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ESSAYS IN MICROSTRUCTURE OF SECURITIES MARKETS

by

AMBER ANAND

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Bell & Howell Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

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July 9, 2001
Date

Terrence F. Martell
Chair of Examining Committee

July 9, 2001
Date

Executive Officer

Aloke Ghosh

Daniel Weaver

Avner Wolf

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

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Adviser: Professor Terrence F. Martell

Using proprietary data and an event unique in the history of financial markets, the first essay studies the value that a specialist system adds vis-à-vis a multiple market maker system. Specifically, it analyzes the "natural experiment" of the institution of a specialist system for equity options on the Chicago Board Options Exchange (CBOE) in the second half of 1999. The extant literature predicts an increase in market quality due to the change to a specialist system on the CBOE. We find support for these hypotheses. We also offer limited evidence of increased competitiveness of the CBOE. The essay also analyzes the possibility of the rise of preferencing arrangements in the options markets.

The second essay contributes towards an understanding of pre-trade transparency by studying the value limit-order traders place on the ability to hide their intentions in an open electronic limit order book. The paper studies the "natural experiment" of the Toronto Stock Exchange disallowing the use of hidden limit orders. The policy change did not have any visible benefits for the market. However, traders who had optimally used the ability to hide size switched to, a conceivably sub-optimal, use of market orders. This would indicate a welfare loss for at least some traders. Since we do not find a corresponding welfare gain for other traders, the results point towards a welfare loss for the market as a whole as a result of the rule change.

The third essay examines the difference in the performance of the informed versus the uninformed limit order flow. To the extent that some investors are better informed than others we should expect to see a difference in the performance of their orders. Our results indicate that institutional limit orders perform significantly better than the limit orders placed by individuals. These results suggest that institutions are better able to predict at least the flow of information and use this knowledge to submit trades, which avoid adverse selection problems commonly associated with limit orders. The results also point to the use of limit orders by informed traders, an area not previously explored in the literature.

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ESSAY I

Should Order Exposure be Mandated? The Toronto Stock Exchange Solution

Should Order Exposure be Mandated? The Toronto Stock Exchange Solution

Abstract

In this article we address the issue of pre-trade transparency that arises as a result of the ability of market participants to hide order size on most auction markets. We contribute towards an understanding of pre-trade transparency by specifically studying the value limit-order traders place on the ability to hide their intentions in an open electronic limit order book, or from the viewpoint of the market-order traders, the ability to get a complete picture of the order flow available. We look at the "natural experiment" of the Toronto Stock Exchange disallowing the use of hidden limit orders for the stocks traded on its electronic CATS system. From March 18, 1996 onwards traders in stocks listed on the CATS system could no longer hide additional quantity behind their orders. The issue also assumes significance due to the trade-off exchanges face between attracting liquidity and getting traders to display liquidity. The policy change did not have any visible benefits for the market or the investors. Liquidity, market share and volume remained intact. However, traders who had optimally used the ability to hide size in the book had to switch to (a conceivably sub-optimal) use of market orders. This would indicate a welfare loss for at least some traders. Since we do not find a corresponding welfare gain for other traders, the results point towards a welfare loss for the market as a whole as a result of the rule change.

I. Introduction

Transparency in the trading process has recently emerged as an area of sharp disagreement between regulators, exchanges, market participants and academics. The drive towards disclosure that began with the Securities Act of 1934 (largely credited for the growth of securities markets in the United States)[1] is now fuelling the initiatives towards integrated markets, the push towards an open centralized limit order book and mandatory disclosure by brokers' of their ties with exchanges and execution costs.[2] The Securities and Exchange Commission is clear on its stand that the more transparent a market the better it is for the investors[3]. While this view largely had the desired effects where disclosure of company information was concerned[4] recent studies have taken issue with this view as applied to securities markets. We also see the emergence of anonymous crossing networks as evidence that non-transparent markets have a place in the future of securities markets. The difference here is easy to see, while disclosure of company information puts all traders on an equal footing and mitigates insider trading profits, causing a transfer from informed insiders to the uninformed traders, transparency of the kind now being advocated in securities markets could work to the benefit of the informed trader.

Market transparency has been looked at in two dimensions: pre-trade and post-trade. Post trade transparency refers to the timely reporting of trade information, while pre-trade transparency refers to issues associated with the visibility of the order book to

[1] "The New Deal's Gift to Wall Street," *The Wall Street Journal*, November 11, 1999.

[2] "Let Investors Know What They Really Pay," *Business Week*, August 7, 2000.

[3] SEC Market 2000 Study

[4] For a review and additional results on increased disclosure refer Greenstein and Sami (1994).

traders. No consensus has yet emerged on either issue. Different market structures might have different "optimal" levels of transparency that maximize welfare. Glosten (1999) in his introduction to two experimental studies (Bloomfield and O'Hara (1999) and Flood, Huisman, Koedijk and Mahieu (1999)), notes the opposite conclusions reached by the two given the differences in the set-up of their experiments. Outside a laboratory setting, the task of predicting the response of market participants to different levels of transparency is even more difficult, thus underlining the importance of empirical analysis to resolve the issues involved.

In this paper, we contribute towards an understanding of pre-trade transparency by specifically studying the value limit-order traders place on the ability to hide their intentions in an open electronic limit order book, or from the viewpoint of the market-order traders, the ability to get a complete picture of the order flow available. We look at the "natural" experiment of the Toronto Stock Exchange disallowing the use of hidden limit orders for the stocks traded on its electronic Computer Aided Trading System (CATS). From March 18, 1996 onwards traders in stocks listed on the CATS system could no longer hide additional quantity behind their orders. This exogenous shock to the system forms the basis for our study of the response of different market participants to this change and the market quality impact thereof.

The exchange's decision can be understood as a means to enhance displayed liquidity in the book in the belief that a higher displayed liquidity would attract additional order flow from market order traders (Harris (1996)).

However, limit order traders hide quantity in the limit order book to limit the option value of their order, to reduce the risk of being front run,[5] and to minimize losses due to trading with informed investors. Once the feature is removed from the system, these traders are essentially faced with three choices, 1) display the hidden portion of their order, 2) move to an alternate trading venue, or 3) manage their orders actively.

We find that spreads are not impacted by the change. This coupled with the fact that quoted depth as well as actual depth (measured using Kyle's lambda) remained unchanged, leads us to conclude that limit order traders did not expose the hidden portion of the depth in the market but actively managed their orders to avoid exposing themselves to losses to informed traders. This is corroborated by a decrease in the number of quote updates indicating fewer limit orders being placed into the book. We find no evidence that market quality either improved or deteriorated as a result of the change. Volume weighted effective spreads, used as a measure of spreads earned by limit order traders, do not show any significant change. This shows that no significant wealth transfer took place from limit-order traders to market order traders. However, if limit orders now had to be actively managed, the costs of doing so could lead to a net welfare loss as a result of the rule change.

The CATS system works as an electronic open limit order book and formed the foundation of the Paris CAC. The move towards electronic centralized limit order book, as well as the formation of several electronic trading networks increases the significance of policy level lessons drawn from CATS. Also, ours is the only study that looks at this specific dimension of pre-trade transparency. Regulators deciding on mandating

[5] Parasitic traders described by Harris (1996).

transparency and exchanges competing for order flow will be able to draw from the experience of TSE, as described here.

In the next section we review related issues dealt with in the literature (Section II). Section III builds and lays down our hypotheses, Section IV describes the data and gives a brief description of trading on TSE, Section V discusses the results and Section VI concludes.

II. Literature Review:

Bloomfield and O'Hara (1999) use experimental economics to study certain facets of market transparency. Specifically, they set up a market with two market makers, a number of computerized informed and noise traders and two human active traders. Bloomfield and O'Hara address the two issues of trade and quote disclosure by conducting trading under various levels of transparency. They find that trade disclosure leads to greater informational efficiency (prices converge to their true values faster), higher bid-ask spreads and welfare effects that involve a transfer from informed and uninformed traders towards market makers. Note here that trade disclosure falls under the realm of post-trade transparency. In studying quote disclosure, Bloomfield and O'Hara venture into the area of pre-trade transparency but find no discernible effects beyond that found for trade disclosure. The authors also point out the various facets of transparency, which they are not able to address in this study, one of them being the issue of the availability of data on the size of limit orders.

Bloomfield and O'Hara (2000) further analyze the issue of trade reporting from the perspective of competing dealers and find that low transparency dealers are typically more aggressive and more profitable than their high transparency counterparts.

Porter and Weaver (1998) examine late reporting of trades on NASDAQ to empirically study post-trade transparency. Gemmill (1996) and Naik, Neuberger and Vishwanathan (1994) focus on the London Stock Exchange which allows dealers to delay the disclosure of large trades by 90 minutes.

Flood, Huisman, Koedijk and Mahieu (1999) set up their experimental study to closely resemble the foreign exchange market. Theirs is a multiple-dealer market with interdealer trading. The opaque market structure does not allow dealers to view each other's quotes. They also identify the same trade-off as Bloomfield and O'Hara but in the opposite direction. They find that opaque markets are more efficient but have higher spreads as compared to transparent markets. As Bloomfield and O'Hara discuss, given the differences in the microstructures of the two markets as well as the type of transparency studied the results look more contradictory than they are. However, it does underscore the point that different structures will likely have different optimal levels of transparency, and the issue is of a degree of complexity that precludes any simple answers.

Madhavan, Porter and Weaver (1999) conduct an empirical study of the impact of a change in pre-trade transparency in studying the market quality effects of opening up the limit order book on the Toronto Stock Exchange. Their results indicate that this increase in transparency actually served to deteriorate market quality with an increase in spreads and volatility. Using confidential data they also determine that RT (Registered

Trader, the TSE counterpart of the NYSE specialist) profits remain unchanged. Thus, in this particular case, the increase in transparency served to benefit informed traders which, in turn, led to limit order traders increasing their spreads to counteract the increased risk of trading with an informed trader.

In a study closely related to ours, Harris (1996) explores the relation between tick size and order exposure on the Paris CAC and Toronto CATS systems. Harris discusses the trade-off exchanges face between attracting liquidity and getting traders to display liquidity. He conjectures that forcing traders to display might result in driving away liquidity from the market. He finds that traders display more in stocks with larger relative ticks, and less in volatile stocks. This forms the basis of our empirical work.

In our study, we are able to directly test the liquidity effects of the exchange's efforts to mandate display of liquidity.

Therefore, the issue of order display is highly relevant from the perspective of transparency as well as the policy debate on increasing the competitiveness of an exchange.

III. Hypotheses Development:

The issue of transparency in securities markets is inevitably linked to the issues of efficiency and liquidity. As Bloomfield and O'Hara (1999), and Flood et. al. (1999) discuss, it is not clear whether increased transparency results in an increase in both, and that there might be a trade-off involved between the two.

Bloomfield and O'Hara (1999) find that an increase in post trade transparency leads to an increase in spreads and poorer execution for all classes of traders (to the benefit of market makers). Further, they find no additional benefit of pre-trade transparency. Madhavan, Porter and Weaver (1999) find that an increase in pre-trade transparency leads to wider spreads and higher volatility in the markets. Flood et. al. find their set up of an opaque market to have higher spreads than the transparent market. Although, these studies study different market structures and different kinds of transparency the significance of liquidity effects is obvious. Thus, our first hypothesis:

H1.a. *Higher transparency in the form of the display of size of the limit orders in the book leads to wider spreads, lower depth and higher volatility.*

It is reasonable to conjecture that the primary motive of the exchange in instituting the rule change is enhancing liquidity of their markets. As Harris (1996) points out they face a dilemma in mandating display of liquidity as it might serve to drive away liquidity instead. This is so due to the increased risk traders now face of trading with informed traders. The move to mandate display also limits the choices limit order traders have in controlling the option value of their orders.

In another framework, the "gravitational pull" (Cohen, Maier, Schwartz and Whitcomb, 1983) of the opposite quote increases causing the limit order traders to switch away from limit orders to market orders. This would result in less trading via limit orders while keeping the total liquidity in the system intact.

This leads us to the following alternate hypothesis.

H.1.b: *Liquidity moves out of the book but stays in the system causing quoted spreads to increase. Effective spreads remain constant in the transparent market. Total depth in the market remains unchanged. The number of quote updates in the post period decreases relative to the number of quotes in the pre period.*

Bloomfield and O'Hara and Flood et. al. also find differences in market efficiency between a transparent and an opaque market. Bloomfield and O'Hara find that the transparent system is more efficient, while Flood et. al. find higher efficiency in the opaque system. The increased price volatility hypothesized above (H.1.a) also could be due to an increase in efficiency in the system, as price move faster to their full information values. If the exchange succeeds in its objective of making limit order traders to display their complete intentions to trade then we should see higher efficiency in the market.

H.2. Prices converge to their true values faster after hidden limit orders are disallowed.

For stocks listed on other venues the limit order traders have the alternative of shifting their orders to such exchanges. Madhavan, Porter and Weaver (1999) test this hypothesis for their study on pre-trade transparency and find no evidence in support of a migration of trading. However, we test the following hypotheses:

Hypothesis 3: The migration of limit order traders to alternative venues causes TSE's market share to decrease for cross-listed stocks.

In the following sections we describe the data, detail the empirical methods used to test these hypotheses and discuss the results.

IV. Data:

The automated trading system at TSE, Computer Aided Trading System (CATS), was one of the two trading systems on TSE during the period of this study. The other being the TSE Floor, which was organized much like the NYSE specialist system. [6]

On March 18, 1996 TSE disallowed the ability to hide quantity on the limit order book on the CATS system.[7] This rule change defines the focus of our study.

The data used are for two 19 trading day periods before and after the rule change. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. On April 15, 1996 TSE decimalized trading and lowered tick sizes for most stocks,[8] thus precluding a longer data period.

We restricted our sample to common stocks, trading in Canadian dollars that traded throughout the sample period (pre and post) and those that had at least 50 valid quotes in the period before the rule change. We only included trades and quotes between 9.30 a.m. and 4.00 p.m., only included quotes that were no wider than $5 and where the spread was positive. If a particular company had two (or more) classes of stocks trading,

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[6] For a detailed description of the organization of trading on the TSE floor please refer to Madhavan et. al (1999).

[7] No such provision existed on the TSE floor.

[8] A detailed analysis of the impact of decimalization can be found in Bacidore (1997), MacKinnon and Nemiroff (1999) and Porter and Weaver (1997).

then we used the most active class and dropped the other(s). We also excluded a stock if it traded on two different ticks anytime during the sample period.

Our final sample consists of 272 stocks. Following the results of Harris (1996), we divide the data into four portfolios on the basis of their relative tick size and volatility of returns. Volatility is measured as the average 30-minute standard deviation of a stock's return. Table 1 describes the full sample as well as the resulting four portfolios. Average price of one portfolio is much higher than the other three (low tick, low volatility). Thus, we would have to be careful in interpreting any disparate results that we find for this portfolio.

V. Empirical Tests:

We draw from Harris (1996) in designing our empirical tests of the hypotheses outlined earlier. Harris finds that the decision to display order size is determined by the relative tick size and the volatility of the particular stock. Specifically, traders display more in stocks, which have high relative tick size and low volatility. Intuitively, the risks of being front-run are greater if the relative tick size is smaller, and the higher the volatility the higher the option value of the limit order. Therefore, to most clearly study the effects of TSE's disallowing hidden limit orders we form portfolios based on the average relative tick size and the average 30 minute standard deviation of returns in the pre-period. This divides the sample into four portfolios.

V.A. Liquidity:

As a first step, we analyze the impact on liquidity of the rule change. The most commonly used measure of liquidity is the quoted bid-ask spread. Table 2 presents the results for time weighted quoted dollar spreads. The results show that the overall sample as well as one of the four portfolios experiences a positive and significant impact, while the others portfolios experience a positive impact but this is not statistically significant. Percentage spreads (expressed as a percentage of the midpoint of the bid and ask prices) do not show the same trend. Most changes are negative and insignificant. Percentage spreads went up significantly for only one portfolio. Thus, dollar spreads increase while percentage spreads do not. To clarify the impact on trading costs we turn towards measures of effective spread, since trades can also occur inside and outside quoted spreads. We examine dollar effective spreads and percentage effective spreads. Results are similar to those obtained by the analysis of dollar and percentage quoted spreads. While effective dollar spreads experience a positive impact due to the change, effective percentage spreads experience a negative impact. For the full sample these changes are significant at the 10% level of significance. Thus results from Table 2 indicate that, adjusted for price, the costs of trading decrease, albeit insignificantly.

The importance of controlling for other variables is illustrated by the results discussed above. While percentage spreads take the price of the stock into account, there are other factors documented in the literature that need to be accounted for. We regress average spreads on average price, total volume (total number of shares traded), average number of trades, average volatility of returns and a dummy variable for the post period. The results (Table 3) for the above mentioned four measures of trading costs indicate that none of these measures experienced a significant change solely due to the rule change. Thus, the rule change left spreads in the market largely unaffected.

Lee, Mucklow and Ready (1993) suggest that spreads alone provide an incomplete picture of the demand schedule for liquidity. To be able to draw any conclusions one has to study spreads as well as depth of the limit order book. Therefore, we turn to depth in the book in our analysis. Results for quoted depth, presented in Table 4, show that none of the portfolios experienced any change in depth. It is important to note here that, all else equal, if the exchange had succeeded in its objective and traders exposed all available depth then we should see an increase in quoted depth since the hidden portion would be exposed. An absence of this increase indicates that traders did not simply reveal the hidden portion of their orders in the book. To further examine this hypothesis, we use a comprehensive measure of liquidity and depth given by Kyle (1985) known as Kyle's lambda. Intuitively lambda measure the volume required to move price by a dollar and is an inverse measure of liquidity (higher the lambda, lower the liquidity and vice versa). We modify the following equation to study the impact on total depth in the system:[9]

$$\Delta p_t = \lambda q_t + \gamma \mu_t + \varepsilon_t \qquad (1)$$

where Δp_t is the change in price ($p_t - p_{t-1}$), q_t is the signed order flow (positive for buy orders and negative for sell orders) μ_t is a market index used to control for positive drift in returns and ε_t is a random noise term. λ is an inverse measure of liquidity.

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[9] We are grateful to Ananth Madhavan for suggesting the addition of the market index to the Kyle (1985) equation as a control variable.

To identify buy and sell orders we use Lee and Ready (1991) algorithm. Instead of a 5-second lag suggested for NYSE by Lee and Ready, we lag quotes by one second only since CATS is a fully automated market. [10] Trades at the ask are classified as customer buys, at the bid as customer sales, a price higher than the midpoint indicates a buy and one lower than the bid-ask midpoint a customer sale. For trades at the midpoint, we examine the last price change and classify the trades as buys for upticks and sales for downticks.

The market index is constructed using all 272 stocks and measures the per second return on all the stocks in the sample.

The modified equation to study the liquidity effects of the rule change is presented below:

$$\Delta p_t = (\lambda_0 + \lambda_1 D_t)q_t + (\gamma_0 + \gamma_1 D_t)\mu_t + \varepsilon_t \qquad (2)$$

the only new term, D_t is a dummy which takes on the value 1 for the post-period and 0 for the pre-period. λ_1 and γ_1 capture changes that occur in the two coefficients as a result of the rule change. A positive value for λ_1 would indicate lower liquidity in the post period and a negative value would point towards an increase in liquidity. Table 4 shows that the coefficient for signed volume is positive and significant for all portfolios. The slope dummy coefficient, λ_1, however is insignificant for all portfolios. Thus, largely liquidity remained unchanged after the exchange imposed order display on its participants. This result corroborates our earlier discussion of traders moving to actively manage their orders as a result of the rule change.

[10] Exchange officials suggested the lag and an examination of the data confirms the adjustment.

Hypothesis H.1.a also predicts a rise in volatility in the period after the new rule came into effect. This would be consistent with a withdrawal of liquidity from the system. Our results do not support this hypothesis. Volatility changes significantly only for 2 of the 4 portfolios, at the 10% level (Table 5). These two portfolios also experienced a significant decline in unconditional effective percentage spreads. This would indicate an improvement in liquidity for these stocks. However, we found that the decrease in spreads loses significance after controlling for various factors. The lack of change in lambda measure for the portfolios also acts to discredit the perceived improvement.

Therefore, we do not find any support for hypothesis H.1.a. Quoted Spreads and quoted as well as actual depth remains unchanged. Effective spreads do not widen in response to the rule change. Volatility decreases for 2 portfolios but is not, in itself, sufficient to conclude a gain in liquidity.

