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The Review of Financial Studies (1986-1998); Fall 1997; 10, 3; ABI/INFORM Global
pg. 871

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The probability of entry and exit of dealers on the NASDAQ National Market (NNM) is significantly affected by trading intensity, volatility and the quoted bid-ask spread. Entry and exit of market makers is a pervasive phenomenon. Large-scale entry (exit) is associated with substantial declines (increases) in quoted end-of-day inside spreads, even after controlling for the effects of changes in volume and volatility. The spread changes are larger in magnitude for issues with few market makers; however, even for issues with a large number of market makers, substantial changes in quoted spreads take place. The results are consistent with the competitive model of dealer pricing.

Competition between market makers is crucial to dealer markets. Consequently, understanding the mechanics of competition between market makers is important not only to academics, but also to policy makers seeking to regulate these markets and to investors wishing to trade on them. Christie and Schultz (1994) and Christie, Harris and Schultz (1994), observe an absence of odd-eighth quotes for 70 out of the 100 most highly capitalized NASDAQ stocks. Harris (1991)

Part of the work on this article was done while I was at the University of North Carolina and at Purdue University. I would like to thank Franklin Allen (the editor), George Benston, Jennifer Conrad, James Cotter, David Guilkey, Mustafa Gultekin, Joel Hasbrouck, Paul Irvine, Eugene Kandel, Ajay Khorana, Pete Kyle, Peggy Lee, Marc Lipson, Harold Mulherin, Henri Servaes, Marc Zenner, and an anonymous referee for exceptionally detailed comments. This article was presented at the 1993 Western Finance Association meetings and the finance seminar at the University of North Carolina at Chapel Hill. I am grateful to the Center for Research in Security Prices at the University of Chicago for providing daily market-maker data and to the Cato Center for Research at the University of North Carolina for partial funding. The expert programming assistance of Doug McIntyre is gratefully acknowledged. Mehmet Ozbilgin provided excellent research assistance.

The Review of Financial Studies Fall 1997 Vol. 10, No. 3, pp. 871–901

also observes price clustering on the NYSE/AMEX but suggests that coarse price increments are used to minimize negotiation costs between traders. Christie and Schultz (1994), however, are unable to account for the paucity of odd-eighths on NASDAQ stocks by the negotiation hypothesis of Harris (1991), and suggest that dealers tacitly collude to set wide quotes. This suggestion has triggered class-action lawsuits against many NASDAQ market makers and investigations by the Department of Justice and the Securities and Exchange Commission. The lawsuits have prompted academic investigations that seek to understand the theoretical underpinnings of collusive behavior [Dutta and Madhavan (1997), Kandel and Marx (1996)] or to provide empirical evidence on the collusion hypothesis [Doran, Lehn, and Shastri (1995), Godek (1995), Grossman et al. (1995), Huang and Stoll (1996), Kleidon and Willig (1995), and Laux (1995a)].

Fluid entry and exit is central to a competitive dealer market. The NASDAQ National Market (NNM) is characterized by a virtual absence of barriers to entry. After a one-day registration period, a dealer wishing to make a market in a security merely has to "sign on" to the computer system and is able to start quoting prices within half an hour. Likewise, dealers can exit within half an hour, although NASDAQ rules prevent a dealer from exiting and then reentering within 30 days. This article seeks to enhance our understanding of competition by analyzing the determinants, frequency, and impact of entry and exit of market makers for stocks on the NNM.

Using daily data on the number of market makers for all stocks listed on the NNM from 1982 to 1993, I show that the number of dealers in a security is a function of trading intensity (as proxied by trading volume and the number of trades), volatility, and the bid-ask spread. These variables are also important determinants of the probability of entry and exit. I find that entry and exit of dealers is a pervasive phenomenon. Large-scale entry (exit) is associated with substantial declines (increases) in end-of-day quoted spreads, even after controlling for the effects of changes in volume and volatility. The spread changes are larger in magnitude for securities with few market makers; even for stocks with a large number of market makers, however, substantial changes in spreads take place subsequent to large-scale entry. Further, in the sample of 50 highly capitalized stocks analyzed by Christie and Schultz (1994), entry is associated with declines in the end-of-day quoted spread. These results are consistent with the competitive model of dealer pricing.

This study relies on end-of-day quotes. Therefore, understanding dealers' incentives to post quotes at the end of the day is important. These incentives are greatly affected by order preferencing arrangements on the NASDAQ. Under the prevailing system, dealers either purchase or exchange retail order flow. Dealers typically guarantee execution at the inside spread, even if their own quotes are wider. Therefore, narrowing quotes does not necessarily guarantee order flow. Moreover, institutions typically trade at prices better than the inside spread; institutional order flow is directed to dealers based on established relationships and expectations of price improvements. These factors suggest that dealer competition is expressed through explicit and implicit payments for order flow, and through price improvements to institutional traders.

Fortunately, competition is also expressed through quoted spreads to the extent that dealers use quotes to obtain unpreferenced order flow, consisting mostly of orders from dealers and orders from institutions that route orders based on quotes. Dealers may also quote aggressively because their quotes are an indication of the willingness to provide price improvement to institutional traders. Finally, it is important to recognize that the narrowing of spreads at the end of the day observed by Chan, Christie, and Schultz (1995) may result as much from dealers competing to "go home flat" as from dealers competing for order flow. While both processes represent competition among dealers, only the latter results in more liquidity for the public.

Entry and exit of market makers is not the sole source of competition on the NNM. On exchanges such as the NYSE or AMEX, the specialist faces competition for order flow from floor traders, other exchanges, and from public limit orders [see Harris and Hasbrouck (1996)]. NASDAQ limit orders are not exposed to the public, however, and executed only if the inside spread reaches the limit price. Thus, the public cannot directly compete with market makers via limit orders.[1] Reuters' Instinet, however, is a significant source of competition for NASDAQ dealers. Individuals can enter orders into Instinet (through a participating dealer) that bypass the NASDAQ quotes. No academic evidence on the impact of Instinet or even reliable statements of trading volume exists. Nonetheless, anecdotal reports suggest that Instinet is an important source of competition.[2] In addition to Instinet, the NASDAQ also faces competition for listings from the exchanges (NYSE and AMEX).

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[1] The NASD has attempted to improve limit order execution on the NASDAQ. In November 1994, a service called NProve was started to allow limit order execution. The SEC, however, killed NProve in January 1995. On March 20, 1995, the NASDAQ announced a new limit order system called Aqcess. Further changes are expected as a result of the settlement between the NASDAQ and the SEC.

[2] Daily trading volume on Instinet is estimated to be more than 20% of overall NASDAQ volume (see, for example, "Reuters's Instinet is biting off chunks of NASDAQ's Territory," *Wall Street Journal*, October 4, 1994). Also, non-Instinet NASDAQ volume includes a larger fraction of interdealer trades than Instinet volume. Therefore, Instinet volume would appear to be larger if presented on a comparable basis.

Two other sources of competition may also be important. First, traders can compete against market makers through NASDAQ's Small Order Execution System (SOES). These traders, known as "SOES bandits" (or "SOES sharks") profit from quote discrepancies across market makers by simultaneously buying and selling shares [see Stoll (1992)]. The activities of SOES bandits have been a source of consternation for many market makers, who have widened spreads in response to what they call an abuse of SOES. Others (most notably, the bandits themselves) have argued that SOES bandits are a source of competition to complacent market makers. Second, nondealer competition can be important. Institutions who trade passively provide liquidity, thereby earning, rather than paying, the spread. Schwartz and Whitcomb (1988) and Harris (1990) discuss how passive institutional trading (via limit orders) can provide liquidity, and Laux (1995b) provides empirical evidence on the subject. While this article documents the impact of entry and exit, alternative sources of competition remain to be explored.

This article is organized as follows: Section 1 describes the data and sample construction. Section 2 provides an empirical examination of the determinants of the number of dealers for a security. The determinants of entry and exit and its impact on spreads is documented in Section 3. Section 4 concludes.

