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Liquidity Provision and Noise Trading: Evidence from the "Investment Dartboard" Column

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ABSTRACT

How does increased noise trading affect market liquidity and trading costs? We use *The Wall Street Journal*'s "Investment Dartboard" column, which stimulates noise trading, as a natural experiment to evaluate models of the bid-ask spread. We find that substantial increases in trading volume and significant but temporary abnormal returns occur when analysts recommend stocks in this column, especially when recommendations come from analysts with successful contest track records. We also find an increase in liquidity and a decrease in the adverse selection component of the bid-ask spread.

HOW DOES INCREASED NOISE TRADING affect market liquidity and trading costs? A common thread of the theoretical market-microstructure literature suggests that noise trading allows specialists to recoup losses from trades with better-informed investors.[1] Theory states that with lower adverse selection costs the equilibrium bid-ask spread falls and market liquidity increases. Not all bid-ask spread models arrive at this result, however. Some show increased noise trading merely providing cover for informed investors, affecting the spread either not at all or ambiguously. Though noise trading actually constitutes a fundamental component of most microstructure models, little or no empirical evidence exists to reveal the effect of noise-trading changes on liquidity. This lack of evidence is perhaps due to the difficulty of identifying sudden, large shifts in noise trading. Identifying noise trading's pure effect on liquidity requires an environment in which exogenous noise-trading changes can be observed and the subsequent behavior of market-makers can be measured. In this paper, we use a "natural experiment" with precisely these characteristics to study the relationship between noise trading and liquidity. Our results support theoretical models that derive a positive relationship between noise trading and liquidity.

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[1] By "noise trading" we mean trading by investors with no private information to exploit. The literature sometimes refers to such trading as "uninformed" or "liquidity trading."

We measure market responses to investment advice published in *The Wall Street Journal*'s "Investment Dartboard" column and associate these responses with liquidity changes. Using daily and intraday data, we examine the pattern of abnormal returns and abnormal trading volume in recommended stocks. We argue that the column generates temporary price pressure by increasing noise (i.e., uninformed) trading from its readers. We marshal two main pieces of evidence leading us to conclude that the trading this column generates is primarily noise: (1) most of the abnormal returns following the column's publication disappear within a few weeks and (2) abnormal trading volume and (temporary) abnormal returns are greater for stocks recommended by analysts with successful contest records—even though previous contest winners perform no better than other contestants. The data imply that securities with the greatest initial price run-up and the greatest increase in trading volume experience the largest price reversals.

Our evidence suggests that the "Investment Dartboard" column provides a natural experiment in which to test models of specialists' behavior when noise trading increases. The elevated trading activity is substantial, exogenous to the firm, and unanticipated. We exploit this opportunity by examining changes in quoted spreads and depths immediately after these recommendations appear. Additionally, we estimate spread-component changes to test established predictions about specialist-behavior models.

Market microstructure theories (see O'Hara (1995) for a review) examine marketmakers' costs of posting bid and ask prices and depths that reflect their commitment to trade. The theories predict that liquidity providers react differently to changed demands from privately informed versus uninformed traders. Of particular interest in this paper are competing theoretical implications about how noise-trading changes may affect liquidity.

In Glosten and Milgrom's (1985) model, a risk-neutral marketmaker sets a bid-ask spread allowing expected noise-trading profits to offset expected informed-trading losses. When marketmakers believe they face a pool of informed traders, they react by increasing the bid-ask spread. Lee, Mucklow, and Ready (1993) confirm such behavior in their empirical study of changes in market liquidity surrounding earnings announcements. Specifically, they find that marketmakers widen spreads and decrease quoted depths immediately before and after earnings announcements. Lee et al. interpret the decline of both indicators of liquidity as a rational response by marketmakers more likely to trade against informed investors near a significant information event. Our work complements that of Lee et al. in that we examine liquidity changes surrounding just the opposite event.

In contrast to the case of increased informed trading around earnings announcements, the marketmaker will decrease the spread when faced with a larger proportion of noise traders. Indeed, an increased proportion of noise trading decreases the specialist's adverse selection cost and results in a decreased spread in the Glosten–Milgrom framework, where the ratio of informed to uninformed trading is exogenously given. Alternatively, the amount of informed trading could be endogenously determined. In this case, increased uninformed trading induces informed traders, who might otherwise remain on the sidelines, to rush onto the playing field. Some traders may react by becoming informed about the stocks, since informed traders may be able to trade even more aggressively in the camouflage of increased noise trading. This situation obtains in Kyle (1985), in whose model informed traders adjust their demands in proportion to uninformed trading. Kyle's model reveals that the effects of increased informed trading exactly offset those of increased noise trading. Thus, liquidity is invariant to changes in the level of noise trading.