The alternative hypothesis (H.1.b) predicts that limit order traders switch to trading via market orders leaving liquidity intact. This would imply that the quoted depth does not increase (as it would if hidden quantity were revealed), effective spreads remain constant and total liquidity in the market (as measured by Kyle's lambda) stays at previous levels. We find support for all these predictions in our results. We should also be able to capture lesser limit orders being submitted in lesser quote updates in the data. Our analysis supports this prediction as well. We find that the number of quote updates goes downin all 4 portfolios and significantly so in 2 cases (Table 6, Panel A). The overall sample also experiences a significant decline. This decline is not accompanied by any significant change in either the total share volume traded or the total dollar volume traded (Table 6, Panel B), lending further weight to our conclusions.

V.B. Efficiency:

Testing for a change in impact on the efficiency of the market presents a problem in an empirical study, since the "true" value of the security is not known as it is in an experimental study. To analyze the convergence of prices to their true values we make the assumption that the rate of information arrival remains constant in the pre and post period. Given that, we use the time the midpoint of the bid-ask quote spends at the same level as a measure of market efficiency. The greater this time the quicker prices converge to their true value, and spend more time at that value till the arrival of new information starts a move in the direction of the new "true" value. Figure 1 graphically illustrates the intuition behind the test. Results do not support the hypothesis that prices converge faster to their true values after hidden limit orders are disallowed. Table 7 reports that none of the portfolios experienced a significant change. Thus, we find that the rule change did not yield any benefits in the form of increased efficiency in the market. This result is not surprising, as the total liquidity in the system remains unchanged, traders do not exit the market, they just change their trading strategy.

V.C. Market Share:

Madhavan, Porter and Weaver (1999) test for a change in market share due to the increase in pre-trade transparency. We test the same hypothesis for our case of increased transparency. There are 53 stocks that were listed on at least one other exchange in February, March and April of 1996. Of these 53, 39 are a part of our sample. Consistent with Madhavan et. al., we find no significant change in market share for these stocks (Table 8).

V.D. Liquidity Provision Revenues:

Finally, we study the effective volume weighted spreads as a measure of revenues earned by liquidity providers (in this case, limit order traders, Table 9). Results indicate that limit order traders did not earn significantly different revenues after the rule change. This is consistent with our earlier findings. Limit order traders shift to using market orders since the returns to using limit orders goes down and market orders become more attractive (the "gravitational pull" of Cohen et. al.). However, this happens only until the point where the remaining limit order traders do not start making excess profits. Thus, we see market forces at work enforcing normal returns to liquidity providers.

VI. Conclusion:

Previous research has shown that transparency has significant impact on market behavior. But where the disclosure of inside information has contributed to the success of securities markets in widening participation and enhancing liquidity, the recent initiatives towards increase in transparency have been shown to not always benefit the markets or investors. Such results go directly to the root of the optimal design of a trading system to maintain a liquid, competitive market. Our study contributes to the understanding of transparency by focusing on a specific dimension of pre-trade transparency – the display of size in the limit order book.

We analyze the issue from the perspectives of market quality and trader behavior. As Harris (1996) points out limit order traders are concerned with being front-run, trading with informed traders and limiting the option value of their orders. Hiding size in the limit order book is a mechanism to manage these concerns. Since the concerns do not go away but the tool to manage them does, these traders face the choice of moving to other markets or using some other trading strategy.

Our evidence points towards limit order traders switching from limit orders to market orders to manage the hidden part of their orders. In support of this conclusion we find that quoted spreads and depths do not change and number of quote updates decreases after the rule change indicating that fewer limit orders are submitted. Evidence on total liquidity in the market, however, indicates that markets remained as liquid as they were prior to the rule change. Effective spreads do not change and neither does Kyle's lambda measure of liquidity. That the switch to market orders is limited to the previously hidden portion is confirmed by an examination of volume weighted effective spreads, as a measure of revenues earned by liquidity providers, which remain at levels similar to those before the rule prohibiting limit orders with hidden size came into effect. Further, the market share of TSE for cross-listed stocks does not change following the rule change.

Our test of the speed with which prices converge to their true values indicates no change in market efficiency following the increase in transparency of size in the limit order book.

Thus, our analysis of TSE's experience with mandating display of size in the limit order book yield certain important insights. The policy change did not have any visible benefits for the market or the investors. Liquidity, market share and volume remained intact. However, traders who had optimally used the ability to hide size in the book had to switch to (a conceivably sub-optimal[11]) use of market orders. This would indicate a welfare loss for at least some traders. Since we do not find a corresponding welfare gain

[11] Assuming that they were trading optimally prior to the rule change.

for other traders, the results point towards a welfare loss for the market as a whole as a result of the rule change.

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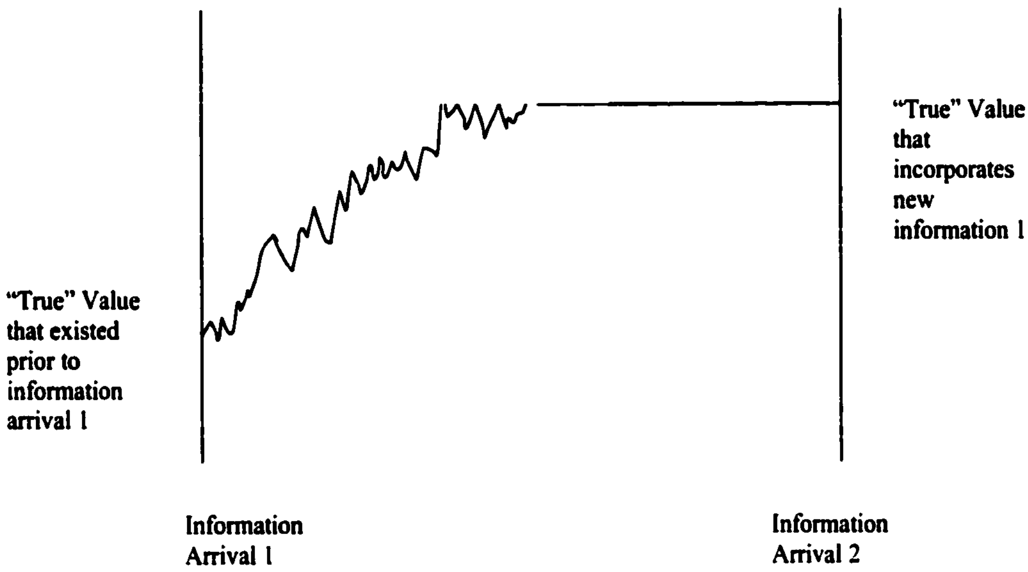
Figure 1

Panel A represents a lower efficiency market as compared to Panel B. Given that the rate of information arrival remains constant, prices take relatively longer to move to the new "true" value that information event 1 occurs, thus spending less time at the tru value. In Panel B. prices converge to the new true value quicker and thus spend relatively longer at the new value of the asset.

Panel A



Panel B

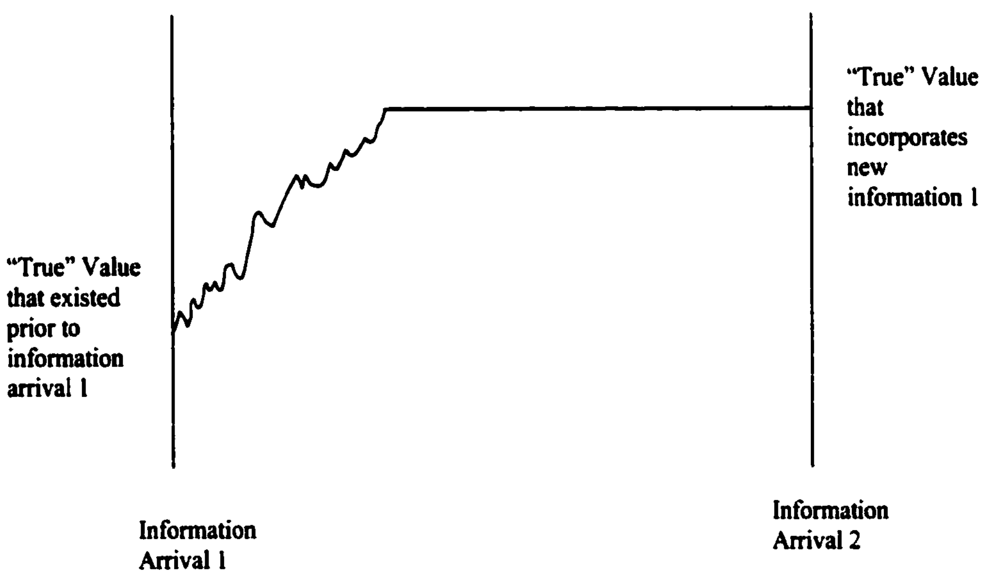


Table 1: Descriptive Statistics

This table outlines the average daily share volume, average daily standard deviation of returns and the average price for the CATS stocks included in our sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return. This table presents the statistics for the period before the rule change. All the numbers presented below are calculated for each stock and then aggregated cross-sectionally.

	NO. OF STOCKS	MEAN DAILY SHARE VOLUME: PRE	MEAN DAILY STANDARD DEVIATION: PRE	AVERAGE PRICE: PRE
Full Sample	272	62860.10	0.0768	9.84
Low tick, low volatility	79	57654.27	0.1031	20.16
Low tick, high volatility	57	64937.50	0.0818	6.11
High tick, low volatility	57	31253.50	0.0661	7.79
High tick, high volatility	79	89371.80	0.0544	3.70

Table 2

Panel A: Quoted Spreads

In this table, we summarize the results for quoted dollar and percentage spreads. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in spreads is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Dollar Spreads

	Number of Stocks	Mean Pre	Mean Post	Change	T-statistic for Change
Full Sample	272	0.1788	0.1921	0.013363	*2.33***
Low tick, low volatility	79	0.2631	0.2897	0.0265	*1.74*
Low tick, high volatility	57	0.1336	0.1372	0.0036	*0.35*
High tick, low volatility	57	0.1945	0.2234	0.0289	*2.52***
High tick, high volatility	79	0.1157	0.1117	-0.0040	*-0.72*

Percentage Spreads

	Number of Stocks	Mean Pre	Mean Post	Change	T-statistic for Change
Full Sample	272	0.0329	0.0320	-0.0010	*-1.22*
Low tick, low volatility	79	0.0185	0.0176	-0.0008	*-0.6*
Low tick, high volatility	57	0.0391	0.0351	-0.0040	*-2.65***
High tick, low volatility	57	0.0260	0.0300	0.0040	*2.48***
High tick, high volatility	79	0.0480	0.0455	-0.0025	*-1.48*

* denotes significance at 1% level
** denotes significance at 5% level

Panel B: Effective Spreads

In this table, we summarize the results for effective dollar and percentage spreads. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in spreads is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Dollar Spreads

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	0.1499	0.1576	0.0077	*1.84*
Low tick, low volatility	79	0.2174	0.2381	0.0206	*1.94*
Low tick, high volatility	57	0.1174	0.1164	-0.0010	*-0.1*
High tick, low volatility	57	0.1642	0.1751	0.0109	*1.48*
High tick, high volatility	79	0.0954	0.0941	-0.0013	*-0.35*

Percentage Spreads

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	0.0276	0.0261	-0.0016	*-2.52***
Low tick, low volatility	79	0.0151	0.0146	-0.0005	*-0.51*
Low tick, high volatility	57	0.0326	0.0286	-0.0040	*-3.0**
High tick, low volatility	57	0.0219	0.0233	0.0014	*1.41*
High tick, high volatility	79	0.0407	0.0376	-0.0031	*-2.11***

* denotes significance at 1% level
** denotes significance at 5% level

Table 3
CONTROL REGRESSIONS

Panel A: Quoted Spreads

In this table, we summarize the results of control regressions for quoted dollar and percentage spreads. The regression equation estimated is

$$S_{i,t} = \beta_0 + \beta_1 \operatorname{Pr}ice_{i,t} + \beta_2 N\_Trades_{i,t} + \beta_3 Volume_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Dummy + \varepsilon$$

regressing the average value of spread in pre and post periods on pre and post averages of price, number of trades, total share volume, average standard deviation and a dummy variable indicating whether the observation belongs to the pre or the post period. The numbers are calculated for each stock and cross-sectional regressions are run to obtain the results. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Dollar Spreads

	Intercept	Average Price	Number of Trades	Share Volume (Total)	Volatility	Post Dummy	R-Square	F-Statistic
FULL SAMPLE	0.0089	-0.0001	-2.09E-06	9.05E-08	1.5743	-0.0001	0.81	454.1
	*8.55**	*-4.12**	*-3.11**	*1.03*	*36.17**	*-0.13*		
Low tick, low volatility	0.00498	-0.00011	-2.51E-06	6.11E-07	2.0142	-0.0016	0.57	40.9
	1.66	*-1.49*	*-1.86*	*2.65**	*9.58**	*-1.02*		
Low tick, high volatility	0.01339	-8.6E-05	-3.78E-06	-3.71E-07	1.3915	-0.0009	0.76	68.7
	*5.19**	*-1.92*	*-2.42***	*-1.67*	*14.65**	*-0.51*		
High tick, low volatility	0.00852	-0.00046	-2.23E-06	4.59E-08	1.7298	0.0020	0.68	46.1
	*3.4**	*-2.55***	*-0.99*	*0.25*	*11.98**	*1.76*		
High tick, high volatility	0.00957	-2.2E-05	-1.16E-06	-8.06E-10	1.5830	-0.0005	0.86	183.9
	*3.78**	*-0.08*	*-1.04*	*-0.01*	*21.38**	*-0.32*		

Percentage Spreads

	Intercept	Average Price	Number of Trades	Share Volume (Total)	Volatility	Post Dummy	R-Square	F-Statistic
FULL SAMPLE	0.0728	0.0105	-4.26E-05	-2.42E-06	0.7897	0.00445	0.67	215.9
	*6.34**	*29.79**	*-5.73**	*-2.49***	*1.64*	*0.52*		
Low tick, low volatility	0.01287	0.00863	-5.9E-05	-1.32E-06	11.8000	0.0131	0.44	23.5
	0.34	*9.31**	*-3.49**	*-0.46*	*4.48**	*0.65*		
Low tick, high volatility	0.04919	0.01265	-2.75E-05	-1.53E-06	0.8926	-0.0136	0.96	594.5
	*3.57**	*53.16**	*-3.3**	*-1.29*	*1.76*	*-1.46*		
High tick, low volatility	-0.11833	0.02208	-3.56E-05	5.07E-07	11.7134	0.0090	0.79	81.7
	*-6.38**	*16.53**	*-2.14***	*0.38*	*10.96**	*1.06*		
High tick, high volatility	0.00973	0.02743	-3.19E-05	-1.23E-06	0.8614	-0.0093	0.79	115.2
	0.73	*19.94**	*-5.45**	*-1.89*	*2.22***	*-1.24*		

Panel B: Effective Spreads

In this table, we summarize the results of control regressions for effective dollar and percentage spreads. The regression equation estimated is

$$S_{i,t} = \beta_0 + \beta_1 \text{Price}_{i,t} + \beta_2 N\_Trades_{i,t} + \beta_3 Volume_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Dummy + \varepsilon$$

regressing the average value of spread in pre and post periods on pre and post averages of price, number of trades, total share volume, average standard deviation and a dummy variable indicating whether the observation belongs to the pre or the post period. The numbers are calculated for each stock and cross-sectional regressions are run to obtain the results. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Dollar Spreads

	Intercept	Average Price	Number of Trades	Share Volume (Total)	Volatility	Post Dummy	R-Square	F-Statistic
FULL SAMPLE	0.0665	0.0096	-2.12E-05	-8.24E-09	0.5238	0.00141	0.69	244.2
	*6.68**	*31.38**	*-2.36***	*-3.04**	*1.31*	*0.19*		
Low tick, low volatility	-0.01332	0.00849	-3.59E-05	-7.31E-09	12.8313	0.0099	0.51	31.2
	-0.43	*10.98**	*-1.65*	*-1.02*	*5.8**	*0.58*		
Low tick, high volatility	0.03692	0.01167	-0.000021	-4.64E-10	1.0990	-0.0131	0.96	546.0
	*2.92**	*50.12**	*-1.82*	*-0.13*	*2.25***	*-1.47*		
High tick, low volatility	-0.07008	0.01956	-6.34E-05	4.70E-09	8.9459	-0.0021	0.81	94.8
	*-4.79**	*18.57**	*-2.78**	*0.87*	*10.47**	*-0.32*		
High tick, high volatility	0.00794	0.02427	-2.16E-05	-2.10E-09	0.5631	-0.0056	0.85	174.3
	0.81	*24.11**	*-4.15**	*-1.42*	*2.11***	*-1.04*		

Percentage Spreads

	Intercept	Average Price	Number of Trades	Share Volume (Total)	Volatility	Post Dummy	R-Square	F-Statistic
FULL SAMPLE	0.0072	-0.0001	-1.95E-06	4.71E-11	1.5952	-0.00081	0.85	599.3
	*8.02**	*-3.9**	*-2.43***	*0.19*	*44.63**	*-1.22*		
Low tick, low volatility	0.0036	-0.0001	-2.47E-06	2.94E-10	2.1724	-0.0011	0.75	92.0
	1.88	*-2.2***	*-1.85*	*0.67*	*16.04**	*-1.07*		
Low tick, high volatility	0.01057	-6.8E-05	-3.16E-06	-2.01E-10	1.3754	-0.0016	0.76	67.6
	*4.3**	*-1.49*	*-1.41*	*-0.29*	*14.5**	*-0.9*		
High tick, low volatility	0.01487	-0.00065	-6.87E-06	7.46E-10	1.2607	0.0006	0.64	38.8
	*6.66**	*-4.04**	*-1.98*	*0.91*	*9.67**	*0.58*		
High tick, high volatility	0.00675	-0.00021	-2.19E-07	-2.57E-11	1.6397	-0.0012	0.88	216.0
	*2.71**	*-0.81*	*-0.16*	*-0.07*	*24.06**	*-0.89*		

* denotes significance at 1% level
** denotes significance at 5% level

Table 4
DEPTH MEASURE: QUOTED DEPTH AND KYLE'S LAMBDA

Panel A: Quoted Depth

In this table, we summarize the results for quoted depth. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in depth is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

	Number of Stocks	Mean Pre	Post	Change	T-statistic for Change
Overall	272	1025.20	942.99	-82.17	*-1.32*
Low tick, low volatility	79	515.47	477.67	-37.80	*-0.97*
Low tick, high volatility	57	816.47	743.73	-72.74	*-0.94*
High tick, low volatility	57	765.81	862.91	97.09	*1.00*
High tick, high volatility	79	1872.50	1609.90	-262.67	*-1.38*

Panel B: Lambda

In this table, we summarize the results for regressions run to obtain the measure known as Kyle's lambda. The regression equation is of the form:

$\Delta p_t = (\lambda_0 + \lambda_1 D_t) q_t + (\gamma_0 + \gamma_1 D_t)\mu_t + \varepsilon_t$, where Δp_t is the change in price ($p_t - p_{t-1}$), q_t is the signed order flow (positive for buy orders and negative for sell orders) μ_t is a market index used to control for positive drift in returns and ε_t is a random noise term. D_t is a dummy which takes on the value 1 for the post-period and 0 for the pre-period. λ_1 and γ_1 capture changes that occur in the two coefficients as a result of the rule change. λ is an inverse measure of liquidity.

