

CIRJE-F-357

**The Market Structure of Nasdaq Dealer and
Quoting Conventions**

Joe Chen

University of Tokyo

August 2005

CIRJE Discussion Papers can be downloaded without charge from:

<http://www.e.u-tokyo.ac.jp/cirje/research/03research02dp.html>

Discussion Papers are a series of manuscripts in their draft form. They are not intended for circulation or distribution except as indicated by the author. For that reason Discussion Papers may not be reproduced or distributed without the written consent of the author.

The Market Structure of Nasdaq Dealer Markets and Quoting Conventions*

Joe Chen

Faculty of Economics

University of Tokyo

7-3-1 Hongo, Bunkyo-ku

Tokyo 113-0033, Japan

3-5841-5649, -5521 (Fax)

joechen@e.u-tokyo.ac.jp

www.e.u-tokyo.ac.jp/fservice/faculty/view.e.htm

November 11, 2004

*I gratefully acknowledge my advisors Joseph E. Harrington and Matthew Shum for encouragement and support. Jimmy Chan, Christopher J. Flinn, Daniel B. Gubits, Robert A. Moffitt, and Yasmeen Salahuddin provided valuable input to this study. Finally, I also want to thank the comments from Ginger Z. Jin, Kartikeya Singh, Eric Zitzewitz, and participants in the presentations at the Johns Hopkins University, the securities practice division at NERA, University of Tokyo, Peking University, National Chengchi University, Academic Sinica, National Tsing Hua University, National Taiwan University, the 3rd Annual Johns Hopkins - Maryland Joint Workshop in Applied Micro and Microeconometrics, and the 2004 International Industrial Organization Conference.

Abstract

The well-publicized Christie-Schultz collusion hypothesis provides an experiment for studying the determinants of market structure in Nasdaq markets. Some markets experienced substantial compression in the profit margins for market makers due to the change of quoting convention from odd-eighth avoidance to the use of the full spectrum of eighths. Contrary to what competitive theory predicts, the empirical results suggest that this change led to *net entry* of market makers, after controlling for a time fixed effect, trading activity, information aspects of trading, market size, volatility, and unobserved individual market effects. Moreover, the robustness and significance of this finding do not change as different estimation methods are employed to correct for possible self-selection bias of the estimated average treatment effect. Surprisingly, dealer firms entered these markets despite the compression of profit margins. An explanation is provided based on collusion and investment in entry deterrence related to the practice of “preferencing”. (JEL L11 G20 C33)

1 Introduction

How do entry and exit decisions respond to profit margins? How sensitive is market structure to change?¹ To what extent is there hysteresis in the number of firms? This study intends to shed light on these questions. Specifically, I study the impact on the number of firms (market makers) in Nasdaq markets in response to an unpredicted exogenous compression of profit margins.

One main difficulty in studying the relationship between the number of firms in the market and profit margins is the simultaneity problem. Typically, it is hard to distinguish causality. Moreover, most exogenous changes in the market environment are predetermined policy changes that are foreseen by firms (both incumbents and potential entrants). Since rational firms adjust their behavior beforehand, the study of such changes can be difficult (anticipation effect). The attractiveness of exploring Nasdaq markets is that they experienced an exogenous and unpredicted decline in profit margins.

On May 27, 1994, due to extensive media coverage of an allegation of collusion (the Christie-Schultz collusion hypothesis), the spreads of some of the most important issues in the Nasdaq market dropped by almost 50%. Since the spread represents the profit margin of market making, this unpredicted exogenous drop in the spread creates an excellent opportunity to examine the sensitivity of entry and exit in Nasdaq market makers. It is important to emphasize that the media blitz associated with the collusion story, and the ensuing drop in spreads, was *exogenous and unpredicted* by market makers in Nasdaq.

To be specific, I am interested in changes to the numbers of firms in markets where market makers practiced odd-eighth avoidance (the absence of quote prices ended with $1/8$, $3/8$, $5/8$, and $7/8$) before the media blitz, and switched to the use of the full spectrum of eighths afterwards.^{2,3}

¹There are many different aspects for the term “market structure”. In this study, it refers to the number of market makers. I use these two terms interchangeably.

²The origin of trading stocks in (integer) multiples of eighths, the tick size rule, is unclear. Angel (1997) points out the lack of evidence for the Wall Street lore which claims the one-eighth tick size is an anachronism traceable to the colony-use of the Spanish “pieces of eight” coins (so-called because they were equal to eight silver reals). Dyl, Witte, and Gorman (2002) believe it originates from the pre-decimal British currency “half-crown”, which equals one-eighth of a pound. In an introductory book of stock markets, Dalton (1988) believes it originates from cutting bars of silver into pieces of eight to purchase shares in the cargo (bills of lading, a primitive form of securities).

³For the time period that I am interested, the tick size is one-eighth of a dollar, $\$1/8$, for issues with bid prices

Note that when firms use only even-eighth quotes, the resulting minimum spread is at least \$1/4. As they switch to the full spectrum of eighths, the resulting minimum spread becomes \$1/8. This is, potentially, a 50% drop in the profit margin for these markets. It is this impact on the market structure that I am interested in. In the following I refer to the markets that switched their quoting convention as the “treatment group”. The “treatment” here is the compression of profit margins caused by the change in the quoting convention associated with the media blitz.

To evaluate this impact to the market structure, I need a comparison group that did not experience a change in the quoting convention, but otherwise experienced the same changes in other aspects of the environment. There are two candidate groups of markets for this purpose. One comprises markets where firms price issues in the full spectrum of eighths consistently, and the other comprises markets where firms practice odd-eighth avoidance consistently. Both groups do not experience the drop in profit margins caused by the media blitz of the collusion story; and hence, can be used as the comparison group.

As in other natural experiment studies, the potential selection bias is always a concern. Some markets switched their quoting convention from odd-eighth avoidance to full spectrum, while others remained odd-eighth avoidance. Although I assume the switch of quoting convention to be exogenous, different empirical strategies – control functions, instrumental variable estimations, propensity score matching estimation, and other methods based on estimated propensity scores – are used in the estimation to address the selection problem.

The main finding of the study is surprising. Controlling for different market characteristics (time fixed effect, trading activity, information aspects of trading, market size, volatility, and unobserved individual market effects), I do indeed find that there is a statistically significant change in numbers of firms for markets that went from largely quoting even-eighths to quoting the full spectrum. Moreover, this result is robust to various estimation methods. However, the effect of the change in the quoting convention (and thus the compression of profit margins) was to *induce* net entry; resulting in about one to two *more* market makers. This is completely at odds to the prediction based on a competitive market framework with free entry and exit (see Section 3).

One possible explanation is as follows. Suppose there exists some market practice in Nasdaq

larger than \$10. Effective June 2, 1997, market makers with bid prices exceeding \$10 are free to post quotes in increments of \$1/16. As to issues with bid prices less than \$10, quotes continue to be posted in increments of \$1/32. The Nasdaq stock market decimalized in April, 2001.

markets, unobserved by econometricians, that can be used as a device for entry deterrence. To what extent the incumbent firms choose to deter entry depends on the size of profits to be protected. In those high profit margin markets (such as the odd-eighth avoidance ones), entry is successfully “blockaded” to preserve high profit margins. The resulting drop in the profit margin due to the switch to quoting all-eighths reduces (or eliminates) incumbent market makers’ incentive to invest in entry deterrence and thereby invites entry.

This scenario seems to be consistent with the collusion story. Firms in the odd-eighth avoidance markets (tacitly or explicitly) collude to use only even eighth quotes and artificially maintain high spreads that would otherwise not be achievable. Furthermore, investment in entry barriers preserves cartel rents in these markets. Once the media exposes the collusive scheme and causes a shift in the quoting convention, entry occurs. I will later argue that the practice of “preferencing” may be that entry barrier.

The next section provides more background information related to the Christie-Schultz hypothesis. It also reviews some empirical studies related to the Nasdaq market structure. Section 3 provides a simple theoretical structure to organize our thoughts on what to expect in a competitive framework with free entry and exit. Section 4 explains the construction of the data set and provides some summary statistics. Section 5 describes the empirical approach, presents the findings, and proposes the conjectured explanation. The final section concludes the study.

2 Background

2.1 The Christie-Schultz Collusion Hypothesis

The collusion debate started when several national newspapers published stories on the research finding of Christie and Schultz (1994) on May 26 and May 27, 1994. After examining the 1991 quote data of the top 100 actively traded Nasdaq securities, Christie and Schultz (1994) find that odd-eighth quotes are virtually nonexistent for 70 of these issues. Furthermore, the absence of odd-eighth quotes cannot be explained by the negotiation hypothesis of Harris (1991), trading activity, or other variables thought to influence spreads. The failure to justify the practice of odd-eighth avoidance by economic factors raised the question of whether Nasdaq market makers implicitly collude to maintain artificially high spreads.

What makes things even more interesting is that some market makers in those odd-eighth avoid-

ance issues adopted odd-eighth quotes *immediately* after the media coverage. As pointed out in Christie, Harris, and Schultz (1994), on May 27, dealers in Amgen, Cisco Systems, and Microsoft sharply increased their use of odd-eighth quotes, and as a result spreads fell by nearly 50%. This pattern is repeated for Apple Computer the following trading day. They also note that virtually all dealers for these issues moved in unison in adopting odd-eighth quotes.

Dutta and Madhavan (1997) provide a game-theoretic framework of dynamic dealer pricing, and characterize the possibility of tacit collusion in a dealer market. They demonstrate the ability for dealer firms to earn above normal profits in the absence of price discreteness or asymmetric information, and show that the ability to collude depends on factors that restrict access to order flows.⁴ Christie and Schultz (1999) provide empirical evidence on market makers' ability to coordinate on initiating and withdrawal of odd-eighth quotes within the span of one trading day. There are also studies that provide additional evidence supporting the collusion hypothesis. Examining spread data on issues that change listings (from Nasdaq to NYSE or AMEX, or the other way around), Barclay (1997) and Barclay, Kandel, and Marx (1998) find that there is a decrease in the spread when an issue moves from Nasdaq to NYSE or AMEX, and the decrease is largest when market makers practice odd-eighth avoidance. Furthermore, there is an increase in the spread when an issue moves from AMEX to Nasdaq, and the increase is largest when Nasdaq market makers practice odd-eighth avoidance. As in Christie and Schultz (1994), they cannot identify security-specific characteristics that contribute to the large spreads observed when Nasdaq market makers avoid odd-eighth quotes.

There are other studies that provide alternative explanations to the wide spreads in Nasdaq.⁵ Kandel and Marx (1999, 1997) argue the wide spreads in Nasdaq odd-eighth avoidance markets can be justified in a competitive framework where firms compete in discrete prices. The discreteness of the quote prices (due to the tick size rule) results in multiple equilibria, and the practice of odd-eighth avoidance is used as a coordination device to "select" the equilibrium with a higher spread. Grossman et al. (1997) argue the absence of odd-eighth quotes in some Nasdaq markets is no different from

⁴Following this direction, Parlour and Rajan (2003) explicitly model the effect of one of these factors – preferencing – on competition in the retail brokers and market makers. They show that, with preferencing, there is no equilibrium in which market makers earn zero profits. Spreads widen to more than the decrease in the intermediation fee. This provides a game-theoretical justification to the experimental results in Bloomfield and O'Hara (1998) where they find preferencing may significantly degrade market performance in laboratory financial markets (e.g., wider spreads).

⁵As a result of the practice of odd-eighth avoidance, the minimum spread is higher than it would otherwise be. However, the spread can be artificially high due to other reasons. To the extent that these studies offer alternative explanations to the high spreads in Nasdaq markets, they do not explain why market makers avoid odd-eighth quotes.

that of price clustering in other financial markets (first documented in Harris (1991)), and provide a competitive theory of price clustering. Demsetz (1997) attributes the relatively high spreads in Nasdaq markets to the way that market makers accommodate limit orders. Huang and Stoll (1996) emphasize the importance of other market aspects (e.g., internationalization, preferencing of order flows, and alternative interdealer trading systems) in explaining the relatively high spreads found in Nasdaq markets. Finally, Godek (1996) characterizes the absence of odd-eighth quotes in a competitive equilibrium with preferenced orders.

The bottom line is: to what extent the findings in Christie and Schultz (1994), Christie, Harris, and Schultz (1994), and other studies actually reflect collusive behavior among Nasdaq market makers remains highly controversial. As Woodward (1996, p.33) puts it: “... *not just a casual observation of clustered prices or other arcana, should persuade us that the industry is anything other than competitive.*”

2.2 Market Structure and Entry and Exit in Nasdaq Markets

In a review article one year later, Christie and Schultz (1995) make a reference to the non-responsiveness of entry and exit in those markets that are studied in Christie and Schultz (1994). They note that the significant reduction in market maker revenues subsequent to May 27, 1997, does *not* appear to have dissuaded dealers from making markets in any of these stocks. The same market makers that find it profitable to trade these issues with a minimum spread of \$1/4 are still making markets despite a decline in the minimum spread to \$1/8. Given the apparent ease of entry and exit in Nasdaq market making, this contradicts what conventional wisdom would suggest in a competitive environment.

Nevertheless, several empirical studies on the relationship between spreads and entry and exit decisions provide a different picture. Wahal (1997) documents the pervasiveness of entry and exit in Nasdaq markets. Entry and exit (both the number of market makers and the probability of entry and exit) are significantly affected by trading intensity, volatility, and the quoted bid-ask spread. Controlling for the effects of changes in volume and volatility, more entry (exit) is associated with a decrease (increase) in the spread. Goldstein and Nelling (1999) and Klock and McCormick (1999) also find a negative relationship between spreads and the number of market makers. Weston (2000) examines a reform that results in significant declines in market making rents, and concludes it induces exit, and markets are less concentrated.

These observations are consistent with a typical competitive environment of dealer pricing: as there are more market makers in the market, the intensified price competition reduces the spread, and market makers exit markets when there is an exogenous compression of the profit margin. Based on these results, one expects to see decreases in the number of market makers in those markets where firms moved away from odd-eighth avoidance practice due to the compression of profit margins.

Nevertheless, none of the studies in the current literature takes advantage of the unpredicted exogenous change in spreads caused by the media blitz associated with the Christie-Schultz collusion hypothesis. Due to the simultaneity problem and the anticipation effect involved in the determination of the relationship between market structure and profit margins, one needs to be careful in choosing the econometric methods and in interpreting the results.⁶

3 A Simple Model

In this section I use a simple two-stage game to provide a theoretical construct for the relationship between the profit margin and the equilibrium number of market makers in a competitive environment with free entry and exit. At the first stage, potential firms decide whether or not to enter where entry requires a (sunk) fixed cost $K > 0$. At the second stage, firms compete in bid and ask prices.⁷ The firm with the highest bid price gets all the sell orders, and the firm with the lowest ask price gets all the buy orders. When two or more firms have the highest bid or lowest ask, they share the orders. At the end of the game, market makers “go home flat” (unwind longs and cover up shorts) at the market clearing prices.

The main result is that the discreteness of price and the go-home-flat assumption result in multiple equilibria where firms earn normal profits. The equilibrium spread is determined by the marginal cost of trading and the tick size. There are at least two equilibrium spreads, one higher than the other. For the one with a higher spread, there will be more firms than that of the one with a lower spread.