Admati and Pfleiderer (1988) also develop a model with endogenous informed trading, but demonstrate that equilibria exist in which market depth increases as noise trading does. This result obtains even if informed trading increases in response. In this context, increased noise trading raises informed traders' profits. Increased profits then attract more traders with the same information. As a result, each informed trader must trade more aggressively to exploit the short-lived information. Since informed traders compete away their informational advantage, the marketmaker ultimately faces a smaller adverse selection problem. In other words, the level of asymmetric information between the marketmaker and informed traders decreases when noise trading increases. Thus, empirical evidence of a positive relationship between noise trading and liquidity would favor the Admati–Pfleiderer and Glosten–Milgrom models over the Kyle model.

In contrast to predictions motivated by asymmetric information, liquidity may not increase with increased noise trading because of inventory considerations. Stoll (1978) points out that facing an order imbalance may cause marketmakers to revise quotes away from their initial values. Increased noise-trading purchases would require specialist sales, which would, on average, alter the specialist's inventory away from the desired level. In addition to (or instead of) increasing the quoted bid-ask spread, the marketmaker may raise the quoted prices to encourage sales by other traders.[2]

In summary, increased uninformed trading's net effect on liquidity indicators is ambiguous and depends on such factors as informed traders' responses to shocks in uninformed trading, whether increased noise trading concentrates on a particular side of the market, the significance of adverse selection versus inventory holding costs, and the extent to which marketmakers adjust quotes to balance supply and demand. By looking at these factors' relative magnitudes, we indirectly test the implications of competing microstructure models. Specifically, we seek to determine the net effect of increased noise trading on market depth, the bid-ask spread, and the spread's components. Our findings suggest that market liquidity increases modestly in response to increased noise trading stimulated by the Dartboard column. Generalized Method of Moments (GMM) estimates of the spread components

[2] The literature refers to quote adjustments resulting from a temporary imbalance between supply and demand for a security as "price pressure." The models of Stoll (1978) and Ho and Stoll (1981) imply that an order-flow imbalance changes the spread's midpoint but not its size.

indicate that adverse selection costs decline after stocks receive publicity in the column. Partially offsetting reduced adverse selection costs are increased inventory and order-processing costs, though this increase is only marginally significant. We believe that the evidence favors the Glosten–Milgrom and Admati–Pfleiderer approaches, in which informed trading does not fully offset shocks to uninformed trading, resulting in a positive relationship between noise trading and market liquidity.

The remainder of the paper is organized as follows. Section I describes our sample of "Investment Dartboard" contests and presents evidence that this column's recommendations generate substantial noise trading. We confirm findings from previous studies that the Dartboard contest generates price pressure, and we identify short-lived reputation effects explaining some of our sample's cross-sectional variation in abnormal returns and volume. In Section II we use the natural experiment created by the contest to examine increased noise trading's effect on market liquidity. We examine spread and depth changes and estimate spread components around the contest. Thus we can test the empirical implications of various microstructure models. Section III offers some conclusions and suggestions for further research.

I. Noise Trading and the Dartboard Column

Our sample consists of 100 analysts and the 199 securities they recommended in the Dartboard column in contests between October 1988 and December 1992. In the typical contest, four investment professionals each select one stock they expect to perform well over the next six months.[3] The first- and second-place finishers among the group are usually invited back to participate in the next contest. About half of the analysts in the sample (53) appear only once in the column. Of the remainder, 27 appear just twice, 11 make three appearances, and 9 appear in at least four contests. Table I provides our sample's descriptive statistics.

The Wall Street Journal describes the Dartboard contest as an informal test of the efficient market hypothesis. Several academic researchers have examined contest results to determine whether its featured investment professionals select stocks that earn excess returns. These studies reach different conclusions. Metcalf and Malkiel (1994) conclude that pros' picks generally do not earn significant abnormal returns and that no subgroup of contestants consistently beats the market. Thomas and Ghani (1996) study earnings forecast revisions and find no evidence of upward revisions in earnings estimates in response to analysts' recommendations in the Dartboard column. Barber and Loeffler (1993) conclude that analysts' picks contain *some* information, but also

[3] Analysts may also recommend short sales on stocks expected to fare poorly over the subsequent six months. Our sample contains nine short-sale recommendations, for which we multiply postrecommendation returns by -1 to indicate earnings from selling short. Before June 1990, the pros' picks were evaluated over a one-month horizon. The editors realized that large announcement effects could go a long way toward determining the outcome of a one-month contest, so they extended the time horizon.

