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The value of the specialist: Empirical evidence from the CBOE ☆

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Abstract

Using intraday options data, this paper analyzes the "natural experiment" of the Chicago Board Options Exchange (CBOE) superimposing a specialist system on an existing multiple market maker system during 1999. We find support for the demand uncertainty literature which states that specialists are better able to resolve uncertainty about investor preferences. In particular, we find that quoted, current, and effective spreads decrease following the specialist system adoption. This translates into a $221 million annual savings for investors. We further find that following the switch, the market share of the CBOE increases significantly, suggesting that specialists use spreads to attract order flow.

JEL classification: G20

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This paper studies an enduring issue related to optimal market structure. Using intraday options data around the introduction of the specialist system on the CBOE for a large number of options, the paper is able to address the question – does the specialist system add value?

Considerable theoretical and empirical literature is devoted to this debate. However, previous empirical studies either examine a matched sample of securities trading under two different trading systems, or examine equities that switch markets. Studies in the former group may suffer from errors induced through less than perfect matching.[1] Studies in the latter group may contain biases due to externalities not related to the different trading systems used by the two markets.[2] This study examines the same securities on the same exchange under two different trading systems. Further, we are able to control for any market-wide trends by examining the same securities trading on other exchanges that did not experience any change in market structure.

Specifically, we analyze the "natural experiment" of the Chicago Board Options Exchange (CBOE) superimposing a specialist system onto the existing multiple market maker system for a large number of equity options in the second half of 1999. On June 29, 1999, the CBOE Board approved a plan to assign specialists, called Designated Primary Market Makers (DPMs), for all equity options.[3] Option classes were transferred to the DPM system in stages between August and October 1999.[4] The CBOE did not eliminate market makers. Both before and after the system change, orders away from the best prices were not revealed to members. Prior to the option's being assigned to a specialist, the limit order book was maintained (and viewed) by an exchange employee who could not trade for her own account. After the change in the system, specialists could see the limit order book and base their trading decisions on the book's contents. Thus, an analysis of the event allows us to estimate the incremental benefits and/or costs of a specialist system relative to a multiple market maker system.

The nature of the market structure change also allows us to disentangle three theoretical models: adverse selection, inventory control and investor uncertainty. The models predict lower spreads in specialist systems but for different reasons. Benveniste, et al. (1992), in the context of the equity markets, focus on information sharing on the floor to predict lower adverse selection and consequently lower spreads on a floor-based (NYSE specialist) system vis-à-vis an electronic (Nasdaq multiple market maker) system. Ho and Macris (1985) predict that a specialist system will have lower spreads because of the elimination of

[1]For example, in Mayhew (2002) including volatility as a matching criterion reduces his sample observations by 98% over matching on just date, option price, and volume. Examining his Tables VI and VII reveals that including volatility as a matching criterion changes some conclusions regarding the comparison of effective spreads between trading systems.

[2]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).

[3]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.

[4]We define an option class to include all option series (calls and puts) traded on an underlying stock Thus, for example, all options traded on Alcoa form one option class in our sample.

fixed cost and minimum inventory level replication necessary in a multiple market marker system. Saar (2001) also predicts that a specialist system will have lower spreads because the specialist's knowledge of the limit order book reduces uncertainty about investor demand. In previous empirical studies at least two of the three effects coexist, making it difficult to explicitly attribute the benefits of the specialist to any one of them. For example, inventory as well as uncertainty resolution related effects coexist in studies that compare markets where the specialist acts as the sole market maker with a multiple market maker system. Similarly, all three models predict lower spreads for studies comparing the floor-based NYSE specialist system to the electronic Nasdaq multiple market maker system.

Since our focus in this study is on an event where a specialist was added to an existing market maker system on the floor of an options exchange where significant information sharing among traders on the floor already existed,[5] we are able to isolate a particular feature of specialist markets that adds value for investors. In particular, we are able to test the Saar (2001) uncertainty resolution hypothesis, without the confounding effects of changes in adverse selection suggested by Benveniste et al. (1992) and inventory effects suggested by Ho and Macris (1985).

Finally, during the period of our study, no formal linkage existed among U.S. options exchanges.[6] Battalio et al. (2004) examine whether, over time, options markets have developed a de facto national market system. In the same spirit, we test whether the institution of a specialist (and hence a focal point for liquidity) on the CBOE brought the options markets closer to a national market system. Towards that goal, we 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"). If the specialist does indeed monitor the prices at other markets better, then we would expect a decrease in trade throughs on the CBOE.

Our results indicate a statistically significant decrease in quoted, current, and effective spreads following the trading system change. Economically, the savings to investors translate into approximately $18 million during our sample period, or more than $221 million annually. We thus find support for the Saar (2001) hypothesis that a specialist system reduces uncertainty concerning investor demand and hence narrows spreads. The lower spreads on the CBOE are associated with a statistically significant increase in CBOE market share for the affected options.

We also find that the volume traded through shows a significant increase on the CBOE, while on other exchanges it is largely unchanged over our sample period. This suggests that CBOE specialists did not actively contribute to the creation of a national market system in options.

In addition to academics, this paper should also be of interest to exchanges. For example, this paper contributes to the current debate on the future of the specialist system on the NYSE. We show that the presence of a specialist helps resolve uncertainty that adds

[5]The "give up" rule in options markets further formalizes information sharing by requiring a floor trader to reveal the name of the member firm initiating the order. ("Options Markets," Cox and Rubinstein,1985, p. 80-81.) The "trade or fade" rule allows market makers to back away from their quotes for professional traders (SEC (2000) describes the trade or fade rule).