1. Data and Sample Construction

The sample consists of all stocks traded on the NNM between 1982 and 1993. Many stocks did not trade continuously on the NNM over the entire sample period. In fact, a security may trade on the NNM for a period of time, be denied NNM status for a subsequent period (perhaps because it does not meet listing requirements), and return to trading on the NNM again. The change from NNM to non-NNM represents a change in trading system. Additionally, bid-ask spreads are not available for non-NNM stocks. Accordingly, the sample is restricted to stocks only when they are traded on the NNM. Thus, the sampling criteria do not require continuous trading on the NNM over the period. No other restrictions are imposed on the sample. The final sample, or more appropriately, the universe of NNM securities, consists of 5569 securities from 1982 to 1993.

The data were obtained from two CRSP files. Daily end-of-day inside bid and ask quotes, transaction prices, trading volume, the number of trades, and market value from 1982 to 1993 were obtained from the CRSP NNM file (previously known as the NMS file). This file also includes information on the number of market makers for each security, but this information is not updated daily. CRSP censors daily data (to conserve space) before disseminating it in the NNM file. The censoring may be related to systematic movements in prices, volume, and spreads. Therefore, I obtained the original daily market-maker data from CRSP.[3] Using daily data avoids spurious correlation in the analysis variables due to CRSP reporting conventions in the NNM file. The daily market-maker data are then matched with daily spread, price, volume, and trades data from the NNM file.

The bid and ask prices reported in the CRSP NNM file are the end-of-day (closing) inside quotes. These data pose two problems. First, inside quotes may not represent individual dealer spreads. Stoll (1989) argues, however, that four factors cause inside quotes to behave as if they were coming from one dealer: competition between dealers, the desire of investors to trade at the inside spread, knowledge by dealers of the quotes of other dealers, and knowledge of transaction prices. Consistent with this argument, Chan et al. (1995) find that the same dealer almost never makes both sides of the inside spread (during the day or at close). Moreover, as mentioned earlier, most dealers fill orders at the inside spread even if their individual quotes are wider. Thus, dealers may trade actively without making the inside spread.

The second problem arises from the use of closing quotes. Chan et al. (1995) document that spreads on the NASDAQ are relatively high at the open, decline during the day and are at their narrowest at the close. This is in contrast to the NYSE where a U-shaped pattern is observed [Brock and Kleidon (1992), McInish and Wood (1992)]. If closing spreads do not fairly represent intraday competition, the results that follow may be suspect. Fortunately, unlike the NYSE where the closing quote may be "artificial," the closing quote on the NNM is likely to represent competitive conditions at the end of the day. In fact, end-of-day inside quoted spreads may result from two distinct processes. First, dealers may compete at the end of the day to avoid overnight inventory positions. Second, dealers may compete to serve the public and obtain unpreferenced order flow. Order routing decisions for unpreferenced order flow are more likely to rely on closing quotes than intraday quotes, since closing quotes are more widely disseminated. Both processes (inventory adjustment and competition for unpreferenced order flow) represent competition among dealers, but only the latter results in increased liquidity for the public. If more dealers are taking intraday positions, however, it may

[3] In the NNM file, the number of market makers is updated only when one of four conditions are met: (i) the security changes from being actively traded to being suspended, delisted, or trading with only one market maker, (ii) the security is denied or attains NNM status, (iii) the issue's industry classification changes, perhaps due to a merger, or (iv) if the number of market makers changes by more than 25%.

be reasonable to believe that more liquidity is being offered to the public.[4]

2. The Number of Market Makers

Before embarking on an investigation of the determinants and impact of entry and exit of market makers, understanding what determines the number of market makers in a stock is important. This section provides such an empirical investigation.

2.1 Data description

The number of market makers (*NumMkMkrs*) per security varies from a minimum of 2 (the listing requirement for the NNM) to a maximum of 68. The number of days over which the number of market makers remains unchanged (i.e., no entry or exit takes place) varies from a minimum of 1 to a maximum of 857. The average number of days over which the number of market makers does not change (*AvgNoChgDays*) is 14.68.

Given the distribution of the number of market makers, quintiles are formed as follows:

Quintile 1: $2 \leq NumMkMkrs \leq 7$
Quintile 2: $8 \leq NumMkMkrs \leq 10$
Quintile 3: $11 \leq NumMkMkrs \leq 14$
Quintile 4: $15 \leq NumMkMkrs \leq 19$
Quintile 5: $20 \leq NumMkMkrs \leq 68$

These are approximate quintiles (i.e., the number of observations in each quintile are not exactly the same) because the number of market makers is a discrete variable. A firm can appear in several quintiles as the entry and exit of market makers takes place.

The time-series mean of each analysis variable is calculated over the period where the number of market makers remains unchanged. For example, if a security has four registered market makers over a 30-day period, the mean relative quoted spread (*RelSpread*) over the 30-day period constitutes one observation. Similarly, time-series means for dollar spreads (*DolSpread*), the logarithm of trading volume (*LogVol*), the logarithm of the number of trades per day (*LogNtrades*), price, the inverse of price (*InvPrice*), and market value (*MktVal*) are calculated over the period where the number of market makers does not change. The square root of the sum of squared returns (*SqrtSumSqRet*)

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[4] In this study, since quote sampling before and after entry (exit) is at the same time of day (i.e., at the close), no systematic bias should be introduced in tests that use spread changes, particularly over a period of several days.

is used as a measure of volatility and is also calculated over the same period.[5]

The sample created by this procedure contains means (and in the case of *SqrtSumSqRet*, the sum of squares) of the variables of interest contemporaneous with a unique market-maker count. Weighted averages are used as summary measures because the number of days over which the time-series means are calculated varies substantially. The weight assigned to each observation is the number of days in the time series. Table 1 presents these weighted averages classified by market-maker quintiles. Similar results are obtained for unweighted averages.

Several interesting patterns emerge from the data. First, the average period over which the time-series means are calculated declines monotonically across quintiles. For the first quintile, the average number of days where the number of market makers does not change is 27.5. The corresponding figure for quintile 5 is only 7.8 days. Not surprisingly, these figures show that entry and exit take place more frequently in securities with a large number of market makers.

Second, end-of-day quoted spreads decline monotonically across the quintiles (a chi-square test easily rejects the hypothesis of equality of means across the quintiles). This is not surprising since both volume and the number of trades increases across the quintiles. The average market value also increases monotonically from a low of $57.5 million in quintile 1 to a high of $560 million in the quintile 5. Since smaller, low-volume securities have more volatile returns, it is also not surprising that *SqrtSumSqRet* declines across the quintiles. Given the patterns described above, one might expect the average price to increase across the quintiles. Surprisingly, however, the average price does not change much across the quintiles. In fact, even after eliminating all stocks below $5.00, the average price does not increase across the quintiles.

Panel A of Table 2 shows Pearson correlation coefficients between the number of market makers and two measures of trading activity (volume and the number of trades), volatility, firm size, and relative and dollar spreads. The number of market makers is strongly positively correlated with the level of trading activity and firm size, but

[5] This measure of volatility assumes that the expected mean return is equal to zero—a reasonable assumption in daily data. Moreover, squared returns are preferable to the standard deviation of returns for several reasons. First, in situations where the time series consists of only one day, *SqrtSumSqRet* can be calculated, whereas the standard deviation of returns cannot. Second, if all returns in a time series decline at a constant rate, the sum of squared returns reflects the impact of this return pattern on dealer inventories, whereas the standard deviation of this series is equal to zero. The results reported in this article remain qualitatively unchanged, however, if the standard deviation of returns is used as a volatility measure.