Table I

"Investment Dartboard" Column Sample Description

The table reports sample characteristics by exchange listing for stocks selected in *The Wall Street Journal*'s "Investment Dartboard" column. Stocks in the *First* appearance category are those stocks recommended by first-time contestants. *Second* refers to those stocks recommended by contestants who have won or finished second in the contest. Picks by contestants who have won or finished second in the contest on two or more occasions appear in the *Third or higher* category. We also report the number of stocks that were *First place winners*. Volume is reported in shares and prices and spreads are reported in dollars. The percentage bid-ask spread is calculated as the dollar spread divided by the midpoint of the bid and ask prices.

	All	NYSE/AMEX	Nasdaq
First appearance	100	61	39
Second appearance	47	29	18
Third or higher appearance	52	25	27
All picks	199	115	84
First place winners	50	24	26
Average share price	27.87	35.42	17.20
Median share price	19.50	29.50	15.50
Average spread	0.2407	0.2116	0.4062
Median spread	0.2071	0.1968	0.3686
Average % spread	0.0066	0.0052	0.0148
Median % spread	0.0042	0.0036	0.0129
Average daily volume	300,596	354,730	223,965
Median daily volume	132,510	176,650	83,889

generate substantial temporary price pressure. They base this conclusion on the fact that half of the event-day stock price run-up is quickly reversed, though trading volume remains unusually high for several weeks.

Though Barber and Loeffler discover a positive correlation between abnormal volume and temporary abnormal returns, they do not explain the cross-sectional variation in abnormal returns and volume among the recommended securities. Below we establish that what drives abnormal volume (and, hence, abnormal returns) is the reputation of the analyst recommending the stock. However, an analyst's reputation does not help predict future contest results. A simple experiment sheds light on the prospect that returning contestants' successes result as much from the luck of the draw as from their expertise. Suppose we start with 100 analysts (our sample size) and select half at random to "play another round" (recall that two of four contestants return for the next round in each contest). In this case, 50 pros would appear only once, 25 would appear twice, and 25 would appear three or more times. Compare this hypothetical outcome with the number of pros actually appearing once (53), twice (27), or more (20) in our sample. A chi-square test fails to reject the hypothesis that the observed distribution differs from the expected random selection pattern. Metcalf and Malkiel (1994) perform the same test for their sample with similar results. Since an ana-

Table II

Abnormal Returns and Volume by Reputation

We calculate abnormal returns by subtracting the CRSP equally-weighted index return from each individual stock return and abnormal (log) volume by using a market model adjustment. Percentage increase is in shares traded. We estimate abnormal returns and volume for the full sample as well as subsamples based on the analyst's reputation. Our reputation proxy is the number of times an analyst has appeared in the contest. Significance on the abnormal return and abnormal volume is reported for the null hypothesis that the mean is zero. Significance on the "Percentage > 0" is reported for the null hypothesis that 50 percent of the abnormal return observations are positive.

Event Period	Abnormal Return	Percentage > 0	Abnormal Volume	Percentage Increase
Full sample				
Day 0	0.030**	77.4%**	0.876**	140.1%
Day 1	0.005**	58.4%**	0.679**	97.2%
Days −1 to +30	0.001	44.2%		
First appearance				
Day 0	0.002**	71.7%**	0.627**	87.2%
Day 1	0.004*	55.6%	0.527**	69.4%
Days −1 to +30	−0.001	46.5%		
Second appearance				
Day 0	0.031**	79.5%**	1.047**	184.9%
Day 1	0.002	61.4%	0.745**	110.6%
Days −1 to +30	−0.005	43.2%		
Third or higher appearance				
Day 0	0.055**	87.2%**	1.207**	234.3%
Day 1	0.015**	61.7%*	0.913**	149.2%
Days −1 to +30	0.009	40.4%		

* and ** indicate significance at the 5- and 1-percent levels, respectively.

lyst's contest history is not a good predictor of future success, establishing a link between reputation and abnormal volume and returns strengthens the price pressure case.