[6]On October 19, 1999 the 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.

value to the trading system. Hence, any reform of the NYSE would be well served to include the continuance of the specialist in some form. Also, newly established exchanges face the decision of instituting a trading system that makes them competitive with established exchanges. Recent examples are the creation of Nouveau Marche in Paris, Neuer Markt in Frankfurt, Euro NM in Amsterdam and Brussels, and Nuovo Mercato in Milan. The first three adopted a multiple market maker system while Nuovo Mercato organized its trading based on the specialist system. The International Securities exchange started trading options in the US in 2000 on an electronic system but organized itself around a system similar in spirit to the one described here for the CBOE, with a specialist and multiple market makers for each option class. Our study has direct relevance for such decisions. Our results are especially significant as they indicate that a specialist would be beneficial to markets even in a screen-based environment.

In the next section we provide institutional details of trading on the CBOE as well as a summary of the changes resulting from a move to the DPM system. Section 2 contains a literature review and develops our hypotheses. In Section 3 we describe the data and methodology, Section 4 discusses the results, and Section 5 concludes.

1. Institutional Background

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. Prior to this change, all 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. A member could serve as a broker and a market maker, though not on the same day. On a given day, a member chose whether she would act as a broker or a dealer in the market. This trading crowd provided liquidity in equity options on the CBOE. Only the inside bid and ask were revealed to the trading crowd by the OBO.

Byrne (1987) gives an excellent account of the environment that fostered the creation of DPMs. During 1987, the CBOE was losing overall market share to other exchanges. Newly listed option contracts were typically thinly traded and market makers tended not to trade them. To improve liquidity in thinly traded options, DPMs were created and charged with maintaining a market in the options they were assigned. The original intent of the CBOE was to change the trading method from DPM to multiple market makers once the options achieved sufficient liquidity levels. Newly listed options, which tended to be on NASDAQ stocks, were also assigned to DPMs. On June 29, 1999 the CBOE board approved a resolution expanding this program to all equity options. By the time the change was announced, the DPM program had expanded to 20 DPM firms accounting for less than 50% of the CBOE's total volume, including most internet and biotech firms.[7] All remaining option classes were rolled over to the DPM system between August and October 1999.

A 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

[7]See Cavaletti (1999).

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, 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 she can participate in 100% of the incoming order flow. However, even when the DPM does not have time priority but matches the best quote, she is entitled to a pro rata share of the order flow (CBOE Rule 8.80(c)(7)(ii)).[8] The participation rate is a declining function of volume for single listed options and a constant 40% for multiple listed options.[9]

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 evaluate value the incremental benefit of the specialist system over the multiple market maker system.

2. Literature Review and Hypothesis Development

Several theoretical studies of single versus multiple dealers are relevant to our paper. For example, Saar (2001) argues that investors' preferences and endowments are just as important in pricing assets as is information about the future cash flows of the firm. He develops a model of sequential order flow in which orders contain information about investor demand for individual assets. As orders arrive, aggregate demand is revealed. The model allows for two types of investors, who differ in their level of risk aversion and endowment, and a market maker who sets the prices based on her knowledge of supply and demand (the opening call of the NYSE is an excellent example of the Saar (2001) model. Madhavan and Panchapagesan (2000) determine that specialists set opening call prices that are different from the strict market clearing price and are more indicative of future prices.) In Saar (2001), market makers maximize their expected profit per unit of time subject to the constraint that their inventory does not drift. Saar (2001) shows that if a market maker does not know the supply and the demand for a security she is less certain of the clearing price and will widen the spread to maximize the chances of the spread bounding the price. As supply and demand are revealed through investors' orders, the spread tightens. Therefore, the Saar (2001) model would predict narrower spreads in a market with a specialist since the specialist's exclusive knowledge of the limit order book enables her to resolve uncertainties better regarding investor preferences.

In the inventory control literature, Ho and Macris (1985) examine the relationship between the number of market makers and measures of spread and depth. They argue that the revenue to all dealers must equal the costs to all dealers of staying in the market. Therefore, replication of operations 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). Ho and Macris present a model that illustrates the

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

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

relationship:

$$(1/2)Vs = QK\Psi(m) + Cm,$$

where s is the percentage quoted spread; V is the dollar value of transaction volume per unit of time; K is the per share inventory cost per unit of time; Q is the average transaction size; m is the number of market makers; C is each market maker's fixed costs per unit of time; and Ψ is some increasing function of m. Examining the above equation reveals that percentage spread is directly related to the number of market makers. Thus, a single market maker (specialist) system would have lower spreads than a multiple market maker system.

Benveniste et al. (1992) predict lower asymmetric information costs in a floor-based vis-à-vis an electronic market because information sharing is higher among market participants on the floor. In the NYSE-Nasdaq framework, this implies lower spreads for the NYSE specialist system. They also suggest that a specialist can use her market power to force other traders to give up information about the likelihood of their orders being informed.

Ho and Macris (1985), Benveniste et al. (1992) and Saar (2001) predict lower spreads for a floor-based specialist system versus a multiple market maker system, but for different reasons. Previous research on this subject has largely focused on comparisons of a multiple market maker system on one market, with the specialist as the only market maker on another market, and for a different set of securities (to the best of our knowledge, ours is the only study that compares the specialist and the market maker system on the same exchange, for the same set of securities). For example, Vijh (1990) compares the spreads on multiple market maker based CBOE options with their underlying specialist based NYSE stocks. He finds that CBOE options have higher spreads than their underlying stocks.