Table 1
Weighted averages of variables classified by market-maker quintiles

Market-maker quintile	*N*	Number of firms	*AvgNoChgDays* (days)	*RelSpread* (%)	*DolSpread* ($)	*LogVol*	*LogNTrades*	MktVal ($M)	*SqrtSumSqRet*	Price ($)
Quintile 1 ($2 \le NumMkMkrs \le 7$)	81,446	4017	27.5	8.53	0.82	7.96	0.92	57.5	4.40	15.42
Quintile 2 ($8 \le NumMkMkrs \le 10$)	70,726	4308	16.6	5.44	0.43	9.24	1.99	93.5	3.94	13.28
Quintile 3 ($11 \le NumMkMkrs \le 14$)	87,229	3867	13.4	4.34	0.34	9.92	2.55	130.9	3.69	13.68
Quintile 4 ($15 \le NumMkMkrs \le 19$)	72,454	2689	10.8	3.36	0.28	10.59	3.14	203.6	3.47	14.38
Quintile 5 ($20 \le NumMkMkrs \le 68$)	80,461	1494	7.8	2.33	0.22	11.69	4.12	560.0	3.21	16.92
Full Sample	392,316	5569	15.29	5.79	0.52	9.32	2.07	150	3.93	14.68

The sample includes all stocks traded on the NASDAQ National Market (NNM) between 1982 and 1993. Time-series means of the variables (except *AvgNoChgDays*) are calculated over the period where the number of market makers stays the same; the figure reported is the cross-sectional average of these time-series means, weighted by the length of the time series. For *AvgNoChgDays*, a simple average of the length of the time series is reported. *N* represents the number of observation intervals where there is no change in the number of market makers.

Table 2
Pearson correlation coefficients and Poisson regression models

Panel A: Pearson correlation coefficients of independent and dependent variables

	NMkMkrs	*LogVol*	*LogNtrades*	*SqrtSumSqRet*	*LogMktVal*	*RelSpread*	*DolSpread*
NMkMkrs	1	0.69	0.70	−0.08	0.52	−0.32	−0.35
LogVol		1	0.92	0.03	0.56	−0.36	−0.36
LogNtrades			1	−0.01	0.62	−0.45	−0.32
SqrtSumSqRet				1	−0.34	0.59	−0.01
LogMktVal					1	−0.60	0.01
RelSpread						1	0.17
DolSpread							1

Panel B: Poisson regressions with *NMkMkrs* as dependent variable

Variable coefficient	Unweighted Poisson regression	Unweighted Poisson regression	Weighted Poisson regression	Weighted Poisson regression
Intercept	−0.47	−2.71	0.33	−1.54
	(0.00)	(0.00)	(0.00)	(0.00)
LogVol	0.14	0.05	0.19	0.10
	(0.00)	(0.00)	(0.00)	(0.00)
LogNtrades	0.11	0.11	0.15	0.15
	(0.00)	(0.00)	(0.00)	(0.00)
SqrtSumSqRet	−1.90	−1.06	−2.44	−1.68
	(0.00)	(0.00)	(0.00)	(0.00)
LogMktVal	0.01	0.07	0.04	0.02
	(0.00)	(0.00)	(0.00)	(0.00)
Trend	0.01	0.03	0.01	0.03
	(0.00)	(0.00)	(0.00)	(0.00)
RelSpread	−0.03	—	−0.10	—
	(0.05)		(0.00)	
DolSpread	—	−0.94	—	−0.52
		(0.00)		(0.00)
Scaled deviance	710,808	552,861	7,549,326	6,565,185

The sample includes all stocks traded on the NNM between 1982 and 1993. Each observation for the independent variables (except Trend) is the time-series mean computed over the number of days where the number of market makers does not change. The *Trend* variable is the calendar year for the observation. The dependent variable of the Poisson regression is the number of market makers contemporaneous to the other variables. *P*-values are in parentheses.

negatively correlated with closing quoted spreads. The high correlation between volume, the number of trades, and firm size suggest that multicolinearity problems may be present in regression models in which these variables appear as regressors.

2.2 Poisson regressions

Most microstructure models [two prominent examples include Glosten and Milgrom (1985) and Kyle (1985)] assume Bertrand competition and infinite risk-bearing capacities of market makers, so that the number of market makers is irrelevant (as long as there are more than two). In the aftermath of the 1987 crash, however, Grossman and Miller (1988) and Diamond and Verrecchia (1991) argue that the assumption of infinite risk-bearing capacity is worth questioning. Both studies model market makers with limited risk-bearing capacity and treat the number of dealers as endogenous. Their results suggest that the number of market makers for a security is related to the level of trading activity and the risk of providing liquidity services; this implies that entry and exit of market makers should be related to changes in volume and volatility. They do not, however, account for the competitive effect of dealer entry.

Table 1 shows that the number of market makers for a security is indeed closely related to the level of trading activity (volume and the number of trades) and the risk of providing those services (volatility of returns). However, the results also suggest that the number of dealers is closely related to price charged for providing services (relative and dollar spreads).

Panel B of Table 2 presents the results of regressions of the number of market makers on volume, the number of trades, volatility, firm size, and spreads. Over the 1982 to 1993 period, trading activity increased, and there may be trends in the number of market makers per security and in bid-ask spreads. Accordingly, a trend variable equal to the calendar year of the observation is also employed as an independent variable. The preponderance of small, discrete values (but not categorical values) for the dependent variable suggests that a Poisson regression that takes into account the "count" property of the data is more appropriate than OLS.[6] An excellent treatment of Poisson regressions can be found in Madalla (1983), and further econometric development as well as an application is contained in Haùsman, Hall, and Griliches (1984).

Poisson regressions assume that the dependent variable has a Poisson distribution with parameter λ such that λ depends log linearly on the explanatory variable. The regression is essentially a form of nonlinear least squares, although the estimation is more conveniently done via maximum likelihood procedures. Standard (unweighted) Poisson regressions assume that the size of the relevant population is constant (in this case, the length of time over which the number of market makers does not change). This is clearly not the case in this sample. The implication of this assumption is that the length of time over which the time-series means are calculated is absorbed in the constant term. Fortunately, a weighted least squares estimator suggested by Lancaster (1974) treats this issue by performing weighted least squares regression (or a "weighted" Poisson regression). The interpretation of parameter estimates from Poisson regressions is the same as OLS. Tests of whether a parameter is significantly different from zero are conducted via a chi-square statistic. The goodness of fit of

[6] I am indebted to David Guilkey for making this point.

the model is assessed by the scaled deviance, which is defined as twice the difference between the maximum achievable log likelihood and the log likelihood at the maximum likelihood estimates of the regression parameters. The scaled deviance has a limiting chi-square distribution, with degrees of freedom equal to the number of observations minus the number of parameters estimated. A large value for the scaled deviance is indicative of a model with good explanatory power. Hausman et al. (1984) show that the adequacy of the Poisson specification can be judged by an investigation of the Poisson and standardized residuals.

The first two models in panel B (Table 2) present unweighted Poisson regressions with volume, the number of trades, volatility, firm size, time trend, and relative and dollar spreads as independent variables.[7] The second two models present weighted Poisson regression models with the same variables. *P*-values for tests of parameter significance are presented in parentheses.

The coefficient on volume and the number of trades is positive and significant in all four specifications. The sign of the coefficient on the sum of squared returns suggests that volatility is significantly negatively related to the number of market makers for a security. The coefficient on firm size is positive, implying that larger firms with less information asymmetry have more market makers. The coefficient on the trend variable is also positive, indicating that there has been an increase in the number of market makers per security over the sample period. Finally, across all four specifications, the coefficients on both relative and dollar spreads are negative and significant. This confirms that end-of-day quoted spreads are lower in securities with more competing market makers. In general, these results are consistent with those reported by Tinic and West (1972), Benston and Hagerman (1974), and Hamilton (1976, 1978).

