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Is Sound Just Noise?

JOSHUA D. COVAL and TYLER SHUMWAY*

ABSTRACT

We analyze the information content of the ambient noise level in the Chicago Board of Trade's 30-year Treasury Bond futures trading pit. Controlling for a variety of other variables, including lagged price changes, trading volumes, and news announcements, we find that the sound level conveys information which is highly economically and statistically significant. Specifically, changes in the sound level forecast changes in the cost of transacting. Following a rise in the sound level, prices become more volatile, depth declines, and information asymmetry increases. Our results offer important implications for the future of open outcry and floor-based trading mechanisms.

FOR MOST OF HISTORY, MANKIND HAS RELIED on face-to-face interaction to convey information between individuals. The past two thousand years have witnessed a secular trend away from this face-to-face interaction. This trend has been aided by a variety of technological advances which help relax the constraints of geography, including the development of smoke signals, paper, moveable type, the telephone, and, of course, the modern computer. The evolution of financial market operation has mirrored the overall trend away from face-to-face human interaction. For instance, during the past two hundred years, the New York Stock Exchange (NYSE) has introduced a steady stream of technological advances that allow traders to participate in its market from greater distances, including the telegraph (1840s), the stock ticker (1867), the telephone (1878), the pneumatic tube system (1918), radio paging (1966), designated order turnaround system (DOT) (1976), and wireless devices (1996). In this paper, we use the financial market setting to address a question confronted by sociologists and exchange presidents alike: How important is face-to-face human interaction? We ask whether the face-to-face interaction characteristic of floor-based and open outcry trading systems plays a vital and irreplicable role in the price-setting process, or whether it is merely an anachronism in the modern financial landscape.

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The metric we propose for assessing the role of face-to-face interaction in the price-setting process is the exchange sound level—or what is commonly referred to by traders as the "buzz" of the exchange. Although sound is certainly not unique to face-to-face interaction, we argue that current electronic exchanges are not equipped to convey sound levels or the information for which they are likely to proxy. We demonstrate that the exchange sound level proxies for the degree of trader anxiety on the floor of the exchange. In particular, increased sound levels presage a variety of changes to market conditions of which traders are likely to be fearful, including declining depth and increases in volatility and information asymmetry. Our results suggest that electronic exchanges will continue to be imperfect substitutes to open outcry trading as long as they cannot fully replicate exchange sound levels and the variables for which they are likely to proxy.

Some prior evidence exists that traders find the exchange sound level to be informative. First, Madhavan and Panchapagesan (1998) point out that NYSE specialists often cite the ambient sound level as containing information that is useful for setting prices. Second, when the financial product trading floor of the Chicago Board of Trade (CBOT) was moved to a new building in 1997, traders in the 10-year note pit complained they had less "feel" for what was happening in the 30-year bond pit. Their new pit's location was no longer adjacent to the bond pit, but now separated from it by 25 feet. When the CBOT responded by placing television monitors in the center of the 10-year pit with live video feed from the inside of the bond pit, the monitors went unused. This suggests that traders in the 10-year pit view the sound level of the bond pit to be important information that cannot simply be reconstructed from other publicly observable variables. Our study focuses on high-frequency measures of the sound level in the CBOT's bond futures pit. The bond pit, with over 400 pit participants and the world's second largest volume levels, offers an ideal setting in which to test the importance of sound.[1]

It is important to emphasize that our inquiry is conducted within the well-established market microstructure framework. We investigate the importance of sound in the context of a number of broadly accepted microstructure variables and relationships. We relate sound levels to return volatility, market depth, trader price concessions, and order flow. This allows us to relate our results directly to those obtained previously in the microstructure literature, and permits a direct assessment of the role of sound levels in the price-setting process.