The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return

	Signed Volume	Signed Volume*Post	Returns Index	Returns Index*Post
Full Sample	9.97E-06	-1.22E-06	0.00016	-7.7372E-05
	*4.53**	*-0.53*	*1.55*	*-0.76*
Low tick, low volatility	0.000020281	-5.52E-06	0.00028988	-0.00012758
	*2.84**	*-0.78*	*1.18*	*-0.51*
Low tick, high volatility	4.86E-06	1.62E-07	0.00018273	-0.00010043
	*2.60***	*0.05*	*1.68*	*-0.87*
High tick, low volatility	8.84E-06	-1.13E-06	1.7346E-05	2.7722E-05
	*4.57**	*-0.46*	*0.05*	*0.09*
High tick, high volatility	4.17E-06	2.01E-06	0.00011663	-8.6359E-05
	*3.79**	*0.96*	*1.63*	*-1.1*

* denotes significance at 1% level
** denotes significance at 5% level

TABLE 5
Volatility

In this table, we summarize the results for volatility as measured by the standard deviation of return of stocks in the sample. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in volatility is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	0.0140	0.0135	-0.0005	*-1.54*
Low tick, low volatility	79	0.0067	0.0069	0.0002	*0.65*
Low tick, high volatility	57	0.0175	0.0156	-0.0019	*-1.75*
High tick, low volatility	57	0.0105	0.0111	0.0006	*1.03*
High tick, high volatility	79	0.0213	0.0201	-0.0012	*-1.69*

Table 6

Panel A: Quote Updates

In this table, we summarize the results for the number of quote updates in the pre and post periods. Quote updates are used to proxy the number of orders submitted into the book. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in the number of quote updates is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change (Daily)	Change
Full Sample	272	542.88	461.06	-4.31	*-3.16**
Low tick, low volatility	79	602.81	523.13	-4.19	*-2.95**
Low tick, high volatility	57	589.28	475.56	-5.99	*-1.45*
High tick, low volatility	57	290.53	275.07	-0.81	*-0.66*
High tick, high volatility	79	631.56	522.71	-5.73	*-1.78*

* denotes significance at 1% level
** denotes significance at 5% level

Panel B

In this table, we summarize the results for the volume as measured by the number of shares traded and the dollar amount transacted in the pre and post periods. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in the number of quote updates is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Share Volume

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	1,170,000	1,100,000	-72,725	-0.83
Low tick, low volatility	79	1,080,000	993,516	-86,930	-0.61
Low tick, high volatility	57	1,210,000	1,110,000	-106,096	-0.49
High tick, low volatility	57	574,296	669,223	94,928	0.74
High tick, high volatility	79	1,660,000	1,510,000	-155,408	-0.78

Dollar Volume

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	10,600,000	9,190,000	-1,380,392	-1.25
Low tick, low volatility	79	22,600,000	19,800,000	-2,858,956	-0.81
Low tick, high volatility	57	4,550,000	3,730,000	-811,943	-1.03
High tick, low volatility	57	5,070,000	5,550,000	483,546	0.41
High tick, high volatility	79	6,830,000	5,170,000	-1,656,839	-1.66

* denotes significance at 1% level
** denotes significance at 5% level

Table 7
Market Efficiency

This table presents the results for the time that a stock spends at one value, or until it is moved to a different value. The midpoint of the bid-ask quote is used as a measure of the value of the stock. The use of this measure makes the assumption that the rate of information arrival remains constant in the pre and post period. Given that, we use the time the midpoint of the bid-ask quote spends at the same level as a measure of market efficiency. The greater this level the quicker prices converge to their true value, and spend more time at that value till the arrival of new information starts a move in the direction of the new "true" value. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in the time spent at one value is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation of returns.

		Mean			T-statistic for
	Number of Stocks	Pre	Post	Change	Change
Full Sample	272	3000.7	2934.6	-66.0	-0.72
Low tick, low volatility	79	2990.2	2931.3	-58.9	-0.32
Low tick, high volatility	57	2541.3	2557.7	16.4	0.08
High tick, low volatility	57	3740.6	3602.4	-138.2	-0.79
High tick, high volatility	79	2808.8	2728.1	-80.7	-0.47

* denotes significance at 1% level
** denotes significance at 5% level

Table 8
Change in Market Share

This table outlines the change in market share for the stocks that were listed on at least one other exchange apart from TSE and form a part of our sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return. This table presents changes, in percentage points, for each portfolio. The changes presented below are calculated for each stock and then aggregated cross-sectionally.

	Number of Stocks	Mean	T-Statistic
Full Sample	39	1.8%	*0.35*
Low tick, low volatility	6	15.0%	*0.68*
Low tick, high volatility	8	-6.3%	*-0.53*
High tick, low volatility	10	1.0%	*0.16*
High tick, high volatility	15	1.3%	*0.18*

* denotes significance at 1% level
** denotes significance at 5% level

Table 9: Volume Weighted Effective Spreads

In this table, we summarize the results for effective volume weighted dollar and percentage spreads. These two measures are used to proxy the revenues earned by liquidity suppliers. The pre-period data covers the period from February 5, 1996 to February 29, 1996 and the post-period data from March 18, 1996 to April 12, 1996. The numbers are calculated for each stock and then summarized cross-sectionally. Similarly, the change in spreads is calculated for each stock and then aggregated across the sample. Results are presented for the full sample as well for each of the four portfolios formed on the basis of relative tick size and average 30 minute standard deviation return.

Dollar Spreads

	Number of Stocks	Mean Pre	Mean Post	Change	T-statistic for Change
Full Sample	272	388.43	428.84	40.42	*0.51*
Low tick, low volatility	79	448.74	529.33	80.59	*0.57*
Low tick, high volatility	57	361.75	230.07	-131.67	*-1.14*
High tick, low volatility	57	375.94	715.57	339.62	*1.31*
High tick, high volatility	79	356.37	264.90	-91.47	*-0.80*

Percentage Spreads

	Number of Stocks	Mean Pre	Mean Post	Change	T-statistic for Change
Full Sample	272	153.42	139.95	-13.47	*-0.46*
Low tick, low volatility	79	36.12	73.57	37.44	*1.55*
Low tick, high volatility	57	176.65	104.87	-71.78	*-1.16*
High tick, low volatility	57	52.69	99.19	46.50	*1.40*
High tick, high volatility	79	326.64	261.06	-65.58	*-0.80*

* denotes significance at 1% level
** denotes significance at 5% level

ESSAY II

The Value of the Specialist: Empirical Evidence from the CBOE

The Value of the Specialist: Empirical Evidence from the CBOE

Abstract

Using proprietary data and an event unique in the history of financial markets, this paper studies the value that a specialist system adds vis-à-vis a multiple market maker system. Specifically, we analyze the "natural experiment" of the institution of a specialist system for equity options on the Chicago Board Options Exchange (CBOE) in the second half of 1999. The extant literature predicts a decrease in spreads and an increase in depth due to the change to a specialist system on the CBOE. We find support for these hypotheses. These changes are more pronounced for lower volume securities and smaller trades. We also offer limited evidence that the market share of the CBOE increases in the period after the option class moves on to the specialist system suggesting increased competitiveness for the CBOE. The paper also analyzes the implications of the move arising from single listing of certain options and the lack of a national market system for options during the sample period.

I. Introduction

This paper studies an enduring issue related to optimal market structure. Using proprietary data and an event unique in the history of financial markets, the paper is able to address the deceptively simple question, does the specialist system add value?

Considerable theoretical and empirical literature has been devoted to this debate. However, previous empirical studies have either examined a matched sample of securities trading under two different trading systems, or examined equities that switched markets. Studies in the former group may suffer from errors induced through less than perfect matching. Studies in the latter group may contain biases due to externalities not related to the different trading systems used by the two markets.[1] This study examines the same securities on the same exchange under two different trading systems. We therefore provide the strongest test possible of the value of the specialist system.

Specifically, we analyze the "natural experiment" of the switch from a multiple market maker system to a specialist system for equity options on the Chicago Board Options Exchange (CBOE) during the second half of 1999. On June 29th, 1999 the CBOE Board approved a plan to assign specialists, called Designated Primary Market Makers (DPMs), for all equity options.[2] Option classes were transferred to the DPM system in stages between August and October 1999. The CBOE did not eliminate market makers. A

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[1] For example, in studies examining stocks that switched from Nasdaq to the NYSE, there may be a certification effect. In other words, some investors may only invest in NYSE listed stocks because they view the listing process as a certification that the firm is of a certain caliber. Also studies comparing Nasdaq's market maker system to the NYSE's specialist system cannot separate market structure from the increased prevalence of preferencing that exists on Nasdaq (see Bessembinder (1999) for a discussion of this issue.

[2] DPMs on the CBOE have duties very similar to NYSE specialists. Each option class is assigned to one DPM who is then responsible for maintaining the limit order book. The DPM stands ready to trade in the assigned option classes and has many of the same associated functions as a specialist. Due to the similarity of their functions, we will use DPM and specialist interchangeably throughout the paper.

specialist system was superimposed on the existing multiple market maker system. Thus, an analysis of the event allows us to estimate the incremental benefits or costs of a specialist system relative to a multiple market maker system.

The nature of the event also allows us to examine whether the CBOE trading system change impacted its competitiveness by examining changes in the CBOE's market share, after the adoption of the specialist system, for a group of options that were multiple listed over the entire sample period. In addition, we are able to examine the competitive response of other exchanges after the switch. Previous studies have been unable to examine this issue.

During the period of our study, no formal linkage existed between U.S. option exchanges.[3] Therefore, we are able to examine the extent to which orders routed to an options exchange were executed at prices inferior to those quoted by other exchanges (called a trade through). Ceteris paribus, we would not expect a statistically significant change in the number of trade throughs following the switch. However, one of the parameters a DPM can compete on is paying for order flow.[4] If specialists enter into order preferencing arrangements then we should see an increase in the number of trade throughs on the CBOE after the institution of the DPM system.

In summary, this paper's contributions to the literature are threefold: 1) we study the marginal impact of a specialist system on market quality and competition; 2) we

[3] On October 19, 1999 the Securities and Exchange Commission (SEC) issued an order directing the options exchanges to file a national market system plan for linking the options markets (Securities Exchange Act Release No. 42029). Such a plan was filed by the U.S. options exchanges on January 19, 2000.

[4] CBOE has, in fact, started "taxing" its members 40 cents per option contract traded to build a financial base for the specialist to purchase order flow. SEC approved this move (Wall Street Journal, September 7, 2000).

examine competitive responses between exchanges following system changes; and 3) we provide an analysis of the importance of formal linkages between exchanges in terms of trade execution quality and preferencing.

In addition to academics this paper should be of interest to exchanges and regulators. For example, new exchanges setting up face the decision of instituting a trading system that makes them competitive with established exchanges. A recent example is the rise of Nouveau Marche in Paris, Neuer Markt in Frankfurt, Euro NM in Amsterdam and Brussels, and Nuovo Mercato in Milan. All these exchanges were set up to combat EASDAQ. The first three adopted a multiple market maker system while Nuovo Mercato organized its trading based on the specialist system. Our study has direct relevance for such exchanges. Regulators should be interested in the results of our paper since they decide on such things as formal linkages between exchanges.

Finally, a well functioning and credible stock exchange is essential to the growth of capital markets in any economy. Thus, the welfare effects of trading mechanisms are relevant. Benveniste, Marcus and Wilhelm (1992) provide theoretical predictions on the welfare effects of the specialist system that we are directly able to test in this paper. Thus, economies in the nascent stages of development will be able to draw lessons from our paper.

Our results indicate a statistically significant decrease in quoted spreads following the trading system switch, as well as a decrease in effective spreads for small sized trades vis-a-vis large trades. Depth, as measured by Kyle's lambda, undergoes a statistically significant increase. We find a competitive response from the other major options exchange, the AMEX, following the change in the CBOE's trading system. However, we also offer limited evidence that the CBOE gained market share as a result of the change in its trading system. In short, we find an improvement in market quality following the adoption of a specialist system on the CBOE.

We also find support for the hypothesis that preferencing increases in a specialist system that allows it.[5] Specifically, we find that the volume traded through and the loss due to trade throughs both experience a significant increase on the CBOE as a result of the move to a specialist system.

In the next section we provide a literature review. Section III develops our hypotheses, Section IV provides institutional details of trading on the CBOE as well as a summary of the changes resulting from a move to the DPM system and describes the data, Section V discusses the results and Section VI concludes.

II. Literature Review

Theoretical studies of single versus multiple dealers have centered on two components of the bid-ask spread, one arising out of the risk of trading against an informed trader (asymmetric information) and the other arising out of deviations from an optimal portfolio (inventory).

Glosten (1989) models the amount of trading based on private information in a market as a critical ingredient to market structure. A specialist system is expected to work better when there is a significant adverse selection problem since a specialist takes a long-term view and does not expect to profit from every trade. Thus, a specialist can take

[5] In equity markets, the NYSE and AMEX do not pay for order flow or enter into other agreements with brokers. In contrast, the regional stock exchanges do.

a loss on a trade with an informed trader and use the information learned to profit on trades with uninformed traders.

Benveniste, Marcus and Wilhelm (1992) focus on the effect of the trading mechanism chosen on the level of asymmetry in information in the market. Their model extends Glosten (1989) by incorporating certain realities of the NYSE floor. Specifically the "active" specialist seeks to identify informed orders. The ability of a specialist to impose penalties on floor brokers encourages brokers to reveal information about their orders.[6] Knowing the information content of a trade, the specialist is able to offer different prices to informed and uninformed trades. They show that such a mechanism dominates an equilibrium where the specialist sets the same price to all orders by offering better terms of trade not only to uninformed traders but also to informed traders. The improved terms for informed traders occur due to increased uninformed volume resulting from lower costs. They also find that brokers are expected to be more profitable because of specialist intervention.

The level of anonymity in security markets is empirically studied by Garfinkel and Nimalendran (1998). Specifically, they analyze the impact of insider trading on market maker behavior to test the hypothesis that the NYSE is less anonymous than Nasdaq due to the difference in their market structures. Their results support the notion that NYSE specialists are better able to discriminate between informed and uninformed orders, thus reducing the level of information asymmetry in the market.

[6] These penalties could come in the form of refusal to offer price or depth improvement to orders from a floor broker who did not reveal his information. On the CBOE floor, since the same individuals can act as market makers and floor brokers, the DPM gains even more influence. For example, the DPM in allocating order flow to market makers can choose not to "hear" a particular market maker in some situations.

These studies suggest that changing from a market maker system to a specialist system would decrease information asymmetry, which in turn suggests a reduction in spread width.

Ho and Macris (1985) argue that a multiple dealer market is likely to have higher bid-ask spreads than a single dealer market but is also more likely to quote higher depth. Their results hinge on the higher collective ability of multiple dealers to absorb any inventory imbalances. However, market makers carry higher inventories in aggregate thus bearing a higher inventory cost. Replication of operations also causes their combined fixed costs to be higher. Higher inventory and fixed costs leads to higher spreads in their model. This is also the result obtained by Ho and Stoll (1983).

Vijh (1990) empirically examines this hypothesis by comparing CBOE options with their underlying NYSE stocks. The comparison is done by noting that an option can be replicated by holding "delta" units of stocks plus a bond. He finds that CBOE options have higher spreads than their underlying stocks, but display much higher depth as well. Thus, his results support the hypothesis put forward by Ho and Macris (1985) and Ho and Stoll (1983).

Given that the CBOE did not eliminate any market makers, but superimposed a specialist system on the existing system, there can be assumed a net increase in dealers (existing market makers plus a specialist). Thus, the inventory control literature predicts an increase in depth.

Grossman and Miller (1988) develop a model that relates the demand for liquidity (immediacy) to the optimal market structure for an asset. Assets that generate an extreme demand for liquidity are traded in a multiple market maker system. Therefore, volume is linked to the optimal market structure. A specialist system is preferred, according to their model, when trading volume is low and a competitive market maker structure when volume is high.

Neal (1992) uses the Grossman and Miller model as the basis for his empirical comparison of execution costs on the CBOE and AMEX. During his sample period CBOE options are traded in a competitive market maker system while the AMEX uses a specialist system. Consistent with the predictions of his model, he finds that spreads on AMEX options are lower than that on CBOE options for low volume options, with little separating the two for high volume options.

Our study differentiates itself from Neal (1992), as it is able to control for all confounding factors, as well as being able to examine competitive responses. Neal analyzes single listed options on the CBOE and AMEX in his study and argues that the SEC allocation plan created a system with no systematic biases in the two groups of options studied. We have, however, the perfect control for firm specific characteristics as the same option classes moved from one regime to the other giving us the cleanest test possible of the value of the specialist system. Also, due to the nature of the event we study, we are able to examine the competitive response of the AMEX to the CBOE switch to a specialist system.

We analyze the effects on depth of a change in the market structure. Neal does not look at this aspect of liquidity. Lee, Mucklow and Ready (1993) suggest that spreads alone provide an incomplete picture of liquidity, since market makers often adjust both their spreads and depth to manage liquidity provision. Therefore, to be able to draw any conclusions, one has to study spread as well as depth effects. Since depths are not disseminated in options markets, no previous study has directly analyzed this dimension of liquidity in options. We use the lambda measure suggested by Kyle (1985) to measure depth. Finally, we use a more recent data set, which is more comprehensive in option classes covered as well as the length of the data period.

In equity markets, various studies have compared trading costs on similar stocks on the specialist based NYSE and the multiple market maker based Nasdaq. Huang and Stoll (1996) examine large capitalization firms and find that execution costs on Nasdaq were almost twice as high as that on NYSE in 1991. Bessembinder and Kaufman (1997) extend the analysis to smaller firms and find that NYSE has the greatest advantage in terms of execution costs for smaller firms and for small trades. Bessembinder (1998) examines companies that switch from Nasdaq to the NYSE and finds that they experience a significant reduction in trading costs. Bessembinder (1999) compares trade execution costs on Nasdaq and the NYSE after the implementation of the SEC imposed order-handling rules and finds that differences in execution costs persist. These studies lend support to the theoretical predictions discussed earlier but do not perfectly control for firm or market structure effects. As Bessembinder (1999) notes, it is not possible to fathom whether these differences in costs are due to structural differences between specialist and multiple market maker systems or the pervasive practice of order preferencing on Nasdaq which might curtail competition among market makers.[7] Studies that use data before these order-handling rules are imposed are not able to contribute

[7] An additional difference between the exchanges may be a certification effect. See Footnote 1.

towards this debate, as there is considerable evidence that Nasdaq spreads were kept artificially high.[8]

Our study does not suffer from the same constraints. The only change is in the trading structure that moved from a multiple market maker system to a specialist system. No confounding factors contaminate our results or make them difficult to interpret.

III. Hypotheses Development

Benveniste, Marcus and Wilhelm (1992) predict lower asymmetric information costs in specialist markets vis-à-vis multiple dealer markets since the specialist is able to extract information from market participants and set his spreads accordingly. Garfinkel and Nimalendran (1998) find lower anonymity on NYSE than on Nasdaq in support of this hypothesis. Recent studies have found that this component is significant for options markets and further that informed traders prefer options markets.[9] Therefore, a reduction in asymmetric information costs should accompany the adoption of the DPM system by the CBOE. This in turn suggests that spreads will decrease following the change in trading systems. In addition, the theoretical work of Grossman and Miller (1988) combined with empirical studies by Neal (1992) and Bessembinder and Kaufman (1997) suggest that this decrease is more likely in lower volume options than in higher volume options and for smaller trades.

Options markets have recently experienced a marked increase in competition beginning with the CBOE's listing of options on Dell Computer Corporation (traded only

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[8] See Christie and Schultz (1994)

[9] Easley, O'Hara and Srinivas (1998) and Cao, Chen and Griffin (1999)

on the Philadelphia Stock Exchange prior to the CBOE listing on August 23, 1999). The notion cannot be altogether dismissed that the change to the DPM system was to equip the CBOE to better handle competition. High volume options are likely to be the most lucrative and thus more likely to receive competition. To the extent that anticipated competition results in lower spreads, we would expect this impact to be greatest in high volume options.

H1: The institution of the DPM system on the CBOE leads to lower spreads for its listed options. Moreover, very low volume and very high volume options experience the highest decline. Small trades benefit more than large trades from the reduction in spreads.

Benveniste, Marcus and Wilhelm (1992) do not explicitly discuss the issue of depth on the two markets they considered. However, their model does predict improved terms of trade for investors in a specialist system. This would imply that depth is not adversely affected. Models building on inventory control theory (Ho and Macris (1985) and Ho and Stoll (1983)) hypothesize that a direct relationship between the number of dealers and depth. Since the CBOE, did not eliminate other market makers when they adopted the DPM system, the result was an increase in the number of market makers.[10] Thus, given the predicted relationship between the number of market makers and depth we construct our second hypothesis:

H2: Depth of the market increases due to the change in trading systems on the CBOE.

If market quality improves on the CBOE we would expect an increase in the CBOE's market share of trading in multiple listed options. Therefore, our third hypothesis:

[10] There is anecdotal evidence that trading is more concentrated with the presence of the DPM.

H3: For multiple listed options, the CBOE is able to attract orders away from other markets by offering tighter spreads and higher depth.

During the period of our study options markets, unlike equity markets, did not have a national market system that prevented trading through a better quote on a competing exchange.[11] Therefore, preferencing arrangements did not have to match the BBO. If order preferencing arrangements gain increased significance after the move to the DPM system on the CBOE, then we would expect to see an increased percentage of order flow routed to the CBOE for reasons other than best prices bid or offered. This leads us to the following hypothesis:

H4: The number of trade throughs increases after the institution of the DPM system on the CBOE.

In the next section we discuss certain institutional details and describe our data.

IV. Institutional Background and Data

The DPM system first began on the CBOE as a pilot program in 1987 with 4 DPMs allocated a total of 11 equity option classes. The extent of the program was limited to low volume options that were thought not to have adequate liquidity to generate enough market maker interest. On June 29, 1999 the CBOE board approved a resolution expanding this program to all equity options. All option classes were converted to the DPM system between August and October 1999.

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[11] In fact, an SEC study analyzing data from June 26, 2000 still finds that 5% of all trades in the 50 most active multiple-listed equity options were executed at prices inferior to the best price quoted on a competing market. Considering that the current SEC initiative on the trade through issue on options markets began in October 1999, we should expect a higher rate of trade throughs during our sample period.