2.3 Specification issues

A variety of robustness checks have been conducted on the regressions described above. As in Hausman et al. (1984), I estimate the models described above via OLS and WLS with the logarithm of the number of market makers as the dependent variable. Although the results are not reported in the interest of brevity, they are similar in spirit. The R^2s of the OLS and WLS regressions range from 60% to 70%, implying that even without modeling the count property of the dependent variable, the models fit the data well. Further, an exami-

[7] Diamond and Verrecchia (1991) suggest that information asymmetry is an important determinant of the number of market makers in a security. Therefore, firm size is included in the regressions as a proxy for the level of information asymmetry as well as a control variable.

nation of the residuals from the Poisson regressions does not indicate misspecification.

Given the correlations shown in panel A, collinearity may be a severe problem in the regressions. Two robustness checks are conducted to ensure that the results are not severely tainted by this problem. First, both the Poisson and OLS/WLS regressions are reestimated after orthogonalizing the other independent variable with respect to firm size (firm size is highly correlated with all other variables). The results are qualitatively similar. Second, both the Poisson and OLS models are estimated with volume and the number of trades as regressors in separate models. These specifications are motivated by evidence in Harris (1987) and Jones, Kaul, and Lipson (1994) that the volume-volatility relation is driven by the number of trades. Even in these regressions, however, the coefficients on volume and the number of trades are similar to those reported. These results indicate that collinearity does not cause major specification problems, perhaps due to the large sample.

The regressions reported above suffer from simultaneous equations bias. Harris (1994) encounters a similar issue in models that describe spreads, quotation sizes, and volume. Following Harris (1994), I employ an instrumental two-stage least squares approach (with both the Poisson and OLS regressions) to determine whether these biases are significant. Specifically, I calculate means (and sum of squared returns) of the independent variables from the quarter prior to the beginning date of the observation interval for the dependent variable. These lagged values are used as instruments in the first-stage regressions. The results (not reported) are similar to those reported in panel B. I also calculate instruments from one- and two-month lagged data and use these instruments in the two-stage least squares procedure. Once again, the results are qualitatively unchanged. Thus, similar to the results in Harris (1994), simultaneous equations bias does not appear to significantly affect the reported results.

3. Entry and Exit of Market Makers

3.1 Determinants of entry and exit

The previous section documents that the number of dealers in a security is related to trading intensity, volatility, and the bid-ask spread. These variables may also be important determinants of changes in the number of market makers, that is, entry and exit.

I model the determinants of entry and exit by estimating ordered discrete variable regressions to describe changes in the number of market makers over fixed time intervals. Both dependent and independent variables are computed (as time-series means) over monthly intervals. The dependent variable is an entry/exit indicator variable equal to +1 for an increase, 0 for no change, and −1 for a decrease in the number of market makers over the previous month. Note, however, that the average number of market makers in each month need not be a whole number; in this case, the dependent variable is not discrete and I use the mode of the number of market makers in that trading month to calculate the indicator variable.[8]

In addition to being discrete, the dependent variable is also naturally ordered. Therefore, the regression is estimated using ordered probit procedures. Hausman, Lo, and MacKinlay (1992) provide an excellent description of ordered probit regressions. Following Hausman et al. (1992), an underlying regression model with a continuous dependent variable (Z^*) is assumed. Although Z^* is not observed, it is related to a discrete random variable Z by partition boundaries (α_j). For example, the entry/exit indicator variable (Z) takes on a value of -1 whenever $Z^* \leq \alpha_1$, the value 0 whenever $\alpha_1 < Z^* \leq \alpha_2$, and the value +1 whenever $Z^* > \alpha_2$. The ordered probit regression estimates the coefficients on the explanatory variables in the model (whose sign can be interpreted as in OLS) as well as the partition boundaries (α_j). The partition boundaries can be thought of as the intercepts of the regression. Estimation is done via maximum-likelihood procedures using the Berndt et al. (1974) algorithm.

The purpose of the ordered discrete variable regressions is to predict entry/exit. Therefore, the independent variables employed must be part of a market-maker's information set at the time of an entry/exit decision. Accordingly, I use lagged values of variables that are likely to affect market-maker profits. Specifically, lagged measures of trading volume, the number of trades, volatility, and bid-ask spreads are used. Since average market-maker profits are likely to drive entry/exit decisions, I also use dollar volume per market maker and the number of trades per market maker as independent variables.

The data are time series and cross-sectional, but primary interest is in the time-series effects. Accordingly, the regressions are estimated on a security-by-security basis. I do not estimate regressions for securities where the number of time-series observations is less than 40 to ensure convergence of the maximum-likelihood estimator. [The maximum number of observations is 144 (12 years times 12 months per year)]. Also, I do not use $\Delta NMkMkrs$ as a dependent variable because the number of αs to be estimated can be quite large, and given limited degrees of freedom, convergence may not be achieved. Finally,

[8] Naturally, if the average number of market makers in a particular month is a whole number (i.e., no entry/exit takes place in that month) then the mode is equal to the mean.

Table 3
Ordered probit regression estimates of entry/exit

	Entry/exit indicator			
$LogDolVol_{t-1}$	0.086	0.063	—	—
	(0.043)	(0.047)		
$LogDolVol_{t-1}/NMktMkrs_{t-1}$	—	—	0.827	0.847
			(0.246)	(0.215)
$LogNtrades_{t-1}$	0.034	0.070	—	—
	(0.066)	(0.066)		
$LogNtrades_{t-1}/NMktMkrs_{t-1}$	—	—	1.678	1.381
			(0.773)	(0.734)
$SqrtSumSqRet_{t-1}$	−0.265	−0.886	−1.913	−0.903
	(0.209)	(1.926)	(0.219)	(0.995)
$LogMktVal_{t-1}$	−0.026	−0.279	−0.001	−0.115
	(0.008)	(0.089)	(0.096)	(0.089)
$RelSpread_{t-1}$	11.015	—	10.835	—
	(3.653)		(4.477)	
$DolSpread_{t-1}$	—	1.269	—	0.312
		(0.349)		(0.377)
Pseudo-R^2	0.05	0.06	0.06	0.06
Number of securities	2926	2926	2926	2926

The table presents weighted-average coefficients of ordered probit regressions using time-series data for each security. The regressions are estimated separately for each security. Regressions are only estimated for securities with a time series of at least 40 observations. The coefficients report are weighted averages where the weight is equal to the number of observations employed in each regression. The dependent variable in the regressions is an entry/exit indicator that is equal to −1 if the mode of the number of market makers for the month is less than that for the previous month, 0 if there is no change in the number of market makers, and +1 if there is an increase in the number of market makers. The standard deviation of the coefficient estimates is presented in parentheses.

estimating the regressions separately for each security ensures comparability of results across securities.

Results of the ordered probit regressions are reported in Table 3. The table presents weighted-average coefficients of the regressions where the weight is equal to the number of observations employed in each regression. The coefficients are cross-sectional weighted averages, calling for cautious interpretation. For example, an average positive coefficient for trading volume does not imply that increases in trading volume attract market maker entry in all securities. Rather, such statistics imply that on average, across securities, increases in trading volume attract entry. Since reporting test statistics for individual parameter estimates is unfeasible, I report the standard deviations of the estimates in parentheses. These standard deviations provide some idea of the distribution of the estimates and therefore allow an assessment of the strength of the results. In general, the weighted-average parameter estimates are at least twice as large as their standard deviations. Weighted-average pseudo-R^2 are also reported to indicate goodness of fit.

The average coefficients on all measures of trading volume and the number of trades are positive, implying that increased trading activity attracts the entry of market makers. The coefficient on the sum of squared returns is negative, indicating that increases in volatility can be linked to decreases in the number of dealers. This result is consistent with the notion that an increase in volatility results in an increase in the riskiness of carrying inventory, thereby causing market making to be less attractive. The negative sign is also consistent with the Poisson regression results in Table 2. The coefficient on firm size is negative, suggesting that entry of market makers is less likely in larger firms. Finally, the coefficients on both relative and dollar spreads are positive and significant in all specifications. The sign of these coefficients suggests that, on average, entry is more likely in securities with larger spreads. Although this result is consistent with competitive markets, it does not necessarily imply that dealer markets are competitive. Indeed, entry may not be a very frequent phenomenon or may not result in a change in quoted spreads. These issues are examined in the following subsections.

