markets can and should respond to changes in their environment by modifying the design of their trading systems to better cater to investor needs.

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Table 1
Sample Summary Statistics

The universe of stocks for the study consists of all domestic common stocks listed on the NYSE, excluding firms with multiple classes of shares traded, closed-end funds, and investment trusts. We sort the stocks according to median dollar volume in the last quarter of 2001 and divide the universe into four quartiles. From each quartile we choose a stratified sample of 100 stocks, creating a final sample of 400 stocks. The table presents summary statistics for the five periods used in the study: the pre-event period (January 7–18) and the four post-event periods: February 4–15, March 4–15, April 1–12, and May 6–17. From the TAQ database, AvgVol is the average daily number of shares traded; QSpread is the average quoted spread calculated in dollar terms and in percentage terms (the bid-ask spread divided by the quote midpoint); QDepth is the average total quoted depth (sum of the depths on the bid and ask sides) measured in dollars and in number of shares; ESpread is the average effective spread (the transaction price minus the midquote) in dollars and percentage terms (scaled by the quote midpoint); and AvgPrc is the average transaction price of the stock.

		AvgVol (in million $)		**AvgVol** (in 100s)		**QSpread** (in cents)		**QSpread** (in %)		**QDepth** (in $1000)		**QDepth** (in 100s)		**ESpread** (in cents)		**ESpread** (in %)		**AvgPrc** (in $)	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Entire Sample	Jan.	31.70	5.69	8,498.44	2,372.30	7.6	6.2	0.439	0.250	77.69	60.04	30.62	23.34	5.0	4.0	0.296	0.156	30.25	25.49
	Feb.	31.59	5.89	9,419.32	2,131.70	7.5	6.3	0.458	0.254	76.60	58.76	31.38	23.90	5.0	4.3	0.313	0.160	29.77	24.87
	Mar.	35.16	6.68	9,305.33	2,505.20	7.1	6.0	0.406	0.228	76.35	57.87	29.37	22.11	4.8	3.9	0.270	0.145	31.64	26.37
	Apr.	30.43	6.11	7,675.17	2,254.15	6.8	5.7	0.378	0.207	70.91	53.84	26.44	20.35	4.5	3.7	0.248	0.133	32.14	27.04
	May	30.53	5.78	8,225.61	2,290.75	6.6	5.6	0.372	0.194	73.29	53.80	26.91	20.31	4.4	3.6	0.239	0.126	32.31	27.81