Similarly, Neal (1992) compares execution costs for single listed options on the CBOE (at the time a multiple market maker system) with those that were single listed on the AMEX (a specialist based system). He finds that spreads for AMEX options are lower than those for CBOE options for low volume options, with little separating the two for high volume options. Studies comparing equities trading on the NYSE versus NASDAQ also find a floor-based specialist system to have better market quality than a decentralized multiple market maker system.[10]

As discussed earlier, previous studies are not able to distinguish between the fixed and inventory costs effects (Ho and Macris, 1985), the adverse selection cost effects (Benveniste et al. 1992) and the investor demand uncertainty resolution effect (Saar, 2001). However, we are able to conduct such an analysis, since the CBOE did not eliminate any market makers, but superimposed a specialist system on the existing system. Therefore there was either a net increase in dealers (existing market makers plus a specialist) or no change in the number of dealers.[11] Thus, the inventory control literature predicts an increase in spreads or no change in spreads. Also, given that the CBOE was always floor based, and the

[10]See Huang and Stoll (1996), Bessembinder and Kaufman (1997), and Bessembinder (1998, 1999), among others.

[11]The specialist was chosen from among the existing market makers. CBOE specialists are required to make a market at all times, while CBOE market makers can choose not to make a market on any particular day. Therefore, assuming other market makers did not exit the market, there is a positive probability that there is a net increase on average. At the very least there was no decrease in the number of market makers.

existence of the "give up" rule in options markets (which mandates the kind of information-sharing Benveniste, Marcus and Wilhelm envision), the adverse selection literature would predict no change in spreads. However, since CBOE specialists have exclusive access to the limit order book and hence can better estimate supply and demand, Saar (2001) predicts a reduction in spreads. This leads to our first hypothesis.

H1: *The institution of the DPM system on the CBOE leads to less demand uncertainty and thus lower spreads for its listed options.*

Ho and Macris (1985) argue that each dealer in a multiple market maker system supplies depth to the market. Therefore the amount of depth in a multiple dealer market is directly related to the number of market makers. As noted earlier, the CBOE superimposed the DPM (specialist) system on a multiple market maker system. We therefore argue that the number of market makers may have increased for a particular option on average. This suggests our second hypothesis:

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

To the extent that order flow is directed to a market based on market quality characteristics, a narrowing of spreads and an increase in depth will attract more order flow. Battalio et al. (2004) find a positive relationship between market share and the quoting aggressiveness of an exchange. Therefore, 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:

H3: *For multiple listed options, the CBOE is able to attract orders away from other markets by quoting more aggressive prices.*

Our paper is closely related to a recent comprehensive paper, Mayhew (2002), which uses a much larger data set than Neal (1992) to examine the determinants of bid ask spreads on CBOE options over the period 1987 to 1997. He compares spreads on CBOE listed options over several dimensions including: volume; implied volatility; and single vs. multiple listing. Mayhew finds, among other interesting results, that competition among exchanges results in narrower spreads.[12]

Mayhew (2002) also matches options traded on the CBOE under a multiple market maker and specialist system. He finds that quoted spreads are lower under a specialist system for all but one of the years in his study. In addition, Mayhew finds that effective spreads are significantly lower under a specialist in 6 of the 11 years he examines, while in 5 years options traded under a specialist system have significantly higher effective spreads. We are able to add to this literature since the nature of our event allows us to avoid problems associated with matched samples. We study the same securities on the same market under two different market structures. This is especially significant given our focus on distinguishing between the inventory control and investor uncertainty hypotheses, as it requires holding the number of market makers constant. Also, Mayhew employs the Berkeley Options Database, which only contains data for CBOE quotes and trades. Our database contains data for all exchanges allowing us a natural tool (in the form of a competing exchange for the same securities) to control for market wide effects and hence, isolate the effects of the CBOE regime shift.

[12]Battalio et al. (2004) and De Fontnouvelle et al. (2003) also examine competition among exchanges. Battalio et al. examine a group of actively traded multiple listed options and find that trades frequently occur at prices inferior to quoted prices on another exchange. De Fontnouvelle, Fishe, and Harris examine the impact on spreads as options move from single to multiple listed, reaching conclusions similar to Mayhew (2002).

3. Data and Methodology

The CBOE provided us with a list of the exact dates on which options were brought into the DPM system. We find that a total of 583 option classes were placed in the DPM system between August 2, 1999 and September 23, 1999. During our sample period, option classes in our sample were either solely listed on the CBOE (single listed) or listed on the CBOE plus one or more competing exchanges (multiple listed). In testing our hypotheses, we control for two events that are concurrent with the adoption of a specialist system by the CBOE. First, there was an investigation of options market trading practices initiated around the time of our study. Second, options markets experienced a marked increase in competition around the time of the system switch. In particular, the CBOE listed options on Dell Computer Corporation on August 23, 1999. Prior to that, Dell options were traded only on the Philadelphia Stock Exchange. Other occurrences of multiple-listing followed. Mayhew (2002), De Fontnouvelle et al. (2003), and Battalio et al. (2004) all find that competition between options exchanges narrows spreads. Observed changes may then be associated with an increase in competition and not the adoption of the DPM system.

If either were the case, then we would expect all options markets to experience similar changes in market quality. If any observed changes are instead associated with the CBOE's change in trading systems, we would not expect other exchanges to exhibit similar patterns for those option classes multiple listed on the CBOE and another exchange. Therefore, we control for the impact of federal investigations or general trends by only including in our sample options that are multiple-listed on the CBOE and at least one other exchange (American, Philadelphia, or Pacific Stock Exchange) during the period of our study.