Table II contains our estimates of abnormal returns and trading volume around the contest. The first group of data reports full-sample abnormal volume and returns for the first two days after the column appears, as well as cumulative abnormal returns from the day before through 30 days after publication. We measure abnormal returns by simply subtracting the daily return on the CRSP equally weighted index from each stock's daily return. We adopt this approach to avoid possible bias from analysts basing their recommendations on past performance.[4] Our results corroborate Barber and

[4] In fact, abnormal return estimates from a market model reveal larger price reversals than Table II documents and negative abnormal returns over the event window (0, +30). Table II's estimates are more conservative, yet still indicate that the initial price run up for recommended stocks is reversed over time. We obtain Table III's results from a market model, but regression-alpha bias should not affect results over a one- or two-day period and because we are not cumulating abnormal returns.

Loeffler's report of a significant publication-day (day 0) return of 3.0 percent. We note that, given our sample's average (median) price of stocks of \$27.87 (\$19.50) and the average (median) spread of \$0.24 (\$0.21), we cannot attribute our reported abnormal returns to bid-ask bounce. Over the (−1,30) event window, however, we find no evidence of persistent abnormal returns. Neither the mean return nor the percentage of recommendations with positive abnormal returns is significant. Statistically and economically significant negative abnormal returns beyond event day +1 essentially cancel out the initial announcement effect.

We calculate abnormal trading volume by first taking the logarithm of one plus the number of shares traded in a particular stock as well as in the market and then estimating a market model for volume:[5]

$$\log(1 + vol_{i,t}) = \alpha_i + \beta_i \log(mktvol_t) + \epsilon_{i,t}. \tag{1}$$

Note that exponentiating the abnormal volume measure estimated by this model yields the ratio of one plus actual trading volume to one plus predicted trading volume. For example, an abnormal volume residual of 0.500 in the event period translates approximately into an increased trading volume of

$$e^{0.5} = \frac{1 + vol_{i,t}}{1 + predictedvol_{i,t}} = 1.65 \tag{2}$$

or 65 percent above expected volume. Our sample's mean publication-day abnormal volume is 0.876, or about 240 percent of normal volume. Applying this percentage to the average firm in our sample yields an increase in trading volume from 300,596 to 721,731 shares. We also confirm (but do not report) previous findings that significant abnormal volume persists for at least 10 trading days after the column appears.[6]

Table II also reports different subgroups' abnormal returns and volume estimates based on analysts' contest track records, which we use as a naive measure of reputation. The first-time contestants' recommendations show that abnormal returns and volume are significant here, though this subgroup's point estimates are smaller than those of the full sample. The second subgroup contains picks by analysts with one previous first- or second-place contest finish. This subgroup's event-day abnormal returns and volume appear very close to the full-sample average. The third subgroup shows picks by analysts with at least two previous appearances. This subgroup's

[5] To account for serial correlation in trading volume, we estimate the market model by estimated generalized least squares. The mean of the autoregressive parameter is approximately 0.3. These results approximate those of Ajinkya and Jain (1989). We rely on their results demonstrating that the distribution of residuals from the log volume model is approximately normal.

[6] In the accounting literature, Morse (1981) and Bamber (1986, 1987) document a similar pattern. They report that prices adjust quickly after earnings announcements, though abnormal volume persists for several days.

Table III

Half-Hour Average Abnormal Percentage Returns and Abnormal Volume for Event Days 0 and +1

We calculate abnormal returns and abnormal (log) volume from market model adjustments for each half hour and estimate market model parameters separately for each half hour to control for the U-shaped patterns in intraday returns and volume. Percentage increase is in shares traded. Statistics are reported for the first two half hours of the trading day. Average statistics are reported for the remaining half hours. Results are for the 170 sample stocks for which complete data are available.

	Abnormal Return	*t*-stat	*p*-value	Abnormal Volume	Percentage Increase	*t*-stat	*p*-value
Day 0							
9:30–10:00	1.47%	11.82**	$<$0.001	1.147	214.9%	8.73**	$<$0.001
10:00–10:30	0.32%	4.28**	$<$0.001	0.945	157.3%	6.72**	$<$0.001
Avg. of other half hours	0.02%	—	0.534	0.748	111.4%	—	$<$0.001
Day +1							
9:30–10:00	0.47%	3.87**	$<$0.001	0.828	128.9%	6.47**	$<$0.001
10:00–10:30	0.01%	1.17	0.244	0.654	92.3%	4.72**	$<$0.001
Avg. of other half hours	0.00%	—	0.360	0.591	80.6%	—	0.001

** indicates significance at the 1-percent level.

publication-day abnormal return is 5.5 percent, nearly twice the full-sample average, its volume more than three times normal. The mean event-day return for this subgroup is also significantly higher than that of either of the other groups at the 5 percent level.[7] Note, however, that returns over the (−1, 30) window are insignificant for *every* subgroup. Taken together, Table II's results support the view that the Dartboard column generates temporary price pressure, that this pressure's magnitude depends on a variable with no predictive power for long-run returns (i.e., the analyst's reputation), and that postpublication abnormal trading is uninformed trading.