Group 1 (most active stocks)	Jan.	109.80	59.43	26,433.18	14,941.40	4.9	4.4	0.119	0.108	159.94	131.84	40.56	34.45	3.2	3.0	0.079	0.070	45.86	42.74
	Feb.	108.78	60.61	29,888.36	14,868.15	5.1	4.6	0.130	0.115	152.89	124.74	41.45	29.80	3.4	3.1	0.087	0.077	44.94	41.25
	Mar.	120.85	67.28	29,056.45	17,172.45	4.7	4.3	0.114	0.098	156.88	130.14	39.90	33.13	3.2	2.9	0.077	0.066	47.73	43.19
	Apr.	104.20	57.70	23,608.54	13,764.15	4.4	3.9	0.106	0.090	143.92	123.43	36.86	28.14	2.9	2.6	0.070	0.059	47.82	43.91
	May	102.63	60.53	24,815.17	17,110.85	4.3	4.0	0.109	0.092	153.54	130.90	40.61	29.49	2.9	2.6	0.073	0.062	47.13	42.23
Group 2	Jan.	13.25	11.03	5,345.64	3,443.70	6.0	5.6	0.208	0.192	77.85	70.19	28.55	24.37	3.8	3.5	0.133	0.121	32.08	31.21
	Feb.	13.80	11.98	5,523.12	3,954.65	5.9	5.7	0.214	0.190	78.09	77.67	30.18	23.31	3.8	3.6	0.138	0.122	31.94	31.39
	Mar.	15.18	13.12	5,498.91	4,198.90	5.7	5.3	0.191	0.169	76.02	70.95	27.07	22.94	3.7	3.4	0.125	0.109	33.87	33.64
	Apr.	13.14	12.10	4,604.03	3,705.15	5.2	4.9	0.175	0.167	70.77	68.94	24.24	20.48	3.3	3.1	0.111	0.105	34.12	32.80
	May	14.72	11.24	5,440.99	3,549.60	5.0	4.8	0.173	0.145	70.48	69.80	24.52	20.62	3.2	3.1	0.112	0.094	34.45	33.51
Group 3	Jan.	3.26	2.72	1,638.28	1,217.05	9.3	7.0	0.355	0.300	49.08	42.68	23.87	18.65	5.9	4.5	0.229	0.194	28.25	23.61
	Feb.	3.18	2.36	1,614.53	1,165.90	8.8	7.3	0.372	0.306	52.47	44.86	26.89	19.61	5.9	4.6	0.242	0.195	27.61	23.13
	Mar.	3.91	3.19	1,937.55	1,333.00	8.6	6.6	0.324	0.270	48.35	44.98	22.51	17.42	5.7	4.4	0.208	0.175	29.37	24.81
	Apr.	3.70	2.84	1,743.91	1,078.30	8.4	6.4	0.302	0.249	45.86	43.16	19.95	15.81	5.5	4.2	0.195	0.156	30.33	25.03
	May	3.78	2.92	1,646.25	1,212.00	8.2	6.2	0.296	0.236	44.95	39.08	19.51	15.00	5.5	3.9	0.189	0.153	30.70	25.78
Group 4 (least active stocks)	Jan.	0.48	0.37	576.64	326.60	10.3	8.9	1.076	0.833	23.90	19.08	29.49	16.07	7.2	6.3	0.744	0.568	14.82	11.15
	Feb.	0.59	0.43	651.26	361.60	10.0	9.5	1.118	0.849	22.94	19.78	27.01	17.10	7.1	6.4	0.786	0.589	14.59	10.89
	Mar.	0.72	0.54	728.39	445.45	9.6	8.8	0.995	0.751	24.15	20.84	28.00	14.53	6.6	5.9	0.669	0.508	15.57	11.18
	Apr.	0.69	0.58	744.21	432.65	9.4	8.9	0.930	0.689	23.09	19.65	24.70	14.02	6.5	6.1	0.617	0.459	16.30	12.51
	May	1.00	0.61	1,000.03	394.40	8.8	8.2	0.909	0.591	24.19	19.57	23.00	14.19	5.9	5.2	0.582	0.382	16.94	13.07