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 price during the sample period is eliminated.

We use Options Price Reporting Authority (OPRA) data for our analysis. 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 did not provide data on quoted size during our sample period. 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. Quotes representing spreads greater than $2 are excluded, as they are likely to be incorrect entries. Our final sample consists of 177 option classes.

Table 1 contains summary statistics for our sample. We report mean, range, and dispersion statistics for both the pre and post periods. In addition to measures of trading activity and price, we also report "moneyness" and time to maturity. The moneyness of an option is defined as the ratio of the underlying stock price (from CRSP) divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options. Comparing the results between the two periods reveals that on average our sample option classes show no discernable change over the sample period.

As an initial examination of each market quality measure we examine the pre and post means as well as the change for the CBOE and separately for the three other exchanges (aggregated together). However, other authors have found that some characteristics of an

Table 1
Summary statistics

This table summarizes the characteristics of our sample in the period before and after the CBOE's change in trading system. The pre period covers 20 trading days before the option class began trading in the specialist system. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Mean, range, and standard deviation estimates are reported for both periods. There are 177 options classes in both the pre and post periods. The total number of trades (volume) is 182,669 (2,685,281) in the pre period and 169,929 (2,598,074) in the post period. We use an option series on a trading day as our basic unit of observation to calculate the market quality statistics. There are a total of 36,309 (34,188) such "options series days" in pre (post) period The moneyness of an option is defined as the ratio of the underlying stock price divided by the strike price for call options, and the ratio of strike price and the underlying stock price for put options.

	Pre				Post			
	Mean	Min	Max	σ	Mean	Min	Max	σ
Price ($)	6.27	0.0625	154.00	10.12	6.22	0.0625	149.25	9.52
Average trade size/day (# contracts)	15.33	1.00	5000.00	58.93	15.83	1.00	3333.33	49.42
Daily number of trades	5.03	1.00	315.00	11.39	4.97	1.00	280.00	11.86
Daily number of contracts traded	73.96	1.00	13,700.00	270.54	75.99	1.00	10,000.00	245.43
Time to maturity (days)	74.81	1.00	243.00	63.58	78.19	1.00	243.00	64.99
Moneyness	0.99	0.15	6.79	0.28	0.99	0.13	5.98	0.26

option class have an impact on market quality measures for those options. For example, Neal (1987, 1992) shows that activity is inversely related to length of time to maturity. Also, the rules of the CBOE impose different tick sizes for options trading below $3 ($1/16) and those trading above $3 ($1/8). We explicitly control for these factors in the following regression where appropriate:

$$MQ_{j,t} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*}CBOE,$$

where: $MQ_{j,t}$ is the market quality measure for contract j on day t (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the Maturity of the contract in days; *Moneyness* is as defined above; *Tick* is a dummy variable assigned the value 1 if the average price of contract j on day t was less than $3; *CBOE* is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; *Post* is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post*CBOE* is an interaction variable which equals 1 if the observation is based on CBOE data in the post period, zero otherwise. Our parameter estimate of interest is the interaction variable. If observed changes in market quality measures are due to the adoption of a specialist system by the CBOE, then we would expect that estimate to be statistically significant.

In the next section we examine various measures of market quality for our aggregation categories and compare them across exchanges to examine the impact of the CBOE's specialist system adoption.

Table 2
Quoted spreads

This table summarizes the results for changes in quoted percentage spreads following the CBOE's change in trading system. The pre period covers 20 trading days before the option class began trading in the specialist system and the post period covers 20 trading days immediately after. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A contains univariate results for quoted percentage spreads (defined as the difference between the bid and ask prices divided by the midpoint of the quote.) Quoted spreads (weighted by the time the quote is valid for) are calculated for each option series on each day it trades. The cross-sectional averages and the test of differences are weighted by the number of contracts traded in the option series on the particular day. Panel B contains parameter estimates for the following conditioning regression:

$$QS_{j,t} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*} CBOE,$$

where $QS_{j,t}$ is the quoted spread for contract *j* on day *t* (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the maturity of the contract in days; *Moneyness* is the ratio of the underlying stock price divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options, on day t ; *Tick* is a dummy variable assigned the value 1 if the average price of contract j on day t was less than $3; *CBOE* is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; *Post* is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post*CBOE* is an interaction variable which equals 1 if the observation is based on CBOE quotes in the post period, zero otherwise.

A. Univariate results

	Pre	Post	Difference	*t*-statistic
CBOE	15.67%	13.82%	−1.85%	−13.40*
Other exchanges	16.21%	15.04%	−1.17%	−7.75*

B. Control regression parameter estimates

Parameter	Estimate	*t*-statistic
Intercept	0.2442	87.92*
Maturity	−0.0004	−48.24*
Moneyness	−0.1338	−58.93*
Tick	0.1328	136.52*
CBOE	−0.0085	−6.63*
Post	−0.0100	−7.43*
CBOE*Post	−0.0047	−2.60*

*Denotes significance at the 0.01 level.