⁶To address the simultaneity (endogeneity) problem involved in the determination of the relationship between market structure and profit margins, Goldstein and Nelling (1999) use a simultaneous equations framework, while Klock and McCormick (1999) adopt an instrument for the number of market makers variable.

⁷At the second stage, the game is essentially the same as the discrete price game introduced by Kandel and Marx (1997, 1999) though with a few differences. First, I explicitly model the demand and supply for liquidity. Second, the market clears at the bid and ask prices such that the expected supply of liquidity equals the expected demand. Third, market makers are assumed to unwind longs and cover up shorts at the market clearing prices.

As in other two-stage settings, I solve the game through backward induction. Let there be $n \geq 2$ market makers in the market. Denoting the tick size as ∇ , market makers are only allowed to compete in (bid, ask) $\equiv (B_i, A_i)$, where B_i and A_i are both integer multiples of the tick size ∇ . Assume the marginal cost of trading one share of the issue is constant and equal to $C \equiv c\nabla$, $c \geq 0$. There is no other cost of trading. For bids $(B_1, B_2, \dots, B_n) \equiv (b_1, b_2, \dots, b_n)\nabla$ and asks $(A_1, A_2, \dots, A_n) \equiv (a_1, a_2, \dots, a_n)\nabla$, market makers expect there to be: $D(a) \equiv E[\tilde{D}(\min\{a_1, a_2, \dots, a_n\})] \geq 0$ buy orders, and $S(b) \equiv E[\tilde{S}(\max\{b_1, b_2, \dots, b_n\})] \geq 0$ sell orders.⁸ A pair of prices (b, a) clears the market if and only if: $S(b) = D(a)$. Denote the market clearing quantity as $Q(b, a)$. Finally, I assume $D(\cdot)$ and $S(\cdot)$ to be monotonic and symmetric as in Dutta and Madhavan (1997).

To look for a pure strategy symmetric equilibrium that clears the market, consider $n - 1$ market makers quoting the price pair $(\hat{B}, \hat{A}) \equiv (\hat{b}, \hat{a})\nabla$, such that $D(\hat{a}) = S(\hat{b})$. For the n^{th} market maker, there are eight pure strategies to consider:

$$\{b\nabla, (b-1)\nabla, (b+1)\nabla\} \times \{a\nabla, (a-1)\nabla, (a+1)\nabla\} \setminus \{(b-1)\nabla, (a+1)\nabla\}.$$

These strategies and the associated expected profits are listed below:

Stg.	(Bid , Ask)	Expected Profits
A	$(\hat{b}, \hat{a})\nabla$	$(\hat{a} - c)\nabla D(\hat{a})/n - (\hat{b} + c)\nabla S(\hat{b})/n$
B	$(\hat{b} + 1, \hat{a} - 1)\nabla$	$(\hat{a} - 1 - c)\nabla D(\hat{a} - 1) - (\hat{b} + 1 + c)\nabla S(\hat{b} + 1)$
C	$(\hat{b}, \hat{a} - 1)\nabla$	$(\hat{a} - 1 - c)\nabla D(\hat{a} - 1) - (\hat{b} + c)\nabla S(\hat{b})/n$
		$-[D(\hat{a} - 1) - S(\hat{b})/n][p(\hat{b}, \hat{a} - 1) + C]$
D	$(\hat{b} + 1, \hat{a})\nabla$	$(\hat{a} - c)\nabla D(\hat{a})/n - (\hat{b} + 1 + c)\nabla S(\hat{b} + 1)$
		$+ [S(\hat{b} + 1) - D(\hat{a})/n][p(\hat{b} + 1, \hat{a}) - C]$
E	$(\hat{b}, \hat{a} + 1)\nabla$	$-(\hat{b} + c)\nabla S(\hat{b})/n + S(\hat{b})[p(\hat{b}, \hat{a} + 1) - C]/n$
F	$(\hat{b} - 1, \hat{a})\nabla$	$(\hat{a} - c)\nabla D(\hat{a})/n - D(\hat{a})[p(\hat{b} - 1, \hat{a}) + C]/n$
G	$(\hat{b} + 1, \hat{a} + 1)\nabla$	$-(\hat{b} + 1 + c)\nabla S(\hat{b} + 1) + S(\hat{b} + 1)[p(\hat{b} + 1, \hat{a} + 1) - C]$
H	$(\hat{b} - 1, \hat{a} - 1)\nabla$	$(\hat{a} - 1 - c)\nabla D(\hat{a} - 1) - D(\hat{a} - 1)[p(\hat{b} - 1, \hat{a} - 1) + C]$

where $p(\cdot, \cdot)$ is the price that market maker n disposes longs and covers up shorts. The remaining work is to figure out the values for $p(\cdot, \cdot)$ and derive conditions under which market maker n would not deviate from strategy A.

⁸Note that since B_i and A_i are integer multiples of the tick size, a_i and b_i are both integers for all $i = 1, 2, \dots, n$.

Note that, strategy B reduces the spread to $(\hat{\rho} - 2)\nabla$ and increases the liquidity demand (supply) to $D(\hat{a} - 1)$ ($S(\hat{b} + 1)$). By symmetry, $D(\hat{a} - 1) = S(\hat{b} + 1)$, and the market clears. For strategies C and H, there is excess demand of $D(\hat{a} - 1) - S(\hat{b})$ for liquidity in the market; therefore, for the market to clear, symmetry requires $p(\hat{b}, \hat{a} - 1) = p(\hat{b} - 1, \hat{a} - 1) = (\hat{b} + 1)\nabla$. For strategies D and G, there is excess supply of $S(\hat{b} + 1) - D(\hat{a})$ for liquidity in the market; therefore, for the market to clear, symmetry requires $p(\hat{b} + 1, \hat{a}) = p(\hat{b} + 1, \hat{a} + 1) = (\hat{a} - 1)\nabla$. Finally, strategies E and F both result in the same spread as strategy A, $\hat{\rho}\nabla$. Since they change neither demand nor supply, $p(\hat{b}, \hat{a} + 1) = \hat{b}\nabla$ and $p(\hat{b} - 1, \hat{a}) = \hat{a}\nabla$.

Substitute $p(\cdot, \cdot)$ into the profit expressions, one can derive the following sufficient condition for (\hat{B}, \hat{A}) to be a (pure strategy) symmetric equilibrium:

$$2c \leq \hat{\rho} \leq 2c + 2.$$

Hence, at the second stage of the game, there are *at least* two equilibrium spreads: one with the marginal trading cost plus one tick size ($2C + \nabla$) and the other with the marginal trading cost plus two ticks ($2C + 2\nabla$).⁹ Both equilibria result in profits above the marginal cost of trading.¹⁰

Given free entry at the first stage, firms join the market until above normal profits are competed away. Thus, the equilibrium number of market makers, n^* , is determined by the zero profit condition:

$$n^* = (\hat{\rho} - 2c)\nabla Q(\hat{b}, \hat{a})/K.$$

It is clear from this expression that an exogenous compression of the spread $\hat{\rho}$ should reduce the equilibrium number of firms n^* as long as it does not increase the equilibrium quantity $Q(\hat{b}, \hat{a})$ by a “large” amount.¹¹

The basis for the ensuing empirical analysis is that the media blitz was a focal event causing the *equilibrium to shift* to one with a smaller spread. By the theory in this section, those markets experiencing such a shift should be expected to experience net exit.

⁹Unless c is an integer, it is unlikely to have an equilibrium where the spread equals marginal cost: $\hat{\rho}\nabla = 2C$. It is possible to have more than two equilibria depending on n , $D(\cdot)$, and $S(\cdot)$. However, for “large” n 's and quantities, it is most likely there are only these two equilibria.

¹⁰As far as the theory is concerned, the equilibrium spread is decided by the tick size ∇ as well as the marginal trading cost $2C$. It is silent as to which equilibrium, $2C + \nabla$ or $2C + 2\nabla$, that the market eventually resolves.

¹¹For example, an exogenous shift in the equilibrium so that the spread goes from $2C + 2\nabla$ to $2C + \nabla$ causes the number of market makers to change from $2\nabla Q(\hat{b}, \hat{a})/K$ to either $\nabla Q(\hat{b} + 1, \hat{a})/K$ or $\nabla Q(\hat{b}, \hat{a} - 1)/K$. As long as $\max\{Q(\hat{b} + 1, \hat{a}), Q(\hat{b}, \hat{a} - 1)\} < 2Q(\hat{b}, \hat{a})$, the shift reduces the equilibrium number of market makers.

4 Data and Empirical Methods

4.1 Data Sources

I use two different data sources for this study: the New York Stock Exchange Trade and Quote Database (NYSE TAQ), and the Center for Research in Security Prices US Stock Database (CRSP). The TAQ database provides intraday quotes for all securities listed on the Nasdaq National Market (NNM) and the Nasdaq SmallCap. These intraday quote data can be used to identify markets where firms practice odd-eighth avoidance. The CRSP database provides time series data on the number of market makers, trading activity, volatility, capitalization, shares outstanding, and other information.

The complete sample period starts from the first trading day in 1993 to the last trading day in 1995 for a three-year span. I divide it into two separate periods, the pre-impact period: from January 1, 1993 to May 26, 1994, and the post-impact period: from June 3, 1994, to December 31, 1995.

4.2 Identifying Odd-eighth Avoidance Issues

The first step in organizing the data is to identify odd-eighth avoidance issues. Given the two quoting conventions in Nasdaq markets (odd-eighth avoidance or full spectrum) and the two segments (before and after the impact), a tick size one-eighth issue belongs to one of the following four possible groups:

	Quoting Conventions	
	Before the Impact: Jan.1, '93 – May 26, '94	After the Impact: June 3, '94 – Dec. 31, '95
Case OO:	odd-eighth avoidance	odd-eighth avoidance
Case OA:	odd-eighth avoidance	all-eighth
Case AA:	all-eighth	all-eighth
Case AO:	all-eighth	odd-eighth avoidance

Following Christie and Schultz (1994), I designate an issue as an odd-eighth avoidance one when fewer than 25% of the (inside) quotes include odd-eighths; otherwise, it is an all-eighth one. As a robustness check, I also consider different cutoff points: 20%, 15%, 10%, and 5%.

As of May 1994, there were 13,810 issues in the TAQ database. Among them, 5,807 are Nasdaq issues and 4,280 are Nasdaq common stocks or capital stocks. These 4,280 issues account for the 18,089,613 quote entries that I extracted from the TAQ database. Since I am interested only in tick size one-eighth issues, only data entries with daily minimum bid prices greater or equal to \$10 are used.¹² There are 10,687,739 quote entries for 2,760 tick size one-eighth issues. Using these quote entries, ratios of odd-eighth quotes before and after the impact for each issue are calculated. After getting rid of issues that do not have data entries for periods both before and after the impact, the sample size reduces to 2,154 issues. These 2,154 issues are the “markets” that I study below.

As an example, in the pre-impact period there are 40,906 quote entries (combined bids and asks) for MSFT (ticker symbol for the Microsoft Corporation). Of these quotes, only 124 bids and 158 asks include odd-eighths, less than 0.69% of total quotes. However, things change dramatically after the impact. In the post-impact period there are 97,404 quote entries for MSFT. Of these quotes, 24,272 bids and 24,431 asks are in odd-eighths, more than 50% of total quotes. Hence, by all five cutoff criteria (25%, 20%, 15%, 10%, and 5%), MSFT is a case OA market.

Table 1 presents the classification of markets into these four groups. As one can see, dealer firms practice odd-eighth avoidance in the vast majority of markets. A substantial amount of markets switch from avoiding odd-eighth quotes to using the full spectrum of eighths (case OA), and a comparable amount of markets use the full spectrum of eighths consistently (case AA). However, most odd-eighth avoidance markets remain odd-eighth avoidance (case OO). Market makers do *not* change their quoting convention from odd-eighth avoidance to the use of all-eighth *en masse*. In some rare cases (1.53% to 2.74%, depending on the cutoff criterion), I even find an all-eighth market becomes an odd-eighth avoidance one after the impact (case AO).

¹²The Nasdaq tick size rule (for both NNM and Nasdaq SmallCap) in May, 1994 is as follows: for issues with bid prices greater or equal to \$10, the tick size for prices is one-eighth, \$1/8; otherwise, the tick size is \$1/32. Any market maker who posts a bid price of less than \$10 can use a tick of \$1/32 for quotes. Note that the tick size for an issue could change throughout the day depending on market makers’ quoted prices. Note also that the tick size rule only affects quoted prices. Trades can occur at an increment of \$1/256. For more information about the tick size rule and other aspects of Nasdaq markets, see Smith, Selway, and McCormick (1998).

4.3 Variables and Summary Statistics

Time weighted daily average prices (*twavgp*) and absolute and relative spreads (*twavgs* and *twavgrs*) are calculated using the TAQ quote data.¹³ All other variables – numbers of market makers (*mmcnt*), trading volumes (*vol*), numbers of trades (*numtrd*), shares outstanding (*shrout*), returns, and returns without dividends – are extracted from the CRSP database.

The dependent variable is the number of dealer firms in the market (*mmcnt*). The variable of interest is a “treatment” variable (*treat*) that identifies markets switching from odd-eighth avoidance to all-eighth. It is called “treatment” because the switch causes compression in the profit margin, and it is exactly the effect on the market structure of this compression in profit margin that I am studying. The other two variables of interest are the absolute and relative spreads (*twavgs* and *twavgrs*) which measure profit margins in the markets. There are five other variables – trading volume (*vol*), numbers of trades (*numtrd*), shares outstanding (*shrout*), returns, and returns without dividends – that I use to construct the control variables for trading activity, information-based trading, market size, and volatility for each market.

Three variables are used to measure trading activity in each market: trading volume (*vol*), number of trades (*numtrd*), and turnover (*tnover*).¹⁴ Market value or capitalization (*mcap*) and average trade size (*voltrd*) are used to pick up the information-based trading in each market.¹⁵ It is generally believed that the amount of information trades (as opposed to noise trades) decreases as the company that issues the stock gets larger (and hence a higher market value). However, a higher market value also requires market makers to commit more capital in the market. This would reduce the incentive of market making in high-priced issues. Therefore, a priori, the effect of the market value variable (*mcap*) on market making is unclear. Another variable measuring the extent of information-based trading is the average trade size (*voltrd*). As pointed out by Easley and O’Hara (1987), given they wish to trade, information traders prefer to trade larger amounts at any price. Therefore, trade size is also included as a control variable. Shares outstanding (*shrout*) measures the

¹³The price is defined as: $p = (bid + ask)/2$; the spread is defined as: $s = ask - bid$; and the relative spread is defined as: $rs = s/p \times 100$. The three variables: *twavgp*, *twavgs*, and *twavgrs*, are averages of p , s , and rs , weighted by the associated length of time that the (*bid*, *ask*) price pair is active.

¹⁴Turnover is defined as: $tnover = vol/shrout$.

¹⁵Market value is defined as $mcap = twavgp \times shrout$; average trade size is defined as: if $numtrd > 0$, $voltrd = vol/numtrd$; otherwise, $voltrd = 0$.

size of the market. Finally, I use the absolute values of returns (*aret*) and returns without dividends (*aretx*) to measure daily volatility in the markets.