Central to our argument is the notion that sound levels reflect the anxiousness of traders to trade at current prices. Since trades can be conducted entirely with hand signals in an open outcry setting, we argue that periods of high sound level reflect high trader demand for immediacy in their trades. We claim that this demand for immediacy is likely to be

[1] The CBOT's bond futures traders traded 99,827,659 contracts in 1997. Only the CME's Eurodollar futures contract exhibited greater volume.

strongest when traders are fearful of potential increases in the costs of executing their trades. With this as our point of departure, we examine whether the sound level, as a measure of trader anxiety, conveys significant information regarding future trading conditions. We find that, indeed, after controlling for all available transaction information, increases in the sound level precede changes in conditions that would be associated with higher costs of trading, including greater volatility, lower market depth, and increased information asymmetry. The high statistical and economic significance of the results indicates that face-to-face communication among traders is central to the determination of market equilibrium in an open outcry exchange.

Our research contributes directly to the study of market microstructure and exchange design. It adds to a growing literature investigating the role of nontransaction information in the price formation process, including DeMarzo, Vayanos, and Zweibel (1998), who investigate the role of intertrader communication; Benveniste, Marcus, and Wilhelm (1992), who study professional exchange floor relationships; Biais, Hillion and Spatt (1999) who look at preopening signaling; and Cao and Lyons (1999), who study inventory information. More broadly, our findings offer a point of departure toward understanding how our economy will evolve into the future, as the constraints of geography continue to melt away, and face-to-face interaction becomes increasingly rare.

The paper proceeds as follows. Section I contains a discussion of the ambient noise level, the circumstances under which sound may contain useful information, and what kinds of information might be expected from the sound level. In Section II, we outline the features of the sound, price, and trade data used in this study, commenting on a number of data collection and implementation issues. In Section III, we analyze the importance of the sound level at the minute frequency in accounting for future changes in prices, volume, trade breadth, and trader type. Section IV discusses some robustness issues, and Section V concludes the paper.

I. Sound Levels and Open Outcry

In the past decade, improvements in computer technology have given rise to a number of electronic alternatives to open outcry markets. Electronic exchanges in the United States and Europe have emerged as threats to open outcry's position as the standard for trading highly liquid securities. In 1990, the Deutsche Terminborse (DTB) began electronic trading of the 10-year German government bond futures contract, offering investors an alternative to the open outcry setting offered by the London International Financial Futures Exchange (LIFFE). By April 1998, the DTB had captured 81 percent of the Bund market. Recently, traders in LIFFE's Euromark contract (LIFFE's strongest product) threatened to switch their trades to Eurex, blaming the inefficiencies of the open outcry mechanism. In the summer of 1998, the French futures exchange, Matif, opened electronic trading alongside its open outcry markets. By the end of the summer, trading in short-term interest rate futures had migrated entirely to the computer terminals.

In the United States, the CBOT, which has traded futures contracts in an open outcry exchange since 1848, has recently seen its 30-year U.S. Treasury bond futures contract come under threat from electronic competition. In the fall of 1997, Cantor Fitzgerald, the world's largest interdealer government bond broker, applied for a license to offer electronic trading of 30-year U.S. Treasury Bond futures contracts. During the subsequent week, CBOT seat prices fell by 30 percent and were down a total of over 50 percent a year later. In September 1998, Cantor gained CFTC approval and began placing electronic orders. By January 2000, the CBOT board of directors had voted to introduce electronic trading capabilities.

Much of this suggests that electronic trading, in spite of its inherent limitation on participant communication, is nonetheless more efficient than open outcry. Indeed, Breedon and Holland (1998), who examine concurrent trading in the LIFFE and DTB Bund markets, find bid-ask spreads were generally lower on the DTB's electronic exchange than LIFFE's open outcry market. Nevertheless, they find that volumes tend to migrate to the open outcry setting during periods of high volatility, indicating that there are conditions under which participants view open outcry as superior.

This study instead focuses on market inputs to identify material differences between open outcry and electronic exchanges. In doing so, we ask whether there exists information that is regularly communicated across an open outcry pit but cannot be easily transmitted over a computer network. Any signals that convey information regarding the emotion of market participants—fear, excitement, uncertainty, eagerness, and so forth—are likely to be difficult to transmit across an electronic network. For instance, a trader who tries to unwind a large short position by waving his arms and jumping up and down in an open outcry exchange might have difficulty communicating such eagerness across a computer screen. Certainly more complex signals, such as fear in his eyes or voice, would be impossible to discern across a network. Our paper focuses on a pit's sound level as an easily quantifiable example of such information.