Prior to this change, most equity options on the CBOE traded under a multiple market maker system. An exchange employee, the Order Book Official (OBO), maintained the limit order book. The OBO was responsible for entering all eligible orders into the limit order book and disseminating the best bid and ask quotes from the book to the trading crowd in front of her station. The trading crowd was composed of floor brokers and market makers. The same individual could serve as a broker and a market maker, though not on the same day. On a given day a member chose whether he would act as a broker or a dealer in the market. This trading crowd provided liquidity in equity options on the CBOE.

The DPM is defined by CBOE Rule 8.80 "as a member organization that is approved by the Exchange to function in allocated securities as a Market-Maker, Floor Broker, and Order Book Official." Each option class is assigned to a particular DPM who now maintains the limit order book. Thus, the DPM has exclusive knowledge of the book. The DPM can act as both a broker and a dealer on the same day or the same trade, a privilege denied to other market makers in the option class. The DPM is also guaranteed a portion of the order flow in the assigned options in return for maintaining an orderly market in the assigned options. If the DPM's quote is the first to set the best standing quote then he can participate in 100% of the incoming order flow. However, even when the DPM does not have time priority but matches the best quote, he is entitled to a pro rata share of the order flow (CBOE Rule 8.80(c)(7)(ii)).[12] The participation rate

[12] The participation right does not apply when an order is executed against the public limit order book.

is a declining function of volume for single listed options and a constant 40 % for multiple listed options.[13]

When the DPM system was instituted, other market makers were not eliminated. They still form the trading crowd in front of the DPM's station. This is especially significant for our study as it lets us value the incremental benefit of the specialist system over the multiple market maker system.

A total of 583 option classes were placed in the DPM system between August 2, 1999 and September 23, 1999.[14] Typically, several option classes were assigned to one DPM firm. This period coincides with increased competition between option exchanges resulting in an increase in cross-listed options. To remove the confounding effect of the increased competition, we eliminate any option classes that became multiple listed during the sample period. In other words, we only included option classes there are single listed (or multiple listed) throughout the sample period. Our sample is thus reduced to 367 option classes. We then match stock symbols from the CBOE with CRSP stock symbols and eliminate any classes that do not have symbols on CRSP or where the company names do not match. Also, any option class where the underlying stock split or underwent a 50% change in prices during the sample period is eliminated. This further reduces our sample size to 263 option classes.

[13] The Modified Trading System (MTS) Committee decides the participation rate. At present, this participation right entitles the DPM an initial 40% participation right, a 30% participation right when average daily volume in the security over the previous calendar quarter reached 2501 contracts, and no guaranteed participation right when average daily volume in the security over the previous calendar quarter reached 5000 contracts.

[14] An option class includes all the series of options trading on a particular stock. The series differ by their strike prices and expiration dates.

We obtain our data from an anonymous trading firm, which provided us with Options Price Reporting Authority (OPRA) data acquired through one of the major data vendors. The OPRA is the disseminator of options price and quote data for all options markets. Thus, we have time stamped data on all trades and quotes generated on all options exchanges from July 26, 1999 to October 28, 1999 (66 trading days). OPRA does not currently provide data on quoted size. We restrict our study to normal trading hours for options (9.30 a.m. – 4.02 p.m.). We only include option classes that have 20 trading days of data before and after the date the option class was placed in the DPM system. Consistent with previous options studies, we focus our study on near term (less than 30 days to maturity) at the money (strike price within 10% of the spot price) call options since these options are typically the most actively traded options in a class.[15] Further, the rules of the CBOE impose different tick sizes for options trading below \$3 (\$1/16) and those trading above \$3 (\$1/8). To avoid any contamination of our results due to difference in minimum price moves we restrict our study to options trading below \$3 over the entire period.[16] Quotes representing spreads greater than \$2 are excluded, as they are likely to be incorrect entries. Our final sample then contains 104 options classes, of which 44 are single listed on the CBOE and 60 are multiple listed with the CBOE as one of the trading venues.

In addition to calculating market quality measures for our entire sample, we separately examine options solely listed on the CBOE, as well as those multiple listed on

[15] See Neal (1987, 1992).

[16] Ronen and Weaver (2000) discuss the effects of discreteness on spread reductions. In the context of our study, their model would imply that we would see a change only if the difference between the old quoted spread and new spread is higher than 1/16 for options trading below \$3 and higher than \$1/8 for options trading above \$3. Thus, we are more likely to be able to isolate the market quality impact of the change on options with prices below \$3.

exchanges in addition to the CBOE. For multiple listed options we construct Best Bid and Offer (BBO) quotes and compare them to individual exchange quotes. Crossed BBO quotes are excluded. We are thus able to draw direct comparisons between changes on the CBOE and competing exchanges. Since, the CBOE and AMEX are the major options exchanges we only present results for those two exchanges. Results are also presented separately for single and multiple listed securities. This facilitates an analysis of the impact of competition on market quality resulting from the adoption of the DPM system.

Grossman and Miller (1988) suggest that trading volume is related to optimal market structure. Therefore, we divide our sample into volume quartiles based on the number of contracts traded in the pre-period (20 days before the switch to DPM system).

V. Results

In this section, we discuss our results. We separately discuss results for liquidity, market share, and trade throughs.

V.A. Liquidity

As a first step, we analyze the impact on liquidity of the change in market structure. The most commonly used measure of liquidity is the quoted bid-ask spread. Table I presents the results for time weighted quoted dollar (Panel A) and percentage spreads (Panel B). Results are shown separately for single and multiple listed options. Results are provided for the overall sample as well as by volume quartile. In the case of multiple listing, spreads are calculated separately for quotes originating from the CBOE and those originating from the AMEX. BBO spreads are also calculated for multiple listed options.

Table I, Panel A. shows that for the 60 multiple listed stocks in our sample, AMEX and CBOE quoted dollar spreads are fairly equal in the pre-period (around 20 cents). However, after the change in trading system on the CBOE, spreads on the CBOE decline by about 7% (statistically significant at the 5% level). Similarly, quoted BBO dollar spreads also declined by approximately 8% and this decline is also statistically significant at the 5% level. However, AMEX spreads decline by less than 1% and this change is not statistically significant. The fact that CBOE spreads reduced by a statistically significant amount, while AMEX spreads did not is consistent with our hypothesis that the adoption of a specialist system on the CBOE improved market quality.

Interestingly, an even larger decline (about 9%) is found for single listed options on the CBOE. Perhaps DPMs were preparing for anticipated competition from other exchanges. Alternatively, it may be that the decline is largely confined to low volume options. This is consistent with the notion that specialists are most beneficial to low volume securities.

Examining the results for volume quartiles, we find that the observed decrease in CBOE spreads is evidenced across all quartiles. Statistically significant declines in CBOE spreads for multiple listed options are found in the lowest volume and largest volume quartiles. This U shaped pattern is consistent with the decline being a result from both increased competition (the highest volume quartiles) and the increased marginal benefits of a specialist to low volume securities. BBO spreads exhibit a similar pattern, while

AMEX spreads show a statistically significant decline only for the highest volume quartile. The AMEX response is consistent with competition being most intense for highest volume options.

An analysis of percentage quoted spreads (expressed as a percentage of the midpoint of the bid and ask quotes, (Table I, Panel B.)) indicates a pattern similar to that observed for quoted dollar spreads. For the full sample of 60 multiple listed option classes, percentage spreads decline by 1.5 percentage points on the CBOE but the decline is not significant. BBO spreads do experience a significant decline while AMEX spreads do not. Again, single listed option classes on the CBOE experience a higher decline than multiple listed options (3.1 percentage points versus 1.5 percentage points). This is similar to the behavior of quoted dollar spreads. An analysis of volume quartiles reveals that the largest (and significant) declines occur in the lowest and highest volume quartiles for CBOE and BBO spreads on multiple listed options. The patterns are similar to those found for dollar spreads. For single listed stocks on the CBOE, the only statistically significant decline occurs in the lowest volume quartiles.

To be able to isolate the effects of the change in the trading system, it becomes essential to control for other confounding factors known to influence spreads. Using the findings of Neal (1992) as a starting point, we estimate the following equation:

$$S_{i,t} = \beta_0 + \beta_1 Price_{i,t} + \beta_2 NTrades_{i,t} + \beta_3 Volume_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 PostDummy + \beta_6 SingleDummy + \varepsilon \qquad (1)$$

regressing the average value of spread in pre and post periods, $S_{i,t}$, on: pre and post averages of price of the option class i, $Price_{i,t}$; the number of trades in the option class, $Ntrades_{i,t}$; total share volume in the option class, $Volume_{i,t}$; the average standard deviation of daily return of the underlying stock, $\sigma_{i,t}$; a dummy variable indicating whether the observation belongs to the pre or the post period, *PostDummy*$_{i,t}$; and a dummy variable indicating whether an option is single or multiple listed, *SingleDummy*$_{i,t}$. Average price of the security, volatility and volume are frequently used as determinants of bid-ask spreads in studies of equity market microstructure, and are consistent with the factors considered by Neal (1992) for option spreads. Jones, Kaul and Lipson (1994) suggest that number of trades is a more significant explanatory variable for spreads than volume. We perform the regressions for the overall results for each category as well as by volume quartile for each category. Due to the small number of observations in the volume quartiles for CBOE single listed options, we combine that category with the CBOE multiple listed options and control for the generally higher spread level for single listed options by including the *SingleDummy* variable. The combined multiple and single listed CBOE categories are denoted Full Sample in the table.

These regressions are run for dollar as well as percentage quoted spreads for the CBOE, BBO quotes and the AMEX. The results are listed in Table II. For the CBOE regressions (Panel A.) all but one of the *PostDummy* coefficients are negative and the significance of the coefficients is generally the same as reported in Table I. (low volume and high volume quartiles). The results for BBO spreads also are consistent with those reported in Table I. Examining the coefficients for the AMEX regressions (Panel C.) reveals that none are significant and only six of ten are of the expected negative sign. This suggests that the results presented in Table I. are robust with respect to confounding factors and provide further support for our hypothesis that the adoption of a specialist system improves market quality.

The single dummy has a positive and significant coefficient for overall CBOE dollar spreads and for all BBO spread regressions, indicating that after controlling for differences in price, volume, volatility, and number of trades in the option class, single listed options still display higher spreads than multiple listed options. This is consistent with the results of Neal (1987) and speaks to the benefit of multiple listing of options.

We next examine changes in effective spreads. The study of effective spreads is useful since not all trades occur at the bid or ask quotes. Effective spreads are defined as twice the difference between the price of the trade and the midpoint of the contemporaneous bid and ask quotes. Table III, Panel A.1. summarizes the results for effective dollar spreads. Overall, effective dollar spreads decrease for CBOE (both multiple and single listed) and BBO quotes and increase for AMEX quotes. However, none of these changes are statistically significant. Although two volumes quartiles exhibit negative and statistically significant changes, no clear pattern emerges from examining the volume quartiles. The results for effective percentage spreads (Panel B.1.) are qualitatively similar to those for effective dollar spreads.

Bessembinder and Kaufman (1997) find that the NYSE offers a greater advantage to smaller sized trades. Thus, we divide our sample by trade size. We separately analyze trades of 1 to 10 contracts, 11 to 50 contracts, and more than 50 contracts (Table III, Panel A.2.).[17] We do not see a significant decline in effective dollar spreads across trade sizes.

Examining effective percentage spreads according to trade size (Table III, Panel B.2.), however, presents a different picture. Trades in the two lower size categories

[17] Each contract represents 100 shares of the underlying stock.

experience a decline while trades in the highest size category experience an increase on the CBOE. For trades up to 10 contracts the decline is significant at the 10% level of significance. While AMEX spreads show the same pattern in size, the declines are much smaller and insignificant throughout.

The similarity to the CBOE in pattern, but not in magnitude, that we have seen on the AMEX is not unexpected. The two exchanges are the two biggest options exchanges and a reduction in trading costs on CBOE is likely to exert pressure on the AMEX specialists to remain competitive. That we find a more pronounced effect on the CBOE points to the strength of our results, at least for multiple listed options.

Table IV presents the results for control regressions for effective dollar and percentage spreads based on Equation 1. The findings here are not markedly different from the unconditional results in Table III. We also see that single listed options continue to have higher spreads than multiple listed options even after controlling for differences in option characteristics. The *PostDummy* parameter value for the CBOE and BBO regressions, is of the proper sign, but not significant. This is consistent with the results reported in Table III.

In summary, the results for spreads generally support our first hypothesis, that the adoption of a specialist system is associated with an improvement in market quality.

We next examine the impact of the adoption of a specialist system on another measure of liquidity – depth. OPRA does not disseminate data on depth making it difficult to directly analyze the depth of options markets.[18] Lee, Mucklow and Ready

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[18] Market makers and DPMs in options markets are required to post quotes good for at least 1 contract for professional customers and 20 contracts for public customers. Orders from public customers are executed through CBOE's Retail Automated Execution System (RAES). Participation in RAES is voluntary and market makers choose every month whether to sign up for RAES or not.

(1993) suggest that spreads alone provide an incomplete picture of liquidity, since market makers often adjust both their spreads and their depth to manage liquidity provision. In order to study the depth of the market, we use a more comprehensive measure of depth than quoted depth suggested by Kyle (1985) known as Kyle's lambda. Intuitively lambda measures the volume required to move price by a dollar and is an inverse measure of liquidity (the higher the lambda, the lower the liquidity and vice versa). Kyle's lambda is a better measure of depth than quoted depth since it captures orders that are held by brokers, or undisclosed liquidity of market makers, which is not reflected in the limit order book. It also is a more comprehensive measure as it encompasses depth behind the best quote. Thus, if narrower spreads come at the expense of lower depth in the market, the lambda measure would be able to capture that fact. To calculate Kyle's lambda, we modify the following equation:

$$\Delta p_t = \lambda q_t + \varepsilon_t \tag{2}$$

where Δp_t is the change in price ($p_t - p_{t-1}$), q_t is the signed order flow (positive for buy orders and negative for sell orders) and ε_t is a random noise term. λ is an inverse measure of liquidity.

The modified equation to study the liquidity effects of the change in market structure is presented below:

$$\Delta p_t = (\lambda_0 + \lambda_1 D_t) q_t + \varepsilon_t \tag{3}$$

the only new term, D_t is a dummy, which takes on the value 1 for the post-period and 0 for the pre-period. λ_1 captures changes that occur in depth as a result of the change. A negative value for λ_1 would indicate a lower λ in the post period relative to the pre period. Since λ is an inverse measure of liquidity a lower value in the post period would imply an increase in depth. Similarly, a positive value would point towards a decrease in depth.

To identify buy and sell orders we use the Lee and Ready (1991) algorithm. We use contemporaneous quotes and trades to identify standing quotes. Trades at the ask are classified as customer buys, at the bid as customer sales, a price higher than the midpoint indicates a buy and one lower than the bid-ask midpoint a customer sale. For trades at the midpoint, we examine the last price change and classify the trades as buys for upticks and sales for downticks.

Table V presents the results separately for options markets as a whole, the CBOE and the AMEX.[19] When treating options markets as one system, all trades (regardless of where they occur) are compared with the BBO bids and asks to classify them as buys or sells. For examining depth on the CBOE, only trades that occurred on the CBOE are considered and compared with quotes originating from the CBOE. A similar procedure is adopted for the AMEX.

Examining the results for the (Signed Volume * Post) parameter in Table V, we find that options markets as a whole as well as the CBOE experience a significant increase in depth following the switch to the DPM system. The AMEX also experiences an increase but this change is not statistically significant. The increase in liquidity for options markets, as well as for the CBOE is statistically significant only for the lowest volume quartile. For AMEX options, the increase is significant only for the highest

[19] Consistent with other regressions run for this study, to overcome the small sample size for some CBOE single listed volume quartiles, we combine the CBOE multiple listed and single listed observations together.

volume quartile. This would be consistent with a competitive response from the AMEX specialist to the shift in trading mechanism on the CBOE.

Thus, we find support for our second hypothesis that depth is at worst not adversely affected and at best increases following the adoption of a specialist system.

V.B. Market Share

Given the results so far, we find that liquidity significantly improved on the CBOE. Quoted dollar and percentage spreads decreased significantly. Effective percentage spreads also declined, especially for small trades. Evidence on depth also points towards an increase in total depth offered on the CBOE. We see a limited competitive response on the AMEX but not of the same magnitude or uniformity as the CBOE. Assuming that investors take market quality into account in their order routing decision, we would expect to see some market share impact following the change in trading mechanism on the CBOE. Quoted spreads here play the most important role, as these are the spreads visible to a customer deciding on a trading venue for his trade. As discussed above, these spreads experience a significant decline on the CBOE.

Table VI presents the results for the market share of the CBOE and AMEX in multiple listed options. The overall share of the CBOE (Panel A.) went up from 52.7% to 56.7%. At the same time, AMEX market share declined from 39.3% to 36% for these options. The increase in the CBOE market share is not significant at traditional levels of confidence? Examining the results for volume quartiles (Panel B.) reveals that the CBOE gained market share in all but the highest volume quartile. The AMEX, in contrast, lost market share in all volume quartiles. However, none of the results for volume quartiles are statistically significant at traditional levels. Therefore, we can offer only limited evidence that the move to a DPM system helped the CBOE gain market share.

V.C. Trade Throughs

The lack of a national market system in options markets during our sample period makes execution quality an important issue. Trades routed to a particular exchange were not required to be executed at the best existing quote across exchanges, nor were market participants required to route orders to the exchange with the best quote. This allows us to test the hypothesis that order preferencing arrangements became more prevalent after the introduction of the DPM. If the hypothesis holds, then we should see an increase in orders being routed to an exchange due to reasons other than the best quote and hence an increased likelihood of trade throughs.

Table VII provides the results for multiple listed options on the CBOE and the AMEX. We list the average proportion of orders per option class that are traded through, the average proportion of volume traded through per option class, and the loss to investors as a result of the trade throughs. The loss is calculated as number of contracts for a trade that was executed at a price inferior to that quoted on another exchange multiplied by the difference in quotes on the two exchanges. Loss is represented in hundreds of dollars per option class. Thus, 11.9% of trades (for the 49 option classes with trade throughs) on the CBOE occurred at quotes inferior to those on a competing exchange in the pre-period and 14.4% in the post period. These trades represented 9.8% of total volume (for the 49 option classes where there were any trade throughs) in the pre-period and 16.6% in the post period. This constituted a loss of $1,617 per option class in the pre period and $2,622 per option class in the post period.[20]

Results show that orders traded through (as a percentage of total number of trades in the option), the percentage of volume traded through, and the loss due to the practice all undergo an increase after the institution of the DPM system. Further, volume traded through and loss experience a statistically significant increase. The direction is similar for the AMEX options but none of the increases are significant. Thus, we conclude that the adoption of a specialist system on the CBOE resulted in an increase in preferencing arrangements.

VI. Conclusion

The search for the market structure that provides the best market quality to investors and maximizes exchange competitiveness traces its genesis to the very beginning of market microstructure literature. The issue has gained new relevance in recent years due primarily to the advent of new technologies bringing with them the increased threat of competition to established exchanges. One of the first decisions new exchanges setting up face is the trading system to use in their marketplace. The choice is crucial as they try to gain market share. Older exchanges, gearing up for competition, face similar decisions. Our analysis contributes to this decision-making process by studying the value of the specialist form of trading. The institution of the DPM system on the CBOE (similar to the NYSE specialist) lets us evaluate the incremental benefits or costs of such a system as compared to a multiple market maker system.

[20] Only those trades that occurred at the quoted bid or ask, on the executing exchange, are included for trade through analysis.

We find a significant decrease in spreads and a significant increase in depth due to the change to a specialist system on the CBOE. These changes are more pronounced for lower volume securities and smaller trades. The results support our hypotheses drawn from related literature.

We also offer limited evidence that market share of the CBOE increases in the period after the option class moves on to the DPM system relative to the period before.

These results indicate a benefit to traders in their terms of trade and an increase in the competitiveness of the CBOE.

We also find that single listed options have higher spreads than multiple listed options. Thus, the increase in multiple listings in options markets is likely to have led to an increase in market quality. This issue deserves a detailed look.

Finally, we consider the implications of a lack of a national market system in options markets on our analysis. Consistent with our apriori expectations, we find an increase in the number and volume of trade throughs, as well as an increase in the loss that traders bear due to this practice.

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TABLE I

QUOTED DOLLAR AND PERCENTAGE SPREADS

This table summarizes the results for changes in quoted dollar (Panel A) and percentage spreads (Panel B.) following the CBOE's change in trading systems. The CBOE instituted a specialist system for all its equity options between August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. The numbers are calculated for each option class and then summarized cross-sectionally. Similarly, the change in spreads is calculated for each underlying stock and then aggregated across the sample. Results are presented for single and multiple listed options as well as volume quartiles. Separate results are presented for the CBOE, AMEX and the National Best Bid and Offer (BBO) quotes. BBO quotes are calculated for multiple listed stocks from the highest bid and lowest ask outstanding at the time. The sample consists of near term, at the money options trading below $3 only. t-statistics are italicized.