The product is a daily data set of 2,154 markets. A three-year panel data set is then constructed by taking the average of these variables except that square roots of the sum of squared returns (*srssqr*) and returns without dividends (*srssqrx*) are used to measure volatility. Table 2 provides the definitions and units of measure for all the variables. The rest of this subsection provides a general picture of the markets that I am studying. To save space, the data for only two cutoff criteria – 25% (as in Christie and Schultz (1994)) and 10% – are presented in some of the following tables and figures. The data for the other cutoff criteria are qualitatively similar.

Table 3 presents the means and standard deviations for all the variables (daily) in the data set. There are on average 11.55 dealer firms in one market. For an equal amount of buy and sell orders, the average daily trading revenue is: $vol/2 \times twavgs = \$41,665.30$, while the average revenue per trade is: $voltrd/2 \times twavgs = \540.85 .

Table 4 presents the means and standard deviations of the three-year panel by cases for two of the five cutoff criteria that I used. In general, the issues in the case OO markets have average prices (*twavgp*) higher than those of the issues in other market groups. As expected, the average and relative spreads (*twavgs* and *twavgrs*) in the case OO markets are the highest, and those of the case AA markets are the lowest. The average and relative spreads decrease monotonically across years in the case OO, OA, and AA markets, while they increase monotonically in case AO markets.

The table also shows that the case OO markets are thinly traded issues (*vol*, *numtrd*, and *tnover*) compared to others. This may justify higher spreads in these markets due to higher costs of market making in inactive markets. An important observation is that: the case AA markets are more comparable to the case OA markets in terms of the average numbers of market makers (*mmcnt*) and the control variables (trading activity, information-based trading, and market size), except the differences in spreads and volatility.

How do the spreads and the market structure respond to the unpredicted exogenous compression in the profit margins? From 1993 to 1995, compared to the small declines in the average absolute spreads of the case OO and AA markets, the decrease (increase) in the average spreads of the case OA (case AO) markets is considerable. The spreads decrease by about \$0.08 and \$0.02 in the case OO and AA markets, while it decreases (increases) by about \$0.20 (\$0.16) in the case OA (case AO) markets. It is evident that the effects of switching quoting conventions to the spreads are

substantial. How does the market structure respond? Surprisingly, the average number of market makers increases (decreases) in the case OA markets (case AO markets) across years despite the slump (boost) in the average spread. Moreover, while there has been virtually no change (or small declines) in the average spreads in both case OO and AA markets, the number of market makers remains roughly the same in the case OO markets, while it decreases in the case AA markets. Of course, these results are tentative as they fail to control for other market characteristics.

4.4 Empirical Method

To evaluate the effect of an unpredicted exogenous compression in the profit margins to the market structure, I study the change in the number of dealer firms caused by the change of quoting convention in the case OA markets. Thus, the treatment group is the case OA markets. The goal is to estimate the “average treatment effects” of the change. For this, I need to find a control (or comparison) group that does not experience the drop in the profit margin, but otherwise experiences the same changes in other aspects of the environment. There are two candidate groups of markets for this purpose. One comprises markets where firms consistently price issues in the full spectrum of eighths (case AA markets), and the other comprises markets where firms consistently practice odd-eighth avoidance (case OO markets). Both groups do not experience the drop in profit margins caused by the media blitz of the collusion story.

There are several problems that needed to be addressed in designing an empirical strategy for the estimation of the average treatment effects. First, as I have pointed out in the previous section, there are multiple equilibria and the theory is silent as to which equilibrium that a market eventually settles upon. A maintained hypothesis is that the odd-eighth avoidance practice serves as an equilibrium selection device to pick out the one with a higher spread. The basis of the ensuing empirical analysis is that the media blitz was a focal event causing the equilibrium to shift to one with a smaller spread. Those markets experiencing such a shift should be expected to experience net exit.

As pointed out by Meyer (1995, p.151): “*Good natural experiments are studies in which there is a transparent exogenous source of variation in the explanatory variables that determine the treatment assignment. ... If one cannot experimentally control the variation one is using, one should understand its source. ...*” In the context of my study, the question to be understood is: why are there different quoting conventions used in different markets in the first place? Can the assignment to the treatment or control group be random? The model in Section 3 shows that different quoting conventions can be supported in competitive equilibrium. However, in a subgame perfect equilibrium,

firms earn normal profits no matter which equilibrium spread at which the market settles. Therefore, from a potential entrant’s point of view, other things being equal, it can be considered “as if” it were random to join a market where the full spectrum of eighths are used (one-tick equilibrium), or one where only even-eighths are used (two-tick equilibrium). Therefore, when the collusion story hits the market, it is “as if” some markets (the treatment group) are randomly subjected to the profit margin compression caused by the change in the quoting convention while others (the control group) are not.¹⁶

Nevertheless, as in other natural experiment studies, selection bias is always a concern (see Heckman and Smith (1995) and Heckman et al. (1998)). Some markets switched their quoting convention from odd-eighth avoidance to full spectrum, while others remained odd-eighth avoidance. Although I would like to assume the switch of quoting convention to be exogenous, concerns of selection bias would weaken the estimation results hinged on the exogeneity assumption. Hence, for the empirical investigation, several econometric tools that control for potential selection bias are employed.

5 Empirical Results

The response of market structure to a change in profit margin is explored by measuring the change in the numbers of market makers in the treatment group before and after the switch in quoting convention (from odd-eighth avoidance to using the full spectrum of eighths). Hence, it is necessary to establish a link between the change in profit margin as a result of the change in the quoting convention. I interpret the switch as being unexpected and exogenous; being caused by the extensive media coverage of the collusion allegation associated with the odd-eighth avoidance practice.

5.1 Profit Margins, Quoting Convention, and the Market Structure

As pointed out in Section 4, for the markets that do not change quoting conventions (cases OO and AA), Table 4 shows that there were small declines in the average absolute spreads from 1993 to 1995; about \$0.08 and \$0.02 in case OO and AA markets, respectively (see the 25% cutoff part of

¹⁶Given that the assignment to the treatment and control groups is indeed random, case AA markets would be a better candidate as the control group. As the summary statistics in Table 4 suggest that the case OO markets are relatively thinly traded issues, it is difficult to justify that they provide the “would-be results” for the actively traded markets in the treatment group in the absence of the compression in the profit margins.

the table for values of *twavgs* across years). One may want to attribute this to overall changes in the industry; for example, greater efficiency in trade executions, decreasing average and marginal costs of order processing, and so on. However, those factors cannot, at the same time, explain the considerable decline of \$0.2 in the average absolute spread in those markets that switched from odd-eighth avoidance to the use of the full spectrum of eighths (case OA), nor can they explain the considerable increase of about \$0.16 in the average absolute spread in those markets that switched from the use of the full spectrum of eighths to odd-eighth avoidance (case AO).

The theory in Section 3 establishes a link between changes in profit margin and a switch in the quoting convention. Recall that there are most likely two equilibrium spreads at the second stage of the game: one being the marginal trading cost plus one tick ($2C + \nabla$) and the other being the marginal trading cost plus two ticks ($2C + 2\nabla$). For simplicity, let $C = 0$. Given the one-eighth tick size, the equilibrium spread would then be \$0.125 or \$0.25. If the market makers of a certain issue eliminate either odd-eighth or even-eighth quotes, then the market would result in an equilibrium spread of \$0.25. Hence market makers can use the odd-eighth avoidance practice as a device to coordinate their quotes, and thereby “select” the equilibrium with a higher spread. With this explanation, the decrease (increase) in the average absolute spread in case OA (AO) markets immediately follows. By switching the quoting convention from odd-eighth avoidance to the use of the full spectrum of eighths, the equilibrium spread in the case OA markets (the treatment group) decreases from the marginal trading cost plus two ticks to the marginal trading cost plus one or two ticks. This is potentially a \$0.125 decrease in the equilibrium spread. Furthermore, by switching the quoting convention from the use of the full spectrum of eighths to odd-eighth avoidance, the equilibrium spread in the case AO markets increases from the marginal trading cost plus one or two ticks to the marginal trading cost plus two ticks. This is potentially a \$0.125 increase in the equilibrium spread.

The changes in the absolute spreads caused by the switch in quoting conventions are most clearly shown by the time series plots of the spreads. Figure 1 presents the monthly average absolute spreads for all four cases from the beginning of 1993 to the end of 1995. In general, the (average absolute) spreads in the case OO markets are an upper bound on the spreads, while the spreads of the case AA markets serve as a lower bound. Since there have been no changes in the quoting conventions in the upper and lower bound markets, I do not observe substantial changes in the spread levels. The spreads in the case OA markets start at a level a bit higher than the spreads in the case AO markets in the beginning of 1993. Although there is a slight upward trend in the spreads of the case AO markets, they never exceed those of the case OA markets before the impact hits the markets on

May 27, 1994. However, by the end of the observation period (1995), the spreads of the case AO markets are converging to the upper bound, while the spreads in the case OA markets are converging to the lower bound. Moreover, the spreads in the case AO markets are much higher than those of the case OA markets. The “crossings” happen exactly at the point when the collusion story hits the markets. The same results are shown in Figure 2 where the time series plots of the relative spreads are presented.

The time series trend of the number of market makers is presented in monthly averages in Figure 3. It shows that the number of market makers in the case AA markets serves as an upper bound, while the number of market makers in the case OO markets serves as a lower bound. The average number of market makers in the case OA markets starts at a level higher than that of the case AO markets by 1 to 2.5, depending on the cutoff criteria. By the end of 1995, the numbers of market makers in the case OA and AA markets converge, as do the numbers of market makers in the case OO and AO markets. However, the converging trends start before the media story hits the market. It is difficult to draw conclusions about the change in market structure using the time series plot alone. An econometric analysis is provided next to account for different characteristics of the markets.

5.2 Fixed Effect Panel Regressions

The main regression analysis is based on the unobserved effects panel data model that is popular for program evaluations and policy analyses. The following is a time and individual fixed effects panel regression setup that eliminates omitted variable bias arising from unobserved variables for individual markets that are constant over time, and from unobserved variables for the industry that are constant across markets.

Let i index a market, $i = 1, 2, \dots, N$, and t index the time period, $t = 1, 2, \dots, T$. I assume the relationship between the number of market makers for market i at time t , y_{it} , and a $1 \times K$ vector of observed market characteristics, \mathbf{x}_{it} , is linear, and can be expressed as follows:

$$y_{it} = \theta_t + \gamma T_{it} + \mathbf{x}_{it}\boldsymbol{\beta} + c_i + u_{it}; \quad i = 1, 2, \dots, N, \text{ and } t = 1, 2, \dots, T. \quad (1)$$

θ_t is a time-varying intercept term that captures the aggregate time effect (time fixed effect). Note that θ_t changes over time but not across markets, thus it controls for overall intertemporal changes in the industry that affect market structure regardless of whether the market is in the treatment or control group. The time-invariant c_i is the unobserved heterogeneity for market i , and u_{it} is

the idiosyncratic error that changes across markets as well as time periods. Note that c_i is the unobserved individual effect, different across markets but not over time, that affects the market structure. T_{it} is a binary variable (0–1) that indicates the receipt of the treatment. For markets in the treatment group (where market makers practice odd-eighth avoidance before the media blitz and change to full spectrum afterwards), $T_{it} = 1$, if t belongs to time periods after the media blitz, and $T_{it} = 0$, if t belongs to time periods before that. As to markets in the control group, $T_{it} = 0$, for all t .¹⁷ In the following, I use 1993 and 1995 data (a typical “before and after” comparison setup) to perform fixed effect estimations. Specifically, depending on the choice of the control group, there are three specifications for T_{it} :

1. Case AA markets as the control group. For this setup, $T_{i1993} = 0$ for all $i = 1, \dots, N$; and,

$$T_{i1995} = \begin{cases} 0, & \text{if } i \text{ is one of the case AA markets;} \\ 1, & \text{if } i \text{ is one of the case OA markets.} \end{cases}$$

2. The pool of case OO and AA markets as the control group. For this setup, $T_{i1993} = 0$ for all $i = 1, \dots, N$; and,

$$T_{i1995} = \begin{cases} 0, & \text{if } i \text{ is one of the case OO or AA markets;} \\ 1, & \text{if } i \text{ is one of the case OA markets.} \end{cases}$$

3. case OO markets as the control group. For this setup, $T_{i1993} = 0$ for all $i = 1, \dots, N$; and,

$$T_{i1995} = \begin{cases} 0, & \text{if } i \text{ is one of the case OO markets;} \\ 1, & \text{if } i \text{ is one of the case OA markets.} \end{cases}$$

Note that the treatment group – case OA markets – is the same for all three specifications. Based on the summary statistics in the previous section, case OO markets are relatively thinly traded compared to case OA and AA markets; therefore, more attention is given to the estimation results of the first specification. Given the strict exogeneity assumption and the rank condition, the fixed effect estimation of equation (1) gives us consistent estimators for the coefficients of interest $(\theta_1, \dots, \theta_T, \gamma, \beta')$.¹⁸

¹⁷To draw a direct analogy to the program evaluation problems, one may want to consider T_{it} as participating in a program that causes a compression in the profit margin.

¹⁸Denote $\mathbf{w}_{it} \equiv (\theta_t, T_{it}, \mathbf{x}_{it})$, and $\mathbf{w}_i \equiv (\mathbf{w}_{i1}, \mathbf{w}_{i2}, \dots, \mathbf{w}_{iT})$. The strict exogeneity assumption requires: $E[u_{it} | \mathbf{w}_i, c_i] = 0$, $t = 1, 2, \dots, T$. Denoting $\bar{y}_i = T^{-1} \sum_{t=1}^T y_{it}$, and $\bar{\mathbf{w}}_i = T^{-1} \sum_{t=1}^T \mathbf{w}_{it}$, the rank condition requires: $\text{rank} \left(\sum_{t=1}^T E[(\mathbf{w}_{it} - \bar{\mathbf{w}}_i)'(\mathbf{w}_{it} - \bar{\mathbf{w}}_i)] \right) = K + 2$.

The dependent variable, y_{it} , in the estimation equation is the number of market makers, $mmcnt_{it}$, and the regressors (in addition to the two fixed effects θ_t and c_i) T_{it} and \mathbf{x}_{it} are: $treat_{it}$ and $(vol_{it}, numtrd_{it}, tnover_{it}, voltrd_{it}, mcap_{it}, shrout_{it}, srssqr_{it}, srssqrx_{it})$.¹⁹ The estimation equation with the full collection of regressors is:

$$mmcnt_{it} = D93_{it} + \gamma treat_{it} + \beta_1 vol_{it} + \beta_2 numtrd_{it} + \beta_3 tnover_{it} + \beta_4 voltrd_{it} + \beta_5 mcap_{it} + \beta_6 shrout_{it} + \beta_7 srssqr_{it} + \beta_8 srssqrx_{it} + c_i + u_{it};$$

where: $i = 1, 2, \dots, 2154$, and $t = 1993, 1995$.