A number of robustness checks have been conducted on the results in Table 3. Eliminating securities where the time series is shorter than 40 observations causes firms with short life spans to be removed from the sample. This may result in a sampling bias. To test whether this criteria materially affects the results, I also estimate regressions for all securities. An analysis of the distribution of these parameter estimates shows that large outliers originate from regressions with a short time series. In these cases, the statistical package used for the estimation (STATA) reports that the estimates may be unreliable. The sign of the average coefficients remain unchanged, although the standard deviations of the coefficient estimates are larger. Thus, it is unlikely that the sampling criteria bias the results. I also estimate ordered probit regressions over weekly and quarterly intervals. Although the standard deviations of these estimates are larger for these regressions, the qualitative nature of the results remains unchanged. Finally, controlling for long-term trends in entry and exit by including a trend variable in the regression also leaves the results unchanged.

3.2 Entry and exit frequency

Panel A of Table 4 presents information on the frequency of entry and exit for the entire sample of market-maker changes, classified by quintile.[9] There were a total of 385,053 market-maker changes

[9] Market-maker changes corresponding to initial listing on the NNM (which are usually characterized by the number of market makers increasing from one to two) and delisting from the NNM are not included in the sample.

over the 12-year period. Interestingly, the distribution of these events across the quintiles is fairly even. The vast majority (93%) of market-maker changes involve the entry or exit of a single dealer. This figure is misleading about the manner and scale of entry and exit.[10] In fact, the data show three distinct types of market-maker changes, which are characterized as follows:

1. Consider an increase in the number of market makers from four to five on day 1, followed by the entry of another market maker on day 2 and yet another one on day 5. Clearly, the sequence of entry events over this short period are related. The number of market makers prior to the first change (four) is the "initial" number of market makers; the number of dealers after the last change (seven) is the "final" number of market makers. Intermediate changes (from four to five and five to six) exist because of two possible reasons. First, if entry and exit are driven by profits, these decisions are likely to be made on a monthly basis (at their most frequent). These decisions are unlikely to be synchronized across market makers, introducing discreteness into the frequency of entry/exit. Second, a one-day registration period is required before dealers can quote prices. I refer to these types of market-maker changes as *collapsed events* because, for our purposes, the sequence of events should be collapsed into a single event. Since the intermediate sequence of market-maker changes might involve both entry and exit, the determination of whether a collapsed event constitutes entry or exit depends on the initial and final number of market makers. Specifically, if the initial number of market makers is less (greater) than the final number of market makers, the collapsed event is regarded as representative of market maker entry (exit). The analysis that follows is based on a five-day cutoff such that a minimum of five days is required before the start of another collapsed event.
2. One can also imagine situations where the number of market makers in a security decreases from five to four on day 1 and increases back to five on day 3.[11] NASDAQ rules prevent a dealer from exiting the market-maker designation for a security and then reentering the same designation within 30 days, implying that the exiting dealer must be different from the entering dealer. Since

[10] Any classification of market-maker changes by percentage changes automatically classifies the entry/exit events in quintiles 1 and 2 as "large" percentage changes. This is not true, however, of the other quintiles.

[11] Or equivalently, the number of market makers could decrease from four to three and then from three to two, followed by an increase from two to three and then from three to four, all within two to three days of each other.

Table 4
Frequency distribution of market maker changes

	Increase by 1	Increase by more than 1	Decrease by 1	Decrease by more than 1	Total
Panel A: Full sample of market-maker changes					
Quintile 1 ($2 \leq NumMkMkrs \leq 7$)	43,115	2553	31,981	1104	78,753
Quintile 2 ($8 \leq NumMkMkrs \leq 10$)	33,246	2125	31,870	1963	69,204
Quintile 3 ($11 \leq NumMkMkrs \leq 14$)	39,561	2490	40,651	3156	85,858
Quintile 4 ($15 \leq NumMkMkrs \leq 19$)	31,995	2117	34,497	2922	71,531
Quintile 5 ($20 \leq NumMkMkrs \leq 68$)	35,073	3013	37,697	3923	79,706
Total	182,990	12,298	176,696	13,068	385,053
Panel B: Independent market-maker changes					
Quintile 1 ($2 \leq NumMkMkrs \leq 7$)	21,897	457	16,293	249	38,893
Quintile 2 ($8 \leq NumMkMkrs \leq 10$)	14,844	387	14,632	409	30,272
Quintile 3 ($11 \leq NumMkMkrs \leq 14$)	16,076	459	17,142	618	34,295
Quintile 4 ($15 \leq NumMkMkrs \leq 19$)	11,475	338	12,977	577	25,367
Quintile 5 ($20 \leq NumMkMkrs \leq 68$)	9723	330	11,119	544	21,716
Total	74,015	1971	72,163	2397	150,540
Panel C: Collapsed market-maker changes					
Quintile 1 ($2 \leq NumMkMkrs \leq 7$)	1249	2737	1068	1034	6088
Quintile 2 ($8 \leq NumMkMkrs \leq 10$)	1345	2491	1208	1832	6876
Quintile 3 ($11 \leq NumMkMkrs \leq 14$)	1800	3205	1776	2929	9710
Quintile 4 ($15 \leq NumMkMkrs \leq 19$)	1674	2706	1751	2863	8994
Quintile 5 ($20 \leq NumMkMkrs \leq 68$)	1943	3391	2051	3644	11,032
Total	8011	14,530	7857	12,302	42,700

The sample includes all stocks traded on the NNM between 1982 and 1993. Panel A presents the distribution of market-maker changes for the full sample. Panels B and C present the distribution of market-maker changes for independent and collapsed events. If a market-maker change occurs on day 0 and there are no other market-maker changes over days −5 to +5, the event is classified as an "independent" market-maker change. If a sequence of market-maker changes occur within five days of each other, adjacent events are "collapsed" into a single event, with the market-maker count prior to the first event in the sequence regarded as the initial number of market makers, and the market-maker count after the last event regarded as the final number of market makers.

the initial and final number of market makers is the same, the number of dealers remains unchanged. I refer to these types of market maker changes as *adjustment events*.
3. Finally, market-maker entry might take place on day 1 with no other entry or exit taking place over a long period of time thereafter. These market-maker changes are referred to *independent events*.

The time between successive events is crucial to the classification of entry or exit as an independent event or part of a sequence of events (collapsed or adjustment events). As mentioned above, the results presented in the following sections of the article are based on a five-day cutoff; that is, if a market-maker change takes place within five days of another market-maker change, it is classified as a collapsed or adjustment event, depending on the initial and final number of market makers. Admittedly, the choice of a five-day cutoff is arbitrary. Accordingly, the analysis that follows is replicated with 10- and 20-day cutoffs. The results are qualitatively identical to those presented, and in some cases, the quoted spread changes are larger.

The classification system outlined above is all-inclusive, in the sense that it classifies all entry/exit events. However, the system is not entirely data driven. In fact, the three different types of events represent distinct patterns in entry and exit. Adjustment events, by definition, involve the replacement of one dealer by another. Therefore, they are unlikely to be related to systematic changes in the profitability of market making or the security's information environment. Thus, a priori, one does not expect significant changes in trading intensity, volatility, or spreads around adjustment events. Independent or collapsed events, on the other hand, are more likely to be associated with systematic changes in trading intensity, volatility, or spreads. The tests in the remainder of this article are conducted separately for adjustment, independent, and collapsed events. Consistent with the conjecture above, no systematic patterns in spreads, volume, or volatility are detected for adjustment events. Moreover, less than 1% of the entire sample constitutes adjustment events. Therefore, only results of independent and collapsed events are presented.