We find two additional pieces of evidence suggesting that postcontest trading is primarily noise. First, using intraday data from The Institute for the Study of Security Markets (ISSM), we find that most event-day abnormal returns are realized within the first hour of trading. Table III reports abnormal returns and volume for each half-hour trading interval on event days 0 and +1.[8] Significant returns appear only during the first hour of day 0

[7] The difference in mean returns between the third-appearance and first-appearance subgroups is 3.8 percent, with a *t*-statistic of 5.73. The difference between the third and second subgroups is 2.4 percent, with a *t*-statistic of 3.61. We do not report median event-day returns, but they are also significantly higher for the third group.

[8] The careful reader may note that the total daily returns on day 0 and +1 reported in Table III do not precisely match those reported in Table II. The explanation for the difference is that intraday data are not available for NASDAQ securities before 1990 (24 firms in our sample), and the ISSM tapes contain incomplete data for five additional stocks.

and the first half hour of day +1. Approximately 90 percent of the total abnormal return on day 0 occurs by 10:30 a.m. Even if the pros' picks cause a permanent abnormal return, our evidence suggests that traders attempting to follow the column's advice would not earn abnormal profits unless their orders were executed very early in the day.[9] Nevertheless, abnormal volume is significant in every trading interval on both days. For our second piece of evidence suggesting that postcontest trading is primarily noise, we employ Lee and Ready's (1991) trade-typing technique to identify trades as either buy- or sell-initiated. Price pressure implies that abnormal trading volume should concentrate on the buy side when an analyst recommends purchasing a stock (or on the sell side for short-sale recommendations). Not surprisingly, we find that abnormal buy volume exceeds abnormal sell volume throughout day 0 and for most of day +1.[10]

In summary, we have presented evidence that the "Investment Dartboard" column stimulates a large increase in uninformed trading. This increase is both exogenous to the firm and unanticipated, providing a natural experiment in which to study marketmakers' responses to increased noise trading. We turn to that topic in the next section.

II. Liquidity and Trading Costs

Our event-study results suggest that noise trading accounts for much of the trading increase around publication of the "Investment Dartboard." In this section, we use the event of the contestant-analyst's recommendation to explore how market characteristics change under increased noise trading. We examine the implications of theoretical microstructure models for this event and offer some indirect tests for distinguishing among the various theories. We also compare our results with the literature regarding earnings announcements to compare the statistical and economic significance of our findings with those of one of the most frequent and widely studied corporate events.

The prediction that market liquidity increases with increased noise trading appears intuitive, though the direction and magnitude of changes in observed spreads depend on the relative sizes of inventory and adverse selection costs. Since more noise traders decrease the adverse selection problem, the specialist should require less compensation to cover adverse selection

[9] In fact, we find that a strategy of shorting stocks recommended by our most "successful" subgroup of analysts would have earned profits of about five percent after covering the bid-ask spread. Details of the trading strategies are available upon request.

[10] For all of our intraday analysis, we construct a market model benchmark in which the unit of observation is a particular half-hour period on a particular day. Thus, we estimate half-hour abnormal returns (volume) at the beginning of the day by subtracting the first half-hour's expected return from the actual return. We use a similar approach to calculate abnormal buy and sell volume. We estimate a different market model for each half hour to control for the familiar U-shaped patterns in intraday returns and volume. Tables with estimates and significance levels are available upon request.

costs. Both the Glosten–Milgrom and the Admati–Pfleiderer models imply that quoted spreads should decrease and/or that quoted depths should increase during the increased noise trading after the Dartboard column's publication. The next two subsections test the models' predictions by examining spreads, depths, and the components of the bid-ask spread following the column's publication. We emphasize that these are not structural tests designed to reject specific models. Rather, we employ the available data to examine the implications of several competing microstructure models and in so doing make a first attempt to study the empirical relationship between noise trading and liquidity.