The theory in Section 3 predicts next exit in markets that belong to the treatment group. Hence, I expect the sign of the coefficient of the treatment variable ($treat$), $\hat{\gamma}$, to be negative. As to the control variables, recall that the three variables vol , $numtrd$, and $tnover$ measure trading activity in the markets. One then expects $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ to be positive. The sign of the coefficient of the variable $mcap$, that measures the information aspects of trading, is undetermined for reasons discussed above. I do expect the sign of coefficient of $voltrd$, that also measures information trading, to be negative. The sign of the coefficient of the variable $shrout$, that measures the size of the market, should have a positive sign. As to the variables measuring volatility, $srssqr$ and $srssqrx$, negative signs are expected.

Table 5 presents the estimation results for the case OA vs. case AA markets. There are five panels in the table for the five cutoff criteria. The sample size of markets increases monotonically as the cutoff criterion is lowered (from 579 markets with the 25% cutoff criterion to 1,093 markets with the 5% cutoff criterion). For each cutoff criterion, 11 different combination of control variables are estimated. The figures in parentheses are estimated standard errors. A three-star superscript is used to denote that the estimated coefficient is significant at the 1% significance level, a two-star superscript for the 5%, and a single star superscript for the 10% significance level.

The results are surprising. As one can see immediately from panel A (the 25% cutoff criterion), the associated coefficients for the treatment variable ($treat$), $\hat{\gamma}$, are positive and significant at the 1% significance level. Furthermore, the positive significance of $\hat{\gamma}$ holds no matter which cutoff criterion is used and the magnitude is fairly robust; ranging from 2.08 to 2.68 for cutoff criteria of at least 10%. While the values of $\hat{\gamma}$ differ across columns within each panel, the differences are “small”.

¹⁹I make some changes to the units of measure for some variables. The unit of measure is millions for vol , millions of dollars for $mcap$, and percentages for $tnover$.

The one with the largest difference across columns is in panel A, where the discrepancy between the largest and smallest values of $\hat{\gamma}$ is 0.34.

These results suggest that the treatment (the switch from odd-eighth avoidance to full spectrum) results in *net entry* of about two market makers, controlling for the time fixed effect, trading activity, information aspects of trading, market size, volatility, and unobserved individual market effects. Considering the average number of market makers is about 13.65 to 17.37 in the treatment group, an increase of two market makers is substantial. Moreover, this result is completely at odds with what the competitive theory predicts in Section 3. I will return to this point later and offer a possible explanation.

The coefficients of the variable that controls for the time fixed effect, $D93_{it}$, are positive and significant in columns VI to XI. This implies that there are, *ceteris paribus*, fewer market makers in both groups in 1995 than in 1993. From 1993 to 1995, the average number of dealer firms in a market is decreasing regardless of whether the market is in the treatment or control group. The values vary across columns and different cutoff criteria. Taking the estimates in columns X and XI, panels A and B suggest there are on average about 1.25 fewer market makers in 1995 than in 1993. The value is 1.13 in panel C, 1.06 in panel D, and 0.81 in panel E.

As to the control variables, the signs are as expected. The associated coefficients of the three variables that measure trading activity in the markets: *vol* (average number of daily trading volumes), *numtrd* (average number of daily trades), and *tnover* (average turn over ratio), all have positive signs, when they enter the estimation equation separately (columns II, III, and IV). However, since they are highly correlated, the signs of the coefficients for *numtrd* turn negative and the magnitudes of the associated coefficients of *vol* become unreasonable (see column V), when all three variables enter the equation. Thus, I drop *numtrd* for the other regressions (columns VI to column XI). Taking the figures in columns X and XI, an increase in daily trading volume by a million shares would increase the number of market makers by 2.23 (see panel D) or 2.74 (see panel C), depending on the cutoff criteria. Note that, in general, an increase in trading volume raises the turnover ratio as well. Therefore, the effect of increasing average daily trading volume on market structure is reinforced by the increase in the average turnover ratio. The estimation results suggest that an increase of 1% in the turnover ratio would increase the number of market makers by 1.2 to 1.33.

The coefficients of the two variables that measure the information aspects of trading, *voltrd* (volume per trade) and *mcap* (market capitalization), are both negative. While the coefficients of the variable *voltrd* is insignificant when *voltrd* enters the equation alone (column VI) in panels A,

B, and C, they are significant at the 10% level in panels D and E. The coefficients of the variable *mcap* are significant at the 1% level across columns (columns VII to XI), and for all cutoff criteria (panels A to E). Although the values of the associated coefficients are small, these results imply that, *ceteris paribus*, market makers prefer small-sized trades with low values of market capitalization. The negatives signs are reasonable considering that information traders tend to trade larger amounts to take advantage of their information advantage, and higher values of market capitalization imply higher capital commitment in the issues that dealer firms market.

The coefficients of the variable measuring the size of the market, *shrout* (shares outstanding), are significant at the 1% significance level across columns (columns IX to XI), and across all cutoff criteria; however, the value is small. Since the unit of measure for *shrout* is thousands of shares, this suggests the partial effect of an additional public offering of 10 million shares would increase the number of market makers by two. By way of comparison, the average number of outstanding shares is about 13 million.

Finally, since the two variables used to measure the influence of volatility on market structure, *srssqr* (square root of the sum of squared returns) and *srssqrx* (square root of the sum of squared returns without dividends), are highly correlated, I add them to the estimation equation separately (column X and column XI). The coefficients of both variables are negative but insignificant.

Table 6 presents the estimation results using the pool of case OO and AA markets as the control group (second specification), and Table 7 presents the results using case OO markets as the control group (the third specification). These estimation results are essentially the same as the first specification, though there are some differences. First, the magnitudes of the net entry results are smaller in the second specification, and even smaller in the third specification. For the second specification, the effects of the change in the quoting convention results in net entry, ranging from 1.31 to 2.41 market makers, while it ranges from 0.63 to 2.35 for the third specification. Second, the magnitude of the time fixed effect is also smaller in the second and third specifications. Finally, the two control variables measuring the influence of volatility on market structure, *srssqr* and *srssqrx* are negative as above, but significant at the 1% level.

5.3 Correction for Selection Bias

It is useful to write down the panel fixed effect estimation equation (1) in another format. Since there are only two periods (before and after the media blitz) one can difference (1) across time

periods, and derive the following differenced equation:

$$\Delta y_i = \phi + \gamma T_i + \Delta \mathbf{x}_{it} \boldsymbol{\beta} + \varepsilon_i; \quad i = 1, 2, \dots, N; \quad (2)$$

where: $\Delta y_i \equiv y_{it} - y_{it-1}$; $\phi \equiv \theta_t - \theta_{t-1}$; $\Delta \mathbf{x}_{it} \equiv \mathbf{x}_{it} - \mathbf{x}_{it-1}$; and $\varepsilon_i \equiv u_{it} - u_{it-1}$. Note that $T_i \equiv \Delta T_i \equiv T_{it} - T_{it-1} = T_{it}$ for all i , and (2) is a single cross section estimation equation. If market makers “choose” to switch the quoting convention, the selection problem arises as T_i maybe correlated with the unobservable ε_i . I use several estimation techniques to deal with this concern.

One way to correct for selection bias in (2) is to use the ignorability of treatment assumption of Rosenbaum and Rubin (1983). Loosely, the idea is to control for observables (contained in $\Delta \mathbf{x}$), hoping that T_i is uncorrelated with the unobservables conditional on $\Delta \mathbf{x}$.²⁰ As suggested in Wooldridge (2002), I first use a linear control function to correct for bias caused by the selection on observables. The estimation equation with a linear control function is as follows:

$$\Delta y_i = \alpha + \gamma T_i + \Delta \mathbf{x}_i \boldsymbol{\beta} + T_i \cdot (\Delta \mathbf{x}_i - \overline{\Delta \mathbf{x}_i}) \boldsymbol{\theta} + \mathbf{v}_i; \quad i = 1, 2, \dots, N. \quad (3)$$

Given the availability of one or more instrumental variables, another way to correct for the selection bias in (2) is to use instrumental variables to predict treatment partialing out other control variables. Loosely, an instrumental variable has to be uncorrelated with the unobservable u_i , but correlated with treatment T_i once the other control variables ($\Delta \mathbf{x}_i$) have been netted out. The IV estimation result of the treatment coefficient is essentially the local average treatment effect (LATE) estimator defined in Imbens and Angrist (1994).

Where can one find such an instrument? Define a variable z_i as follows:

$$z_i = \begin{cases} 0, & \text{if } i \text{ is one of the case AA markets;} \\ 1, & \text{if } i \text{ is one of the case OO or OA markets.} \end{cases}$$

In others words, here I use the practice of odd-eighth practice before the media blitz as an instrument to predict the switch of quoting convention. For markets that suffered the media blitz $z_i = 1$, and $z_i = 0$ for those ones that did not. It is obvious that z_i is correlated with the treatment. The question is whether z_i is uncorrelated with the unobservables. For z_i to be a valid instrument, controlling for the observables, the practice of odd-eighth avoidance before the media blitz has to be as if it were

²⁰The exact expression of the ignorability of treatment assumption of Rosenbaum and Rubin (1983) requires a counterfactual framework that would complicate the discussion. See Wooldridge (2002) for a rigorous discussion.

randomly decided. The study of Christie and Schultz (1994) justifies my choice of the instrument as they found no variables that can account for the difference in quoting conventions.²¹

More recent studies use propensity scores to correct for selection on observables. Define the propensity score as:

$$p(\Delta x) = \Pr.\{T = 1 | \Delta x\}$$

which is the probability of switching (receiving the treatment) given the observables (contained in $\Delta \mathbf{x}$). The idea of propensity score matching is to construct the control group from agents that do not receive the treatment but have the same propensity scores as the treatment group. Ideally, the control of the propensity scores would eliminate selection bias and approximate a randomized experiment.

The average treatment effect of propensity score matching estimation is through the following thought experiment. Suppose one chooses a propensity score at random from the population. Then select two agents from the population sharing the chosen propensity score, where one receives treatment and the other does not. Under the ignorability of treatment assumption, the difference of the outcome is the treatment effect conditional on the chosen propensity score. Averaging across the distribution of propensity scores gives the average treatment effect.

Typically, empirical implementation requires estimating the propensity scores, estimating the differences in the outcomes for pairs matched on the basis of the estimated propensity scores, and then averaging over all such pairs. For my purpose, the estimated propensity scores are used to construct treatment-control matches for the estimation of the differenced equation (2). In particular, I use a 5 to 1 digit match (greedy match) on the probit estimation of the propensity score $\Pr.\{T = 1 | \Delta \mathbf{x}\} = \Pr.\{T^* > 0 | \Delta \mathbf{x}\}$, where:²²

$$\begin{cases} T^* = \eta + \Delta \mathbf{x} \boldsymbol{\psi} + \nu, \\ T = 1[T^* \geq 0]. \end{cases}$$

Denote the estimated propensity score as $\hat{p}_i \equiv \Pr.\{\hat{\eta} + \Delta \mathbf{x}_i \hat{\boldsymbol{\psi}} + \nu_i > 0 | \Delta \mathbf{x}_i\}$. Note that one can also perform the IV estimation using matched samples.

There are two other estimation methods using the estimated propensity scores without matching.

²¹For a direct analogy to the program participation problem, one may want to consider z_i as the randomized eligibility of treatment, while T_i is the actual participation.

²²For more information about the greedy matching algorithm that I use here, see Parsons (2000, 2001).

Wooldridge (1999) shows that under certain conditions, OLS regression of the equation:²³

$$\Delta y_i = \alpha + \gamma T_i + \delta \widehat{p}_i + u_i; \quad i = 1, 2, \dots, N, \quad (4)$$

yields a consistent estimator of the average treatment effect. Rosenbaum and Rubin (1983) suggest a more general format based on the following equation:

$$\Delta y_i = \alpha + \gamma T_i + \delta_1 \widehat{p}_i + \delta_2 T_i \cdot (\widehat{p}_i - \overline{\widehat{p}}_i) + u_i; \quad i = 1, 2, \dots, N. \quad (5)$$

For conditions under which OLS results of (4) and (5) consistently estimate the average treatment effect, see Wooldridge (2002).

As in the fixed effect panel regression analyses above, three different control groups are considered for each of the following estimation methods: linear control function estimation (LCFE), propensity score matching estimation (PSME), and other estimation methods with estimated propensity scores (OPSE). Note that the instrumental variable z_i that I proposed previously is available only when the control group is the pool of case OO and AA markets. In the following, I only report the estimated coefficient for the treatment effect. Complete estimation results are available on request.

There are three panels in Table 8 for the three control group specifications, and five columns with each column presenting the estimated average treat effects of one of the above estimation methods. The figures on the first column are the fixed effect panel estimations of the coefficient $\widehat{\gamma}$ (FEPE), taking from column X 's of Table 5, 6, and 7. The second column presents the LCFE results. The third column presents the PSME results. The fourth column presents the estimation results of equation (4). Finally, the fifth column presents the estimation results of equation (5).

It is evident from Table 8 that the net entry result that I derived from the fixed effect panel estimations is *robust and significant* at the 1% level (except for a few cases in panel C where the case OO markets are taken as the control group). Moreover, within each panel for the same cutoff, there is little variation in the magnitudes of the average treatment effect across estimation methods (read the figures row by row). For example, the average treatment effect in row 1 of panel A (25% cutoff with case AA makers as the control group) is between 2.39 and 2.45 market makers. In general, when the case AA markets are taken as the control group and the cutoff is at least 10%, there is an average net entry of at least *two* market makers (from 2.15 to 2.56) for those markets that switched

²³Equations (4) and (5) can be views as the differenced equation (2) with \widehat{p}_i and $T_i \cdot (\widehat{p}_i - \overline{\widehat{p}}_i)$ as control functions.

their quoting convention from odd-eighth avoidance to the full spectrum. The figure is around 1.25 (from 0.95 to 1.59) when case OO and AA markets together are taken as the control group, while it is about 0.6 to 0.7 (from 0.47 to 1) when the case OO markets are taken as the control group.

The estimation results with the instrumental variable z_i involved are presented in Table 9. The first column shows the estimation results for the local average treatment effects (LATE). The correct interpretation of the estimators is that: they are the average net entry of market makers for markets that use the full spectrum of eighths if they were odd-eighth avoidance and switched their quoting convention to full spectrum. In other words, it is the average treatment effect for those who would be induced to switch by changing z from 0 to 1. The second (OPSE1IV) and third (OPSE2IV) show the IV versions of the other two methods using the estimated propensity scores (equations (4) and (5)). They are quite similar to LATE (the first column) for both the magnitudes and significance.

The “large” values (compared to what I have in Table 8) and monotonic decreasing trends of the first three columns require some explanations. For the former, based on the interpretation for the LATE estimators, these figures can be considered as evidence of excessive entries in the odd-eighth avoidance markets compared to markets quoting the full spectrum. Note that this is also an direct implication of the theory in Section 3. As to the latter, as one lowers the cutoff ratios of being odd-eighth avoidance, more markets are designated as odd-avoidance. This lowers the estimated effects.²⁴

In particular, ignoring $\Delta \mathbf{x}$ in equation (2), the LATE estimator $\hat{\gamma}_{LATE}$ can be expressed as:

$$\hat{\gamma}_{LATE} = \frac{\overline{\Delta y}_i(z_i = 1) - \overline{\Delta y}_i(z_i = 0)}{\overline{T}_i(z_i = 1) - \overline{T}_i(z_i = 0)}. \quad (6)$$

Note that $\overline{T}_i(z_i = 0) = 0$ in (6). Since $1/\overline{T}_i(z_i = 1)$ is about 5 to 6 for the 25% cutoff (see Table 1), it “blows” up $\hat{\gamma}_{LATE}$. As one lowers the cutoff, $1/\overline{T}_i(z_i = 1)$ decreases. As a matter of fact, the estimation results in column 4 (PSMEIV) of Table 9 use only matched treatment-control pairs. The IV estimation results of equation (2) are very close to the estimated average treatment effects in panel B of Table 8.