Before proceeding, however, it is important to address what we can expect to learn from sound levels in an open outcry exchange. Indeed, in some respects, any link between sound levels and trading activity may seem tautological given that an open outcry exchange essentially requires sound to trade. However, casual observation of open outcry exchanges will confirm that sound and trading are far from perfectly linked. Often, there are times when traders conduct brisk trade while relying largely on hand signals. At other times, traders are extremely vocal in communicating their bid and ask prices even when few trades are actually executed. There are reasons to believe that current exchange sound levels, when unmatched by corresponding levels of trading activity, contain useful information about the nature of *future* trading activity.

To see this requires a close look at the behavior of traders in an open outcry exchange. During certain periods, traders offer to trade and execute trades by relying solely on hand signals. At other times, they resort to additional, costly means of conveying their interest in trading, including yelling, waving, jumping up and down, pushing to obtain a more favorable vantage point, and so forth. It is worth noting that on electronic exchanges, even if traders could somehow communicate their eagerness to trade, such signals would be of little use. This is because "priority" is always observed in electronic markets. If two traders submit market orders or limit orders of identical price, the trader who submits first will always be executed first. In the open outcry setting, on the other hand, priority is not always perfectly observed. Traders with market orders cannot always remember which of the outstanding limit orders at a given price was offered first. During periods of heavy activity, traders with market orders often trade with the first limit order they notice instead of the order placed first. As a result, other factors, including how loudly a trader yells, influence the odds and speed with which an order gets filled. It is important to recognize that such efforts to improve an order's priority are not costless—they all require physical energy. As a result, traders are likely to expend such effort only at times when they are particularly eager to execute their trades. Hence, the overall noise level of an exchange ought to provide useful signals regarding how anxious traders are to trade at current prices.

To understand how such measures of the level of trader anxiety in a pit might be informative, consider the conditions under which traders are likely to be highly eager to execute their trades: If traders perceive that the costs of trading might rise in the future, they have strong incentives to execute their trades immediately. Traders will become more impatient if they perceive future execution prices to be more uncertain, future trading depth to be poorer, or future information asymmetry to be higher. Similarly, trader eagerness to execute their trades will rise as the costs of holding onto current positions increase. As trader inventories grow, incentives to trade immediately are likely to be high. Eagerness to trade ought to be particularly evident at times when traders are making large price concessions to flatten inventories. Hence, measures of anxiety in the pit may convey useful information regarding both the nature of future trading conditions as well as information on the current composition of trade.

There are compelling reasons to believe that, controlling for all other information, higher sound levels precede periods of increased volatility. In an open outcry setting, traders can only see directly the quantity being offered for purchase or sale at the current bid and ask. Although certain electronic exchanges allow participants to see the limit order book, since a limit book generally only contains a certain fraction of the volume that can be expected at a given future price (and a potentially misleading indication thereof), it is likely to be a poor substitute for the true aggregate supply and demand schedules at a given point in time.[2] If traders have additional information

[2] McInish and Wood (1995) find latent or "hidden" limit orders to be as significant as the NYSE's displayed limit order book in future trades.

about the nature of underlying supply and demand schedules, it is possible that some of this information is conveyed in changes in the sound level. In particular, if traders perceive weak support beyond the bid or ask, and therefore expect future price volatility to be high, they are likely to be anxious to get their trades executed. This possibility is outlined in Hypothesis 1.

HYPOTHESIS 1: *Conditional on all available transaction information, an increase in the current sound level leads to future price changes of increased magnitude.*

A second, related possibility is that high sound levels indicate that traders perceive a coming decline in trading depth. This is motivated by the models of Diamond and Verrecchia (1991), Madhavan and Smidt (1991, 1993), and Chordia and Subrahmanyam (1992), which allow for time-varying price response to order flow. If traders can foresee changes in the limit book, this may impact their eagerness to trade immediately. For instance, if they perceive that certain limit orders are likely to expire, causing the limit book to empty, they may become more anxious to trade. If traders expect that prices will become more elastic in the future, they will have strong incentives to get their trades executed immediately, before they move prices too much against themselves. If these perceptions are widespread, and create increased overall eagerness to trade, rises in the exchange sound level ought to presage a coming decline in market depth. This notion is captured in Hypothesis 2.