Table 2

Analysis of Trading Strategies

This table presents the analysis of changes in trading strategies of investors and specialists following the introduction of OpenBook. The pre-event period is January 7–18 (**Jan**) and the post-event periods are February 4–15 (**Feb**), March 4–15 (**Mar**), April 1–12 (**Apr**), and May 6–17 (**May**) (each contains 10 trading days). In Panel A, ΔCancRate is the change in cancellation rate defined as the ratio of the number of cancelled limit orders over the number of limit orders submitted, and ΔTimeCanc is the change in the number of seconds between submission and cancellation of limit orders. Panel B presents the results of the duration analysis of time-to-cancellation. For each stock in the sample, we use a parametric approach assuming a Weibull distribution for time-to-cancellation (T):

$$Log\ T_{it} = a_i + ß_i\ I_{it} + ?_i\ Distance\ from\ quote_{it} + e_{it}$$

and a nonparametric analysis applying the Cox (1972) model of the hazard rate ($h(t)$) :

$$Log\ h_{it}(t) = a_i(t) + ß_i\ I_{it} + ?_i\ Distance\ from\ quote_{it} + e_{it}$$

In both models, I is a dummy variable that takes the value of one for post-event observations and 0 for pre-event observations. Distance from the relevant quote sides (i.e., bid for sells and ask for buys), standardized by the quote midpoint, is used as a covariate. Panel B reports the median of $ß_i$s (the coefficients on the dummy variables estimated separately for each stock), the number of $ß_i$s significant at the 5% level, and the p-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. In Panel C, ΔLimitSize is the change in the average size of limit orders between the pre- and post-event periods in shares; and ΔFloor/Lmt is the change in the ratio of the number of shares executed by floor brokers to the number of shares executed using limit orders in the book. Panel D demonstrates the changes in specialist behavior. ΔSpecRate measures changes in the specialists' participation rate in terms of number of shares, and ΔSpecDepth is the change in the specialists' total commitment (in dollars) on the bid and ask sides of the quoted depth. For all variables, the table reports the median and the p-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. "**" indicates significance at the 1% level and "*" indicates significance at the 5% level (both against a two-sided alternative).

Panel A: Analysis of Cancellation of Limit Orders

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
Variables	**Median**	(p-value of Wilcoxon test)	**Median**	(p-value of Wilcoxon test)	**Median**	(p-value of Wilcoxon test)	**Median**	(p-value of Wilcoxon test)
D**CancRate**	0.0068	(0.1009)	0.0259**	(0.0000)	0.0466**	(0.0000)	0.0475**	(0.0000)
D**TimeCanc**	-12.765*	(0.0190)	-25.095**	(0.0000)	-39.902**	(0.0000)	-50.584**	(0.0000)

Panel B: Duration Analysis

	Feb-Jan			**Mar-Jan**			**Apr-Jan**			**May-Jan**		
ß	**Median**	**# of significant**	(p-value of Wilcoxon test)	**Median**	**# of significant**	(p-value of Wilcoxon test)	**Median**	**# of significant**	(p-value of Wilcoxon test)	**Median**	**# of significant**	(p-value of Wilcoxon test)
Weibull	-0.1106**	394	(0.0000)	-0.1621**	393	(0.0000)	-0.2529**	398	(0.0000)	-0.2782**	398	(0.0000)
Cox	0.0636**	397	(0.0000)	0.1007**	398	(0.0000)	0.1570**	397	(0.0000)	0.1590**	399	(0.0000)

Panel C: Differences in Trading Strategies of Investors between Post- and Pre-event Periods

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
Variables	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
D**LimitSize**	-29.513**	(0.0003)	-31.515**	(0.0000)	-55.763**	(0.0000)	-68.423**	(0.0000)
D**Floor/Lmt**	-0.0135	(0.2100)	-0.0323**	(0.0022)	-0.0438**	(0.0001)	-0.0495**	(0.0000)

Panel D: Differences in NYSE Specialists' Behavior between Post- and Pre-event Periods

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
Variables	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
D**SpecRate**	0.0003	(0.5876)	-0.0069**	(0.0001)	-0.0050**	(0.0019)	-0.0088**	(0.0000)
D**SpecDepth**	-1164.76*	(0.0200)	-1320.08	(0.1300)	-2972.83**	(0.0000)	-2599.81**	(0.0000)

Table 3

Analysis of Informational Effects

This table presents an analysis of information and prices around the introduction of OpenBook. The pre-event period is January 7–18 (**Jan**) and the post-event periods are February 4–15 (**Feb**), March 4–15 (**Mar**), April 1–12 (**Apr**), and May 6–17 (**May**) (each contains 10 trading days). We use two types of tests to examine changes in the informational efficiency of prices. The first test uses a variable constructed from the variance decomposition procedure in Hasbrouck (1993). ΔVR (*s/p*) is the change in the ratio (in percentage terms) of the variance of the discrepancies between log transaction prices and the efficient (random walk) price divided by the variance of log transaction prices (to normalize the measure). The second test looks at the change in the absolute value of first-order autocorrelations of midquote returns. We divide the trading day into 30-minute intervals for Δ | Corr30 | and 60-minute intervals for Δ | Corr60 | and compute the returns from prevailing midquotes at the beginning and end of each interval. We also examine the change in the relative measure of trade informativeness developed in Hasbrouck (1991). ΔVR (*x/w*) is the change in the ratio (in percentage terms) of the trade-correlated component to the total efficient price variance. For all variables, the table reports the median and the *p*-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. "**" indicates significance at the 1% level and "*" indicates significance at the 5% level (both against a two-sided alternative).