4. Results

4.1. Spreads

As a first step, we analyze the impact on spreads of the change in market structure. Table 2 presents the results for time-weighted percentage quoted spreads.[13] Time weighted spreads are calculated for each option series each day and then aggregated across days weighted by the trading volume in the option series on the day. Panel A contains the

[13]We also examine dollar quoted spreads. The results are qualitatively similar to those for percentage spreads and are thus not reported here, but are available from the authors upon request.

univariate results for our sample.[14] Both the CBOE and other exchanges experience a statistically significant decline in quoted percentage spreads over the sample period. The significant decline in non-CBOE spreads suggests a market wide trend during the period of this study. Alternatively, non-CBOE exchanges may be reacting to the increased competitiveness of the CBOE. However, the fact that CBOE spreads generally declined by nearly 60% more than non-CBOE spreads suggests that the change in market structure on the CBOE is associated with a reduction in spreads.

Examining the control regressions in Panel B reveals that our variable of interest, *CBOE**Post*, is negative and statistically significant at the 1% level. This supports our conclusion that the observed differential reduction in CBOE spreads is due to its change in market structure.

It is well known that there are many more quote revisions than trades in options markets. Neal (1992) suggests that an examination of market quality on options markets should include an examination of current spreads, defined as those quoted spreads that immediately precede a trade (quotes series is lagged 5 seconds before matching with trades as suggested by Lee and Ready, 1991). Accordingly, we estimate current quoted spreads and report the results in Table 3. Comparing Tables 3 with 2 yields qualitatively similar results. In particular, we find that while all of the exchanges in our sample exhibit a decline in the post period, the decline on CBOE is approximately 50% higher than on other exchanges. Again the regression parameter of interest, *CBOE**Post*, is negative and significant, indicating that the decline in spreads is associated with the introduction of DPMs on the CBOE.

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. Using a sample from 1995, Savickas and Wilson (2003) find that about 26% of the option trades they examine occur inside quoted spreads, while 6% occur outside the spread.

Percentage effective spreads are defined as twice the difference between the price of the trade and the midpoint of the contemporaneous bid and ask quotes divided by the spread midpoint. Effective spreads are weighted within a trading day by trade size. The aggregation across "options series days" is further weighted by the number of contracts traded in the option series during the day. Table 4 summarizes the results. Examining the univariate results in Panel A reveals results similar to that for our other spread measures, except that the decline in spreads on CBOE after the introduction of DPMs is over three times greater than that for other exchanges. The results of the control regressions in Panel B are consistent with the results reported in Panel A and those reported in Tables 2 and 3. In fact, as with the results for quoted and current spread, the parameter estimate of *CBOE**Post* (-0.0114) is roughly equal to the univariate CBOE difference (-1.65%) less than the Other Exchanges difference (-0.50%). This provides convincing evidence that the observed decrease in CBOE spreads is related to their change in market structure.

Overall, we find that all three measures of spread width declined on the CBOE following their adoption of DPMs. The decline appears to be associated with the change in market structure and not a market wide trend or increased competition. We view this as support for H1, that the institution of a specialist on the CBOE reduced the amount of demand uncertainty which then resulted in narrower spreads.

[14]All market quality measures are calculated for each option series on each day. Thus, an "option series day" is our basic unit of observation.

Table 3
Current Spreads

This table summarizes the results for changes in current percentage spreads, following the CBOE's change in trading system. The pre period covers 20 trading days before the option class began trading in the specialist system and the post period covers 20 trading days immediately after. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A contains univariate results for current percentage spreads (defined as the quoted spread (ask – bid) that immediately precedes a trade, divided by the midpoint of the same quote.) Current spreads (weighted by the number of contracts in the trade) are calculated for each option series on each day it trades. The cross-sectional averages and the test of differences are weighted by the number of contracts traded in the option series on the particular day. Panel B contains parameter estimates for the following conditioning regression:

$$CS_{j,t} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*}CBOE,$$

where $CS_{j,t}$ is the current spread for contract j on day t (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the maturity of the contract in days; *Moneyness* is the ratio of the underlying stock price divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options, on day t ; *Tick* is a dummy variable assigned the value 1 if the average price of contract j on day t was less than \$3; *CBOE* is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; *Post* is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post**CBOE* is an interaction variable which equals 1 if the observation is based on CBOE quotes in the post period, zero otherwise.

A. Univariate results				
	Pre	Post	Difference	*t*-statistic
CBOE	15.65%	14.10%	−1.55%	−9.54*
Other exchanges	15.79%	14.81%	−0.98%	−6.11*

B. Control regression parameter estimates		
Parameter	Estimate	*t*-statistic
Intercept	0.2790	87.71*
Maturity	−0.0005	−49.08*
Moneyness	−0.1779	−64.13*
Tick	0.1412	136.83*
CBOE	−0.0024	−1.72**
Post	−0.0063	−4.89*
CBOE*Post	−0.0054	−2.75*

*Denotes significance at the 0.01 level. **Denotes significance at the 0.10 level.

The overall economic consequences of a spread reduction on the CBOE are non-trivial. Based on the overall narrowing of effective spreads on the CBOE we estimate that investors saved approximately \$18 million in transaction costs during our sample period.[15] This is equivalent to an annual savings of over \$221 million.

[15]The savings associated with the institution of the DPM on the CBOE in the post period are calculated as the number of contracts traded on the CBOE in the post period (2,598,074) times 100 (since each contract represents 100 shares of the underlying stock and prices are quoted on a per share basis) multiplied by the average price (\$6.22) times -0.0114 (the CBOE*Post coefficient from the effective spread control regression on CBOE*Post) = \$18,422,423.12. The change is taken as the difference after controlling for market-wide trends, i.e. net of the change on other exchanges.