HYPOTHESIS 2: *Conditional on all available transaction information, an increase in the current sound level leads to a decline in future market depth.*

In a similar way, high sound levels may also precede more pronounced information asymmetry in the exchange. If market participants anticipate that they will face increased adverse selection when executing trades in the future, they will be anxious to rapidly complete their trades. One possibility is that the increase in information asymmetry shows up as a rise in customer-driven trades. Indeed, Daigler and Wiley (1999) find that increases in customer-driven trading volume are linked with increases in return volatility whereas increases in floor-based volume are not. They further suggest that such a relationship exists because the information asymmetry in the market is higher when the fraction of customer-driven trades increases. If traders are eager to avoid such periods, rises in sound levels may precede increases in customer-driven order flow, even when controlling for concurrent volatility and other conditions.

HYPOTHESIS 3: *Conditional on all available transaction information, an increase in the current sound level leads to an increase in the fraction of customer-based orders.*

The above hypotheses propose links between the degree of eagerness to trade immediately, proxied by the exchange sound level, and various measures of the cost of trading in the future. Alternatively, eagerness to trade immediately may be most pronounced when traders have current positions that are costly to maintain. For instance, traders with large inventories ought to find delays in trades to flatten their inventory to be less desirable than others. Even if market conditions are otherwise expected to remain unchanged, if many traders have large inventories their eagerness to control them may be reflected in higher sound levels. Cao and Lyons (1999) study a theoretical setting in which signals of dealer inventories contain useful information regarding the marketwide compensation for bearing inventory risk. If overall sound levels contain such signals, they will likely be an important component of market participants' conditioning information.

The strength of this relationship will, of course, depend on how inclined traders are to control large inventories. For instance, Manaster and Mann (1996) measure the price concessions traders with large inventories tend to make in order to lower their outstanding positions. Without conditioning on additional variables, they are unable to find any evidence of price concessions. However, if sound measures how eagerly traders are unwinding existing positions, a relationship may exist between sound levels and the degree of price concessions made by traders with large inventories. This possibility is outlined below.

HYPOTHESIS 4: *Conditional on all available transaction information, higher sound levels are associated with measures of efforts to manage inventories, such as price concessions.*

We now are in a position to approach the data with four testable hypotheses regarding sound levels and trading conditions. All four hypotheses are motivated by prior theoretical and empirical work in market microstructure. The first three relate the sound level to future trading conditions, whereas the fourth relates the sound level to concurrent trading activity.

II. The Data

A. Data Collection

To conduct this study, we took second-by-second sound-level readings from the CBOT bond pit over a two-month period in 1998—from May 20 to June 19 and from July 30 to September 2.[3] To take sound-level readings, we pointed a directional microphone into the pit from the top of the 20-foot price recorders' tower located at the edge of the pit. The sound level was sampled across 128 different frequencies and recorded with a time stamp.

In conjunction with the sound data, we use the CBOT's second-stamped price and trading volume data of the front-month Treasury bond futures contract.[4] The price data is obtained from the CBOT's "time and sales" data set. Prices are recorded by observers who stand in the price-recorder tower

[3] We were unable to collect data during the intervening period due to problems with the sound recorder—we forgot to disable the laptop's auto-suspend feature.

[4] The front-month contract is the contract 1 to 4 months to delivery and accounts for over 90 percent of the volume. Non-front-month contracts may be traded only at the center of the pit.

(called "Radio"). They watch continuously for signals of executed trades and immediately record whenever a trade occurs at a new price. These updated prices are then posted on the digital readouts in the trading room and broadcast around the world. The timing of price changes is typically accurate to within one second.[5] During the first half of our sample period, the Bond futures market was relatively calm, with total trading volume of 9,054,113 contracts in May (average monthly volume in 1997 was 8,318,972 contracts), and prices hovering in the $120\frac{9}{32}$ to $124\frac{1}{8}$ range. The second half of our sample was considerably more active. The Bond pit set records for total volume, with 12,024,762 contracts traded during August, and prices ranged from $121\frac{3}{4}$ to $127\frac{1}{2}$.