A. The Bid-Ask Spread and Market Depth

In this section we estimate abnormal spreads and depths following publication of the Dartboard column. We employ a methodology comparable to Lee et al.'s (1993). We note for comparison with our results that Lee et al. show spreads to be abnormally high and depths abnormally low before and after earnings announcements. They document an average increase of 12.47 percent (3.1 cents) in the quoted spread in the announcement interval. This spread increase is statistically significant and persists for several hours. Lee et al. also find an insignificant depth decrease of 3.96 percent. They interpret these findings as evidence that marketmakers decrease the liquidity they provide to the market when they perceive themselves at an informational disadvantage, as Glosten and Milgrom (1985) and others predict.

To determine whether market liquidity changes in response to noise trading, we examine data from the ISSM tapes for firms listed on either the NYSE or AMEX, giving us a sample of 105 firms. To calculate abnormal spreads and depths, we employ a methodology controlling for the familiar U-shaped patterns in the intraday data. We compute the mean of the prevailing quoted spread at the end of each half hour during the estimation period (event days -130 to -31), giving us a different "normal spread" estimate for each daily half-hour trading period. We then subtract these "normal spread" estimates from the prevailing quotes at the end of each half hour on days 0 and $+1$ to calculate abnormal spreads. We adopt a similar approach to estimate abnormal market depth. We first aggregate bid and ask depths to obtain the total depth for each quote for each half-hour trading interval. Our baseline depth is the estimation period mean of the logarithm of one plus the total depth. We calculate abnormal depths by subtracting the mean depth from the actual depth quoted at the end of each half hour during the event period.

Table IV shows below-normal spreads on days 0 and $+1$. Our estimates indicate a spread reduction of one to two cents, though the estimates are significant in only three of 26 half-hour trading intervals. The strongest evidence of declining spreads occurs in the morning of day 0, when our estimates are of the opposite sign from and are one-half those of Lee et al. (1993) reported around earnings announcements. We obtain similar results

Table IV

Half-Hour Average Abnormal Dollar Spreads and Share Depths for Event Days 0 and +1

We calculate abnormal spreads and depths by subtracting the estimation period (−130, −30) mean spread (depth) for each half hour from the actual spread (depth) at the end of each half hour on event days 0 and +1. Our measure of depth is the logarithm of the aggregate (bid and ask) depth for each stock. Statistics are reported for the first two half hours of the trading day. Average statistics are reported for the remaining half hours. Results are for the 105 NYSE sample stocks for which complete data are available.

	Abnormal Spread	*t*-stat	*p*-value	Abnormal Depth	*t*-stat	*p*-value
Day 0						
9:30–10:00	−0.017	−2.20*	0.030	0.183	0.98	0.329
10:00–10:30	−0.020	−2.14*	0.035	0.307	2.07*	0.041
Other half hours	−0.010	—	0.302	0.107	—	0.391
Day +1						
9:30–10:00	−0.003	0.39	0.697	0.181	1.35	0.180
10:00–10:30	−0.009	−0.83	0.408	0.038	0.10	0.921
Other half hours	−0.012	—	0.395	0.096	—	0.494

* indicates significance at the 5-percent level.

for abnormal depths. Most point estimates indicate insignificantly increased depths. Table IV's results do not suggest that marketmakers interpret the increased trading volume as informed trading or that increased inventory-holding costs drive liquidity changes. Rather, the numbers suggest that market liquidity either increases modestly or (conservatively) remains unchanged. Failure to reject the null hypothesis of no spread change (especially later in the day) is consistent with offsetting adverse selection and inventory costs. Alternatively, our methodology may lack the power to draw any conclusions concerning trading costs following the Dartboard column's publication. However, we note that Lee et al. use the same methodology, with similar sample attributes, and detect significant spread increases. The next subsection presents a more direct test of the adverse selection and inventory models by estimating the components of the bid-ask spread.

B. Components of the Bid-Ask Spread

Madhavan, Richardson, and Roomans (1997) (MRR) develop a structural empirical model for estimating bid-ask spread components that incorporates both public information shocks and microstructure effects. MRR give bid-ask spread components as parameters in their equation (3). They model price changes as

$$\Delta p_t = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + \mu_t, \tag{3}$$

where ϕ represents the spread component due to inventory and order-processing costs, θ is the adverse selection component, and ρ is the first-order autocorrelation coefficient on the order flow x_t.