Table 4
Effective spreads

This table summarizes the results for changes in effective percentage spreads, following the CBOE's change in trading system. The pre period covers 20 trading days before the option class began trading in the specialist system and the post period covers 20 trading days immediately after. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A contains univariate results for effective percentage (defined as twice the absolute value of the difference between the trade price and the midpoint of the exchange's own bid and offer spread prevailing at least 5 seconds before the trade time.) Percentages are obtained by dividing by the midpoint of the prevailing quote. Effective percentage spreads (weighted by the number of contracts in the trade) are calculated for each option series on each day it trades. The cross-sectional averages and the test of differences are volume-weighted by the number of contracts traded in the option series on the particular day. Panel B contains parameter estimates for the following conditioning regression:

$$ES_{\mathrm{j,t}} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*}CBOE,$$

where $ES_{j,t}$ is volume weighted effective percentage spread for contract j on day t (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the maturity of the contract in days; *Moneyness* is the ratio of the underlying stock price divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options, on day t ; *Tick* is a dummy variable assigned the value 1 if the average price of contract j on day t was less than \$3; *CBOE* is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; *Post* is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post*CBOE* is an interaction variable which equals 1 if the observation is based on CBOE quotes in the post period, zero otherwise.

A. Univariate results

	Pre	Post	Difference	*t*-statistic
CBOE	13.25%	11.60%	−1.65%	−8.38*
Other exchanges	12.68%	12.18%	−0.50%	−3.03*

B. Control regression parameter estimates

Parameter	Estimate	*t*-statistic
Intercept	0.2047	53.36*
Maturity	−0.0004	−34.84*
Moneyness	−0.1231	−36.79*
Tick	0.1162	93.35*
CBOE	0.0050	2.99*
Post	−0.0023	−1.46
CBOE*Post	−0.0114	−4.79*

*Denotes significance at the 0.01 level.

4.2. Depth

We next examine the impact of the adoption of a specialist system on another measure of liquidity—depth. OPRA did not disseminate data on depth during our sample period, making it difficult to directly analyze the depth of options markets.[16] This lack of data has

[16]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 the 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.

led to depth largely being ignored by studies of options markets. Lee et al. (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 suggested by Kyle (1985), which has come to be known as Kyle's lambda. Intuitively lambda measures the volume required to move price by one 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 in that it captures undisclosed liquidity not reflected in the limit order book. It also 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. Details of the methodology used to estimate Kyle's lambda are in the Appendix A.

Recall that Ho and Macris (1985) show that the amount of depth in a market is directly related to the number of market makers for a security. Also recall that the CBOE superimposed a specialist system on top of a multiple market maker system. Since CBOE DPMs must make a market all the time while other market makers can walk away, at the very least there was no reduction in the number of market makers. On average there may have been an actual increase in the number of market makers. Thus the Ho and Macris model predicts an increase in depth following the adoption of DPMs.

Table 5 contains the results for the average lambda parameter. A decrease in the lambda estimate in the post period indicates an increase in depth. Examining the univariate results in Panel A, we find that both the CBOE and other exchanges experience a similar increase in depth after the CBOE adopted a specialist system; however, neither is statistically significant. Thus, we find that, at the very least, there is no reduction in depth associated with the change in market structure. However, we also do not find any significant increase in depth, leading us to reject hypothesis H2.

4.3. *Market Share*

Given the results so far, we find that percentage quoted, current, and effective spreads on the CBOE decrease significantly following the change in trading system. To the extent that investors take market quality into account in their order routing decisions, we would expect to see some market share impact following the change in trading mechanism on the CBOE. We obtain total volume traded from the Options Clearing Corporation for options in our 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. For this portion of the study, we choose months surrounding our sample period. Thus, we define the pre (post) period as July (November) 1999.

Table 6 presents the results for the market share of the CBOE and other exchanges for multiple listed options. The results in Panel A show that the overall average share of the CBOE increases from 55.7% to 59.9%. The increase in market share represents an increase of almost 117,000 option contracts in the post period. The change is statistically significant at acceptable levels. At the same time, the non-CBOE exchanges' average market share declines from 44.7% to 40.06% for the same options. The overall difference between the CBOE and other exchanges (9.07%) is statistically significant at the 1% level. Finding an increase in market share following the narrowing of spreads on the CBOE is consistent

Table 5
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:

$$\Delta p_t = \lambda_0 q_t + \varepsilon_t,$$

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. λ is an inverse measure of liquidity, thus a decrease from the pre to the post period indicates an increase in liquidity. We estimate this equation separately for each option series on each day the series trades. We restrict this analysis to option series with at least 5 price changes (6 trades) in a day. Trades are matched with quotes prevailing at least 5 seconds before the trade time. The Lee and Ready (1991) algorithm is used to classify trades as buyer or seller initiated. The pre period covers 20 trading days before the option class began trading in the specialist system and the post period covers 20 trading days immediately after. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A contains univariate results. Panel B contains parameter estimates for the following conditioning regression:

$$\lambda_{j,t} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*} CBOE,$$

where $\lambda_{j,t}$ is lambda for contract *j* on day *t* (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the maturity of the contract in days; *Moneyness* is the ratio of the underlying stock price divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options, on day *t* ; *Tick* is a dummy variable assigned the value 1 if the average price of contract *j* on day *t* was less than \$3; CBOE is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; Post is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post***CBOE* is an interaction variable which equals 1 if the observation is based on CBOE quotes in the post period, zero otherwise.