A. Dollar Spreads

		Volume Quartiles			
	Overall	**1(Low)**	**2**	**3**	**4(High)**
CBOE - Multiple Listed					
Pre	0.1991	0.2217	0.1926	0.2029	0.1875
Post	0.1859	0.2002	0.197	0.1929	0.1628
Change	-0.0132	-0.0215	0.0044	-0.01	-0.0247
t-statistic	*-2.56***	*-2.38***	*0.42*	*-1.5*	*-2.26***
N	60	12	16	13	19
BBO - Multiple Listed					
Pre	0.1126	0.1241	0.108	0.1154	0.1074
Post	0.1036	0.1107	0.1128	0.1176	0.0817
Change	-0.0091	-0.0134	0.0048	0.0022	-0.0257
t-statistic	*-2.3***	*-1.93****	*0.64*	*0.32*	*-3.58**
N	60	12	16	13	19
AMEX - Multiple Listed					
Pre	0.2025	0.2258	0.197	0.2152	0.1849
Post	0.2005	0.2122	0.2042	0.2285	0.1708
Change	-0.0019	-0.0136	0.007	0.013	-0.0141
t-statistic	*-0.28*	*-1.25*	*0.81*	*0.53*	*-2.57***
N	60	12	16	13	19
CBOE- Single Listed					
Pre	0.2224	0.2109	0.2259	0.2283	0.2294
Post	0.2019	0.1944	0.2044	0.2007	0.2157
Change	-0.0205	-0.0165	-0.0215	-0.0276	-0.0137
t-statistic	*-4.01**	*-1.69*	*-1.99****	*-2.9***	*-1.14*
N	44	14	10	13	7

B. Percentage Spreads

	Overall	Volume Quartiles 1(Low)	2	3	4(High)
CBOE - Multiple Listed					
Pre	24.1%	27.0%	25.6%	22.6%	22.0%
Post	22.6%	20.1%	27.6%	24.7%	18.4%
Change	-1.5%	-7.0%	2.1%	2.1%	-3.6%
t-statistic	*-1.31*	*-2.65***	*1.14*	*0.63*	*-2.6***
N	60	12	16	13	19
BBO - Multiple Listed					
Pre	15.3%	16.9%	16.4%	13.8%	14.4%
Post	12.8%	11.2%	17.0%	13.8%	9.7%
Change	-2.5%	-5.7%	0.6%	0.0%	-4.8%
t-statistic	*-2.17***	*-2.4***	*0.39*	*0.01*	*-3.22**
N	60	12	16	13	19
AMEX - Multiple Listed					
Pre	25.0%	26.4%	27.9%	23.1%	23.2%
Post	24.0%	23.2%	29.9%	22.5%	20.7%
Change	-1.0%	-3.2%	2.0%	-0.6%	-2.4%
t-statistic	*-0.75*	*-1.58*	*0.65*	*-0.27*	*-1.04*
N	60	12	16	13	19
CBOE- Single Listed					
Pre	27.7%	28.4%	27.2%	28.7%	24.9%
Post	24.6%	23.8%	28.4%	23.8%	22.3%
Change	-3.1%	-4.6%	1.1%	-5.0%	-2.5%
t-statistic	*-1.96****	*-2.32***	*0.27*	*-1.53*	*-0.85*
N	44	14	10	13	7

* denotes significance at 1% level
** denotes significance at 5% level
*** denotes significance at 10% level

TABLE II

CONTROL REGRESSIONS FOR QUOTED SPREADS

This table summarizes the results of control regressions for quoted dollar and percentage spreads. The regression equation estimated is

$$S_{i,t} = \beta_0 + \beta_1 Price_{i,t} + \beta_2 N\_Trades_{i,t} + \beta_3 Volume_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 PostDummy + \beta_6 SingleDummy + \varepsilon$$

regressing the average value of spread in pre and post periods, $S_{i,t}$, on pre and post averages of price of the option class, $Price_{i,t}$, number of trades in the option class, $Ntrades_{i,t}$, total share volume in the option class, $Volume_{i,t}$, average standard deviation of daily return of the underlying stock, $\sigma_{i,t}$, a dummy variable indicating whether the observation belongs to the pre or the post period, $PostDummy_{i,t}$,and a dummy variable indicating whether an option is single or multiple listed, $SingleDummy_{i,t}$ (not used in the regressions for the AMEX, as all those option classes are multiple listed). The numbers are calculated for each underlying stock and cross-sectional regressions are run to obtain the results. The CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. Separate results are presented for CBOE (N=104), National Best Bid and Offer (BBO) (N=104), and AMEX (N=60) average quotes. BBO quotes are calculated for multiple listed stocks as the highest bid and lowest ask outstanding at a time. The sample consists of near term at the money options, trading below $3 only. t-statistics, testing the significance of the coefficient, are given below the coefficients in italics.

A. CBOE

QUOTED DOLLAR SPREADS: CBOE

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.1888	0.007530	-0.0000359	1.12E-06	0.1743	-0.01729	0.01668	0.20	8.16
	*21.58**	*2.53***	*-2.01***	*1.12*	*1.00*	*-3.7**	*3.23**		
VLM 1 (Low)	0.1718	0.029160	0.0000830	-1.93E-05	0.4340	-0.01887	-0.00162	0.23	2.29
	*8.31**	*2.8***	*0.41*	*-1.44*	*1.24*	*-1.85****	*-0.15*		
VLM 2	0.1656	0.015320	-0.0001509	5.98E-06	0.5150	-0.00934	0.01835	0.19	1.77
	*9.39**	*1.99***	*-1.13*	*0.98*	*1.25*	*-0.89*	*1.56*		
VLM 3	0.1827	0.006110	-0.0000998	4.30E-06	0.5641	-0.02025	0.02155	0.20	1.92
	*9.44**	*0.87*	*-1.37*	*0.72*	*1.40*	*-2.31***	*2.26***		
VLM 4 (High)	0.2072	0.005690	-0.0000090	-7.52E-08	-0.6647	-0.02226	0.03281	0.45	6.11
	*11.54**	*1.31*	*-0.48*	*-0.07*	*-1.68***	*-2.54***	*2.83***		

QUOTED PERCENTAGE SPREADS: CBOE

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.3853	-0.064310	0.0000090	-8.37E-07	-1.0104	-0.01648	0.01862	0.38	20.69
	*18.91**	*-9.29**	*0.22*	*-0.36*	*-2.49***	*-1.52*	*1.55*		
VLM 1 (Low)	0.3689	-0.068990	-0.0001459	1.29E-05	-0.5034	-0.04555	0.0191	0.32	3.53
	*8.62**	*-3.20**	*-0.34*	*0.47*	*-0.69*	*-2.16***	*0.88*		
VLM 2	0.4527	-0.104960	0.0002015	-2.64E-06	-2.0173	0.01080	0.05418	0.48	6.99
	*9.68**	*-5.14**	*0.57*	*-0.16*	*-1.85****	*0.39*	*1.74****		
VLM 3	0.3682	-0.092820	-0.0003843	1.19E-05	1.3257	-0.01011	0.05278	0.48	6.85
	*7.27**	*-5.03**	*-2.01***	*0.77*	*1.26*	*-0.44*	*2.11***		
VLM 4 (High)	0.3807	-0.034250	-0.0000079	-5.17E-07	-2.0709	-0.03008	-0.01281	0.63	12.83
	*14.41**	*-5.37**	*-0.28*	*-0.33*	*-3.55**	*-2.33***	*-0.75*		

B. BBO

QUOTED DOLLAR SPREADS: BBO

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.1222	0.002590	-0.0000162	1.04E-07	-0.1608	-0.01370	0.09851	0.75	99.19
	*15.03**	*0.94*	*-0.98*	*0.11*	*-0.99*	*-3.16**	*20.53**		
VLM 1 (Low)	0.0933	0.017280	-0.0000379	-8.61E-06	0.3890	-0.01557	0.09087	0.63	12.78
	*4.16**	*1.53*	*-0.17*	*-0.59*	*1.02*	*-1.41*	*8.02**		
VLM 2	0.1193	0.010750	-0.0001087	3.74E-06	-0.3872	-0.00488	0.09565	0.78	25.89
	*7.8**	*1.61*	*-0.94*	*0.70*	*-1.09*	*-0.54*	*9.38**		
VLM 3	0.1114	0.006560	-0.0000657	6.75E-06	-0.1025	-0.01364	0.09803	0.78	25.85
	*6.15**	*0.99*	*-0.96*	*1.21*	*-0.27*	*-1.66*	*10.96**		
VLM 4 (High)	0.1400	-0.003710	0.0000102	-1.14E-06	-0.4960	-0.02202	0.11477	0.84	38.71
	*8.80**	*-0.97*	*0.61*	*-1.22*	*-1.41*	*-2.84**	*11.17**		

QUOTED PERCENTAGE SPREADS: BBO

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.2906	-0.055090	0.0000448	-2.87E-06	-1.3082	-0.02120	0.10826	0.56	42.63
	*15.61**	*-8.71**	*1.18*	*-1.35*	*-3.52**	*-2.14***	*9.86**		
VLM 1 (Low)	0.2622	-0.057670	-0.0001318	1.25E-05	-0.6476	-0.04068	0.11223	0.52	8.17
	*5.83**	*-2.55***	*-0.30*	*0.43*	*-0.85*	*-1.83****	*4.95**		
VLM 2	0.3602	-0.082180	0.0000251	-4.37E-07	-2.5081	0.00390	0.13656	0.62	12.22
	*9.14**	*-4.77**	*0.08*	*-0.03*	*-2.73**	*0.17*	*5.19**		
VLM 3	0.2648	-0.086800	-0.0001982	2.49E-05	-0.2316	-0.01561	0.14256	0.66	14.54
	*6.29**	*-5.66**	*-1.25*	*1.93****	*-0.26*	*-0.82*	*6.87**		
VLM 4 (High)	0.2824	-0.032960	0.0000299	-2.67E-06	-1.5854	-0.03851	0.07767	0.66	14.72
	*9.11**	*-4.40**	*0.92*	*-1.46*	*-2.31***	*-2.55***	*3.88**		

C. AMEX

QUOTED DOLLAR SPREADS: AMEX

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.2081	-0.000528	0.0000079	-1.56E-06	0.0550	-0.00151		0.11	2.74
	*14.6**	*-0.10*	*0.29*	*-1.03*	*0.19*	*-0.17*			
VLM 1 (Low)	0.2256	-0.012070	0.0005211	-4.32E-05	0.3966	-0.01449		0.20	0.69
	*5.40**	*-0.47*	*0.66*	*-0.71*	*0.64*	*-0.82*			
VLM 2	0.1990	0.016460	-0.0000642	-7.12E-06	-0.2612	0.01053		0.11	0.62
	*10.08**	*1.39*	*-0.33*	*-1.00*	*-0.52*	*0.79*			
VLM 3	0.1947	0.049010	-0.0000466	-1.87E-05	-0.0671	-0.00092		0.22	1.13
	*3.37**	*1.88****	*-0.21*	*-1.24*	*-0.06*	*-0.03*			
VLM 4 (High)	0.2224	-0.005960	0.0000174	-1.68E-06	-0.3819	-0.01367		0.22	1.72
	*9.37**	*-1.08*	*0.71*	*-1.22*	*-0.73*	*-1.07*			

QUOTED PERCENTAGE SPREADS: AMEX

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	SHARE VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.4009	-0.081370	0.0000821	-4.79E-06	-0.6070	-0.00541		0.49	20.64
	*16.57**	*-9.19**	*1.78****	*-1.87****	*-1.24*	*-0.36*			
VLM 1 (Low)	0.4503	-0.148790	0.0007440	-5.86E-05	0.2174	-0.03392		0.58	3.86
	*6.74**	*-3.59**	*0.58*	*-0.60*	*0.22*	*-1.2*			
VLM 2	0.5127	-0.181280	0.0002726	-1.37E-06	-0.9231	0.01694		0.68	9.99
	*10.00**	*-5.88**	*0.53*	*-0.07*	*-0.71*	*0.49*			
VLM 3	0.3550	-0.101890	0.0000719	5.89E-07	0.4130	0.01326		0.61	6.34
	*7.65**	*-4.87**	*0.40*	*0.05*	*0.49*	*0.59*			
VLM 4 (High)	0.4218	-0.057810	0.0000564	-4.32E-06	-1.3991	-0.02263		0.60	8.82
	*9.35**	*-5.54**	*1.22*	*-1.65*	*-1.41*	*-0.93*			

* denotes significance at 1% level;
** denotes significance at 5% level
*** denotes significance at 10% level

TABLE III

EFFECTIVE DOLLAR AND PERCENTAGE SPREADS

This table summarizes the results for changes in effective dollar (Panel A) and percentage spreads (Panel B) following the CBOE's change in trading systems. The CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. The numbers are calculated for each option class and then summarized cross-sectionally. Similarly, the change in spreads is calculated for each underlying stock and then aggregated across the sample. Contemporaneous trades and quotes are used to calculate effective spreads. Results are presented for single and multiple listed options as well as volume quartiles. Effective spreads are also presented on the basis of trade size (Panels A.2. and B.2.). Separate results are presented for CBOE, National Best Bid and Offer (BBO), and AMEX quotes. quotes are calculated for multiple listed stocks as the highest bid and lowest ask outstanding at the time. The sample consists of near term at the money options trading below $3 only. t-statistics are italicized.

A.1. Effective Dollar Spreads – Volume Quartiles

		Volume Quartiles			
	Overall	1(Low)	2	3	4(High)
CBOE - Multiple Listed					
Pre	0.1754	0.1850	0.1847	0.1679	0.1666
Post	0.1703	0.1921	0.1670	0.1703	0.1593
Change	-0.0051	0.0071	-0.0177	0.0024	-0.0073
t-statistic	*-0.89*	*0.51*	*-1.44*	*0.31*	*-0.66*
N	60	12	16	13	19
BBO - Multiple Listed					
Pre	0.1521	0.1680	0.1545	0.1479	0.1428
Post	0.1517	0.1681	0.1576	0.1544	0.1345
Change	-0.0004	0.0001	0.0031	0.0065	-0.0083
t-statistic	*-0.06*	*0.01*	*0.33*	*0.81*	*-0.89*
N	60	12	16	13	19
AMEX - Multiple Listed					
Pre	0.1745	0.1602	0.1767	0.1881	0.1707
Post	0.1759	0.1597	0.1892	0.2129	0.1479
Change	0.0014	-0.0005	0.0125	0.0248	-0.0228
t-statistic	*0.1*	*-0.02*	*0.75*	*0.69*	*-3.36**
N	60	12	16	13	19
CBOE- Single Listed					
Pre	0.2361	0.2100	0.1980	0.2096	0.1876
Post	0.2199	0.2102	0.1970	0.1829	0.2037
Change	-0.0162	0.0002	-0.001	-0.0267	0.0161
t-statistic	*-0.79*	*0.01*	*-0.08*	*-3.32**	*1.24*
N	44	14	10	13	7

A.2. Effective Dollar Spreads – Trade Size

Size Categories	1-10 Contracts	11-50 Contracts	Greater than 50
CBOE			
Pre	0.2051	0.1905	0.1789
Post	0.2031	0.1887	0.1713
Change	-0.002	-0.0018	-0.0076
T-Statistic	*-0.35*	*-0.25*	*-0.39*
N	104	100	46
BBO			
Pre	0.1699	0.1692	0.1544
Post	0.1669	0.1584	0.1446
Change	-0.003	-0.0108	-0.0098
T-Statistic	*-0.63*	*-0.98*	*-0.88*
N	104	100	46
AMEX			
Pre	0.1756	0.1739	0.1737
Post	0.1801	0.1698	0.1595
Change	0.0045	-0.0041	-0.0142
T-Statistic	*0.45*	*-0.36*	*-0.5*
N	55	52	18

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

B.1. Effective Percentage Spreads – Volume Quartiles

	Overall	Volume Quartiles 1(Low)	2	3	4(High)
CBOE - Multiple Listed					
Pre	19.8%	20.7%	23.2%	17.2%	18.3%
Post	18.7%	19.0%	22.0%	16.1%	17.4%
Change	-1.2%	-1.6%	-1.1%	-1.2%	-0.9%
t-statistic	*-1.07*	*-0.61*	*-0.42*	*-0.78*	*-0.5*
N	60	12	16	13	19
BBO - Multiple Listed					
Pre	17.3%	17.3%	20.2%	15.3%	16.2%
Post	16.9%	16.9%	21.0%	16.3%	14.0%
Change	-0.3%	-0.4%	0.8%	1.0%	-2.2%
t-statistic	*-0.41*	*-0.23*	*0.4*	*0.77*	*-1.52*
N	60	12	16	13	19
AMEX - Multiple Listed					
Pre	19.2%	17.1%	21.2%	17.6%	19.8%
Post	19.6%	16.8%	23.1%	21.7%	17.1%
Change	0.5%	-0.3%	1.9%	4.0%	-2.7%
t-statistic	*0.53*	*-0.08*	*1.07*	*1.49*	*-1.32*
N	60	12	16	13	19
CBOE- Single Listed					
Pre	23.6%	27.7%	21.4%	23.5%	18.9%
Post	22.0%	23.2%	24.4%	20.0%	19.8%
Change	-1.6%	-4.5%	3.0%	-3.5%	0.8%
t-statistic	*-1.21*	*-1.59*	*1.02*	*-1.83***	*0.41*
N	44	14	10	13	7

*** denotes significance at the 1% level of significance**
**** denotes significance at the 5% level of significance**
***** denotes significance at the 10% level of significance**

B.2. Effective Percentage Spreads – Trade Size

Size Categories	1-10 Contracts	11-50 Contracts	Greater than 50
CBOE			
Pre	22.6%	25.4%	18.9%
Post	20.9%	23.1%	23.2%
Change (% points)	-1.7%	-2.4%	4.3%
T-Statistic	*-1.86****	*-1.31*	*1.39*
N	104	100	46
BBO			
Pre	19.0%	21.2%	16.8%
Post	17.5%	19.5%	17.8%
Change (% points)	-1.5%	-1.7%	0.9%
T-Statistic	*-2.29***	*-1.12*	*0.52*
N	104	100	46
AMEX			
Pre	18.5%	22.2%	17.4%
Post	17.8%	21.6%	21.3%
Change (% points)	-0.7%	-0.6%	3.9%
T-Statistic	*-0.11*	*-0.36*	*1.43*
N	55	52	18

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

TABLE IV
CONTROL REGRESSIONS FOR EFFECTIVE SPREADS

This table summarizes the results of control regressions for effective dollar and percentage spreads. The regression equation estimated is

$$S_{i,t} = \beta_0 + \beta_1 \operatorname{Pr}ice_{i,t} + \beta_2 N\_Trades_{i,t} + \beta_3 Volume_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 PostDummy + \beta_6 SingleDummy + \varepsilon$$

regressing the average value of spread in pre and post periods, $S_{i,t}$, on pre and post averages of price of the option class, $Price_{i,t}$, number of trades in the option class, $Ntrades_{i,t}$, total share volume in the option class, $Volume_{i,t}$, average standard deviation of daily return of the underlying stock, $\sigma_{i,t}$, a dummy variable indicating whether the observation belongs to the pre or the post period, $PostDummy_{i,t}$,and a dummy variable indicating whether an option is single or multiple listed, $SingleDummy_{i,t}$ (not used in the regressions for the AMEX, as all those option classes are multiple listed). The numbers are calculated for each underlying stock and cross-sectional regressions are run to obtain the results. the CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. Contemporaneous trades and quotes are used to calculate effective spreads. Results are presented for the full sample as well volume quartiles. Separate results are presented for the CBOE, AMEX and the National Best Bid and Offer (BBO) quotes. BBO quotes are calculated for multiple listed stocks as the highest bid and lowest ask outstanding at a time. The sample consists of near term at the money options, trading below \$3 only. t-statistics, testing the significance of the coefficient, are given below the coefficients in italics.