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
Variables	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
D**VR (*s/p*)**	-0.00047	(0.5294)	0.00043	(0.4390)	-0.00567**	(0.0000)	-0.00691**	(0.0000)
D**| Corr30 |**	-0.00343	(0.5868)	-0.01181*	(0.0384)	-0.00355	(0.5384)	-0.00100	(0.7996)
D**| Corr60 |**	-0.00370	(0.2498)	-0.00590	(0.1393)	-0.01424	(0.0906)	-0.01749*	(0.0251)
D**VR (*x/w*)**	0.25800	(0.2399)	-0.84400	(0.0864)	-0.66600*	(0.0325)	-0.66550*	(0.0432)

Table 4
Unconditional Analysis of Liquidity

This table presents the analysis of changes to both displayed and "ex-post" liquidity following the introduction of OpenBook. The pre-event period is January 7–18 (**Jan**) and the post-event periods are February 4–15 (**Feb**), March 4–15 (**Mar**), April 1–12 (**Apr**), and May 6–17 (**May**) (each contains 10 trading days). Panel A presents ΔCumShares, the change to cumulative number of shares in the book at several distances from the relevant quote sides (i.e., ask for sells and bid for buys), where the distances are defined in terms of percentage of the stock's price (0.166%, 0.833%, 3.333%, 16.667%, and the entire book). The percentage bounds are determined by deciding on dollar bounds (5 cents, 25 cents, 1 dollar, and 5 dollars) and then dividing them by the average share price in the pre-event period for the sample ($30). Panel B shows ΔESpread¢, the change in effective spreads in cents both for the entire sample and for four groups based on trading intensity in the last quarter of 2001. For all variables, the table reports the median and the *p*-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. "**" indicates significance at the 1% level and "*" indicates significance at the 5% level (both against a two-sided alternative).

Panel A: Differences in Cumulative Number of Shares Displayed in the Book between Post- and Pre-event Periods

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
D**CumShares**	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
0.166% from midpoint	-1.30	(0.7981)	97.78	(0.1273)	-128.43	(0.4355)	-124.64	(0.0623)
0.833% from midpoint	-216.74	(0.4294)	381.35*	(0.0389)	-136.96	(0.3909)	-124.62	(0.2272)
3.333% from midpoint	-193.64	(0.7245)	1072.80**	(0.0050)	-130.44	(0.8803)	-309.11	(0.6914)
16.67% from midpoint	127.26	(0.5025)	2081.44**	(0.0044)	1059.48*	(0.0293)	485.07	(0.3272)
Entire Book	1818.60*	(0.0275)	887.52	(0.1304)	366.11	(0.5364)	-838.74	(0.8916)

Panel B: Differences in Effective Spreads (in cents) between Post- and Pre-event Periods

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
D**ESpread¢**	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
Entire Sample	0.087*	(0.0382)	-0.143**	(0.0000)	-0.330**	(0.0000)	-0.454**	(0.0000)
Group 1 (most active stocks)	0.192**	(0.0000)	-0.082*	(0.0202)	-0.325**	(0.0000)	-0.272**	(0.0000)
Group 2	0.047	(0.6096)	-0.082	(0.2675)	-0.331**	(0.0000)	-0.478**	(0.0000)
Group 3	0.055	(0.9192)	-0.282*	(0.0118)	-0.361**	(0.0000)	-0.635**	(0.0000)
Group 4 (least active stocks)	0.030	(0.7478)	-0.321*	(0.0100)	-0.297**	(0.0034)	-0.772**	(0.0000)