A. Univariate results

	Pre	Post	Difference	*t*-statistic
CBOE	0.0043	0.0042	−0.0001	0.47
Other exchanges	0.0044	0.0043	−0.0001	0.50

B. Control regression parameter estimates

Parameter	Estimate	*t*-statistic
Intercept	0.008642	14.93*
Maturity	−0.000013	−6.15*
Moneyness	−0.001489	−2.91*
Tick	−0.004560	−25.95*
CBOE	−0.000105	−0.44
Post	−0.000350	−1.34
CBOE*Post	0.000002	0.01

*Denotes significance at the 0.01 level.

with our hypothesis as well as the results of Battalio et al. (2004), who suggest that option specialists use spreads to attract order flow.

OPRA data do not allow us to measure directly the contribution of DPMs to the observed narrowing of spreads. However, the OCC partitions their monthly volume data by order type (retail customer, market maker, or firm account) for each option class. We use these data to obtain insight into whether the previously observed increases in depth are due to public orders or specialist/market maker provided liquidity.

Table 6
Market share

This table summarizes the results for changes in market share following the CBOE's change in trading system. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A reports overall results, while Panel B only includes trades by market makers on the CBOE or one of the other exchanges. In both Panels, the pre period is defined as July 1999 and the post period as November 1999. Market share for each option class is taken from the Option Clearing Corporation web site. 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. Market share for market makers is calculated as the percentage of total volume involving market makers on a particular exchange in our sample.

A. Overall			
	Pre	Post	Post-pre
CBOE	55.20%	59.90%	4.5%*
Other exchanges	44.77%	40.06%	−4.53%*
Change CBOE-change others			9.07%*
B. Market makers only			
CBOE-market maker	27.30%	29.30%	1.80%*
Other exchanges-market maker	21.65%	19.49%	−2.02%*
Change CBOE-change others			3.84%*

*Denotes significance at the 0.01 level.

For each option class we determine the monthly percentage of volume involving a market maker for the months of July and November 1999, which surround the trading system change on the CBOE. We compare the market maker trading volume percentages, for each multiple listed option class. Panel B of Table 6 contains the cross-sectional averages. The CBOE exhibits a statistically significant increase in the percentage of volume involving market-makers. Consistent with the findings of Panel A, the other exchanges exhibit a statistically significant decrease in market share. The difference between the CBOE and other exchanges changes is statistically significant, thus illustrating the direct involvement of the CBOE specialist in improving market quality.

4.4. Trade Throughs

Thus far, we have examined typical measures of market quality. However, it is important to point out that 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.[17] Battalio et al. (2004) examine whether a de-facto National Market System exists in the options markets. As the focal point for liquidity in an option class on the exchange, specialists are uniquely positioned to monitor trading in other markets and prevent executions at prices inferior to those on other exchanges. If this occurs, we would expect that the instances of trade throughs decrease after the institution of the DPM system on the CBOE.

[17] Battalio et al. (2004) find that, in June 2000, 15.83% of all trades on the CBOE in their sample were executed at prices inferior to the best price quoted on a competing market.

Table 7
Trade Throughs

This table summarizes the results for changes in trade-through rates following the CBOE's change in trading system. The pre period covers 20 trading days before the option class began trading in the specialist system and the post period covers 20 trading days immediately after. The sample includes multiple-listed options that listed on the CBOE and at least one of the other three exchanges (American, Philadelphia, and Pacific Exchanges) during the period of our study. Only options that do not experience an additional listing during the sample period are included. Panel A contains univariate results for trade throughs. Formally, a trade through occurs when a trade executes at a price worse than the National Best Bid and Offer (NBBO). Trades are matched with quotes prevailing at least 5 seconds before the trade time. Trade through rates are calculated for each option series on each day it trades. The cross-sectional averages and the test of differences are volume-weighted by the number of contracts traded in the option series on the particular day. Panel B contains parameter estimates for the following control regression:

$$TT_{j,t} = \beta_0 + \beta_1 Maturity + \beta_2 Moneyness + \beta_3 Tick + \beta_4 CBOE + \beta_5 Post + \beta_6 Post^{*}CBOE,$$

where $TT_{,t}$ is volume weighted trade through rate for contract j on day t (separate observations are made for contracts traded on the CBOE or on one of the three exchanges listed above); *Maturity* is the maturity of the contract in days; *Moneyness* is the ratio of the underlying stock price divided by the strike price for call options and the ratio of strike price and the underlying stock price for put options, on day t ; *Tick* is a dummy variable assigned the value 1 if the average price of contract j on day t was less than \$3; *CBOE* is a dummy variable assigned the value 1 if the observation is based on CBOE quotes, zero otherwise; *Post* is a dummy variable assigned the value 1 if the observation is in the post period, zero otherwise; and *Post*CBOE* is an interaction variable which equals 1 if the observation is based on CBOE quotes in the post period, zero otherwise.

A. Univariate results

	Pre	Post	Difference	*t*-statistic
CBOE	18.36%	19.37%	1.01%	4.19*
Other exchanges	18.60%	18.30%	−0.30%	−1.11

B. Control regression parameter estimates

Parameter	Estimate	*t*-statistic
Intercept	0.2541	42.71*
Maturity	−0.0003	−15.16*
Moneyness	−0.0250	−4.81*
Tick	−0.0586	−30.42*
CBOE	−0.0013	−0.52
Post	−0.0064	−2.65*
CBOE*Post	0.0147	3.99*

*Denotes significance at the 0.01 level.