The trade data is obtained from the CBOT Office of Investigations and Audits (OIA). The trades are determined by matching the time stamps of the buy and sell receipts obtained from trader clearing houses with the time stamps of the time and sales data. For each trade, the identity of the buyer and seller are recorded, as well as a code distinguishing between trades placed by brokers, by locals, on behalf of other traders, or on behalf of clearing firms.[6]

Finally, in addition to the sound, price, and volume data, we include in our analysis time and sales data from the Dow futures contract that also trades on the financials floor of the CBOT, as well as the timing of any scheduled Treasury news announcements. Our complete data set consists of 1,075,447 seconds during which frequency levels and any trades, changes in Bond or Dow prices, or known news announcements that occurred are recorded.

B. Data Cleaning

There are several problems with our data that require attention prior to any analysis. First, several difficulties exist in ensuring that the time stamps on each of our data sets were accurate to the second. Since our tests focus on identifying statistical causality, it is extremely important that the time stamps on our sound level and price and trade data are precisely synchronized. Because our sound recorder's clock drifted by a few seconds each day relative to that of the exchange, this is a nontrivial problem. However, we correct for this by recovering the opening and closing exchange bells from an analysis of the sound level at particular frequencies, and using these to interpolate time stamps that exactly match those of the exchange's price and trade data. Although we are confident our time stamps are accurate to within one second, we include some tests to verify that our results are robust to any remaining timing inaccuracies.

[5] A small fraction (less than one percent) of the trade prices are incorrectly posted and later revised. Although we use the revised data, our results are robust to dropping these observations.

[6] To protect traders' identities, but still allow us to track their trading activity, trader identities are encrypted.

The transaction data also contain some inaccuracies. The CBOT claims the OIA trade data are recorded accurate to within 1 minute over 95 percent of the time. Since the transactions are reconstructed after the fact, and rely on the handwritten trade cards turned in by brokers and traders to their clearing firms, OIA occasionally has problems identifying the exact time at which a given transaction took place. Indeed, our sample appears to have significant problems with its time stamps. While the probability that a trade should occur on any particular second is about 1/60 or 1.667 percent, we found that 5.8 percent of the trades were recorded on the minute and 7.6 percent were recorded at 1 second past the minute. Furthermore, while the probability that any trade should occur on a particular minute is also about 1/60, we found that about 3 percent of trades were recorded on the hour or at 15, 30, or 45 minutes past the hour. This indicates that OIA is often forced to guess the trade time and reports an approximate figure, rounded to the nearest minute or to the beginning of the nearest 15-minute trading session. Outside of these times, volume levels are relatively uniform across seconds and across minutes.

To accommodate the trade spikes that occurred on the minute and at 1 second past the minute, we aggregate all trades to the minute level, summing variables from 31 seconds past 1 minute to 30 seconds past the next minute.[7] For the 15-minute volume spikes, we record volume observations that fall on the 15-minute intervals as missing from our dataset. However, dropping these observations eliminates a large portion of our sample, since our regressions typically include at least 6 minutes of lagged volume. To avoid losing too many data points, we substitute a corrected volume level for lagged volume levels which fall on the hour and at 15, 30, and 45 minutes past the hour. Whenever the independent volume variable occurs at these times we continue to record the observation as missing. To construct the corrected volume during a particular minute, we predict the fraction of volume erroneously reported during that minute, and then subtract this from the total volume, so that what remains should be a measure of trades that actually occurred at that time.[8]

[7] This leaves open the possibility that some of the traders that incorrectly recorded their time on the minute truncated rather than rounded their trade times. To protect against this bias, we checked our results by lagging the explanatory variables an additional 30 seconds. Lagging the explanatory variables an additional 30 seconds had little impact on the results.

[8] Our predicted erroneous volume is constructed as follows. First, we regress the volume that occurred at 15 minutes past the hour for all hours and all days on two-lagged and two-leading minute volume terms. We then calculate the average of a moving average of three-lagged volume numbers for each minute of the day and the average volume per minute of each day, approximating expected volume at each minute of each day by multiplying the moving average term divided by its long-term mean by the average daily volume for each day. Finally, we use the difference between the predicted excess volume from the regressions and the expected volume from the minute/day average calculations as a correction factor.