Panels B and C of Table 4 show the frequency distribution of market-maker changes for independent and collapsed events. Based on the five-day cutoff criteria, there are 150,540 independent entry/exit events. The patterns of market-maker changes for the independent events sample are similar to those for the full sample; the majority of market-maker changes involve the entry or exit of one market maker.

Approximately 158,000 market-maker changes are condensed into 42,700 collapsed events. On average, 3.2 market-maker changes are condensed into one collapsed event, and the average time between the first and last market-maker change is 5.4 days. The distribution of collapsed events is notably different from that of the full sample or independent events. Of the 22,451 instances of market-maker entry, over 64% (14,530) involve the entry of more than one market maker and almost an equal number (14,112) involve at least a 10% increase in the number of market makers. Similarly, of the 20,159 cases of market-maker exit, over 61% (12,302) involve the exit of more than one market maker and 11,495 involve a market-maker decrease larger than 10%. These cases of large-scale entry (exit) are slightly more concentrated in the lower (higher) quintiles; nonetheless, large-scale entry (exit) is not an infrequent occurrence in the higher (smaller) quintiles.

In general, the entry/exit frequency data show that entry and exit (even large-scale entry and exit) of market makers is pervasive. The ordered probit regressions show that high levels of trading intensity and spreads attract market makers. For the entry/exit mechanism to maintain/enforce a competitive market, however, it must be systematically related to changes in the prices charged by dealers. Accordingly, an investigation of the impact of entry/exit is warranted.

3.3 The impact of entry and exit

Table 5 presents means of end-of-day quoted spreads, volume, the number of trades, and the sum of squared returns before and after entry and exit, classified by market-maker quintile. The means before (after) the event are computed over event days −5 to −1 (1 to 5).[12] *P*-values for paired *t*-tests are presented in parentheses for all variables, except the sum of squared returns for which *F*-tests are used. Panels A and B show the results for independent entry and exit; panels C and D show results for collapsed entry and exit.

End-of-day quoted spreads decrease (increase) following independent entry (exit). There do not appear to be significant changes in volume or the number of trades for independent entry. There are, however, substantial declines in both volume and the number of trades following exit. Whereas independent entry is accompanied by a decline in the sum of squared returns, exit is associated with increases in volatility. The magnitude of the changes in all of these variables is directly related to the number of market makers prior to the event

[12] For collapsed events, the "before" period refers to the five-day period prior to the first market-maker change and the "after" period corresponds to the five-day period after the last market-maker change.

Table 5
Means of variables before and after entry and exit

	Quintile 1 ($2 \leq NumMkMkrs \leq 7$)		Quintile 2 ($8 \leq NumMkMkrs \leq 10$)		Quintile 3 ($11 \leq NumMkMkrs \leq 14$)		Quintile 4 ($15 \leq NumMkMkrs \leq 19$)		Quintile 5 ($20 \leq NumMkMkrs \leq 68$)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Panel A: Independent entry										
RelSpread	8.19	7.50	5.25	4.92	4.15	3.93	3.26	3.13	2.31	2.26
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
DolSpread	0.73	0.67	0.40	0.38	0.33	0.31	0.27	0.26	0.23	0.22
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogVol	7.91	7.90	8.95	8.92	9.68	9.65	10.42	10.39	14.22	14.18
		(0.10)		(0.12)		(0.15)		(0.20)		(0.19)
LogNtrades	1.26	1.24	2.17	2.14	2.73	2.70	3.27	3.24	4.20	4.18
		(0.09)		(0.08)		(0.09)		(0.07)		(0.06)
SqrtSumSqRet	0.045	0.040	0.039	0.035	0.042	0.039	0.035	0.031	0.023	0.022
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Panel B: Independent exit										
RelSpread	7.75	8.53	5.60	5.93	4.54	4.72	3.61	3.71	2.51	2.60
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
DolSpread	0.69	0.75	0.41	0.43	0.33	0.34	0.27	0.28	0.22	0.23
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogVol	7.75	7.59	8.61	8.50	9.31	9.23	10.06	10.01	11.30	11.26
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogNtrades	1.10	0.96	1.90	1.79	2.45	2.37	3.01	2.96	3.99	3.94
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
SqrtSumSqRet	0.041	0.043	0.039	0.041	0.037	0.038	0.035	0.036	0.032	0.033
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)

Table 5
(continued)

	Quintile 1 ($2 \le NumMkMkrs \le 7$)		Quintile 2 ($8 \le NumMkMkrs \le 10$)		Quintile 3 ($11 \le NumMkMkrs \le 14$)		Quintile 4 ($15 \le NumMkMkrs \le 19$)		Quintile 5 ($20 \le NumMkMkrs \le 68$)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Panel C: Collapsed entry										
RelSpread	7.12	5.71	4.66	3.98	3.71	3.31	2.94	2.74	2.09	2.02
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
DolSpread	0.68	0.55	0.38	0.33	0.30	0.27	0.25	0.23	0.20	0.19
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogVol	8.42	8.49	9.37	9.41	10.03	10.06	10.73	10.73	11.93	11.90
		(0.00)		(0.00)		(0.12)		(0.82)		(0.75)
LogNtrades	1.76	1.75	2.54	2.51	3.02	3.00	3.56	3.52	4.52	4.47
		(0.82)		(0.15)		(0.11)		(0.09)		(0.08)
SqrtSumSqRet	0.051	0.035	0.045	0.033	0.037	0.033	0.039	0.032	0.036	0.030
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Panel D: Collapsed exit										
RelSpread	7.02	8.73	4.88	5.75	4.09	4.62	3.34	3.66	2.39	2.57
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
DolSpread	0.61	0.74	0.37	0.42	0.29	0.33	0.24	0.26	0.19	0.20
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogVol	7.96	7.78	9.02	8.73	9.72	9.47	10.31	10.16	11.50	11.38
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
LogNtrades	1.54	1.29	2.19	1.97	2.77	2.57	3.23	3.10	4.13	4.03
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
SqrtSumSqRet	0.042	0.047	0.038	0.042	0.038	0.039	0.036	0.037	0.032	0.033
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)

The sample includes all stocks traded on the NNM between 1982 and 1993. Panels A and B present changes in variables before and after independent events; panels C and D present changes in variables before and after collapsed events. If a market-maker change occurs on day 0 and there are no other market-maker changes over days −5 to +5, the event is classified as an "independent" market-maker change. If a sequence of market-maker changes occur within five days of each other, adjacent events are "collapsed" into a single event, with the market-maker count prior to the first event regarded as the initial number of market makers and the market maker count after the last event regarded as the final number of market makers. The mean of variables before (after) the event are calculated over a five-day window before (after) the event. *P*-values for paired *t*-tests for all variables except *SqrtSumSqRet* are presented in parentheses. For *SqrtSumSqRet*, *p*-values are from *F*-tests and are in parentheses.

(i.e., the market-maker quintile). For example, while the decline in the relative spread for independent entry is 0.69% (6 cents for dollar spreads) for quintile 1, the corresponding figure for quintile 5 is only 0.05% (1 cent). Although, the effects of entry and exit are more pronounced for the smaller quintiles, the entire sample of independent events is characterized by systematic changes in trading intensity, volatility, and spreads.

Substantial changes in closing quoted spreads also take place for collapsed entry and exit events. The spread changes for the collapsed events are larger than those for the independent events for the smaller quintiles; for the larger quintiles, however, the spread changes are similar in magnitude to those for independent events. Once again, the patterns for volume and the number of trades are different for entry and exit. Entry is accompanied by small increases in volume (but only for quintiles 1 and 2) and no change in the number of trades. Exit, on the other hand, is associated with substantial declines in both volume and the number of trades. Similar to the independent events, entry (exit) is associated with declines (increases) in volatility.[13]

In general, the results for collapsed events are similar to those for independent events. The changes in the variables are often more pronounced for collapsed events, most likely due to the scale of entry/exit.