Table 5
Conditional Analysis of Liquidity

This table presents results of analyses of liquidity changes around the introduction of OpenBook controlling for changes in volume, volatility, and price level. The pre-event period is January 7–18 (**Jan**) and the post-event periods are February 4–15 (**Feb**), March 4–15 (**Mar**), April 1–12 (**Apr**), and May 6–17 (**May**) (each contains 10 trading days). We use two liquidity measures: (i) ΔDepth is the change to the total depth in the book in round lots, and (ii) ΔESpread¢ is the change in effective spreads in cents. In Panel A, we report the results of OLS regressions of changes in the liquidity measures on changes in the control variables:

$$DL_i = a + ß_1\, DAvgVol_i + ß_2\, DHiLow_i + ß_3\, DAvgPrc_i + e_i$$

where ΔAvgVol is the difference in average daily dollar volume, ΔHiLow is the difference in intra-day volatility (average daily range of transaction prices), and ΔAvgPrc is the difference in the average transaction price of the stock. All differences are between the post- and pre-event periods. We run the regressions separately for each post-event period. We report the intercepts from the eight regressions and their associated *p*-values calculated using White's heteroskedasticity-consistent standard errors. For the analysis in Panel B we use daily data to estimate (OLS) the following relation:

$$L_{it} = \text{Intercept} + S_k{}^{n}{}_{=1}\,(ß_k D_{itk}) + ?_1\, Vol_{it} + ?_2\, HL_{it} + ?_3\, Prc_{it} + e_{it}$$

where dummy variable D_{itk} (k = 1, …, n) takes the value of one for the k-th day in the n-day post-event period and zero otherwise, Vol is the average daily dollar volume, HL is the daily price range, and Prc is the daily average transaction price of the stock. We estimate the model for each post-event period separately and for a pooled 40-day post-event period. We report the median of the dummy variables' coefficients ($ß_k$s) and the *p*-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. For the analysis in Panel C we estimate (OLS) the following relation using cross-sectional averages at daily frequency:

$$CSL_t = \text{Intercept} + S_k{}^{4}{}_{=1}\,(ß_k D_{kt}) + ?_1\, CSVol_t + ?_2\, CSHL_t + ?_3\, CSPrc_t + e_t$$

where dummy variable D_{kt} (k = 1, 2, 3, 4) takes the value of one for the k-th post-event period and zero otherwise, CSVol is the cross-sectional average of daily dollar volume, CSHL is the cross-sectional average of intra-day volatility, and CSPrc is the daily mean transaction price averaged across stocks. We report the coefficients ($ß_{1-4}$) of the dummy variables and their associated *p*-values calculated using White's heteroskedasticity-consistent standard errors. For all parameters, "**" indicates significance at the 1% level and "*" indicates significance at the 5% level (both against a two-sided alternative).

Panel A: Differences in Liquidity Variables in a Cross-Sectional Multivariate Regression (400 Observations)

	Feb-Jan		**Mar-Jan**		**Apr-Jan**		**May-Jan**	
Variables	***a***	(*p*-value of t-statistic)	***a***	(*p*-value of t-statistic)	***a***	(*p*-value of t-statistic)	***a***	(*p*-value of t-statistic)
D**Depth**	4586.35	(0.1398)	10734.64*	(0.0299)	11713.03*	(0.0298)	9006.07	(0.1347)
D**ESpread¢**	-0.1046	(0.1848)	-0.2817**	(0.0066)	-0.6257**	(0.0000)	-0.8001**	(0.0000)

Panel B: Analysis of Liquidity Changes Estimated from Multivariate Regressions at the Daily Frequency

	Feb (8000 Obs.)		**Mar** (8000 Obs.)		**Apr** (8000 Obs.)		**May** (8000 Obs.)		**All Periods** (20000 Obs.)	
Variables	**Median ß** (n=10)	(*p*-value of Wilcoxon test)	**Median ß** (n=10)	(*p*-value of Wilcoxon test)	**Median ß** (n=10)	(*p*-value of Wilcoxon test)	**Median ß** (n=10)	(*p*-value of Wilcoxon test)	**Median ß** (n=40)	(*p*-value of Wilcoxon test)
Depth	1404.45*	(0.0249)	317.71	(0.6103)	1198.40*	(0.0144)	1569.02**	(0.0080)	1211.95**	(0.0000)
ESpread¢	-0.0087	(0.9188)	-0.4048**	(0.0059)	-0.8600**	(0.0059)	-1.1311**	(0.0059)	-0.6562**	(0.0000)