A. CBOE

EFFECTIVE DOLLAR SPREADS: CBOE

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.1343	0.025200	-0.0000216	7.62E-08	0.2344	-0.00698	0.02407	0.33	16.32
	*13.78**	*7.61**	*-1.09*	*0.07*	*1.21*	*-1.34*	*4.18**		
VLM 1 (Low)	0.0945	0.065100	-0.0001764	-1.45E-05	0.6315	-0.00116	0.03069	0.43	5.62
	*3.90**	*5.33**	*-0.74*	*-0.92*	*1.53*	*-0.1*	*2.51***		
VLM 2	0.1342	0.037840	-0.0002721	7.94E-06	0.3753	-0.01319	0.00593	0.33	3.65
	*6.23**	*4.02**	*-1.67*	*1.06*	*0.75*	*-1.03*	*0.41*		
VLM 3	0.1254	0.034970	0.0000567	-2.34E-06	-0.1853	-0.01507	0.01987	0.62	12.01
	*8.40**	*6.43**	*1.01*	*-0.51*	*-0.60*	*-2.23***	*2.7*		
VLM 4 (High)	0.1189	0.020740	-0.0000052	-3.03E-07	0.2877	-0.00259	0.03356	0.49	7.29
	*6.70**	*4.84**	*-0.28*	*-0.29*	*0.73*	*-0.3*	*2.93**		

EFFECTIVE PERCENTAGE SPREADS: CBOE

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.2919	-0.040050	0.0000018	-2.37E-07	-0.7676	-0.00997	0.02854	0.27	12.16
	*16.15**	*-6.52**	*0.05*	*-0.11*	*-2.13***	*-1.03*	*2.68***		
VLM 1 (Low)	0.2917	-0.038320	-0.0002777	1.08E-05	-0.6204	-0.02119	0.04861	0.18	1.68
	*5.40**	*-1.41*	*-0.52*	*0.31*	*-0.68*	*-0.79*	*1.78****		
VLM 2	0.3788	-0.069840	0.0000425	4.73E-06	-1.9836	-0.00042	0.02577	0.38	4.61
	*8.89**	*-3.76**	*0.13*	*0.32*	*-2.00****	*-0.02*	*0.91*		
VLM 3	0.2464	-0.041460	0.0000178	4.00E-06	-0.4587	-0.01812	0.05425	0.52	8.08
	*9.85**	*-4.55**	*0.19*	*0.52*	*-0.88*	*-1.6*	*4.40**		
VLM 4 (High)	0.2312	-0.019610	-0.0000393	1.78E-06	0.0073	-0.00244	0.00078	0.32	3.53
	*8.79**	*-3.09**	*-1.42*	*1.14*	*0.01*	*-0.19*	*0.05*		

B. BBO

EFFECTIVE DOLLAR SPREADS: BBO

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.1164	0.020670	-0.0000184	-1.08E-07	0.3076	-0.00416	0.04596	0.40	22.53
	*11.74**	*6.13**	*-0.91*	*-0.09*	*1.55*	*-0.79*	*7.85**		
VLM 1 (Low)	0.0500	0.074210	-0.0001012	-1.59E-05	0.9447	-0.00849	0.05495	0.47	6.76
	*1.81****	*5.32**	*-0.37*	*-0.89*	*2.01****	*-0.62*	*3.93**		
VLM 2	0.1184	0.026760	-0.0000334	2.11E-06	0.2283	0.00303	0.02841	0.38	4.63
	*6.18**	*3.20**	*-0.64*	*0.32*	*0.51*	*0.27*	*2.22***		
VLM 3	0.0929	0.034910	-0.0000240	5.79E-06	0.0208	-0.01305	0.04192	0.70	17.76
	*6.38**	*6.58**	*-0.44*	*1.30*	*0.07*	*-1.98****	*5.84**		
VLM 4 (High)	0.1194	0.012870	0.0000106	-1.19E-06	0.0534	-0.00261	0.05429	0.55	9.07
	*6.88**	*3.07**	*0.58*	*-1.17*	*0.14*	*-0.31*	*4.85**		

EFFECTIVE PERCENTAGE SPREADS: BBO

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.2680	-0.039670	0.0000306	-2.10E-06	-0.7670	-0.00483	0.04925	0.35	18.17
	*16.27**	*-7.09**	*0.91*	*-1.12*	*-2.34***	*-0.55*	*5.07**		
VLM 1 (Low)	0.2281	-0.025280	-0.0002330	1.21E-05	-0.2312	-0.02161	0.08084	0.27	2.74
	*4.54**	*-1.00*	*-0.47*	*0.37*	*-0.27*	*-0.87*	*3.19**		
VLM 2	0.3479	-0.068970	0.0001272	1.42E-06	-1.9952	0.01423	0.04411	0.45	6.22
	*9.66**	*-4.39**	*0.47*	*0.11*	*-2.38***	*0.67*	*1.84****		
VLM 3	0.2130	-0.045830	-0.0001441	2.03E-05	-0.0754	-0.00714	0.0714	0.63	12.55
	*9.17**	*-5.41**	*-1.65*	*2.85**	*-0.16*	*-0.68*	*6.23**		
VLM 4 (High)	0.2377	-0.020390	0.0000167	-1.58E-06	-0.7560	-0.01158	0.02122	0.40	5.01
	*9.47**	*-3.37**	*0.63*	*-1.07*	*-1.36*	*-0.95*	*1.31*		

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

C. AMEX

EFFECTIVE DOLLAR SPREADS: AMEX

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.1599	0.015040	0.0000088	-1.66E-06	-0.0678	0.00161		0.10	2.29
	*8.83**	*2.28***	*0.26*	*-0.87*	*-0.19*	*0.14*			
VLM 1 (Low)	-0.0169	0.111980	-0.0003033	4.21E-06	1.1366	-0.00699		0.32	1.33
	-0.22	*2.37***	*-0.21*	*0.04*	*1.01*	*-0.22*			
VLM 2	0.1476	0.051610	-0.0002360	-2.16E-05	0.2078	0.01719		0.51	4.87
	*6.43**	*3.85**	*-1.07*	*-2.67***	*0.36*	*1.12*			
VLM 3	0.2589	0.028760	0.0000323	-2.64E-05	-1.4827	0.00608		0.17	0.8
	*3.50**	*0.86*	*0.11*	*-1.37*	*-1.11*	*0.17*			
VLM 4 (High)	0.1592	0.009960	0.0000105	-1.24E-06	0.0267	-0.02260		0.36	3.38
	*7.96**	*2.15***	*0.51*	*-1.07*	*0.06*	*-2.09***			

EFFECTIVE PERCENTAGE SPREADS: AMEX

	INTERCEPT	AVERAGE PRICE	NUMBER OF TRADES	VOLUME (TOTAL)	VOLATILITY (SD OF RETURNS)	POST DUMMY	SINGLE DUMMY	R-SQUARE	F-STAT
FULL SAMPLE	0.2787	-0.044740	0.0000546	-3.52E-06	-0.3881	0.00831		0.23	6.29
	*11.09**	*-4.88**	*1.15*	*-1.33*	*-0.77*	*0.54*			
VLM 1 (Low)	0.0914	0.044140	-0.0025900	1.81E-04	1.5374	-0.03378		0.11	0.36
	0.83	*0.65*	*-1.24*	*1.13*	*0.95*	*-0.73*			
VLM 2	0.3164	-0.094550	0.0001811	-1.07E-05	0.1973	0.02108		0.42	3.37
	*6.87**	*-3.52**	*0.41*	*-0.66*	*0.17*	*0.68*			
VLM 3	0.3282	-0.075670	-0.0001825	-1.45E-05	0.6142	0.04416		0.42	2.86
	*4.43**	*-2.27***	*-0.64*	*-0.76*	*0.46*	*1.23*			
VLM 4 (High)	0.3376	-0.035330	0.0000554	-4.36E-06	-1.2820	-0.02577		0.44	4.69
	*7.83**	*-3.54**	*1.25*	*-1.74****	*-1.36*	*-1.11*			

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

TABLE V
DEPTH AS MEASURED BY KYLE'S LAMBDA

This table summarizes the results for regressions run to obtain the measure of depth known as Kyle's lambda. The regression equation is of the form:

$$\Delta p_t = (\lambda_0 + \lambda_1 D_t) q_t + \varepsilon_t,$$

where Δp_t is the change in price $(p_t - p_{t-1})$, q_t is the signed order flow (positive for buy orders and negative for sell orders and ε_t is a random noise term. D_t is a dummy variable that takes on the value 1 for the post-period and 0 for the pre-period. λ_1 captures changes that occur in market liquidity as a result of the change in market structure. λ is an inverse measure of liquidity. The lambda estimates are calculated for each option class separately and aggregated cross-sectionally are run to obtain the results. The CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. Contemporaneous trades and quotes are used to assign trades to quotes. Lee and Ready's (1991) algorithm is used to classify trades as buyer or seller initiated. Results are presented for the full sample as well as for volume quartiles. Separate results are presented for the CBOE, AMEX and the National Best Bid and Offer quotes (BBO). BBO quotes are calculated for multiple listed stocks as the highest bid and lowest ask outstanding at a time. The sample consists of near term at the money options, trading below $3 only. t-statistics, testing the significance of the coefficient, are given below the coefficients in italics. The coefficients are multiplied by 1,000.

	Number of	Signed Volume		Signed Volume*Post	
	Option Classes	Parameter	t-statistic	Parameter	t-statistic
FULL SAMPLE	104	1.73	*5.86**	-1.06	*-2.07***
Volume Quartile 1 (Low)	26	3.06	*5.13**	-2.18	*-1.93****
Volume Quartile 2	26	2.67	*2.67***	-2.25	*-1.30*
Volume Quartile 3	26	1.05	*5.46**	-0.12	*-0.32*
Volume Quartile 4 (High)	26	0.50	*4.22**	-0.02	*-0.05*
CBOE	104	1.80	*5.87**	-1.22	*-2.32***
Volume Quartile 1 (Low)	26	2.97	*5.75**	-2.19	*-1.91****
Volume Quartile 2	26	2.76	*2.48***	-2.34	*-1.32*
Volume Quartile 3	26	1.34	*4.57**	-0.35	*-0.83*
Volume Quartile 4 (High)	26	0.47	*5.95**	-0.35	*-0.52*
AMEX	60	2.40	*3.21**	-1.14	*-1.37*
Volume Quartile 1 (Low)	12	9.24	*1.55*	-7.54	*-1.16*
Volume Quartile 2	16	1.93	*5.13**	0.54	*0.65*
Volume Quartile 3	13	1.80	*3.12**	-0.69	*-0.66*
Volume Quartile 4 (High)	19	1.08	*3.40**	-0.63	*-1.94****

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

TABLE VI

MARKET SHARE

This table analyzes the market share impact of the switch in trading mechanism on the CBOE. Market share is calculated as the percentage of total volume that traded on a particular exchange in our sample. The CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. Market share is calculated for each option class as the percentage of total volume in the option traded on a particular exchange, and then summarized cross-sectionally. Similarly, the change in market share is calculated for each underlying stock and then aggregated across the sample. Results are presented for the two dominant exchanges in our sample (and in the US options markets), the CBOE and the AMEX. The sample consists of near term at the money options trading below $3 only.

A. Percentage Share of Total Volume Traded – Overall

	N	Pre	Post	Change (% points)	T-Statistic
Multiple Listed					
CBOE	60	52.7%	56.7%	4.0%	*1.44*
AMEX	60	39.3%	36.0%	-3.3%	*-1.36*

B. Percentage Share of Total Volume Traded – Volume Quartiles

Volume Quartiles	1(Low)	2	3	4(High)
CBOE				
Pre	59.8%	52.7%	50.8%	49.5%
Post	64.3%	56.8%	61.0%	48.7%
Change (% points)	4.5%	4.1%	10.2%	-0.7%
T-Statistic	*0.70*	*0.68*	*1.48*	*-0.20*
N	12	16	13	19
AMEX				
Pre	30.5%	37.7%	35.2%	48.4%
Post	28.5%	34.8%	29.8%	45.5%
Change (% points)	-2.0%	-2.9%	-5.4%	-2.9%
T-Statistic	*-0.32*	*-0.75*	*-0.76*	*-0.76*
N	12	16	13	19

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

TABLE VII

TRADE THROUGHS

This table analyzes the instances where a particular exchange "traded through" (execute an order at inferior prices) a better quote at a competing exchange. The CBOE instituted a specialist system for all its equity options over August and September 1999. The pre-period covers 20 trading days before the option class switched over to the specialist system and the post-period covers 20 trading days immediately after the switch date. The switch date is not included in either sample. Numbers are calculated for each option class and then summarized cross-sectionally. Similarly, the changes are calculated for each underlying stock and then aggregated across the sample. Results are presented for the two dominant exchanges in our sample (and in the US options markets), the CBOE and the AMEX. The sample consists of near term at the money options trading below $3 only. The table presents the number and volume of trade throughs as a percentage of all trades in an option in our sample. The loss is calculated as number of contracts for a trade that was executed at a price inferior to that quoted on another exchange multiplied by the difference in quotes on the two exchanges. Loss is represented in hundreds of dollars per option class.

	N	Pre	Post	Change (% points)	T-Statistic
CBOE					
Number of Trades	49	11.9%	14.4%	2.5%	*1.50*
Volume	49	9.8%	16.6%	6.8%	*2.81**
Loss	49	16.17	26.22	10.05	*1.83****
AMEX					
Number of Trades	30	8.0%	8.8%	0.8%	*0.95*
Volume	30	8.2%	10.5%	2.3%	*1.28*
Loss	30	27.19	35.28	8.09	*0.84*

* denotes significance at the 1% level of significance
** denotes significance at the 5% level of significance
*** denotes significance at the 10% level of significance

ESSAY III

“Informed” Limit Order Trading

“Informed” Limit Order Trading

In this study, we examine the difference in the performance of the informed versus the uninformed limit order flow. If limit order traders are concerned about limiting the option value of their order then the timing of the order, the pricing of the order and even more importantly predicting the future flow of information become critical. To the extent that some investors are better informed than others we should expect to see a difference in the performance of their orders. Our results indicate that institutional limit orders perform significantly better than the limit orders placed by individuals. This difference is significant after controlling for order characteristics. These results suggest that institutions are better able to predict at least the flow of information and use this knowledge to submit trades, which avoid adverse selection problems commonly associated with limit orders. The results also point to the use of limit orders by informed traders, an area not previously explored in the literature.

I. Introduction

One of the key differences in the organization of exchanges is the source of liquidity. While in a quote driven market, liquidity is supplied by market makers, order driven markets (such as the Tokyo Stock Exchange) rely on limit orders to supply liquidity. Hybrid markets such as the NYSE and the AMEX have both a market maker (the specialist) and limit orders acting as suppliers of liquidity.

While the theoretical literature has largely dealt with the case of a (single or multiple) market-maker acting as the liquidity supplier, recent research has focused on the performance and role of limit orders in a market.[1]

A related stream of literature focuses on informed versus uninformed traders, where informed traders are expected to make better trading and investment decisions.[2] However, the significance of information has only been studied in the literature for a trade initiator (a market order trader)[3].

In this study, we add to this literature by examine the difference in the performance of the informed versus the uninformed limit order flow. Specifically, we test the joint hypothesis that institutions are better informed and use their superior information in placing limit orders. The paper thus analyzes the role of limit orders in informed trading, an area that has not received much attention in previous literature. We also provide additional evidence on institutions being informed.

[1] Glosten (1994), Handa and Schwartz (1996), Berkman (1996), Chung, Van Ness and Van Ness (1999)

[2] Kyle (1985), Glosten and Milgrom (1985)

[3] Chakravarty (2001)

Copeland and Galai (1983) model limit orders as options granted by the investors placing the limit order, where the only decision variable for the limit order trader is the price of the option.

While the option might be correctly priced at the time the order is placed, it could become mispriced if new information comes into the market and the order is not instantly updated. This leads to the common reference to limit orders as "free options." This could further lead to such orders being picked off. Berkman (1996) focuses exclusively on large option trades, which are likely to be more actively monitored, and finds support for the hypothesis that informational changes lead to undesirable limit orders executions.

This would lead us to believe that, on average, buy (sell) limit orders would get executed when prices jump to a value below (above) the limit price leading to inferior performance for such orders.

If limit order traders are concerned about limiting the option value of their order then the timing of the order, the pricing of the order and even more importantly predicting the future flow of information become critical. To the extent that some investors are better informed than others we should expect to see a difference in the performance of their orders. It is commonly believed that institutional investors are more informed than individual investors are. Academic literature has also found support for this belief.[4] If institutions are indeed better informed traders, and they use their superior information in placing limit orders then we should expect institutional limit orders to perform better than limit orders placed by individual investors.

[4] Chakravarty (2001)

It has not been clearly established in the literature that institutions are better informed than individuals. Jennings, Schnatterly and Sequin (1997) find that higher institutional holdings result in narrower bid-ask spreads and lower adverse selection costs. Chakravarty (2001) finds that institutions are more informed than individual traders are. Our paper adds to this literature.

The role of information in placing limit orders has not been dealt with in the literature, where informed trading is seen from the viewpoint of initiating trades, which are largely market orders.

Information plays a key role in the trading process and thus in the bid-ask spread. Market makers are concerned about trading with an informed trader and the adverse selection component of the spread is their compensation for bearing this risk. Informed traders, on the other hand, are concerned about managing their information and may trade in ways to minimize the impact of their trades. Barclay and Warner (1993) find support for the stealth trading hypothesis that informed investors tend to trade in sizes that are neither too big nor too small. Chakravarty (2001) finds that institutional investors use medium sized trades to "stealthily" fulfil their demands. However, the ability of the specialist at the NYSE to see the mnemonics associated with trades and detect patterns leads to an unusually large price impact for such trades. Chakravarty (2001) focuses on initiating trades, which are primarily market orders. To the extent that the use of limit orders lets these informed investors trade with incoming market orders they might be a useful tool in minimizing the impact of their trades. In this case also, we should be able to discern a difference in the performance of these informed (institutional) trades versus the performance of the uninformed (individual) trades.

Thus, we provide additional evidence on institutions being informed traders, and more importantly we test whether informed trading occurs via limit orders.

We use a sub-sample of the TORQ database to test the hypotheses that limit orders are, on average, picked off, that institutional investors are better informed than individual investors and that institutions use their superior information in placing their limit orders. Also, the evolution of prices after the execution of the limit order yields some insight into the viability of such orders in an institutional trading program.

We do not find evidence that limit orders are picked off, on average. The price after the execution of the limit order moves favorably for the limit order trader. Further, institutional orders perform significantly better than individual orders for buy orders. For sell orders, institutional orders perform better but the difference does not persist. These results hold after controlling for various order characteristics.

In the next section we discuss relevant literature. Section III describes the data, Section IV presents the methodology and the results and Section V concludes.

II. Literature:

Glosten (1994) derives an equilibrium where limit order traders gain from liquidity driven price changes but lose to information driven price changes. Copeland and Galai (1983) focus on the informational component in describing limit orders as options. Berkman (1996) empirically examines large limit order executions and finds that limit orders are picked off as the option value of the limit order increases due to the arrival of new information and the inability of limit order traders to instantly update their orders.

Handa and Schwartz (1996) extend Glosten (1994) by examining the traders' choice between trading via limit or market orders. They show that gains to limit orders from liquidity driven price movements can offset the losses due to adverse selection. Applying their results to our study, if an investor can minimize the losses due to adverse selection, then trading through limit orders would be profitable for such investors. Investors who can better predict the flow of information are likely to be able to do so.

Chan and Lakonishok (1995) study institutional trades and find that the identity of the institution is the most significant determining factor of the price impact of their orders. The ability of the NYSE floor to adjust the prices according to the identity of the trader could provide an incentive for institutional investors to instead place limit orders and trade against incoming market orders.[5] Chan and Lakonishok (1995) also find that buy orders have a more significant price impact than sell orders.[6] The explanation commonly associated with this observation is that there are many liquidity reasons to sell but not too many to buy.[7] Therefore, buys are likely to be more information motivated than sells. As we study buy and sell orders separately, we should therefore expect differential performance of the two types of orders.

Harris and Hasbrouck (1996) study all limit orders placed through NYSE's SuperDOT system and find that limit orders placed at or better than the prevailing quote outperform market orders.

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[5] That limit orders are informative is also attested to by the recent debate over the specialist "pennying" large institutional trades subsequent to the switch to decimalization on the NYSE.

[6] This is also the finding in Holthausen, Leftwich and Mayers (1987, 1990), and Keim and Madhavan (1996).

[7] Chan and Lakonishok (1993)

Griffiths, Smith, Turnbull and White (2000) also find that order aggressiveness plays an important role in the order's performance.[8] They also find that aggressive buy orders are more likely to be information driven than aggressive sell orders.

Chung, Van Ness and Van Ness (1999) examine the role of the limit order traders in setting the bid-ask spread on the NYSE. They find that "the majority of bid-ask quotes reflect the interest of limit-order traders."[9]

III. Data:

The TORQ database contains transactions, quotes, order data and audit trail data for a sample of 144 NYSE stocks for the months of November 1990 through January 1991. The sample selection criteria for picking the 144 stocks ensures that the firms are representative of the universe of stocks trading on the NYSE.[10]

The level of detail in the TORQ database, makes it unique and is the primary reason why it continues to be widely used in academic studies.[11]

The database consists of four files, which contain the quote information, the trade information, the order processing details and the audit trail data.[12] Our study relies primarily on the order processing data. This database covers the SuperDOT system,

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[8] Order aggressiveness is the limit price of the order relative to the prevailing quote. An order that improves on the existing quote is more aggressive than an order that matches the quote, which is more aggressive than an order behind the quote.