3.4 Regression-based evidence

The univariate statistics presented in Table 5 show that entry (exit) is associated with systematic changes in trading intensity, volatility, and end-of-day quoted spreads. Substantial empirical evidence shows that trading volume, volatility, and price are important determinants of spreads [for example, see Harris (1994) for empirical spread models]. Therefore, attributing spread changes to the impact of entry/exit requires controls for these variables.

Table 6 presents regression-based evidence that the changes in closing quoted spreads documented in Table 5 are due to the impact of entry and exit, rather than the accompanying changes in volume, number of trades, and return volatility. Separate regressions are estimated for independent and collapsed events. Changes in relative and dollar spreads are used as dependent variables. The following two

[13] This analysis implicitly assumes that the identity or size of entering and exiting dealers is unimportant. There is no reason to believe this is the case. Indeed, the entry of a major market-making firm may have a larger impact than a smaller market-making firm. Unfortunately, an analysis based on the type of market maker cannot be conducted since the data do not identify the identity or size of the entrant.

types of regressions are estimated:

$$\begin{aligned}\Delta Spread = {} & a_1 \Delta LogVol + a_2 \Delta LogNtrades + a_3 \Delta SqrtSumSqRet \\ & + a_4 \Delta Price/InvPrice \\ & + a_5 Entry\ Dummy + a_6 Exit\ Dummy \\ & + a_7 Exit\ Dummy * NMkMkrsBefore\end{aligned}$$

$$\begin{aligned}\Delta Spread = {} & b_0 + b_1 \Delta LogVol + b_2 \Delta LogNtrades + b_3 \Delta SqrtSumSqRet \\ & + b_4 \Delta Price/InvPrice + b_5 \frac{NMkMkrsAfter}{NMkMkrsBefore}\end{aligned}$$

where

Δ*Spread* is the mean value of the closing quoted relative (or dollar) spread five days after the event minus the mean value five days before;
Δ*LogVol* is the mean value of the logarithm of trading volume five days after the event minus the mean value five days before;
Δ*LogNtrades* is the mean value of the logarithm of the number of trades five days after the event minus the mean value five days before;
Δ*SqrtSumSqRet* is the square root of the five-day sum of squared returns after the event minus the value five days before;
Δ*Price* is the average price five days after the event minus the average price five days before;
Δ*InvPrice* is the average inverse price five days after the event minus the average inverse price five days before;
NMkMkrsBefore is the number of market makers prior to entry/exit;
Entry Dummy is 1 for entry, 0 for exit;
Exit Dummy is 1 for exit, 0 for entry; and
$\frac{NMkMkrsAfter}{NMkMkrsBefore}$ is the ratio of the number of market makers after entry/exit to the number of market makers before the event. The distance from 1 indicates the scale of entry/exit.

The first four variables (Δ*LogVol*, Δ*LogNtrades*, Δ*SqrtSumSqRet*, and Δ*Price/InvPrice*) control for changes in variables that are known to affect spreads. Spreads typically decrease with volume and the number of trades because market makers spread their fixed costs over more traders, and increase with volatility because the cost of carrying inventory is greater for more volatile securities and also because information asymmetry is probably larger. Spreads are related to prices because of exchange-mandated minimum price variation [see Harris (1994)]. This effect is modeled by including Δ*InvPrice* as a regressor

Table 6
Estimated regressions for changes in spreads

	Independent entry/exit				Collapsed entry/exit			
	Δ*RelSpread*		Δ*DolSpread*		Δ*RelSpread*		Δ*DolSpread*	
Intercept	—	−0.0259	—	0.2229	—	0.0199	—	0.2298
		(0.00)		(0.00)		(0.00)		(0.00)
Δ*LogVol*	−0.0001	−0.0001	−0.0041	−0.0041	−0.0004	−0.0002	−0.0196	−0.0152
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.00)	(0.00)
Δ*LogNtrades*	−0.0059	−0.0058	−0.0231	−0.0221	−0.0067	−0.0067	−0.0145	−0.0137
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*SqrtSumSqRet*	0.2434	0.2406	0.7437	0.7142	0.2499	0.2364	0.7747	0.5691
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*Price*	—	—	0.0096	0.0099	—	—	0.0039	0.0046
			(0.00)	(0.00)			(0.00)	(0.00)
Δ*InvPrice*	0.0359	0.0360	—	—	0.0264	0.0265	—	—
	(0.00)	(0.00)			(0.00)	(0.00)		
Entry dummy	−0.0027	—	−0.0230	—	−0.0028	—	−0.0347	—
	(0.00)		(0.00)		(0.00)		(0.00)	
Exit dummy	0.0053	—	0.0456	—	0.0090	—	0.0622	—
	(0.00)		(0.00)		(0.00)		(0.00)	
*Exit dummy***NMkMkrsBefore*	−0.0002	—	−0.0020	—	−0.0003	—	−0.0022	—
	(0.00)		(0.00)		(0.00)		(0.00)	
$\frac{NMkMkrsAfter}{NMkMkrsBefore}$	—	−0.0259	—	−0.2295	—	−0.0199	—	−0.2283
		(0.00)		(0.00)		(0.00)		(0.00)
Adjusted R^2	—	0.14	—	0.08	—	0.20	—	0.17
N	145,658	145,658	145,658	145,658	41,608	41,608	41,608	41,608

The sample includes all stocks traded on the NNM between 1982 and 1993. Regressions of changes in spreads are presented for both independent and collapsed events. If a market-maker change occurs on day 0 and there are no other market-maker changes over days −5 to +5, the event is classified as an "independent" market-maker change. If a sequence of market-maker changes occur within five days of each other, adjacent events are "collapsed" into a single event, with the market-maker count prior to the first event in the sequence regarded as the initial number of market makers and the market-maker count after the last event regarded as the final number of market makers. Changes in variables are calculated as the difference between the mean value of the variable after the event minus the mean value of the variable before the event. Heteroscedasticity-consistent p-values are presented in parentheses.

for the relative spread regressions and $\Delta Price$ as a regressor for the dollar spread specifications.

Both entry and exit dummies are included in the first specification, and the regression is estimated without an intercept. The advantage of this specification is that the coefficients of the dummy variables provide direct estimates of the impact of entry and exit, controlling for other variables. An interaction term between the exit dummy and the number of market makers prior to entry/exit is also included in the regression to model scale dependencies, that is, the notion that the impact of entry and exit may depend on the absolute number of market makers in the security, prior to the change. The second specification is estimated with the ratio of market makers $(\frac{NMkMkrsAfter}{NMkMkrsBefore})$ as a single regressor that captures the entry/exit event and the scale of entry/exit in one variable. Heteroscedasticity-consistent p-values appear in parentheses below the parameter estimates in Table 6.

The coefficients for changes in volume, number of trades, volatility, and price are significant, have the expected signs, and are stable across comparable specifications. The coefficient on return volatility is positive and particularly high, suggesting that volatility is an important determinant of changes in the spread.

The coefficient on the entry (exit) dummy is negative (positive), implying that entry is associated with a decline in the quoted spread, whereas exit is accompanied by an increase in the quoted spread. The interaction between the exit dummy and the number of market makers prior to entry/exit is negative, suggesting that the larger the number of market makers prior to the event, the smaller the spread change. Finally, the ratio of the postevent number of market makers to the preevent number of market makers is negative. The negative sign indicates that entry is associated with significant declines in the end-of-day quoted spread, while exit is accompanied by increases in the spread.

In general, these results imply that even after controlling for contemporaneous changes in volume, number of trades, return volatility, and price, entry and exit of market makers has a significant impact on quoted end-of-day bid-ask spreads.

3.5 Robustness issues

A variety of robustness checks have been conducted on the results presented in Tables 5 and 6.