In summary, Tables 8 and 9 clearly demonstrate the change in the market structure for markets that went from largely quoting even-eighths to quoting the full spectrum. Moreover, this result is robust to various estimation methods. Surprisingly, the effect of the change in the quoting convention

²⁴See Heckman and Robb (1985), Bjorklund and Moffitt (1987), and Imbens and Angrist (1994) for discussions on marginal vs. average effects in the labor market studies.

(and thereby the compression of profit margins) was to *induce* net entry, instead of exit as the competitive theory suggests.

5.4 Explanation and Discussions

The observed net entry in markets where profit margins have fallen is puzzling. The competitive framework in Section 3 cannot account for net entry occurring in response to a compression of profit margins. A possible explanation is that there exists some market practice in Nasdaq markets, unobserved by econometricians, that can be used as a device for entry deterrence. To what extent the incumbent firms invest in entry deterrence depends on the size of the profit margins to be protected. Before the impact, in those high profit margin markets (most likely the odd-eighth avoidance ones), entry is successfully “blockaded” to preserve high profit margins. However, the drop in the profit margin reduces incumbent market makers’ incentive to invest in entry deterrence and this invites entry. But what is this potential avenue for deterring entry in Nasdaq?

Although market makers compete in bid and ask price pairs for order flows, it is not necessarily the case that the market maker with the highest (lowest) bid (ask) gets the sell (buy) orders. Orders in Nasdaq may not be routed according to strict price-time priority due to a common practice among market makers known as “preferencing”. By building up a relationship with order entry firms (or brokerage houses), market makers receive order flows through their proprietary network connections with order entry firms, rather than through neck-to-neck price competition with other market makers. After receiving a “preferenced” order, a market maker can either re-route it to other dealers or execute it at the best prices (the lowest bid or the higher ask), not necessarily its own bid and ask. This practice is called “preferencing”. In return for the routed orders, market makers reimburse order entry firms with cash or services.

Could this preferencing practice serves as an entry deterrence device? Certainly, few dealer firms would enter a market where most of the orders are preferred. Moreover, according to the above description, market makers’ ability to preference depends on the profitability. Thus, it is possible that the compression in profit margins limits (or eliminates) the use of preferencing. Without preferencing, given there are market making rents, dealer firms enter the markets.

Note also, the picture drawn above is also consistent with the collusion story. Before the impact, firms in the odd-eighth avoidance markets (tacitly or explicitly) collude to use only even eighth quotes and artificially maintain higher spreads than would otherwise be achievable. Furthermore,

entry barriers, perhaps preferencing, preserves cartel rents in these markets. Once the media exposes the collusive scheme and compresses spreads, investment in entry barriers falls which invites entry. The preferencing as an investment for entry barriers explanation conforms with the theoretical exploration of tacit collusion in dealer markets in Dutta and Madhavan (1997) and Parlour and Rajan (2003). In addition, it is in accordance with the microstructure literature (e.g., Huang and Stoll (1996) and Godek (1996)) that emphasizes the importance of institutional factors in explaining financial markets.

Although the above scenario seems plausible and theoretically justified, it is difficult to directly verify it due to the lack of data on preferencing. Nevertheless, evidence for this explanation as well as the equilibrium selection argument that I used for the markets that switched quoting convention can be found in the experimental study of Kluger and Wyatt (2002). In laboratory asset markets, Kluger and Wyatt (2002) find preferencing and internalization of order flows allow market makers to coordinate on less competitive equilibria. Furthermore, in their study, several markets indeed reached a collusive equilibrium with wide spreads and near 100% internalization of order flows.

Finally, most of the estimates for the control variables are qualitatively consistent with those reported in Wahal (1997) and Goldstein and Nelling (1999), except the signs associated with the time trend and market capitalization.²⁵ Nevertheless, the negative estimates for time trend and market capitalization are the same as in Weston (2000); however, he explains the negative time trend as evidence of net exits due to reforms that compressed profit margins in all the markets.

6 Concluding Remarks

The competitive theory suggests a decrease in the profit margin should, *ceteris paribus*, result in net exit from market making, while the main finding of the empirical analysis is just the contrary. I find that the compression of profit margins due to a switch in the quoting convention results in *net entry* of about one to two market makers, after controlling for the time fixed effect, trading activity, information-based trading, market size, volatility, and unobserved individual market effects. Moreover, the robustness and significance of this finding do not change as different estimation methods are employed to correct for possible self-selection bias of the estimated average treatment effect.

²⁵A direct comparison of the magnitudes of the estimates in this study with those in Wahal (1997) and Goldstein and Nelling (1999) is not available due to different setups (semi-log linear in the former and log-linear in the latter).

Another finding that is not mentioned in other studies is that Nasdaq market makers practice odd-eighth avoidance in the vast majority of markets during the time period of the study. After the media coverage of the collusion story, while some markets switch from avoiding odd-eighth quotes to using the full spectrum of eighths, most odd-eighth avoidance markets remain odd-eighth as such. Hence, across markets, Nasdaq dealer firms *do not* change their quoting conventions *en masse*. Nevertheless, for markets that do switch, there is indeed a substantial compression in the spread.

This paper points out several directions for further research. First, this study is another call for theoretical developments on equilibrium selection. It is rare, in both theory and practice, to have markets with an unique equilibrium. In cases of multiple equilibria, theories are often silent as to the questions of how the equilibrium is achieved, at which equilibrium that the market clears, and why. The importance of equilibrium selection study can be seen from the simple model in Section 3 where it demonstrates that the avoidance of using odd-eighth quotes can be non-collusive and consistent with competitive equilibria. However, without a theory of equilibrium selection, collusion is suspected. Second, an increasing number of studies emphasize the importance of the ability for market makers to access order flows in competitive markets. Nevertheless, certain market practices such as preferencing or internalization, create obstacles to access. With data availability, one can study the roles played by such practices in the determination of market structure and their welfare implications.

References

- [1] Angel, James J., "Tick Size, Share Prices, and Stock Splits", *Journal of Finance*, 52 (1997), 655-81.
- [2] Barclay, Michael J., "Bid-Ask Spreads and the Avoidance of Odd-Eighth Quotes on Nasdaq: An Examination of Exchange Listings", *Journal of Financial Economics*, 45 (1997), 35-60.
- [3] Barclay, Michael J., Eugene Kandel, and Leslie M. Marx, "The Effects of Transaction Costs on Stock Prices and Trading Volume", *Journal of Financial Intermediation*, 7 (1998), 130-50.
- [4] Bjorklund, Anders and Robert A. Moffitt, "The Estimation of Wage Gains and Welfare Gains in Self-Selection Models", *Review of Economics and Statistics*, 69 (1987), 42-49.
- [5] Bloomfield, Robert and Maureen O'Hara, "Does Order Preferencing Matter?", *Journal of Financial Economics*, 50 (1998), 3-37.
- [6] Christie, William G., Jeffrey H. Harris, and Paul H. Schultz, "Why Did NASDAQ Market Makers Stop Avoiding Odd-Eighth Quotes?", *Journal of Finance*, 49 (1994), 1841-60.
- [7] Christie, William G. and Paul H. Schultz, 1999, "The Initiation and Withdrawal of Odd-Eighth Quotes among Nasdaq Stocks: An Empirical Analysis", *Journal of Financial Economics*, 52 (1999), 409-42.
- [8] Christie, William G. and Paul H. Schultz, "Did Nasdaq Market Makers Implicitly Collude?", *Journal of Economic Perspective*, 9 (1995), 199-208.
- [9] Christie, William G. and Paul H. Schultz, "Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes?", *Journal of Finance*, 49 (1994), 1813-40.
- [10] Dalton, John M., *How the Stock Market Works*, New York Institute of Finance, 1988.
- [11] Demsetz, Harold, "Limit Orders and the Alleged Nasdaq Collusion", *Journal of Financial Economics*, 45 (1997), 91-95.
- [12] Dutta, Prajit K. and Ananth Madhavan, "Competition and Collusion in Dealer Markets", *Journal of Finance*, 52 (1997), 245-76.
- [13] Dyl, Edward A., H. Douglas Witte, and Larry R. Gorman, "Tick Sizes, Stock Prices, and Share Turnover: International Evidence", *Studies in Economics and Finance*, 20 (2002), 1-18.
- [14] Easley, David and Maureen O'Hara, "Price, Trade Size, and Information in Securities Markets", *Journal of Financial Economics*, 19 (1987), 69-90.
- [15] Godek, Paul E., "Why Nasdaq Market Makers Avoid Odd-Eighth Quotes", *Journal of Financial Economics*, 41 (1996), 465-74.
- [16] Goldstein, Michael A. and Edward F. Nelling, "Market Making and Trading in Nasdaq Stocks", *Financial Review*, 34 (1999), 27-44.

- [17] Grossman, Sanford J., Merton H. Miller, Kenneth R. Cone, Daniel R. Fischel, and David J. Ross, "Clustering and Competition in Asset Markets", *Journal of Law and Economics*, 40 (1997), 23-60.
- [18] Harris, Lawrence, "Stock Price Clustering and Discreteness", *Review of Financial Studies*, 4 (1991), 389-415.
- [19] Heckman, James J., Hidehiko Ichimura, Jeffrey A. Smith, and Petra Todd, "Characterizing Selection Bias Using Experimental Data", *Econometrica*, 66 (1998), 1017-98.
- [20] Heckman, James J. and Richard Robb, Jr., "Alternative Methods for Evaluating the Impact of Interventions", in: *Longitudinal Analysis of Labor Market Data*, Econometric Society Monographs series no. 10, edited by Heckman, James J. and Burton Singer, Cambridge University Press (1985), 156-245.
- [21] Heckman, James T. and Jeffrey A. Smith, "Assessing the Case for Social Experiments", *Journal of Economic Perspectives*, 9 (1995), 85-110.
- [22] Huang, Roger D. and Hans R. Stoll, "Dealer versus Auction Markets: A Paired Comparison of Execution Costs on NASDAQ and the NYSE", *Journal of Financial Economics*, 41 (1996), 313-57.
- [23] Imbens, Guido W. and Joshua D. Angrist, "Identification and Estimation of Local Average Treatment Effects", *Econometrica*, 62 (1994), 467-75.
- [24] Kandel, Eugene and Leslie M. Marx, "Payments for Order Flow on Nasdaq", *Journal of Finance*, 54 (1999), 35-66.
- [25] Kandel, Eugene and Leslie M. Marx, "Nasdaq Market Structure and Spread Patterns", *Journal of Financial Economics*, 45 (1997), 61-89.
- [26] Klock, Mark and Timothy D. McCormick, "The Impact of Market Maker Competition on Nasdaq Spreads", *Financial Review*, 34 (1999), 55-73.
- [27] Kluger, Brian D. and Steve B. Wyatt, "Preferencing, Internalization of Order Flow, and Tacit Collusion: Evidence from Experiments", *Journal of Financial and quantitative Analysis*, 37 (2002), 449-69.
- [28] Meyer, Bruce D., "Natural and Quasi-experiments in Economics", *Journal of Business and Economic Statistics*, 13 (1995), 151-61.
- [29] Parlour, Christine A. and Uday Rajan, "Payment for Order Flow", *Journal of Financial Economics*, 68 (2003), 379-411.
- [30] Parsons, Lori S., "Reducing Bias in a Propensity Score Matched-Pair Sample Using Greedy Matching Techniques", *Proceedings of the Twenty-Sixth Annual SAS Users Group International Conference*, paper 214-26, 2001.

- [31] Parsons, Lori S., "Using SAS Software to Perform a Case-Control Match on Propensity Score in an Observational Study", *Proceedings of the Twenty-Fifth Annual SAS Users Group International Conference*, paper 261-25, 2000.
- [32] Rosenbaum, Paul R. and Donald B. Rubin, "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 70 (1983), 944-61.
- [33] Smith, Jeffrey W., James P. Selway III, and D. Timothy McCormick, "The Nasdaq Stock Market: Historical Background and Current Operation", *National Association of Security Dealers Working Paper*, 98-01, 1998.
- [34] Wahal, Sunil, "Entry, Exit, Market Makers, and the Bid-Ask Spread", *Review of Financial Studies*, 10 (1997), 871-901.
- [35] Weston, James P., "Competition on the Nasdaq and the Impact of Recent Market Reforms", *Journal of Finance*, 55 (2000), 2565-98.
- [36] Woodward, Susan E., "Price Fixing at Nasdaq? A Reconsideration of the Evidence", Paper prepared for Congressional Budget Office, Contract No. 96-0228, 1996.
- [37] Wooldridge, Jeffrey M., *Econometric Analysis of Cross Section and Panel Data*, Cambridge and London: MIT Press, 2002.
- [38] Wooldridge, Jeffrey M., "Estimating Average Partial Effects under Conditional Moment Independence Assumptions", mimeo, Department of Economics, Michigan State University, 1999.

Table 1. Numbers of Markets

	Cutoff Point: 25%		Cutoff Point: 20%		Cutoff Point: 15%		Cutoff Point: 10%		Cutoff Point: 5%	
	Number of Issues	%	Number of Issues	%	Number of Issues	%	Number of Issues	%	Number of Issues	%
Case OO	1,532	71.12	1,459	67.73	1,368	63.51	1,255	58.26	987	45.82
Case OA	291	13.51	338	15.69	388	18.01	464	21.54	645	29.94
Case AA	298	13.83	320	14.86	350	16.25	382	17.73	463	21.49
Case AO	33	1.53	37	1.72	48	2.23	53	2.46	59	2.74
Total	2,154	100	2,154	100	2,154	100	2,154	100	2,154	100

Note: Samples consist of all tick size \$1/8 Nasdaq common or capital stocks with quote data before and after the impact (total markets: 2,154). The sample period is from the first business day in 1993 to the last business day in 1995 (757 trading days). In Case OO markets, dealer firms avoid odd-eighth quotes consistently (both before and after the impact). In Case OA markets, dealer firms change their quoting patterns from odd-eighth avoidance before the impact to the use of the full spectrum of eighths after the impact. In Case AA, market makers uses all-eighth quotes consistently. In Case AO, market makers change their quoting patterns from the use of the full spectrum of eighths to odd-eighth avoidance.