[9] Page 257, Chung, Van Ness and Van Ness, 1999, "Limit orders and the bid-ask spread," Journal of Financial Economics, 53

[10] Hasbrouck (1992) provides a detailed description of the database as well the sample selection criteria. In a related publication, Hasbrouck, Sofianos and Sosebee (1993) describe NYSE systems and procedures.

[11] Recent papers that have used TORQ include Ready (1999), Chung, Van Ness and Van Ness (1999), Finucane (2000) and Chakravarty (2001).

[12] Hasbrouck (1992) is the primary source of our information on the TORQ database.

OARS (the Opening Automated Reporting System) and ITS (the Intermarket Trading System). Thus, orders that are handled manually are not included in this database. For the orders entered into one of the computerized systems, the database contains information on the price and time of order entry, price and time of order execution/cancellation, other details of the order such as whether it is a market or a limit order, special conditions attached to the order, etc. More important for our analysis, is the account type indicator which identifies whether the particular order was placed by an Individual (account type I), whether the order came from a member firm trading on its own account (account type P)[13] or from a member firm trading on behalf of a customer or possibly another member firm (account type A). Chakravarty (2001) discusses the details about how the information on the account type is generated and the incentives associated with identifying an individual order.

We follow Chakravarty (2001) in combining account types A (Agency) and P (Proprietary) into trades by institutions.[14] This classification is further justified since the A and P account types are certainly the super set of all institutional trades. The issue here is that agency orders might also contain some individual trades which were not so identified by the member firms involved.[15] If this were to happen, it would only bias our results downward, that is obscure differences between institutions and individuals. That we find significant differences in spite of this possible problem speaks to the strength of the results.

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[13] Trades from specialists are not identified in the database.

[14] Although we report these combined results only, we conducted the tests for agency and proprietary orders separately with identical results.

[15] Koski and Scruggs (1998)

It is also important to note here that all orders do not carry the account type identifier. Cooney, Van Ness and Van Ness (2001) report a significant proportion of limit orders with missing identifiers, which is reflected in our sample as well.

Since our focus in this study is on the role of information in limit order trading, we restrict our sample to those stocks where there are likely to be significant informational effects. Specifically, we pick the stocks, which experienced a 5% increase in prices over the sample period. This gives us a sample of 97 stocks.[16] The average price increase in these stocks is 28%, which is higher than the 12% for the 144 TORQ stocks over the sample period.

Further, we restrict our attention to executed day limit orders. Since we are concerned with the possibility of the limit order being picked off, unexecuted limit orders do not provide us with information useful for our study. Day limit orders are used since these are likely to be more current and are by far the most commonly placed limit orders.[17] Due to the design of this study and to rule out any opening or closing effects, we eliminate any orders that are executed within the first one-hour or the last one-hour of the day's trading.

For much of our analysis, transactions and quotes information is required for our analysis. The audit data file is used to get transactions information and the quotes file for the quote information. Both these files are screened for common data entry errors. Since the order database comprises orders submitted through the electronic systems only, no lag

[16] This was a period of rising prices. There are only 14 stocks that experienced a decline of 5% or more. This is the same sample selection criterion used by Chakravarty (2001).

[17] Harris and Hasbrouck (1996) also focus on day limit orders only and report that 82% of all limit orders are set to expire at the end of the day.

is used to match the order and the quote data. To match order to audit trail data the "buytim" and "seltim" fields are used as suggested by Hasbrouck (1992).[18]

This leaves us with 87,889 orders, 43,894 of which are limit orders to buy and 46,338 are limit orders to sell. Table I provides information on the number of shares and dollar values of these orders. Institutional limit orders tend to be bigger than individual limit orders, both in number of shares each order represents and its dollar value. Order size is likely to be related to price impact and thus need to be carefully considered in the analysis.

IV. Results:

IV.a: Order Characteristics

Table II provides the statistics on the spreads when the limit orders are placed. Here also we note differences between individual and institutional traders. Institutional traders tend to place the largest proportion of their orders when the spread is an eighth while individual investors tend to do so when spreads are at a quarter.

As mentioned by Copeland and Galai (1983), the price of the limit order is a control variable set by the trader. We measure this price as the aggressiveness of the order. Griffiths, Smith, Turnbull and White (2000) find that order aggressiveness is a key determinant of the performance of the order. Aggressiveness of an order is measured as the amount by which it betters the best quote. Thus, for a buy order aggressiveness is measures as the limit price-bid price, and for a sell order as the ask price-limit price. Results are presented in Table III. Of all the limit orders placed by institutions, 91.86%

[18] "Buytim" is the trade time submitted by the buyer and "seltim" the trade time submitted by the seller.

are placed at the best quote or better, while for individuals the proportion is slightly lower at 87.20%. However, institutions match the best quote much more often (54.3%) than individual investors (42.40%), which implies that individuals better the quote (44.80%) more often than institutions (37.56%).[19] The same pattern holds for buy and sell orders. These results could be influenced by the spread at the time the order in entered. Specifically, if the spread is a tick, it is not possible to better the quotes. To explore this possibility, we break down each sample by the spread at time of order entry. Table III, Panel A.2. presents the results for the full sample when the spread is at an eighth (one tick). Table III, Panel A.3. summarizes the aggressiveness results when the spread is at two ticks or higher. The results corroborate the earlier findings. Institutions place a higher proportion of their orders at the spread, while individuals tend to improve the quote more often. Griffiths, Smith, Turnbull and White (2000) find that aggressive orders have a positive price impact while passive orders have a negative price impact. Thus, order aggressiveness needs to be controlled for before any conclusions can be drawn on an informational difference between institutional and individual traders.

Table IV presents the results on the time to execution of orders. Here we see that institutional orders have to wait much less as compared to individual orders to execute. This could be related to a higher proportion of institutional limit orders being placed at the best quote or better. According to Griffiths, Smith, Turnbull and White (2000), this should impose a cost on the institutional orders.

[19] Table III, Panel A.1

IV.b: Order Performance

Figures 1.A to 1.C analyze the performance of limit orders submitted by institutional and individual investors. This is a cross sectional analysis where the prices are picked at five minute intervals and compared to the limit price. The differences are then averaged across all limit orders in the sample.

Figure 1.A presents the results for the full sample, i.e. buy and sell orders combined. For buy orders, the chart plots the difference between the price existing at a time relative to the execution time of the order and the limit price of the order, for sell orders the corresponding measure is the difference between the limit price and the price. A positive number after the limit order execution reflects a gain to the limit order trader. This analysis tracks the performance of the order starting 30 minutes prior to execution until 60 minutes after execution. As is evident, institutional investors price their orders better than individual investors. After execution, the price moves favorably for institutions and individuals but the price move is greater for institutional orders. Table V tests for statistical significance of the difference 5 minutes after execution and 60 minutes after execution. The difference is higher five minutes after execution and decreases a little with time, but it is still statistically significant at the 1% level after 60 minutes. This indicates that institutional investors posses informational advantages which they use to trade via limit orders.

As discussed earlier, various studies have found buy orders to be more informative than sell orders. Griffiths et. al. also find that aggressive buy orders are much more likely to be information motivated than sell orders. To examine whether such a difference exists we next separately examine buys and sells.

Figure 1.B charts the prices relative to the limit price for buy orders only. Here again we see the same pattern as in Figure 1.A. Institutional orders outperform individual orders and the difference persists across time. Again, Table V shows that these differences are significant at the 1% level of significance.

Figure 1.C analyzes the performance of sell limit orders. Institutional sell orders perform better than individual sell orders after execution but the difference does not persist. An hour after execution, there is no difference in the performances of the two investor types.

Thus our results support the findings in prior literature (refer footnote 6) and specifically those of Griffiths et. al.

While these unconditional results yield insights into informational differences between the two classes of investors studied here, we also documented other differences among the two as far as their limit order strategies are concerned. As a next step we account for these differences in order characteristics to see whether institutional investors perform better due to informational advantages or due to better trading strategies.

Griffiths et. al. describe a trader's decision variables as order direction, order aggressiveness and order size. They find that buy orders convey more information and that more aggressive orders tend to be more informative. Order size can also convey information. Easley and O'Hara (1987) find that large orders are more informative than small orders. Chakravarty (2001) also relates order size to price impact and finds that medium sized trades account for a majority of the cumulative price change in the stocks in their sample.

Berkman (1996) finds that limit orders are picked off when new information flows into the market. The longer an order takes to execute, the more likely that the order will suffer this adverse selection problem. Thus, we need to also control for time to execution of an order.

Given the above, we run the following control regressions for the full sample as well as for buy and sell samples separately:

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Outstanding + \beta_3 Aggressiveness + \beta_4 Inst. + \varepsilon \qquad (1)$$

where $Diff_t$ is the difference between price at time t+n (limit price), where t is the time of execution, and the limit price (price at time t+n) for buy (sell) orders, *Size* is the number of shares in the particular order divided by the mean daily volume of shares traded in the particular stock over the sample period (November 1990 to January 1991).[20] *Outstanding* is the time the limit order stands before execution, *Aggressiveness* is measured as described earlier and *Inst.* is a dummy variable, which takes the value 1 for institutional orders and 0 for individual orders.

These regressions are run for differences that exist 5 minutes and 60 minutes after limit order executions.

Table VI, Panel A.1 presents the results of the 5 minute regression while Panel B.1 presents the results of the 60 minute regression. Following Figures 1 to 3, the results are presented separately for the full sample, the buy sample and the sell sample. For all three samples, we see that the size of the order has a negative and significant coefficient.

[20] The mean daily volume is calculated using CRSP data.

The sign is expected since large orders will tend to have a positive price impact reducing the gains from the order. However, any short term liquidity impact is not expected to last over time. Panel B shows that after 60 minutes, the size of the order has a negative but insignificant impact on the gains on the full sample as well as the buy sample and a positive and insignificant impact for sell orders. Thus, the liquidity effects dissipate over time.

The coefficient of time to execution is insignificant for the full sample for both the 5 minute and 60 minute regressions. However, for buy and sell samples the coefficients have the opposite sign and are both significant for the 60 minute regression. This implies that for buy orders, the longer an order has to wait the worse the performance of the order. This is in line with expectations since the longer an order has to wait the lesser are the chances that it is information motivated and the higher the chances that it is picked off. For sell orders however, we see a significant positive coefficient on time to execution. Due to lower informational content of sell orders we would expect an insignificant coefficient for these orders.

The aggressiveness of the order has the expected coefficients for the full and buy samples. Griffiths et. al. find that aggressive buy orders tend to be information motivated. Thus, for buy order the performance of the buy order is expected to improve with the aggressiveness of the order. However, it is important to note here that this gain in performance comes from more information embedded in such orders. For sell orders aggressiveness does not have a significant impact on their performance in both the 5 minute and the 60 minute regressions.

The institutional dummy measures whether institutions have an informational advantage over individuals after controlling for order characteristics. For the 5 minute regressions, we see that the buy sample as well as the sell sample have a significant positive coefficient indicating that institutional orders show superior performance due to reasons other than such discretionary variables as order direction, order size and order aggressiveness. We attribute this to "informed" limit order trading by institutional investors. Panel B tests whether these differences still exist an hour after order execution. Here again, we confirm our unconditional results. Institutional buy orders continue to outperform individual buy orders whereas the difference vanishes between institutional and individual sell orders. This confirms the results of prior studies where buy orders have been found to contain more information than sell orders.

We also use an alternate specification to test for informational advantages of institutional investors. This is given as:

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Outstanding + \beta_3 At + \beta_4 Inside + \beta_5 Inst. + \varepsilon \qquad (2)$$

where, *At* is a dummy variable, which equals 1 if an order matches the best quote (at the bid for a buy order and at the offer for a sell order) and zero otherwise. *Inside* is a dummy variable which equals 1 if an order improves the best quote (higher than the prevailing bid for buy orders and lower than the prevailing ask for sell orders) and zero otherwise. Other variables are as described above. This specification controls for difference in aggressiveness due to differences in spread at time of order entry. The results (Tables VI.A.2 and VI.B.2) confirm the findings from equation 1. The institutional dummy is positive and significant the full and buy samples 5 minutes and 60 minutes after execution. For the sell sample the dummy is positive and significant 5 minutes after execution but loses significance 60 minutes after execution.

The results thus confirm the joint hypothesis that institutions are better informed than individuals and use this informational advantage in their limit order trades. Previous studies have not differentiated between individual and institutional limit orders and have not mentioned the possibility of informed trading through limit orders.

As checks of robustness, we also run these tests for all 144 stocks in the TORQ universe and find very similar results to the ones described here.

V. Conclusion:

Recent literature has focused on limit order characteristics and comparison of limit order strategies with market order strategies. The literature on the role of information in trading and market microstructure is also well developed. However, the issue of information in limit order trading has not received much attention. We propose that information could be used by limit order traders in determining the order placement decisions such that they avoid any adverse selection problems and reduce the probability of being picked off in the Copeland and Galai (1983) framework, or the "bagging costs" in the Handa and Schwartz (1996) framework.

To test this hypothesis, we use order details provided on the TORQ database to test the joint hypothesis that institutions are informed and that they use this information in framing their limit order strategy. Previous studies do find evidence supporting the view that institutions are more informed than individuals.

Our results indicate that institutional limit orders perform significantly better than the limit orders placed by individuals. This difference is significant after controlling for order characteristics. These results suggest that institutions are better able to predict at least the flow of information and use this knowledge to submit trades, which avoid adverse selection problems commonly associated with limit orders.

The results also point us in the direction of informed limit order trading, as the difference between institutional and individual orders is especially significant and persistent for buy limit orders, which previous literature has identified as more likely to be information driven. The use of limit orders by informed traders deserves a closer look in the literature. If stealth trading is detectable by market makers and causes a significant price impact then it's conceivable that informed traders turn to other trading strategies. Future research needs to further explore and account for the existence of "informed" limit orders in the market.

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TABLE I

ORDER SIZE

This table reports the number of shares and the dollar value of an average order. Results are presented for the full sample (Panel A), the buy sample (Panel B) and the sell sample (Panel C). Each table reports the institutional and individual numbers separately. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

A. FULL SAMPLE

	Full Sample		Individual		Institutional	
	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order
Number of orders	87,889	87,889	17,522	17,522	37,086	37,086
Mean	3,747.44	127,008.28	1,119.20	29,734.07	1,814.94	76,619.70
Median	1,500.00	47,500.00	500.00	11,375.00	1,000.00	38,500.00
Minimum	100.00	62.50	100.00	62.50	100.00	187.50
Maximum	99,900	6,250,000	29,900	925,000	44,800	5,062,400
Standard Error	20.67	771.0762564	13.06	440.4	10.92	667.3114497

B. BUY SAMPLE

	Full Buy Sample		Individual		Institutional	
	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order
Number of orders	43,894	43,894	8,038	8,038	19,131	19,131
Mean	3,414.27	114,942.33	1,104.24	25,352.92	1,767.50	75,385.57
Median	1,500.00	43,875.00	500.00	10,125.00	1,000.00	36,250.00
Minimum	100.00	62.50	100.00	62.50	100.00	250.00
Maximum	99,900	5,062,400	20,000	571,875	44,800	5,062,400
Standard Error	28.97	1077.03	18.264	497.7	17.815	1223.93

C. SELL SAMPLE

	Full Sell Sample		Individual		Institutional	
	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order	Number of Shares/order	Dollar value per order
Number of orders	46,338	46,338	9,484	9,484	17,955	17,955
Mean	4,268.59	143,532.44	1,110.00	31,634.49	1,617.48	70,392.82
Median	1,600.00	49,750.00	500.00	11,750.00	1,000.00	36,206.25
Minimum	100.00	187.50	100.00	225.00	100.00	187.50
Maximum	99,900	6,250,000	29,900	925,000	25,000	1,326,591
Standard Error	33.51	1239.45	18.88	687.7	14.5	778.3778184

TABLE II

SPREADS AT TIME OF ORDER ENTRY

This table reports the frequency distribution of spreads at which the orders were entered. Results are presented for the full sample (Panel A), the buy sample (Panel B) and the sell sample (Panel C). Each table reports the institutional and individual numbers separately. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

A. FULL SAMPLE

	Full Sample	Individual	Institutional
Number of orders	87889	17522	37086
1/8	54.3%	42.9%	48.2%
1/4	38.0%	49.9%	45.9%
3/8	6.1%	6.3%	5.3%
other	1.6%	1.0%	0.7%

B. BUY SAMPLE

	Full Buy Sample	Individual	Institutional
Number of orders	41561	8038	19131
1/8	52.1%	41.1%	46.2%
1/4	42.5%	50.9%	48.0%
3/8	4.8%	6.9%	5.3%
other	0.7%	1.1%	0.5%

C. SELL SAMPLE

	Full Sell Sample	Individual	Institutional
Number of orders	46338	9484	17955
1/8	54.8%	43.9%	47.6%
1/4	40.4%	49.5%	46.6%
3/8	4.4%	5.8%	5.3%
other	0.5%	0.8%	0.5%

TABLE III

ORDER AGGRESSIVENESS

This table reports the summary statistics and frequency distribution of the aggressiveness of the orders in the sample. Results are presented for the full sample (Panel A.1), the buy sample (Panel B.1) and the sell sample (Panel C.1). For each sample, results are further broken up by the spread at the time of order entry. Panels A.2, B.2 and C.2 present the statistics for order that are entered when spreads are at one tick for the full sample, the buy sample and the sell sample. Panels A.3, B.3 and C.3 present the statistics for order that are entered when spreads are at two ticks or more, for the full sample, the buy sample and the sell sample. For buy orders aggressiveness is measured as limit price-best bid. Thus, a positive number indicates an order that improves the best bid, a zero is at the best bid and a negative number indicates an order behind the bid. For sell orders aggressiveness is measured as best offer-limit price. Thus, a positive number indicates an order that improves the best offer, a zero is at the best offer and a negative number indicates an order behind the best offer. The full sample is a combination of the two. Each table reports the institutional and individual numbers separately. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

A.1 FULL SAMPLE

	Full Sample	Individual	Institutional
Number of orders	87889	17522	37086
Mean	0.0132	0.0287	0.0310
Median	0	0	0
Minimum	-2.375	-2.375	-2.25
Maximum	0.5	0.5	0.375
Standard Error	0.0004	0.0011	0.0006
At best quote	58.69%	42.4%	54.3%
Improve best quote by 1/8	27.83%	41.5%	36.2%
Improve best quote by 1/4	1.43%	3.3%	1.4%
1/8 behind best quote	7.96%	7.5%	5.2%
1/4 behind best quote	2.11%	2.3%	1.5%
other	2.0%	3.0%	1.4%

A.2 FULL SAMPLE: SPREAD OF ONE TICK AT ORDER ENTRY

	Full Sample	Individual	Institutional
Number of orders	47059	7466	17375
Mean	-0.0336	-0.0522	-0.0267
Median	0	0	0
Minimum	-2.375	-2.375	-2.25
Maximum	0	0	0
Standard Error	0.0005	0.0016	0.0007
At best quote	83.6%	78.6%	87.3%
improve best quote by 1/8			
improve best quote by 1/4			
1/8 behind best quote	11.3%	13.1%	8.5%
1/4 behind best quote	2.7%	3.7%	2.2%
other	2.4%	4.7%	2.0%

A.3 FULL SAMPLE: SPREAD OF TWO TICKS OR MORE AT ORDER ENTRY

	Full Sample	Individual	Institutional
Number of orders	40829	10053	19703
Mean	0.0673	0.0888	0.0819
Median	0.125	0.125	0.125
Minimum	-2	-2	-1.75
Maximum	0.5	0.5	0.375
Standard Error	0.0006	0.0013	0.0007
At best quote	30.0%	15.5%	25.2%
improve best quote by 1/8	59.9%	72.3%	68.1%
improve best quote by 1/4	3.2%	5.8%	2.6%
1/8 behind best quote	4.1%	3.4%	2.3%
1/4 behind best quote	1.4%	1.2%	0.8%
other	1.4%	1.7%	0.9%

B.1 BUY SAMPLE

	Full Buy Sample	Individual	Institutional
Number of orders	41561	8038	19131
Mean	0.0219	0.0479	0.0357
Median	0	0	0
Minimum	-2	-2	-1.875
Maximum	0.5	0.375	0.375
Standard Error	0.0005	0.0013	0.0007
At best bid	57.73%	43.2%	54.5%
best bid+1/8	30.34%	44.7%	37.1%
best bid+1/4	1.68%	3.7%	1.4%
best bid-1/8	7.24%	5.9%	4.9%
best bid-1/4	1.61%	1.3%	1.0%
other	1.4%	1.2%	1.1%