First, all results were replicated using 10- and 20-day cutoffs for determining collapsed versus independent events. Note that these cutoffs produce slightly different samples for independent versus collapsed events. All tests in Tables 5 and 6 were then replicated with means of variables computed over 10- and 20-day windows (as appropriate). The results of these alternative specifications are qualitatively identical, and in some cases, the spread changes are larger.

Second, to determine whether the results are driven by a few influential outliers, Wilcoxon rank tests on medians were also performed. None of the inferences changed.

Third, diagnostics on the regressions presented in Table 6 indicated that the models were reasonably well specified. Since heteroscedasticity may be important in this sample, the p-values reported are obtained from heteroscedasticity-consistent t-statistics [see White (1980)].

Fourth, the regressions were reestimated on samples created using the 10- and 20-day cutoffs for determining collapsed events. The results were qualitatively identical to those reported in Table 6.

Fifth, the tests in Tables 5 and 6 were replicated with data grouped by the percentage change in the number of market makers. Specifically, the data were categorized into four groups: where the ratio of postevent number of market makers to preevent number of market makers is greater than 1.10 (corresponding to a change of greater than 10%), between 1 and 1.10, between 0.90 and 1.00, and less than 0.9. Once again, the results were similar to those reported.

Sixth, subperiod analysis of the tests in Table 5 and 6 show that the results were not specific to a particular time period.

Finally, the results were not sensitive to alternative transformations of the analysis variables. For example, the results remain unchanged when the logarithm of dollar volume and the inverse of the square root of the number of trades were used as independent variables.

3.6 The Christie–Schultz sample

As mentioned earlier, the controversial Christie and Schultz (1994) study argues that the absence of odd-eighth quotes for 70 of the largest 100 NNM stocks is suggestive of collusion among market makers. Kleidon and Willig (1995) argue, however, that if collusion does exist, then successful entry of market makers should break the colluding group (unless the entrant is co-opted or punished in some manner). Accordingly, this section seeks to determine the impact of entry and exit on the 50 largest stocks in the Christie and Schultz sample.

The NNM portion of the Christie and Schultz sample consists of 100 securities. The first 50 securities are the largest NNM stocks based on the end of 1991 capitalized market value of equity. The second 50 stocks are randomly chosen from NASDAQ firms with an equity value of at least $100 million. In order to focus on the largest and most actively traded securities, I identify the first 50 stocks as in Christie and Schultz. Further, to ensure comparability of results, I eliminate all data prior to 1991.

Table 7
Entry and exit in the Christie–Schultz large firm sample

Panel A: Entry/exit patterns in the Christie–Schultz large firm sample	Increase by 1	Increase by more than 1	Decrease by 1	Decrease by more than 1	Total
Independent events	562	13	480	16	1071
Collapsed events	56	146	52	97	351

Panel B: Spread movements for independent events	*RelSpread* before	*RelSpread* after	*DolSpread* before	*DolSpread* after	*N*
Entry	1.04	1.05	0.36	0.36	575
		(0.61)		(0.89)	
Exit	0.94	0.94	0.36	0.36	496
		(0.69)		(0.66)	

Panel C: Spread movements for collapsed events	*RelSpread* before	*RelSpread* after	*DolSpread* before	*DolSpread* after	*N*
Entry	1.04	1.00	0.33	0.30	201
		(0.05)		(0.00)	
Exit	0.98	0.96	0.34	0.33	148
		(0.11)		(0.29)	

Panel D: Spread movements for collapsed events	*RelSpread* before	*RelSpread* after	*DolSpread* before	*DolSpread* after	*N*
$\frac{NMkMkrsAfter}{NMkMkrsBefore} > 1.10$	1.11	1.08	0.48	0.41	30
		(0.71)		(0.02)	
$1 < \frac{NMkMkrsAfter}{NMkMkrsBefore} \leq 1.10$	1.03	0.99	0.30	0.28	171
		(0.09)		(0.00)	
$0.90 < \frac{NMkMkrsAfter}{NMkMkrsBefore} \leq 1.00$	0.96	0.98	0.30	0.30	129
		(0.21)		(0.93)	
$\frac{NMkMkrsAfter}{NMkMkrsBefore} < 0.90$	0.95	0.99	0.55	0.58	19
		(0.11)		(0.12)	

The sample consists of the 50 most highly capitalized stocks on the NNM at the end of 1991. Spread changes are presented for both independent and collapsed events. If a market-maker change occurs on day 0 and there are no other market-maker changes over days −5 to +5, the event is classified as an "independent" market-maker change. If a sequence of market-maker changes occur within five days of each other, adjacent events are "collapsed" into a single event, with the market-maker count prior to the first event in the sequence regarded as the initial number of market makers and the market-maker count after the last event regarded as the final number of market makers.

The average number of registered market makers for this sample is 34.6. Panel A of Table 7 shows entry and exit patterns in this sample. Over the three-year period from 1991 to 1993, there are 1071 independent events and 351 collapsed events based on the five-day cutoffs. Not surprisingly, for independent events, the majority of market-maker changes involve the entry (exit) of one market maker. For collapsed events, however, there are more cases of large-scale entry and exit. Thus, even in highly capitalized stocks with a large number of market makers, entry (exit) is not an infrequent occurrence.

Panel B shows closing quoted spread movements for independent entry and exit. Neither relative nor dollar spreads appear to be significantly affected by independent entry and exit. Panel C displays spreads for collapsed events. There are significant declines in both relative and dollar spreads following entry in this sample. The effect is asymmetric, however, since spreads do not increase following exit. This asymmetry may also be driven by the large number of market makers prior to entry/exit. To investigate this possibility further, spread changes are calculated by segregating the sample based on the ratio of the number of market makers after the event to the number of market makers prior to the event. When this ratio is greater than 1.10 (less than 0.90), the increase (decrease) in the number of market makers is at least 10%. The results of this procedure (which isolates extreme market-maker changes) are shown in panel D. Notice that the samples for extreme entry and exit are quite small. Nonetheless, the results suggest that spread changes occur following entry but not exit.

The results presented in Table 7 are also replicated using the 10- and 20-day cutoffs for determining collapsed events. The results are qualitatively unaffected by the cutoffs. In general, the results show that even in highly capitalized stocks, entry is associated with significant declines in spreads.

4. Conclusion

The suggestion of collusion between NASDAQ market makers by Christie and Schultz (1994) has spawned a number of academic studies. Kleidon and Willig (1995), for example, argue that the presence of a large number of market makers and relatively free entry into market making makes the possibility of collusion highly unlikely. Rather, it is their contention that the NASDAQ operates as a competitive market. Indeed, Dutta and Madhavan (1997) show that under free entry, no form of collusion (explicit or implicit) is possible. They argue that entry costs exist in the form of establishing reputation and forming relationships in order to gain access to order flow. Their model suggests that order preferencing arrangements on the NASDAQ constitute a real and significant cost of entry. They argue that these costs are sufficient to ensure the sustainability of tacit collusion.

The results presented in this article show that entry and exit is a pervasive phenomenon on the NNM. Large-scale entry (exit) is associated with significant declines (increases) in end-of-day quoted bid-ask spreads, even after controlling for changes in volume and volatility. The spread changes are larger in magnitude for issues with few market makers; however, even for securities with many market makers, substantial changes in spreads take place. Several caveats are worth noting. First, the spread changes documented in this article are based on quoted, not effective spreads. Second, these spread changes are based on end-of-day spreads, which are known to be affected by dealers wishing to "go home flat." While the evidence is consistent with the competitive model of dealer pricing, it does not explicitly refute or confirm the collusion hypothesis. Indeed, given order preferencing arrangements on the NASDAQ, and the results of Dutta and Madhavan (1997), a "clean" test of collusion requires a researcher to observe all (not just closing) quotes from individual dealers (not just the inside spread), quote revisions, and preferenced and unpreferenced order flow around entry and exit. These data may highlight the degree of price competition and show whether entrants break up a colluding group (if it exists) or are co-opted.

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