The univariate results in Panel A of Table 7 provide the (volume weighted) average proportion of volume per option class that is traded through. The univariate results show a statistically significant increase in the proportion of trade throughs on the CBOE in the post period, while other exchanges experience a statistically insignificant decline in trade throughs.

The control regression results contained in Panel B support the univariate results in Panel A. Thus, we conclude that CBOE specialists did not actively seek to develop a national market system for options. It must be noted that although we observe an increase in trade through rates on the CBOE, that increase apparently does not occur at the expense of other market quality measures. We see this in the significant reduction in spreads after the change in market structure.

5. 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. In recent days, the role of NYSE specialist has come under increased scrutiny as investors weigh benefits of the system against the perceived costs. The choice of a trading system is crucial both to new and established exchanges as they compete for market share. Our analysis contributes to the debate on the merits of the specialist form of trading. The institution of the DPM system on the CBOE (similar to the NYSE specialist) allows us to evaluate the incremental benefits or costs of such a system as compared to a multiple market maker system.

We find a decrease in quoted, current, and effective percentage spreads associated with the change to a specialist system on the CBOE. The results support our hypotheses drawn from theory that a specialist system is better able to ascertain investor demand. Resolving uncertainty regarding investor demand then results in narrower spreads.

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

Thus, our results indicate that the specialist is beneficial to the markets. Significantly, the feature that causes the benefit, resolution of investor uncertainty, is likely to extend to electronic systems as well. Then, we see a place for the specialist in the future of screen based trading.

Appendix A. Estimation of Kyle's Lambda

To calculate Kyle's lambda, we use the following equation:

$$\Delta p_t = \lambda q_t + \varepsilon_t, \tag{A1}$$

where Δp_t is the change in price ($p_t - p_{t\text{-}1}$), 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. We estimate this equation separately for each option series on each day the series trades. We restrict this analysis to option series with at least 5 price changes (6 trades) in a day. Since λ is an inverse measure of liquidity, a lower value in the post period would imply an increase in depth. Similarly, a higher value would point towards a decrease in depth.

To identify buy and sell orders we use the Lee and Ready (1991) algorithm. Savickas and Wilson (2003) compare four different trade classification algorithms including Lee and Ready. They find that for option data such as ours, the Lee and Ready algorithm performs better than two of the other algorithms and just as well as the third. Therefore the Lee and Ready algorithm is a reasonable choice for our purposes. We match quotes with trades by lagging quotes by 5 seconds. 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 up ticks and sales for downticks. Lambda estimates are calculated separately for CBOE and the other 3 exchanges as a group.

References

Battalio, R., Hatch, B., Jennings, R., 2004. Does a national market system exist for U.S. exchange-listed equity options? An Analysis of Multiple-Traded Equity Options, Journal of Finance. 59, 933–962.

Benveniste, L.M., Marcus, A.J., Wilhelm, W.J., 1992. What's Special about the Specialist? Journal of Financial Economics 32, 61–86.

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

Bessembinder, H., 1998. Trading costs and return volatility: evidence from exchange listings. New York Stock Exchange Working. Paper #98-02.

Bessembinder, H., 1999. Trade execution costs on Nasdaq and the NYSE: A post-reform comparison. Journal of Financial and Quantitative Analysis 34 (3), 387–407.

Byrne, H.S., 1987. The Futures in the CBOE's Future. Barron's, August 17.

Cavaletti, C., 1999. Market Maker System to Go? Futures, April 1.

Cox, J., Rubinstein, M., 1985. Options Markets. Prentice-Hall, Englewood Cliffs, NJ.

De Fontnouvelle, P., Fishe, R., Harris, J., 2003. The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999. Journal of Finance 58, 2437–2464.

Ho, T., Stoll, H.R., 1983. The dynamics of dealer markets under competition. Journal of Finance 28, 1053–1074.

Ho, T.S.Y., Macris, R.G., 1985. Dealer market structure and performance. In: Amihud, Y., Ho, T.S.Y., Schwartz, R.A. (Eds.), Market Making and the Changing Structure of the Securities Industries. Lexington Books.

Huang, R., Stoll, H., 1996. Dealer versus auction markets: A paired comparison of execution costs on Nasdaq and the NYSE. Journal of Financial Economics 41, 313–358.

Kyle, A., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Lee, C., Ready, M., 1991. Inferring trade direction from intraday data. Journal of Finance 41, 733–746.

Lee, C., Mucklow, B., Ready, M., 1993. Spreads, depths and the impact of earnings information: an intraday analysis. Review of Financial Studies 6, 345–374.

Madhavan, A., Panchapagesan, V., 2000. Price discovery in auction markets: a look inside the black box. Review of Financial Studies 13, 627–658.

Mayhew, S., 2002. Competition, market structure and bid-ask spreads in stock options markets. Journal of Finance 57, 931–958.

Neal, R., 1987. Potential competition and actual competition in equity options. Journal of Finance 42 (3), 511–531.

Neal, R., 1992. A comparison of transaction costs between competitive market maker and specialist market structures. Journal of Business 65 (3), 317–334.

Saar, G., 2001. Investor uncertainty and order flow information. Working paper, New York University.

Savickas, R., Wilson, A.J., 2003. On inferring the direction of option trades. Journal of Financial and Quantitative Analysis 38 (4), 881–902.

SEC, 2000. Final Rule:Firm Quote and Trade-Through Disclosure Rules for Options17 CFR Part 240 [Release No. 34-43591; File No. S7-17-00].

Vijh, A.M., 1990. Liquidity of the CBOE equity options. Journal of Finance 45 (3), 1157–1179.