B.2 BUY SAMPLE: SPREAD OF ONE TICK AT ORDER ENTRY

	Full Buy Sample	Individual	Institutional
Number of orders	21669	3303	8831
Mean	-0.0274	-0.0293	-0.0217
Median	0	0	0
Minimum	-1.875	-1.375	-1.875
Maximum	0	0	0
Standard Error	0.0006	0.0017	0.0009
At best bid	85.3%	85.0%	88.9%
best bid+1/8			
best bid+1/4			
best bid-1/8	11.0%	11.2%	8.1%
best bid-1/4	2.2%	2.2%	1.6%
other	1.6%	1.7%	1.4%

B.3 BUY SAMPLE: SPREAD OF TWO TICKS OR MORE AT ORDER ENTRY

	Full Buy Sample	Individual	Institutional
Number of orders	19887	4735	10295
Mean	0.0757	0.1016	0.0851
Median	0.125	0.125	0.125
Minimum	-2	-2	-1.25
Maximum	0.5	0.375	0.375
Standard Error	0.0008	0.0015	0.0009
At best bid	27.7%	14.1%	25.1%
best bid+1/8	63.4%	75.8%	69.0%
best bid+1/4	3.5%	6.3%	2.5%
best bid-1/8	3.2%	2.3%	2.2%
best bid-1/4	1.0%	0.7%	0.5%
other	1.2%	0.9%	0.8%

C.1 SELL SAMPLE

	Full Sell Sample	Individual	Institutional
Number of orders	46338	9484	17955
Mean	0.0055	0.0125	0.0260
Median	0	0	0
Minimum	-2.375	-2.375	-2.25
Maximum	0.5	0.5	0.375
Standard Error	0.0006	0.0018	0.0009
At best offer	59.54%	41.7%	54.1%
best offer-1/8	25.59%	38.8%	35.2%
best offer-1/4	1.31%	3.0%	1.4%
best offer+1/8	8.61%	8.9%	5.5%
best offer+1/4	2.56%	3.1%	2.0%
other	2.4%	4.5%	1.9%

C.2 SELL SAMPLE: SPREAD OF ONE TICK AT ORDER ENTRY

	Full Sell Sample	Individual	Institutional
Number of orders	25390	4163	8544
Mean	-0.0388	-0.0704	-0.0319
Median	0	0	0
Minimum	-2.375	-2.375	-2.25
Maximum	0	0	0
Standard Error	0.0007	0.0026	0.0011
At best offer	82.2%	73.5%	85.7%
best offer-1/8			
best offer-1/4			
best offer+1/8	11.6%	14.6%	8.8%
best offer+1/4	3.2%	4.9%	2.9%
other	3.0%	7.0%	2.6%

C.3 SELL SAMPLE: SPREAD OF TWO TICKS OR MORE AT ORDER ENTRY

	Full Sell Sample	Individual	Institutional
Number of orders	20942	5318	9408
Mean	0.0593	0.0774	0.0785
Median	0.125	0.125	0.125
Minimum	-1.875	-1.875	-1.75
Maximum	0.5	0.5	0.375
Standard Error	0.0008	0.0020	0.0011
At best offer	32.1%	16.8%	25.3%
best offer-1/8	56.6%	69.1%	67.2%
best offer-1/4	2.9%	5.4%	2.7%
best offer+1/8	4.9%	4.5%	2.6%
best offer+1/4	1.8%	1.7%	1.1%
other	1.6%	2.5%	1.2%

TABLE IV

TIME TO EXECUTION

This table reports the summary statistics on the time it takes for an order placed into the system to execute. Results are presented for the full sample (Panel A), the buy sample (Panel B) and the sell sample (Panel C). Time to execution is measured in seconds from the time an order enters the system to the time the order executes. Each table reports the institutional and individual numbers separately. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

A. FULL SAMPLE

	Full Sample	Individual	Institutional
Number of orders	87889	17522	37086
Mean	2612.5	2555.9	2108.2
Median	967	821	659
Minimum	2	2	3
Maximum	40383	24175	23797
Standard Error	11.6	27.0	15.6

B. BUY SAMPLE

	Full Buy Sample	Individual	Institutional
Number of orders	43894	8038	19131
Mean	2607.8	2454.7	2110.9
Median	931	753	630
Minimum	2	3	3
Maximum	23797	22772	23797
Standard Error	17.9	39.5	24.1

C. SELL SAMPLE

	Full Sell Sample	Individual	Institutional
Number of orders	46338	9484	17955
Mean	2638.4	2592.1	2040.5
Median	972	832	572
Minimum	2	2	3
Maximum	40383	24175	22324
Standard Error	16.9	38.0	24.5

TABLE V

LIMIT ORDER PERFORMANCE

This table presents the average performance of limit orders submitted by institutional and individual traders as well as t-statistics testing for the equality of the performances. Results are presented for the full sample (Panel A), the buy sample (Panel B) and the sell sample (Panel C). Column 1 reports the mean price performances 5 minutes after execution and column 2 the performance 60 minutes after execution. For buy orders, performance is measured as the price 5 minutes (or 60 minutes) after execution less the limit price. For sell orders, performance is measured as the limit price less the price 5 minutes (or 60 minutes) after execution. The full sample is a combination of the two. Each table reports the institutional and individual numbers separately. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

	5 minutes after execution	60 minutes after execution
Full Sample		
Institutional	0.0150	0.0153
Individual	0.0075	0.0083
Difference	0.0075	0.0071
t-statistic	*7.6**	*3.02**
Buy Sample		
Institutional	0.0172	0.0346
Individual	0.0111	0.0242
Difference	0.0061	0.0104
	*3.96**	*3.06**
Sell Sample		
Institutional	0.0099	-0.0046
Individual	0.0030	-0.0059
Difference	0.0069	0.0014
	*5.43**	*0.43*

* denotes significance at 1% level
** denotes significance at 5% level

TABLE VI
LIMIT ORDER PERFORMANCE-CONTROL REGRESSIONS

This table summarizes the results of control regressions testing for a difference is the performance of institutional and individual orders. The regression equation estimated is

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Outstanding + \beta_3 Aggressiveness + \beta_4 Inst. + \varepsilon \qquad (1)$$

where *Diff* is the difference between price at time t+n, where t is the time of execution and n equals 5 minutes in Panel A and 60 minutes in Panel B (limit price) and the limit price (price at time t+n) for buy (sell) orders, *Size* is the number of shares in the particular order divided by the mean daily volume of shares traded in the particular stock over the sample period (November 1990 to January 1991). *Outstanding* is the time the limit order stands before execution. For buy orders *Aggressiveness* is measured as limit price-best bid. Thus, a buy order that improves the best bid yields a positive number, a buy order at the best bid a zero, and a buy order behind the bid a negative number. For sell orders aggressiveness is measured as best offer-limit price. Thus, a sell order that improves the best offer yields a positive number, a sell order at the best offer a zero, and a sell order behind the best offer a negative number. *Inst.* is a dummy variable, which takes the value 1 for institutional orders and 0 for individual orders. Results are presented for mean price performance 5 minutes after execution (Panel A.1) and for the performance 60 minutes after execution (Panel B.1).

An alternate specification is also used to test for informational advantages of institutional investors as:

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Outstanding + \beta_3 At + \beta_4 Inside + \beta_5 Inst. + \varepsilon \qquad (2)$$

where, *At* is a dummy variable, which equals 1 if an order matches the best quote (at the bid for a buy order and at the offer for a sell order) and zero otherwise. *Inside* is a dummy variable which equals 1 if an order improves the best quote and zero otherwise. Other variables are as described above. Results are presented for mean price performance 5 minutes after execution (Panel A.2) and for the performance 60 minutes after execution (Panel B.2).

Results are also presented separately for the full sample, as well as the buy and sell sample in each of the panels. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

A.1: EQUATION 1 - 5 MINUTES AFTER EXECUTION

	Intercept	Shares in order	Time to Execution	Aggressiveness of order	Institutional Dummy	R-Square	F-Statistic
Full Sample	0.00751	-0.03071	4.65E-08	0.0134	0.00768	0.0015	20.38
	*8.04**	*-3.4**	*0.27*	*3.29**	*7.57**		
Buy Sample	0.01029	-0.02743	-4.47E-07	0.04523	0.00673	0.0029	19.95
	*6.91**	*-2.51***	*-1.73*	*6.43**	*4.29**		
Sell Sample	0.00191	-0.03951	7.66E-07	-0.00102	0.00756	0.0018	12.16
	1.62	*-2.22***	*3.37**	*-0.21*	*5.79**		

A2: EQUATION 2 - 5 MINUTES AFTER EXECUTION

	Intercept	Shares in order	Time to Execution	At	Inside	Institutional Dummy	R-Square	F-Statistic
Full Sample	-0.00309	-0.01069	9.70E-08	0.0184	0.00699	0.00587	0.0050	57.63
	-1.81	*-1.86*	*0.64*	*11.73**	*4.20**	*5.90**		
Buy Sample	-0.00548	-0.00598	-1.98E-07	0.0258	0.01412	0.00444	0.0060	34.17
	*-1.96***	*-0.89*	*-0.85*	*10.16**	*5.27**	*2.87**		
Sell Sample	-0.00407	-0.02409	5.21E-07	0.0127	0.00244	0.00569	0.0041	23.47
	-1.93	*-1.69*	*2.60**	*6.46**	*1.16*	*4.45**		

B.1: EQUATION 1 - 60 MINUTES AFTER EXECUTION

	Intercept	Shares in order	Time to Execution	Aggressiveness of order	Institutional Dummy	R-Square	F-Statistic
Full Sample	0.00545	-0.01426	5.72E-07	0.03763	0.00863	0.0005	6.89
	*2.45***	*-0.66*	*1.4*	*3.87**	*3.58**		
Buy Sample	0.02578	-0.02183	-0.00000259	0.07273	0.01217	0.0027	18.72
	*7.76**	*-0.9*	*-4.49**	*4.62**	*3.48**		
Sell Sample	-0.01392	0.00551	0.00000322	0.00616	0.00433	0.0013	9.16
	*-4.67**	*0.12*	*5.59**	*0.5*	*1.31*		

B2: EQUATION 2 - 60 MINUTES AFTER EXECUTION

	Intercept	Shares in order	Time to Execution	At	Inside	Institutional Dummy	R-Square	F-Statistic
Full Sample	-0.00614	-0.000578	4.14E-07	0.0188	0.01345	0.00601	0.0006	7.18
	-1.51	*-0.04*	*1.14*	*5.00**	*3.39**	*2.54***		
Buy Sample	0.01498	0.00254	-2.51E-06	0.0255	0.01048	0.00764	0.0030	17.31
	*2.41***	*0.17*	*-4.89**	*4.51**	*1.76*	*2.22***		
Sell Sample	-0.02244	0.00239	2.78E-06	0.011	0.01226	0.00226	0.0011	6.35
	*-4.23**	*0.07*	*5.49**	*2.21***	*2.32***	*0.70*		

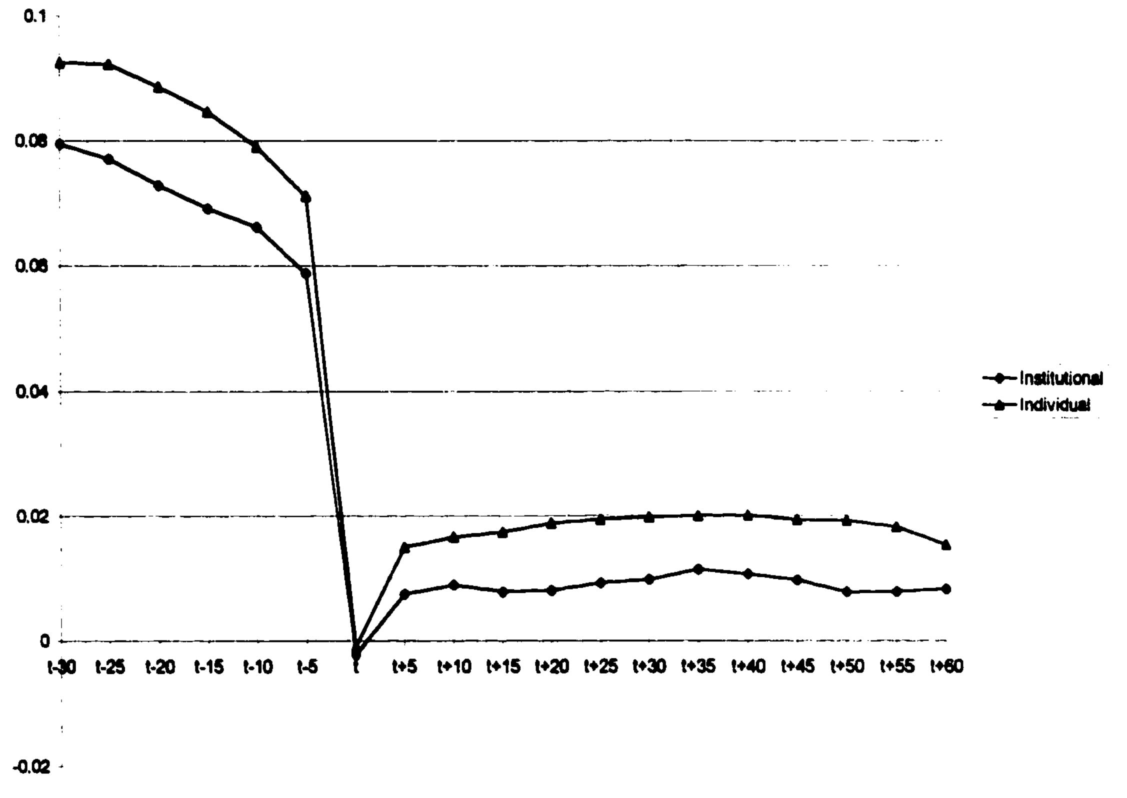
* denotes significance at 1% level
** denotes significance at 5% level

FIGURE 1

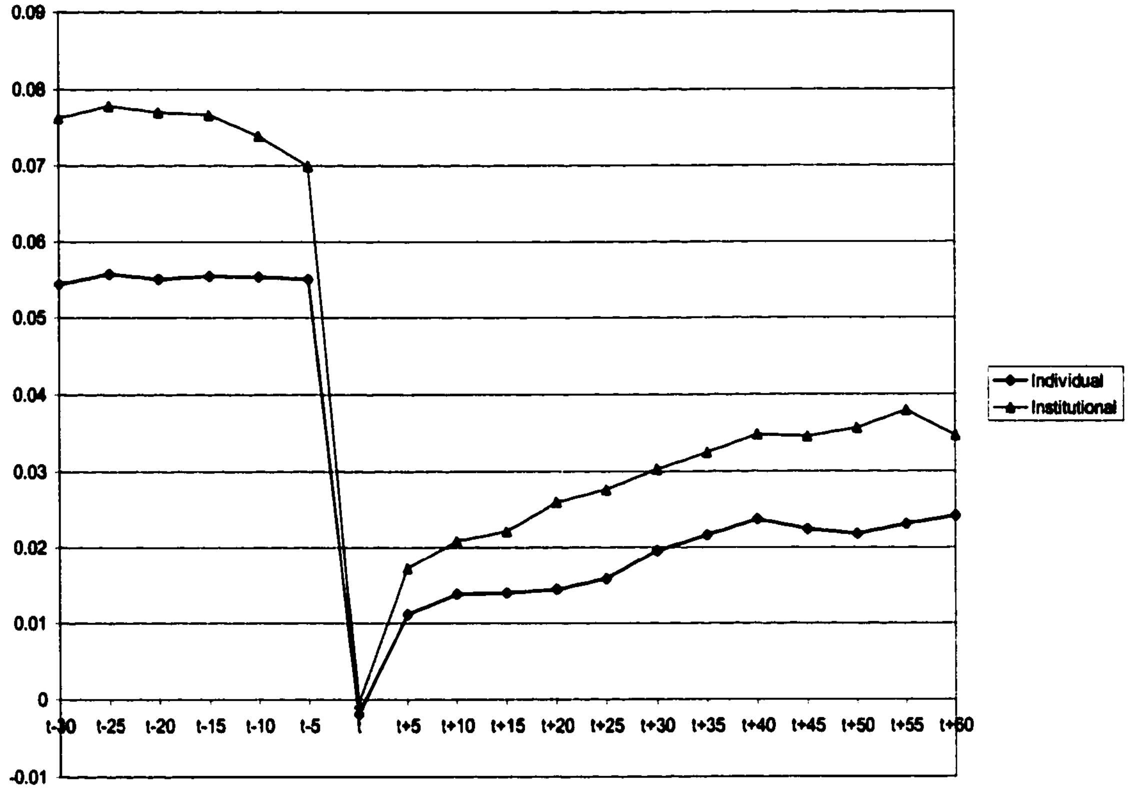
LIMIT ORDER PERFORMANCE

This chart traces the performance of limit orders starting 30 minutes before execution to 60 minutes after execution. The chart plots the difference between price at time t (limit price) and the limit price (price at time t) for buy (sell) orders. The full sample is a combination of the two. This is a cross sectional analysis where the prices are picked at five minute intervals and compared to the limit price. The differences are then averaged across all limit orders in the sample. The lines labeled institutional and individual follow the performance of institutional and individual limit orders respectively. The sample comprises 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991).

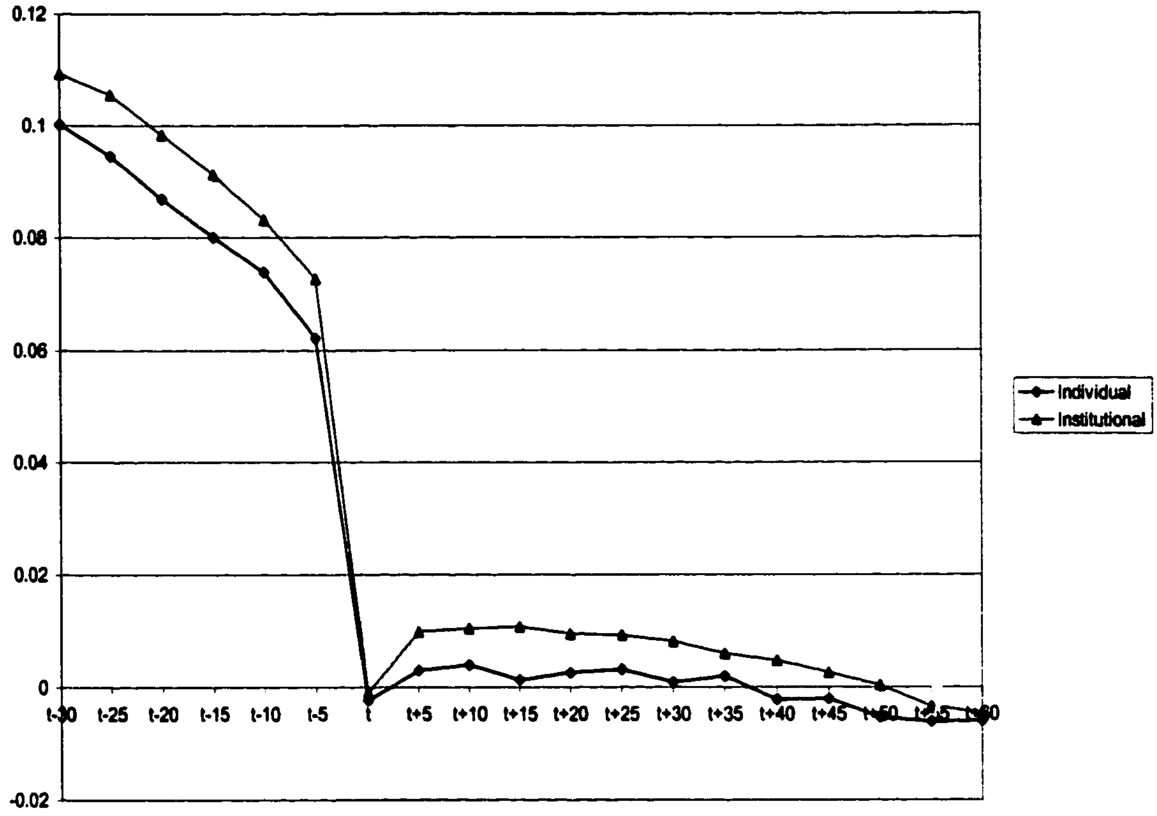
A. FULL SAMPLE



B. BUY SAMPLE


0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-0.01
t-30
t-25
t-20
t-15
t-10
t-5
t
t+5
t+10
t+15
t+20
t+25
t+30
t+35
t+40
t+45
t+50
t+55
t+60
Individual
Institutional

C. SELL SAMPLE



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