Panel C: Time-Series Analysis of Liquidity Changes Estimated from a Multivariate Regression using Cross-sectional Averages (50 Observations)

	Feb		**Mar**		**Apr**		**May**	
Variables	β_1	(*p*-value of t-statistic)	β_2	(*p*-value of t-statistic)	β_3	(*p*-value of t-statistic)	β_4	(*p*-value of t-statistic)
Depth	770.01**	(0.0004)	827.09**	(0.0002)	740.76**	(0.0012)	618.16**	(0.0013)
ESpread¢	0.0790	(0.1819)	-0.1087	(0.2081)	-0.3325**	(0.0000)	-0.4381**	(0.0000)

Table 6
Analysis of Cumulative Abnormal Returns

This table presents an analysis of the price effects of changes in liquidity around the introduction of OpenBook. The pre-event period is January 7–18 (**Jan**) and the post-event periods are February 4–15 (**Feb**), March 4–15 (**Mar**), April 1–12 (**Apr**), and May 6–17 (**May**) (each contains 10 trading days). We compute daily abnormal returns as residuals of a market model using one year of daily returns ending on November 30, 2001 with the Standard and Poor's 500 Index as a proxy for the market. We construct a Cumulative Abnormal Return (CAR) measure by summing the daily abnormal returns up to the end of each post-event period. In Panel A, we report the median CAR between the implementation date (January 24, 2002) and the end of each post-event period and the *p*-value (in parentheses) of a Wilcoxon signed rank test against the hypothesis of a zero median. In Panel B, we report the results of OLS regressions of the Cumulative Abnormal Returns between the beginning of the pre-event period and the end of each post-event period on changes in relative effective spreads (ΔESpread):

$$CAR_i = a + ß\ ?ESpread_i + e_i$$

We run the regressions separately for each of the four 100-stock trading intensity groups (based on median dollar volume in the last quarter of 2001) and for each post-event period. "**" indicates significance at the 1% level and "*" indicates significance at the 5% level (both against a two-sided alternative).

Panel A: Analysis of Cumulative Abnormal Returns (CAR)

	Feb		**Mar**		**Apr**		**May**	
	Median	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)	**Median**	(*p*-value of Wilcoxon test)
CAR	0.0168**	(0.0059)	0.0414**	(0.0000)	0.0840**	(0.0000)	0.0741**	(0.0000)

Panel B: Analysis of the Effect of Liquidity Changes on CAR

	Feb			**Mar**			**Apr**			**May**		
	a (*p*-value)	b (*p*-value)	**Adj R^2** (in %)	a (*p*-value)	b (*p*-value)	**Adj R^2** (in %)	a (*p*-value)	b (*p*-value)	**Adj R^2** (in %)	a (*p*-value)	b (*p*-value)	**Adj R^2** (in %)
Group 1 (most active stocks)	0.033**	-4.731**	50.68	-0.001	-3.322**	31.26	-0.017	-3.962**	22.75	-0.021	-4.545**	36.08
	(0.004)	(0.000)		(0.926)	(0.000)		(0.305)	(0.000)		(0.221)	(0.000)	
Group 2	-0.003	-2.619**	32.90	-0.015	-2.061**	15.53	0.013	-1.344*	4.27	-0.036	-2.489**	16.84
	(0.770)	(0.000)		(0.290)	(0.000)		(0.520)	(0.022)		(0.127)	(0.000)	
Group 3	-0.014	-0.374*	3.49	0.001	-0.647*	5.04	0.022	-1.245**	14.69	-0.029	-1.247**	14.61
	(0.172)	(0.035)		(0.940)	(0.014)		(0.293)	(0.000)		(0.243)	(0.000)	
Group 4 (least active stocks)	0.002	-0.219**	14.80	-0.005	-0.419**	35.72	0.037	-0.501**	38.56	-0.036	-0.618**	46.15
	(0.910)	(0.000)		(0.807)	(0.000)		(0.090)	(0.000)		(0.195)	(0.000)	