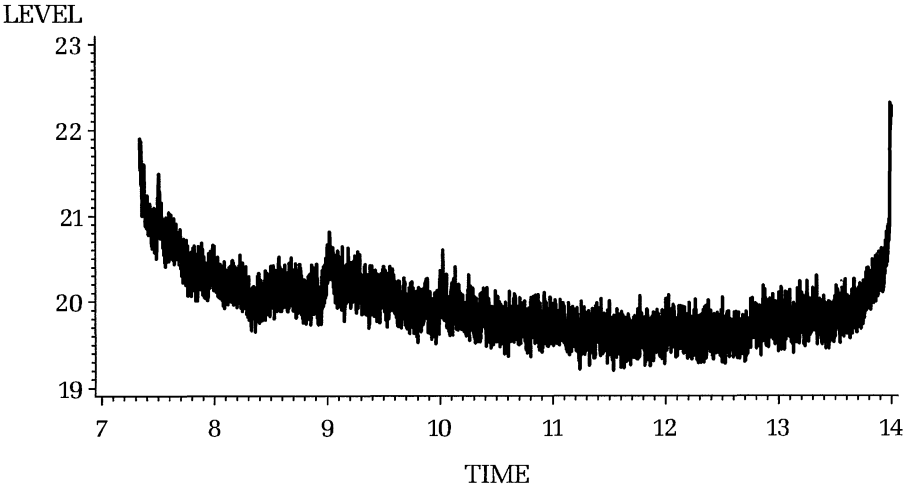

Figure 1. Daily pattern in the sound level. This plots the pattern of the sound level over the typical trading day. The sound level plotted is the average of the sound level taken each second across the 46 days of the sample.

C. Ambient Noise Properties

Our measure of the overall sound level is the sum of the log (base 10) of each frequency's level. This measure is employed as it represents the standard metric of sound level used in the sound engineering field. While we did not calibrate our recording device to measure absolute decibels, our sound level measure can be thought of as relative decibels. Since our sound level measure is based on a logarithmic scale, an increase in our sound level measure of 0.3 indicates approximately a doubling of the sound level. An increase of 0.6 indicates a quadrupling of sound level.

Not surprisingly, the sound level exhibits highly seasonal intraday patterns. As we can see in Figure 1, a second-by-second plot of the average sound level exhibits a U-shaped intraday pattern, with a level much higher at the open and close than during the middle of the day. After the opening, the sound level slowly drops over the next hour, stabilizing at some time after 8:00. At the close, the sound level jumps discretely following the one-minute warning bell, and remains at the high level until the 2:00 close. Also, the sound level appears to jump at 7:30, 9:00, and 10:00, which correspond to times at which Treasury news announcements take place. To adjust for this seasonality, we calculate the mean daily sound level for each second of our sample. We then subtract a five-second moving average of this mean level from each sound observation. Table I displays summary statistics of our deseasonalized sound level measure. Deseasonalizing the data leaves the sound level with an average of −0.15 and a standard deviation of 37.92. Minute-by-minute changes in the sound level have a standard deviation of 27.56.

Table I

Summary Statistics and Price Change Frequencies

Table I presents summary statistics for the variables used throughout the paper. All observations are recorded at the minute frequency over 46 days. There are 17,590 complete observations measured every minute. To deseasonalize the sound level, we average the sound level at each second of the day across all days in the sample. Then we subtract from each sound level observation a five-second moving average of the average sound level. The change in deseasonalized sound level variable refers to minute-by-minute changes in the deseasonalized sound level measure.