Table 2. Variable Definitions

Dependent Variable:

Label	Description
<i>mmcnt</i>	number of market makers

The Variable of Interest:

Label	Description	Unit
<i>treat</i>	treatment variable	-
<i>twavgs</i>	time-weighted average absolute spread	\$
<i>twavgrs</i>	time-weighted average relative spread	%

Control Variables:

Label	Description	Unit
<i>vol</i>	trading volume	-
<i>numtrd</i>	number of trades	-
<i>tnover</i>	turnover ratio	-
<i>voltrd</i>	volume per trade; trade size	-
<i>mcap</i>	market capitalization	\$1,000
<i>shrout</i>	shares outstanding	1,000
<i>srssqr</i>	square root of the sum of squared returns	\$
<i>srssqrx</i>	square root of the sum of squared returns without dividends	\$
<i>aret</i>	Absolute value of returns	\$
<i>aretx</i>	Absolute value of returns without dividends (capital gains)	\$

Note 1.: All variables, except the two square roots of the sum of squared returns (*srssqr* and *srssqrx*) for the three-year panel, are daily time series data. The intraday quote data from the NYSE TAQ Database are degenerated to daily time weighted averages. Non-time series data from the CRSP Database is mapped to time series data according to the associated effective day and end day. For the three-year panel, all variables, except the two square root of the sum of squared returns, are average daily values. The square roots of sum of squared returns (*srssqr*) and returns without dividends (*srssqrx*) are calculated year by year.

Note 2.: Time weighted average absolute spread (*twavgs*) is the average absolute spread weighted by the associate time that a spread is active during a day. Time weighted average relative spreads (*twavgrs*) is the average relative spread weighted by the associate time that a spread is active during a day. The turnover ratio (*tnover*) is defined as trading volume (*vol*) divided by total shares outstanding (*shrout*). Trade size (*voltrd*) is defined as trading volume (*vol*) divided by the number of trades (*numtrd*); if the number of trades is 0 then it is set to 0.

Table 3. Summary Statistics: Daily Data

Variable	# Obs.	Mean	Std. Dev.
<i>mmcmt</i>	1,205,099	11.55	8.29
<i>vol</i>	1,204,446	106,834.09	416,358.86
<i>numtrd</i>	1,203,983	64.57	255.95
<i>tlover</i>	1,187,827	0.006	0.012
<i>voltrd</i>	1,203,983	1,386.80	2,928.39
<i>mcap</i>	1,189,231	374,717.20	1,459,640.25
<i>shrout</i>	1,189,231	13,405.87	29,018.96
<i>aret</i>	1,203,936	0.020	0.022
<i>aretx</i>	1,203,936	0.020	0.022
<i>twavgp</i>	1,205,877	22.38	12.90
<i>twavgs</i>	1,205,877	0.78	0.91
<i>twavgrs</i>	1,205,877	3.87	3.07

Table 4. Summary Statistics by Cases (Cutoff: 25%)

Year: 1993									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	9.01	4.98	15.72	8.65	20.28	10.22	12.07	4.51	
<i>vol</i>	48398.45	85977.48	195927.92	389222.56	234697.83	374502.72	75138.46	75403.24	
<i>numtrd</i>	27.26	50.30	116.50	260.30	123.70	194.83	37.13	39.08	
<i>tnover</i>	0.005	0.006	0.009	0.007	0.010	0.008	0.007	0.004	
<i>voltrd</i>	1352.82	839.49	1823.12	919.27	1969.15	1645.01	1710.83	730.55	
<i>mcap</i>	190070.26	342421.77	579641.62	2174112.47	487150.26	1183140.97	174876.73	183192.37	
<i>shrout</i>	7522.48	8549.14	17763.97	30576.02	22922.34	37848.41	8900.97	7457.40	
<i>srssqr</i>	0.415	0.158	0.413	0.174	0.330	0.168	0.328	0.168	
<i>srssqrx</i>	0.414	0.158	0.413	0.174	0.330	0.168	0.328	0.168	
<i>twavgp</i>	21.20	11.24	20.46	11.54	16.31	7.38	16.83	6.56	
<i>twavgs</i>	0.93	0.83	0.52	0.14	0.30	0.08	0.45	0.30	
<i>twavgrs</i>	4.79	3.12	3.15	1.38	2.10	0.85	3.10	2.33	
Year: 1994									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	9.08	5.14	17.27	10.10	19.66	10.24	10.81	5.16	
<i>vol</i>	45717.62	100506.11	220928.66	501749.22	215685.86	395835.43	70328.02	106241.13	
<i>numtrd</i>	27.07	63.82	124.74	288.15	120.32	219.41	36.90	59.92	
<i>tnover</i>	0.004	0.005	0.009	0.007	0.009	0.008	0.006	0.005	
<i>voltrd</i>	1316.77	817.64	1822.31	700.09	1857.77	903.16	1935.43	1218.53	
<i>mcap</i>	206805.09	373550.79	635972.77	2550676.20	508618.26	1169759.30	202789.44	237790.36	
<i>shrout</i>	8337.87	9629.09	22687.64	44268.63	25323.84	46212.06	9434.02	7890.41	
<i>srssqr</i>	0.435	0.137	0.390	0.154	0.343	0.135	0.362	0.152	
<i>srssqrx</i>	0.435	0.137	0.390	0.154	0.343	0.135	0.362	0.152	
<i>twavgp</i>	21.30	11.94	17.84	8.66	16.50	6.65	17.97	7.32	
<i>twavgs</i>	0.90	0.84	0.44	0.14	0.29	0.07	0.50	0.22	
<i>twavgrs</i>	4.64	2.85	2.96	1.34	1.98	0.80	3.21	1.72	
Year: 1995									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	9.10	5.34	17.37	9.26	19.08	10.52	10.06	5.72	
<i>vol</i>	62275.53	149340.08	299339.88	727917.87	279844.35	535737.90	108207.84	191228.78	
<i>numtrd</i>	40.65	102.42	202.56	557.25	173.42	333.45	69.14	136.81	
<i>tnover</i>	0.005	0.006	0.011	0.009	0.010	0.009	0.008	0.008	
<i>voltrd</i>	1202.83	726.67	1589.51	537.91	1713.19	745.76	1698.77	873.15	
<i>mcap</i>	266884.09	489873.93	860438.07	4246895.76	664152.55	1482020.76	293242.38	426233.24	
<i>shrout</i>	9470.85	10694.82	25382.44	58482.09	28349.02	51923.06	10931.61	9337.27	
<i>srssqr</i>	0.396	0.157	0.384	0.168	0.353	0.169	0.408	0.123	
<i>srssqrx</i>	0.396	0.157	0.384	0.168	0.353	0.169	0.408	0.123	
<i>twavgp</i>	23.37	14.09	18.43	10.46	19.44	9.21	21.79	11.21	
<i>twavgs</i>	0.85	1.07	0.31	0.12	0.29	0.11	0.59	0.28	
<i>twavgrs</i>	4.14	2.86	2.11	1.13	1.80	0.90	3.34	1.87	

Table 4. Summary Statistics by Cases (Cutoff: 10%) (end)

Year: 1993									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	8.54	4.55	13.65	8.03	18.96	9.97	10.47	4.57	
<i>vol</i>	41988.01	68605.99	149602.14	324473.31	206131.88	342250.53	57690.85	69499.52	
<i>numtrd</i>	23.82	41.17	88.54	214.43	108.40	178.48	27.64	32.96	
<i>tlover</i>	0.004	0.006	0.008	0.007	0.010	0.008	0.006	0.004	
<i>voltrd</i>	1301.92	837.85	1701.03	799.00	1934.51	1550.79	1661.62	1058.68	
<i>mcap</i>	183008.63	334399.27	460499.77	1739651.93	419198.64	1062086.53	116237.52	141017.12	
<i>shrout</i>	7135.99	7960.12	14836.37	25465.29	20043.23	34256.12	6182.93	4936.38	
<i>srssqr</i>	0.417	0.159	0.421	0.160	0.334	0.173	0.317	0.147	
<i>srssqrx</i>	0.417	0.159	0.421	0.160	0.334	0.173	0.317	0.147	
<i>twavgp</i>	21.72	11.70	20.55	10.67	16.12	7.03	15.40	5.51	
<i>twavgs</i>	1.00	0.89	0.59	0.27	0.33	0.12	0.51	0.23	
<i>twavgrs</i>	4.99	3.31	3.47	1.64	2.36	1.09	3.72	2.08	
Year: 1994									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	8.57	4.72	14.79	9.24	18.29	9.94	9.51	4.11	
<i>vol</i>	38977.65	75137.51	169074.24	416098.22	182551.14	356717.56	46657.56	83042.56	
<i>numtrd</i>	23.25	48.39	95.81	241.04	102.32	198.11	25.61	46.17	
<i>tlover</i>	0.004	0.005	0.008	0.007	0.008	0.008	0.005	0.004	
<i>voltrd</i>	1267.15	821.48	1703.21	733.54	1841.94	897.45	1491.60	944.53	
<i>mcap</i>	198862.90	354714.75	504723.29	2013780.82	433752.55	1047306.11	133621.96	191065.95	
<i>shrout</i>	7839.96	8378.83	18421.47	36191.84	21990.95	41545.42	6560.06	5668.66	
<i>srssqr</i>	0.435	0.136	0.420	0.152	0.347	0.138	0.406	0.136	
<i>srssqrx</i>	0.435	0.136	0.420	0.152	0.347	0.138	0.406	0.136	
<i>twavgp</i>	21.91	12.37	18.95	9.48	16.15	6.45	16.55	6.37	
<i>twavgs</i>	0.96	0.90	0.54	0.23	0.32	0.11	0.61	0.24	
<i>twavgrs</i>	4.80	2.99	3.38	1.76	2.26	1.07	4.13	1.94	
Year: 1995									
	Case OO		Case OA		Case AA		Case AO		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
<i>mmcnt</i>	8.46	4.82	15.49	8.71	17.77	10.14	8.68	4.61	
<i>vol</i>	51930.10	109375.14	233694.22	607414.42	242632.81	488977.69	65738.58	150292.90	
<i>numtrd</i>	34.47	76.36	155.46	459.71	150.65	304.84	43.96	107.21	
<i>tlover</i>	0.004	0.005	0.010	0.009	0.010	0.009	0.006	0.006	
<i>voltrd</i>	1151.31	711.83	1531.20	629.96	1698.92	745.62	1298.70	811.86	
<i>mcap</i>	259477.95	456452.17	674014.04	3376182.28	567838.96	1341516.23	211751.68	374415.98	
<i>shrout</i>	8931.45	9760.80	20885.43	47320.11	24778.31	47135.26	7358.66	7090.39	
<i>srssqr</i>	0.398	0.153	0.389	0.171	0.354	0.164	0.427	0.175	
<i>srssqrx</i>	0.397	0.153	0.389	0.171	0.354	0.164	0.427	0.175	
<i>twavgp</i>	24.26	14.49	19.40	11.47	18.66	8.68	20.62	10.83	
<i>twavgs</i>	0.92	1.17	0.38	0.15	0.31	0.13	0.69	0.37	
<i>twavgrs</i>	4.34	3.01	2.49	1.37	2.02	1.09	4.15	2.95	

Table 5. Fixed Effect Panel Regression Results: Case OA vs. Case AA

	A. 25% Cutoff Point (cross section sample size: 579 markets)										
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.2954 (0.3698)	0.5520 (0.3658)	0.4827 (0.3719)	0.3836 (0.3662)	0.4861 (0.3551)	0.6906* (0.3701)	0.7385** (0.3543)	0.8355** (0.3584)	1.2562*** (0.3354)	1.2485*** (0.3356)	1.2486*** (0.3356)
<i>treat</i>	2.6794*** (0.5110)	2.5255*** (0.5008)	2.6058*** (0.5071)	2.5068*** (0.5112)	2.3438*** (0.4889)	2.4570*** (0.5035)	2.5003*** (0.4874)	2.5132*** (0.4865)	2.4455*** (0.4506)	2.3904*** (0.4549)	2.3904*** (0.4549)
<i>vol</i>	-	3.2860*** (0.7020)	-	-	16.1979*** (2.5501)	2.8241*** (0.7300)	7.9085*** (1.1443)	8.0155*** (1.1438)	2.4166* (1.2401)	2.4158* (1.2404)	2.4158* (1.2404)
<i>numtrd</i>	-	-	0.0026*** (0.0009)	-	-0.0167*** (0.0030)	-	-	-	-	-	-
<i>mover</i>	-	-	-	1.3766*** (0.3249)	0.7506** (0.3269)	1.0496*** (0.3337)	0.3216 (0.3450)	0.3460 (0.3447)	1.2592*** (0.3361)	1.3291*** (0.3451)	1.3292*** (0.3451)
<i>voltrd</i>	-	-	-	-	-0.0003 (0.0002)	-	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0004** (0.0002)	-0.0004** (0.0002)	-0.0004** (0.0002)
<i>mcap</i>	-	-	-	-	-	-	-0.0013*** (0.0002)	-0.0013*** (0.0002)	-0.0028*** (0.0003)	-0.0028*** (0.0003)	-0.0028*** (0.0003)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002*** (1.9E-05)	0.0002*** (1.9E-05)	0.0002*** (1.9E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.0141 (1.1347)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.0140 (1.1346)

	B. 20% Cutoff Point (cross section sample size: 647 markets)										
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.3080 (0.3543)	0.5613 (0.3501)	0.5023 (0.3557)	0.3782 (0.3510)	0.4848 (0.3417)	0.6930* (0.3539)	0.7353** (0.3391)	0.8354** (0.3425)	1.2621*** (0.3210)	1.2554*** (0.3206)	1.2555*** (0.3206)
<i>treat</i>	2.6253*** (0.4755)	2.4924*** (0.4656)	2.5633*** (0.4712)	2.4370*** (0.4766)	2.3038*** (0.4576)	2.4214*** (0.4689)	2.4762*** (0.4539)	2.4994*** (0.4530)	2.4557*** (0.4199)	2.3724*** (0.4229)	2.3723*** (0.4229)
<i>vol</i>	-	3.3683*** (0.6762)	-	-	15.4358*** (2.4581)	2.8900*** (0.7031)	8.0668*** (1.0995)	8.1549*** (1.0979)	2.5900** (1.1872)	2.5800** (1.1856)	2.5801** (1.1856)
<i>numtrd</i>	-	-	0.0028*** (0.0008)	-	-0.0156*** (0.0029)	-	-	-	-	-	-
<i>mover</i>	-	-	-	1.3409*** (0.3025)	0.7759** (0.3049)	1.0216*** (0.3108)	0.2973 (0.3211)	0.3298 (0.3208)	1.2066*** (0.3126)	1.3120*** (0.3197)	1.3121*** (0.3198)
<i>voltrd</i>	-	-	-	-	-0.0003 (0.0002)	-	-	-0.0003* (0.0002)	-0.0004** (0.0002)	-0.0004** (0.0002)	-0.0004** (0.0002)
<i>mcap</i>	-	-	-	-	-	-	-0.0014*** (0.0002)	-0.0014*** (0.0002)	-0.0028*** (0.0003)	-0.0028*** (0.0003)	-0.0028*** (0.0003)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002*** (1.9E-05)	0.0002*** (1.9E-05)	0.0002*** (1.9E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.5687 (1.0302)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.5687 (1.0301)

Table 5. Fixed Effect Panel Regression Results: Case OA vs. Case AA (continue)