The Glosten–Milgrom and Admati–Pfleiderer models predict that the bid-ask spread's adverse selection component (θ) decreases when noise trading increases. Additionally, inventory models predict that the fixed component (ϕ) increases when the dealer faces increased inventory risk. To test these predictions, we obtain GMM estimates of the spread components by employing the moment restrictions the MRR model implies. Estimating this model requires a significant number of transactions per firm, so we estimate the model for NYSE stocks with at least 50 transactions in each of the event and pre-event windows. We estimate over event days -30 through -11 for the pre-event window. The results are not qualitatively different when using different pre-event windows. First we examine event days 0 and $+1$, when the initial abnormal returns occur. Second, we estimate spread-component changes over the event window ($+11$, $+30$) to determine whether they are long-lived. We are interested in this aspect of the spread changes for two reasons. First, increased trading associated with the contest lasts for at least two weeks, with many trading days beyond that showing higher-than-normal volume. Second, we wish to compare the persistence of our sample's spread changes with that documented around earnings announcements. Recall that spread increases around earnings announcements disappear in a few minutes.

Table V reports the relevant estimated components for the 98 firms meeting the activity screen. The average (median) estimated adverse selection component, θ, decreases from 2.73 cents (2.10 cents) in the pre-event period to 2.42 cents (1.76 cents) in the event window (0, $+1$). Both parametric and nonparametric tests indicate that this decrease is significant. The average estimated inventory component, ϕ, rises by the same magnitude that the adverse selection component falls, though this difference is significant only in the nonparametric sign test.[11] Results are similar for the window ($+11$, $+30$), in which the adverse selection component falls from 2.73 cents to 2.37 cents (significant at the 1 percent level). However, there is no significant difference in the inventory cost component.[12]

One could argue that although it is statistically significant, the implied change in the bid-ask spread due to a change in the adverse selection component appears economically insignificant. The value of its impact for a round-

[11] We also estimate λ, which is the probability that a trade occurs inside the quoted spread, and ρ, the serial correlation in the MRR model's order flow. These parameters exhibit no changes around the Dartboard column event.

[12] We also obtain estimates for the event-day morning. Our previous event study results indicate that if there is *any* information contained in the analysts' recommendations, this information is incorporated into prices almost immediately on the event day. One might expect the spread's adverse selection component to be largest at this time, yet we find no evidence of this for those firms with enough trading activity at the beginning of the trading day to estimate the model.

Table V

GMM Estimates of the Change in the Components of the Bid-Ask Spread under Increased Noise Trading

Estimates of the components of the bid-ask spread follow the methodology of Madhavan, Richardson, and Roomans (1997). The proportion of trades executed within the bid-ask spread (λ), the auto-correlation in the orderflow (ρ), the inventory/order processing component (ϕ), and the adverse selection component (θ) are GMM estimates of the model

$$\Delta p_t = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + u_t.$$

The event date is the day of publication of *The Wall Street Journal*'s "Investment Dartboard" column. The estimation periods consists of event days (−30,−11), (0,+1), and (11,30). We omit firms with fewer than 50 NYSE transactions during any period. The data used in the estimation are drawn from 98 NYSE-listed firms. We report the Wilcoxon sign test of the null hypothesis that the event period's estimated components are equal to the estimation period's estimated components.

Parameter Estimates	λ	ρ	ϕ	θ
Pre-event period (−30,−11)				
Median	0.3098	0.3722	0.0489	0.0210
Mean	0.3000	0.3787	0.0456	0.0273
Std. dev.	0.1169	0.1056	0.0164	0.0283
Event period (0,+1)				
Median	0.3059	0.4156	0.0512	0.0176
Mean	0.2958	0.3989	0.0487	0.0242
Std. dev.	0.1273	0.1426	0.0130	0.0238
Post-event period (+11,+30)				
Median	0.3057	0.3742	0.0502	0.0161
Mean	0.3038	0.3727	0.0481	0.0237
Std. dev.	0.1088	0.0972	0.0113	0.0237
Difference of event (0,+1) − pre-event				
Median	−0.0007	0.0028	0.0016	−0.0018
Mean	−0.0042	0.0202	0.0031	−0.0031*
Std. dev.	0.0796	0.1292	0.0172	0.0164
Percentage of firms negative	50.00	48.98	37.76	61.22
Sign test t-statistic	0.000	−0.202	−2.424*	2.222*
Difference of event (0,+1) − post-event				
Median	−0.0118	0.0200	0.0011	0.0011
Mean	−0.0080	0.0262	0.0006	−0.0004
Std. dev.	0.0732	0.1319	0.0122	0.0136
Percentage of firms negative	55.10	43.88	45.92	54.08
Sign test t-statistic	1.010	−1.212	−0.808	0.808
Difference of postevent − pre-event				
Median	0.0078	−0.0069	0.0011	−0.0009
Mean	0.0038	−0.0059	0.0025	−0.0036**
Std. dev.	0.0598	0.0777	0.0135	0.0123
Percentage of firms negative	46.94	56.12	42.86	60.20
Sign test t-statistic	−0.606	1.212	−1.414	2.020*