	C. 15% Cutoff Point (cross section sample size: 726 markets)										
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.2399 (0.3309)	0.4789 (0.3265)	0.4253 (0.3318)	0.3060 (0.3285)	0.4084 (0.3195)	0.6000 (0.3308)	0.6493 (0.3172)	0.7359 (0.3202)	1.1466 (0.3012)	1.1331 (0.3011)	1.1331 (0.3011)
<i>treat</i>	2.6818 *** (0.4393)	2.5371 *** (0.4301)	2.6197 *** (0.4353)	2.4492 *** (0.4401)	2.3061 *** (0.4226)	2.4379 *** (0.4332)	2.4907 *** (0.4192)	2.5091 *** (0.4185)	2.4739 *** (0.3895)	2.3939 *** (0.3931)	2.3939 *** (0.3931)
<i>vol</i>	-	3.4766 *** (0.6534)	-	-	15.7249 *** (2.3567)	2.9383 *** (0.6817)	8.2192 *** (1.0617)	8.2955 *** (1.0604)	2.7429 *** (1.1508)	2.7372 *** (1.1497)	2.7372 *** (1.1497)
<i>numtrd</i>	-	-	0.0029 *** (0.0008)	-	-0.0159 *** (0.0028)	-	-	-	-	-	-
<i>trmover</i>	-	-	-	1.3305 *** (0.2701)	0.7685 (0.2737)	1.0091 *** (0.2789)	0.2963 (0.2897)	0.3244 (0.2895)	1.1554 *** (0.2836)	1.2390 *** (0.2893)	1.2391 *** (0.2893)
<i>voltrd</i>	-	-	-	-	-	-0.0003 (0.0002)	-	-0.0003 (0.0002)	-0.0004 (0.0002)	-0.0004 (0.0002)	-0.0004 (0.0002)
<i>mcap</i>	-	-	-	-	-	-	-0.0014 *** (0.0002)	-0.0014 *** (0.0002)	-0.0029 *** (0.0003)	-0.0029 *** (0.0003)	-0.0029 *** (0.0003)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002 *** (1.8E-05)	0.0002 *** (1.8E-05)	0.0002 *** (1.8E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.3529 (0.9438)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.3542 (0.9438)

	D. 10% Cutoff Point (cross section sample size: 833 markets)										
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.1857 (0.3079)	0.4007 (0.3040)	0.3617 (0.3083)	0.2663 (0.3057)	0.3399 (0.2997)	0.5295 (0.3081)	0.5425 (0.2972)	0.6287 (0.3001)	1.0722 (0.2817)	1.0570 (0.2808)	1.0570 (0.2808)
<i>treat</i>	2.3540 *** (0.4000)	2.2497 *** (0.3922)	2.3128 *** (0.3962)	2.1987 *** (0.3996)	2.0801 *** (0.3872)	2.2036 *** (0.3942)	2.2446 *** (0.3841)	2.2696 *** (0.3835)	2.2493 *** (0.3558)	2.1488 *** (0.3570)	2.1488 *** (0.3570)
<i>vol</i>	-	3.3019 *** (0.6073)	-	-	14.0344 *** (2.2533)	2.7156 *** (0.6371)	7.4272 *** (0.9921)	7.4863 *** (0.9907)	2.2415 (1.0509)	2.2295 (1.0471)	2.2297 (1.0471)
<i>numtrd</i>	-	-	0.0029 *** (0.0008)	-	-0.0142 *** (0.0027)	-	-	-	-	-	-
<i>trmover</i>	-	-	-	1.2979 *** (0.2488)	0.7609 *** (0.2561)	0.9937 *** (0.2588)	0.3529 (0.2703)	0.3856 (0.2703)	1.1999 *** (0.2630)	1.3222 *** (0.2670)	1.3223 *** (0.2670)
<i>voltrd</i>	-	-	-	-	-	-0.0003 (0.0002)	-	-0.0003 (0.0002)	-0.0004 (0.0002)	-0.0004 (0.0002)	-0.0004 (0.0002)
<i>mcap</i>	-	-	-	-	-	-	-0.0013 *** (0.0002)	-0.0013 *** (0.0002)	-0.0029 *** (0.0002)	-0.0029 *** (0.0002)	-0.0029 *** (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002 *** (1.7E-05)	0.0002 *** (1.7E-05)	0.0002 *** (1.7E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-2.0190 (0.8450)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-2.0205 (0.8450)

Table 5. Fixed Effect Panel Regression Results: Case AO vs. Case AA (end)

	E: 5% Cutoff Point (cross section sample size: 1,093 markets)										
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.0361 (0.2554)	0.2487 (0.2515)	0.2115 (0.2552)	0.1139 (0.2537)	0.2011 (0.2476)	0.3623 (0.2545)	0.3764 (0.2456)	0.4450 (0.2478)	0.8373 (0.2334)	0.8132 (0.2328)	0.8132 (0.2328)
<i>treat</i>	1.7893 (0.3223)	1.7377 (0.3147)	1.7750 (0.3185)	1.7412 (0.3206)	1.6622 (0.3096)	1.7624 (0.3154)	1.8226 (0.3073)	1.8446 (0.3071)	1.8467 (0.2861)	1.7416 (0.2877)	1.7414 (0.2877)
<i>vol</i>	-	3.7298 (0.5397)	-	-	14.7495 (2.0052)	3.1186 (0.5712)	7.9379 (0.8818)	7.9783 (0.8807)	2.7393 (0.9371)	2.6878 (0.9339)	2.6879 (0.9339)
<i>numitrd</i>	-	-	0.0034 (0.0007)	-	-0.0147 (0.0024)	-	-	-	-	-	-
<i>inover</i>	-	-	-	1.2506 (0.2109)	0.6636 (0.2176)	0.8952 (0.2199)	0.2860 (0.2287)	0.3165 (0.2289)	1.0812 (0.2233)	1.1958 (0.2265)	1.1960 (0.2265)
<i>voltrd</i>	-	-	-	-	-0.0003 (0.0001)	-	-	-0.0003 (0.0001)	-0.0004 (0.0001)	-0.0004 (0.0001)	-0.0004 (0.0001)
<i>mcap</i>	-	-	-	-	-	-	-0.0013 (0.0002)	-0.0013 (0.0002)	-0.0030 (0.0002)	-0.0030 (0.0002)	-0.0030 (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002 (1.5E-05)	0.0002 (1.5E-05)	0.0002 (1.5E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.9124 (0.7053)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.9144 (0.7053)

Note 1.: Values reported in parentheses are standard errors. '****' represents the P-value of the t-statistics is smaller or equal to 0.01; '**' represents the P-value of the t-statistics is smaller or equal to 0.05; '*' represents the P-value of the t-statistics is smaller or equal to 0.1.

Note 2: Control group is the case OA markets.

Table 6. Fixed Effect Panel Regression Results: Case OA vs. Case OO & AA (continue)

C. 15% Cutoff Point (cross section sample size: 2,079 markets)											
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	-0.0295 (0.1009)	0.0483 (0.0992)	0.0367 (0.1005)	-0.0399 (0.1007)	-0.0098 (0.0981)	0.0605 (0.1014)	0.0222 (0.0976)	0.0432 (0.0991)	0.2610 *** (0.0949)	0.2962 *** (0.0948)	0.2964 *** (0.0948)
<i>treat</i>	2.4124 *** (0.2295)	2.0840 *** (0.2278)	2.2028 *** (0.2298)	2.2162 *** (0.2317)	1.9561 *** (0.2257)	1.9950 *** (0.2301)	1.9102 *** (0.2252)	1.9031 *** (0.2252)	1.6688 *** (0.2134)	1.5881 *** (0.2130)	1.5882 *** (0.2130)
<i>vol</i>	-	3.6802 *** (0.4254)	-	-	14.9399 *** (1.4960)	3.2847 *** (0.4462)	7.7936 *** (0.6752)	7.8216 *** (0.6755)	3.2286 *** (0.7151)	2.7763 *** (0.7290)	2.7764 *** (0.7289)
<i>numtrd</i>	-	-	0.0032 *** (0.0005)	-	-0.0149 *** (0.0018)	-	-	-	-	-	-
<i>inover</i>	-	-	-	0.8569 *** (0.1356)	0.4509 *** (0.1374)	0.5744 *** (0.1400)	0.1961 (0.1426)	0.2098 (0.1431)	0.7103 *** (0.1396)	0.9846 *** (0.1580)	0.9848 *** (0.1580)
<i>voltrd</i>	-	-	-	-	-	-0.0001 (0.0001)	-	-0.0001 (0.0001)	-0.0002 ** (0.0001)	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)
<i>mcap</i>	-	-	-	-	-	-	-0.0013 *** (0.0001)	-0.0013 *** (0.0001)	-0.0029 *** (0.0002)	-0.0029 *** (0.0002)	-0.0029 *** (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.6778 *** (0.4416)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.6808 *** (0.4416)

D. 10% Cutoff Point (cross section sample size: 2,074 markets)											
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
<i>d93</i>	0.0135 (0.1039)	0.0943 (0.1020)	0.0836 (0.1034)	0.0065 (0.1035)	0.0346 (0.1007)	0.1071 (0.1040)	0.0684 (0.1001)	0.0897 (0.1016)	0.3054 *** (0.0971)	0.3453 *** (0.0970)	0.3455 *** (0.0970)
<i>treat</i>	2.1818 *** (0.2150)	1.8987 *** (0.2127)	2.0014 *** (0.2147)	2.0194 *** (0.2165)	1.7853 *** (0.2105)	1.8270 *** (0.2146)	1.7578 *** (0.2099)	1.7540 *** (0.2099)	1.5424 *** (0.1987)	1.4830 *** (0.1980)	1.4831 *** (0.1980)
<i>vol</i>	-	3.7637 *** (0.4250)	-	-	15.0178 *** (1.4974)	3.3353 *** (0.4459)	7.8852 *** (0.6744)	7.9097 *** (0.6746)	3.2915 *** (0.7141)	2.8315 *** (0.7277)	2.8316 *** (0.7277)
<i>numtrd</i>	-	-	0.0033 *** (0.0005)	-	-0.0149 *** (0.0018)	-	-	-	-	-	-
<i>inover</i>	-	-	-	0.8886 *** (0.1352)	0.4762 *** (0.1370)	0.6007 *** (0.1397)	0.2185 (0.1422)	0.2329 (0.1426)	0.7325 *** (0.1391)	1.0076 *** (0.1570)	1.0078 *** (0.1570)
<i>voltrd</i>	-	-	-	-	-	-0.0001 (0.0001)	-	-0.0001 (0.0001)	-0.0002 ** (0.0001)	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)
<i>mcap</i>	-	-	-	-	-	-	-0.0013 *** (0.0001)	-0.0013 *** (0.0001)	-0.0030 *** (0.0002)	-0.0030 *** (0.0002)	-0.0030 *** (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	-	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.6825 *** (0.4405)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.6854 ** (0.4405)

Table 6. Fixed Effect Panel Regression Results: Case OA vs. Case OO & AA (end)

E. 5% Cutoff Point (cross section sample size: 2,068 markets)											
	II	III	IV	V	VI	VII	VIII	IX	X	XI	
<i>d93</i>	0.1020 (0.1118)	0.1931 * (0.1095)	0.1821 (0.1111)	0.1198 (0.1108)	0.1418 (0.1078)	0.2271 ** (0.1111)	0.1862 * (0.1071)	0.2153 ** (0.1086)	0.4389 *** (0.1034)	0.4624 *** (0.1032)	0.4626 *** (0.1032)
<i>treat</i>	1.8552 *** (0.1935)	1.6651 *** (0.1897)	1.7335 *** (0.1918)	1.7597 *** (0.1928)	1.5955 *** (0.1869)	1.6402 *** (0.1903)	1.6218 *** (0.1860)	1.6229 *** (0.1860)	1.4647 *** (0.1755)	1.4138 *** (0.1754)	1.4138 *** (0.1754)
<i>vol</i>	-	3.9698 *** (0.4218)	-	-	14.8382 *** (1.4985)	3.3520 *** (0.4470)	8.0249 *** (0.6827)	8.0537 *** (0.6826)	3.0581 *** (0.7286)	2.9624 *** (0.7268)	2.9624 *** (0.7268)
<i>numtrd</i>	-	-	0.0036 *** (0.0005)	-	-0.0146 *** (0.0018)	-	-	-	-	-	-
<i>mover</i>	-	-	-	1.1457 *** (0.1484)	0.6342 *** (0.1525)	0.7865 *** (0.1550)	0.2990 * (0.1598)	0.3177 ** (0.1602)	0.9655 *** (0.1573)	1.0750 *** (0.1597)	1.0752 *** (0.1597)
<i>voltrd</i>	-	-	-	-	-	-0.0001 (0.0001)	-	-0.0002 (0.0001)	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)
<i>mcap</i>	-	-	-	-	-	-	-0.0013 *** (0.0001)	-0.0013 *** (0.0001)	-0.0030 *** (0.0002)	-0.0030 *** (0.0002)	-0.0030 *** (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)	0.0002 *** (1.2E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-	-1.6522 *** (0.4388)	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.6545 *** (0.4388)

Note 1.: Values reported in parentheses are standard errors. **** represents the P-value of the t-statistics is smaller or equal to 0.01; *** represents the P-value of the t-statistics is smaller or equal to 0.05; ** represents the P-value of the t-statistics is smaller or equal to 0.1.

Note 2: Control group is the pool of case OO and AA markets.

Table 7. Fixed Effect Panel Regression Results: Case OA vs. Case OO (end)

	E. 5% Cutoff Point (cross section sample size: 1,618 markets)										
	II	III	IV	V	VI	VII	VIII	IX	X	XI	
<i>d93</i>	0.1299 (0.1236)	0.1660 (0.1198)	0.1688 (0.1216)	0.1237 (0.1225)	0.1092 (0.1178)	0.1360 (0.1222)	0.1077 (0.1167)	0.0906 (0.1187)	0.3747 *** (0.1100)	0.4322 *** (0.1101)	0.4325 *** (0.1101)
<i>treat</i>	1.8831 *** (0.1916)	1.6174 *** (0.1877)	1.6965 *** (0.1901)	1.7614 *** (0.1913)	1.5383 *** (0.1852)	1.5815 *** (0.1891)	1.4712 *** (0.1839)	1.4736 *** (0.1839)	1.0422 *** (0.1703)	0.9951 *** (0.1696)	0.9951 *** (0.1696)
<i>vol</i>	-	4.2606 *** (0.4508)	-	-	17.0827 *** (1.8228)	3.5524 *** (0.4761)	9.5238 *** (0.7979)	9.5041 *** (0.7984)	2.0405 ** (0.8637)	1.7827 ** (0.8610)	1.7823 ** (0.8609)
<i>numtrd</i>	-	-	0.0040 *** (0.0006)	-	-0.0170 *** (0.0022)	-	-	-	-	-	-
<i>tmover</i>	-	-	-	1.1641 *** (0.1623)	0.6182 *** (0.1651)	0.7625 *** (0.1678)	0.2069 (0.1738)	0.1982 (0.1742)	1.1040 *** (0.1688)	1.2500 *** (0.1714)	1.2504 *** (0.1714)
<i>voltrd</i>	-	-	-	-	-	0.0002 (0.0002)	-	0.0001 (0.0001)	-0.0002 (0.0001)	-0.0002 * (0.0001)	-0.0002 * (0.0001)
<i>mcap</i>	-	-	-	-	-	-	-0.0015 *** (0.0002)	-0.0015 *** (0.0002)	-0.0042 *** (0.0002)	-0.0043 *** (0.0002)	-0.0043 *** (0.0002)
<i>shrout</i>	-	-	-	-	-	-	-	0.0003 *** (1.8E-05)	0.0003 *** (1.8E-05)	0.0003 *** (1.8E-05)	0.0003 *** (1.8E-05)
<i>srssqr</i>	-	-	-	-	-	-	-	-	-1.9692 *** (0.4494)	-	-
<i>srssqrx</i>	-	-	-	-	-	-	-	-	-	-	-1.9727 *** (0.4495)

Note 1.: Values reported in parentheses are standard errors. ****, represents the P-value of the t-statistics is smaller or equal to 0.01; ***, represents the P-value of the t-statistics is smaller or equal to 0.05; **, represents the P-value of the t-statistics is smaller or equal to 0.1.