* and ** indicate significance at the 5- and 1-percent levels, respectively.

trip transaction (the effective spread) is twice the value of the change. Therefore, our estimates suggest that the bid-ask spread decreases by about 0.7 cents due to the increased noise trading. Clearly, other factors such as price discreteness play a role in determining the size of bid-ask spreads. We note, however, that a reduction in adverse selection costs of this magnitude represents more than a 10 percent decline in that spread component. This estimate is also roughly one-fourth the spread change observed around earnings announcements.[13] We conclude that noise-trading changes can significantly affect marketmakers' adverse selection costs as predicted by Glosten and Milgrom (1985) and Admati and Pfleiderer (1988).

III. Conclusion

This paper uses the natural experiment provided by *The Wall Street Journal* "Investment Dartboard" column to study the behavior of marketmakers in an environment of increased noise trading. We provide evidence consistent with two classes of theoretical microstructure models. First, inventory-cost theories suggest that liquidity providers temporarily raise quoted prices in the face of an uninformed order imbalance. We find that prices rise in response to the increased trading but subsequently fall. Second, the theoretical models suggest that the inventory component of quoted spreads may increase in response to trading volume shocks. We find only weak evidence of this immediately after the Dartboard column appears. Third, in contrast to the adverse-selection cost model of Kyle (1985), the models of Admati and Pfleiderer (1988) and Glosten and Milgrom (1985) predict that increased noise trading reduces the adverse selection problem for the dealer and causes increased liquidity (i.e., more depth, tighter spreads). Our sample reveals an (insignificantly) increased market depth, a decreased total bid-ask spread, and a decreased adverse selection component of the spread.

Our findings complement the work of Lee et al. (1993) documenting decreased liquidity around an information event. However, unlike Lee et al., we find a positive relationship between trading volume and market liquidity. We view the difference between our results and theirs as evidence that marketmakers can (at least sometimes) discern whether volume shocks result from an information event or from noise traders' changing demands. An unconditional test examining the time-series relationship between trading volume and liquidity may therefore mask important information available to specialists.

[13] We note, however, that Lee et al. (1993) do not estimate the spread components and that some of their observed increase may be related to inventory costs rather than adverse selection effects.

REFERENCES

Admati, Anat, and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3–40.

Ajinkya, Bipin B., and Prem C. Jain, 1989, The behavior of daily stock market trading volume, *Journal of Accounting and Economics* 11, 331–359.

Bamber, Linda S., 1986, The information content of annual earnings releases: A trading volume approach, *Journal of Accounting Research* 24, 40–56.

Bamber, Linda S., 1987, Unexpected earnings, firm size, and trading volume around quarterly earnings announcements, *Accounting Review* 62, 510–532.

Barber, Brad M., and Douglas Loeffler, 1993, The Dartboard Column: Second-hand information and price pressure, *Journal of Financial and Quantitative Analysis* 28, 273–284.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Ho, Thomas S. Y., and Hans R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47–73.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1336.

Lee, Charles M. C., Belinda Mucklow, and Mark J. Ready, 1993, Spreads, depths, and the impact of earnings information: An intraday analysis, *Review of Financial Studies* 6, 345–374.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035–1064.

Metcalf, G. E., and Burton G. Malkiel, 1994, *The Wall Street Journal* contests: The experts, the darts, and the efficient markets hypothesis, *Applied Financial Economics* 4, 371–374.

Morse, Dale, 1981, Price and trading volume reaction surrounding earnings announcements: A closer examination, *Journal of Accounting Research* 19, 374–383.

O'Hara, Maureen, 1995, *Market Microstructure Theory* (Blackwell Publishers Inc., Boston, Mass.).

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133–1151.

Thomas, Martin R., and Waqar I. Ghani, 1996, The dartboard column: Analysts' earnings forecast and the information content of recommendations, *Journal of Business and Economic Studies* 3, 33–42.