Note 2: Control group is the case OO markets.

Table 8. Estimated Average Treatment Effects

A. Control Group: Case AA Markets					
	FEPE	LCFE	PSME	OPSE1	OPSE2
25% Cutoff	2.3904 *** (0.4549)	2.4456 *** (0.4349)	2.3524 *** (0.5686)	2.3912 *** (0.5181)	2.4027 *** (0.5185)
20% Cutoff	2.3724 *** (0.4229)	2.4415 *** (0.4056)	2.4629 *** (0.5027)	2.3773 *** (0.4838)	2.3987 *** (0.4846)
15% Cutoff	2.3939 *** (0.3931)	2.4471 *** (0.3786)	2.5555 *** (0.4853)	2.4016 *** (0.4489)	2.4219 *** (0.4500)
10% Cutoff	2.1489 *** (0.3570)	2.2296 *** (0.3427)	2.1995 *** (0.4424)	2.1547 *** (0.4066)	2.1904 *** (0.4068)
5% Cutoff	1.7416 *** (0.2877)	1.8154 *** (0.2779)	1.6158 *** (0.3587)	1.7569 *** (0.3300)	1.7808 *** (0.3307)
B. Control Group: Case OO and AA Markets					
	FEPE	LCFE	PSME	OPSE1	OPSE2
25% Cutoff	1.3054 *** (0.2417)	0.9457 *** (0.2470)	1.3167 *** (0.4609)	1.3391 *** (0.2503)	1.2267 *** (0.2557)
20% Cutoff	1.3712 *** (0.2253)	1.0318 *** (0.2285)	1.4200 *** (0.3786)	1.3546 *** (0.2338)	1.2449 *** (0.2380)
15% Cutoff	1.5881 *** (0.2130)	1.3013 *** (0.2143)	1.4057 *** (0.3627)	1.5447 *** (0.2220)	1.4593 *** (0.2249)
10% Cutoff	1.4830 *** (0.1980)	1.2302 *** (0.1964)	1.4487 *** (0.3160)	1.4394 *** (0.2053)	1.3628 *** (0.2064)
5% Cutoff	1.4138 *** (0.1754)	1.3215 *** (0.1717)	1.3657 *** (0.2423)	1.3907 *** (0.1836)	1.3546 *** (0.1834)
C. Control Group: Case OO Markets					
	FEPE	LCFE	PSME	OPSE1	OPSE2
25% Cutoff	0.6255 *** (0.2256)	0.5631 ** (0.2291)	0.4710 (0.4364)	0.4853 ** (0.2314)	0.4812 ** (0.2352)
20% Cutoff	0.7361 *** (0.2105)	0.6337 *** (0.2127)	0.5085 (0.3837)	0.5479 ** (0.2150)	0.5164 ** (0.2171)
15% Cutoff	1.0048 *** (0.2004)	0.9320 *** (0.2008)	0.9464 *** (0.3420)	0.7893 *** (0.2056)	0.7427 *** (0.2064)
10% Cutoff	0.9224 *** (0.1875)	0.7968 *** (0.1871)	0.7783 *** (0.2937)	0.7198 *** (0.1916)	0.7048 *** (0.1914)
5% Cutoff	0.9951 *** (0.1696)	0.9024 *** (0.1756)	0.8574 *** (0.2084)	0.8683 *** (0.1734)	0.9387 *** (0.1738)

Note 1. FEPE: fixed effect panel estimation results; LCFE: the estimation results of the differenced equation with a linear control function; PSME: propensity score matching estimation; OPSE1: the estimation results of the differenced equation with propensity scores as the control function; OPSE2: the estimation results of the differenced equation with propensity scores and interaction with treatment as the control function.

Note 2.: Values reported in parentheses are standard errors. '***' represents the P-value of the t-statistics is smaller or equal to 0.01; '**' represents the P-value of the t-statistics is smaller or equal to 0.05; '*' represents the P-value of the t-statistics is smaller or equal to 0.1.

Table 9. Instrumental Variable Estimation Results

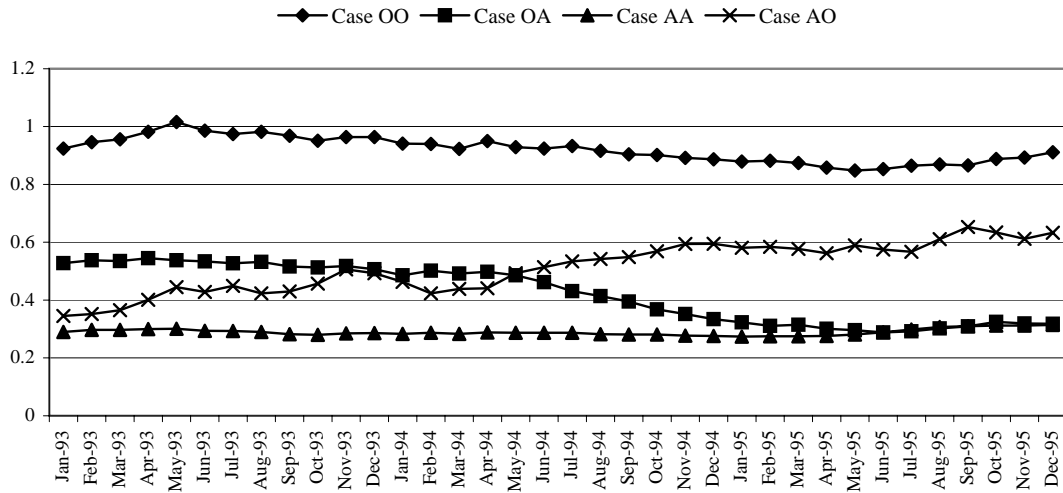
	LATE	OPSEIV1	OPSEIV2	PSMEIV
25% Cutoff	8.1954 *** (1.6379)	7.6410 *** (1.6382)	8.3451 *** (1.9750)	1.3761 (1.4099)
20% Cutoff	7.1142 *** (1.3456)	6.2621 *** (1.3320)	6.5565 *** (1.5275)	1.7593 (1.1390)
15% Cutoff	5.7044 *** (1.0651)	4.7805 *** (1.0645)	4.8063 *** (1.1699)	1.2205 (1.0161)
10% Cutoff	4.4005 *** (0.8160)	3.7880 *** (0.8270)	3.6147 *** (0.8707)	1.7995 ** (0.8341)
5% Cutoff	2.4382 *** (0.4938)	1.7852 *** (0.5171)	1.6497 *** (0.5204)	0.5736 (0.5520)

Note 1. LATE: local average treatment effect; PSME: 2SLS propensity score matching estimation; OPSEIV1: the 2SLS estimation results of the differenced equation with propensity scores as the control function; OPSEIV2: the 2SLS estimation results of the differenced equation with propensity scores and interaction with treatment as the control function.

Note 2.: Values reported in parentheses are standard errors. '***' represents the P-value of the t-statistics is smaller or equal to 0.01; '**' represents the P-value of the t-statistics is smaller or equal to 0.05; '*' represents the P-value of the t-statistics is smaller or equal to 0.1.

Figure 1. Monthly Average Absolute Spreads

A. Cutoff: 25%



B. Cutoff: 10%

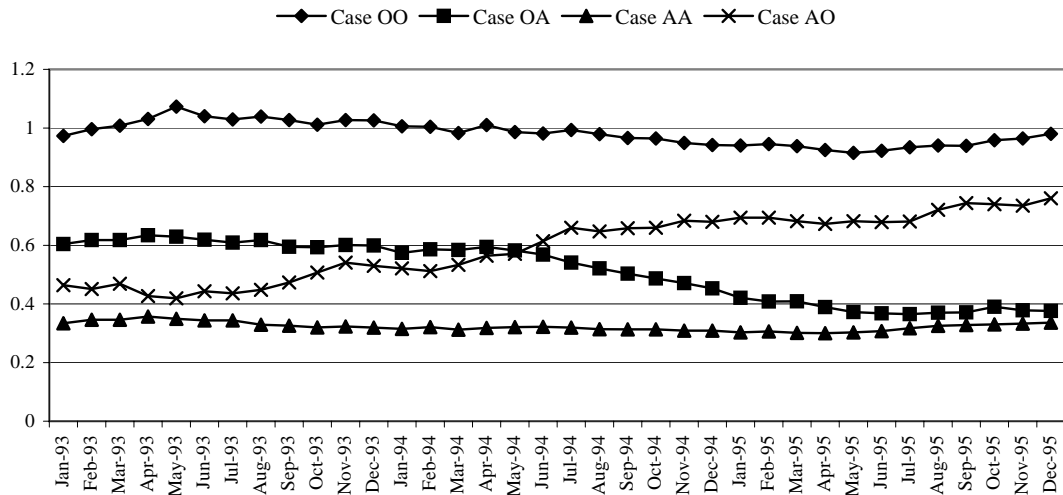
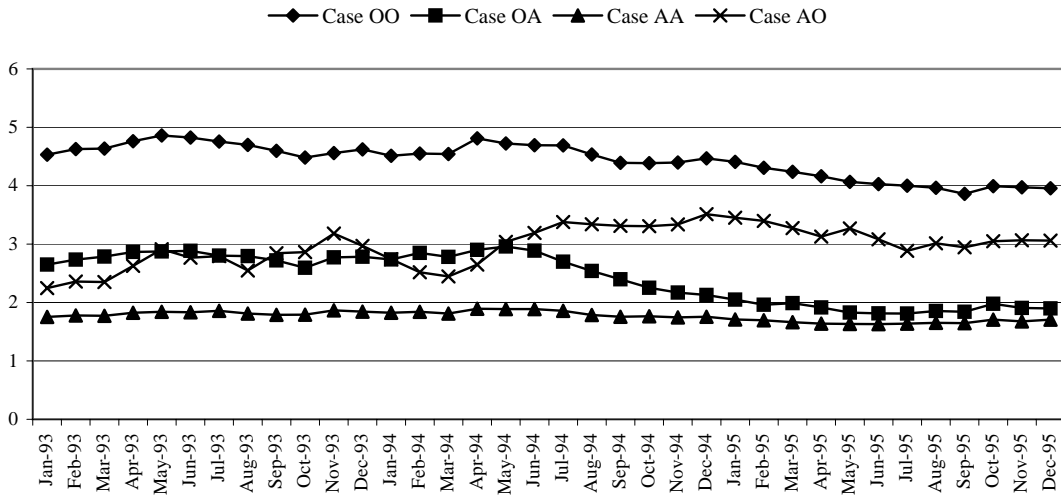


Figure 2. Monthly Average Relative Spreads

A. Cutoff: 25%



B. Cutoff: 10%

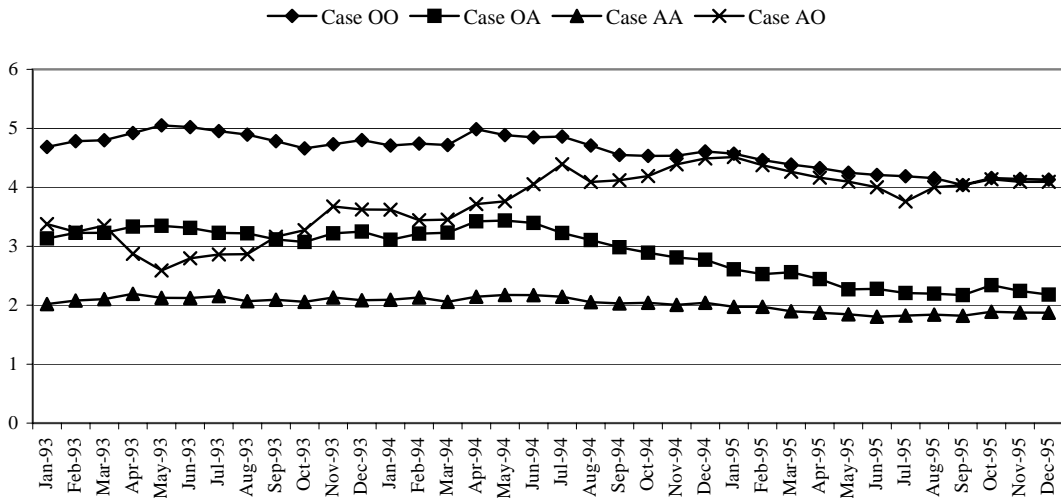
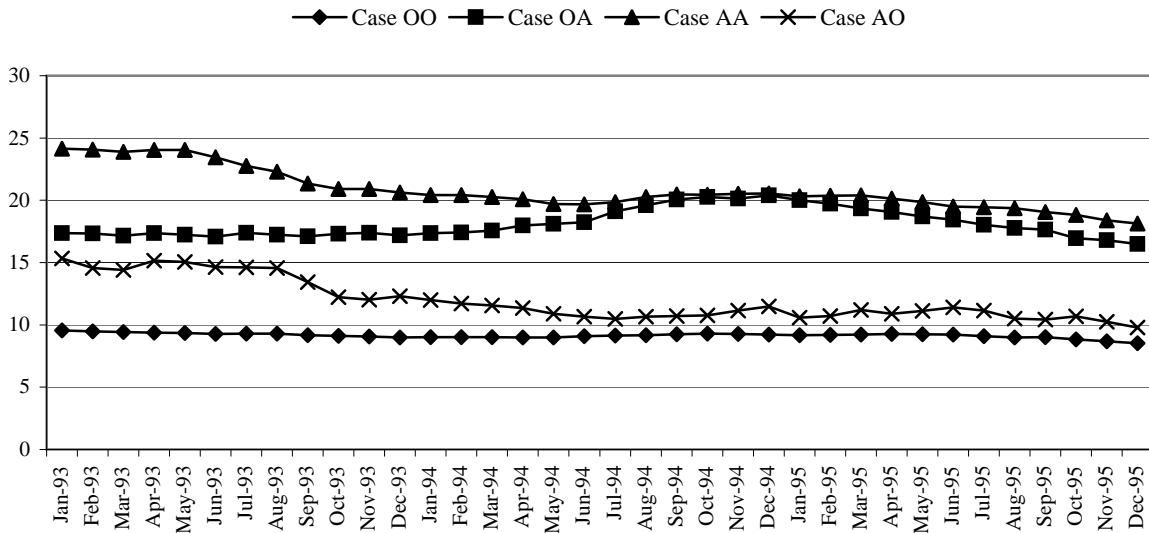


Figure 3. Monthly Average Market Maker Count

A. Cutoff: 25%



B. Cutoff: 10%