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Deseasonalized sound level	−0.15	37.92	−114.9	172.9
Change in deseasonalized sound	0.00	27.56	−124.1	134.3
Absolute change in price (Ticks)	0.40	0.58	0.0	6.0
Trading volume (1,000 contracts)	0.91	1.01	0.0	14.2
Number of traders trading	70.39	58.20	0.0	424.0
Customers' fraction of trade	28.0	13.0	0.0	100.0
Sum of abs. changes in DJIA	6.86	11.11	0.0	771.0

Panel B: Frequency of Absolute Price Changes

Ticks	Frequency
0	11,302
1	5,637
2	579
3	57
4	11
5	0
6	4

D. *Properties of Prices and Trading Volume*

Table I displays summary statistics of the price and trade data during our sample period. Since our volume data is only useful at the minute frequency, we aggregate all other observations to the minute frequency as well. So that our results which involve price changes are not driven by bid-ask bounce, we record a price change only when the newly recorded price is different from that recorded two price changes ago. For instance, the sequence of observed prices of 27, 26, 27, 26 would yield no price changes, whereas the sequence 27, 26, 27, 28 would yield a price change of one tick. Thus, each minute we record the net of all price changes, adjusted for bid-ask bounce, which occurred during that minute.[9] During 6,288 minutes of our sample, or 35.7 percent of our 17,590 observations, a net price change was observed. Most of the observed price changes are one tick. Only 651 (3.7 percent) of the

[9] Our results are qualitatively unchanged and, in general, economically and statistically stronger when we do not make this adjustment.

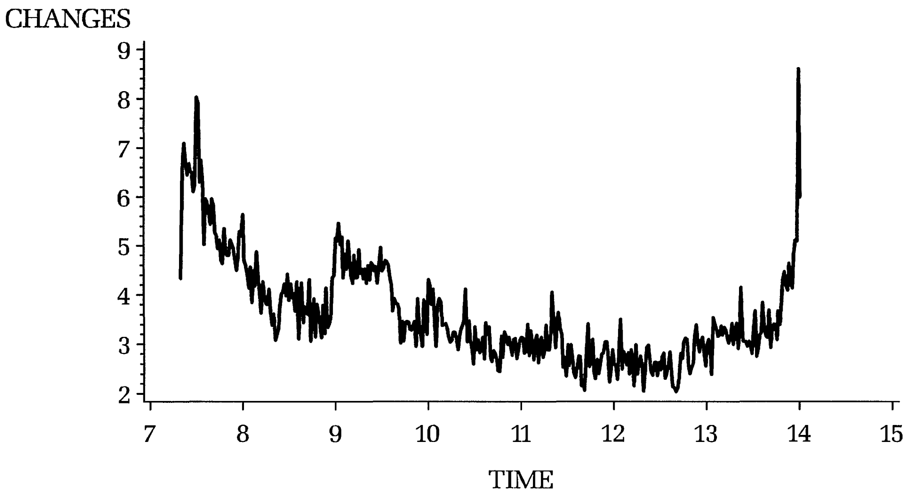

Figure 2. Daily pattern in price changes per minute. This plots the pattern of price changes per minute over the typical trading day. The number of price changes plotted is the average price changes per minute taken each minute across the 46 days of the sample.

minutes included a net price change of greater than one tick. The average minute witnessed 910 traded contracts, though with a standard deviation of 1,010 contracts, the distribution is highly skewed. During an average minute, 70 different traders participated, of which 20 were brokers placing orders for customers.

Figures 2 and 3 plot the average number of price changes and contracts traded per minute. The price-changes plot appears qualitatively similar to the sound level plot. Price changes do not exhibit the exhibit the U-shaped pattern found in the sound levels, though price changes are more frequent at the open and at 7:30, 9:00, and 10:00. The volume graph displays the U-shaped pattern of the sound level data. Here, with spikes at regular 15-minute intervals, we see the inaccuracy of the transaction time stamps. Taking this distortion into account, the jumps at 9:00 and 10:00 do not appear as substantial as those in the price and sound level data.

III. Results

Each of our hypotheses relates sound levels to some property of prices conditional on all available transaction information. Since it is impossible to actually estimate covariances conditional on all available information, we use lagged values of trading volume, absolute change in price, and absolute change in the price of the Dow Jones futures contract as a proxy for all available information. In principle, all available information includes an almost infinite number of lags of these and other variables. However, to be consistent across hypotheses, we generally include five lags of each of our transaction information variables in the results we report in this section.

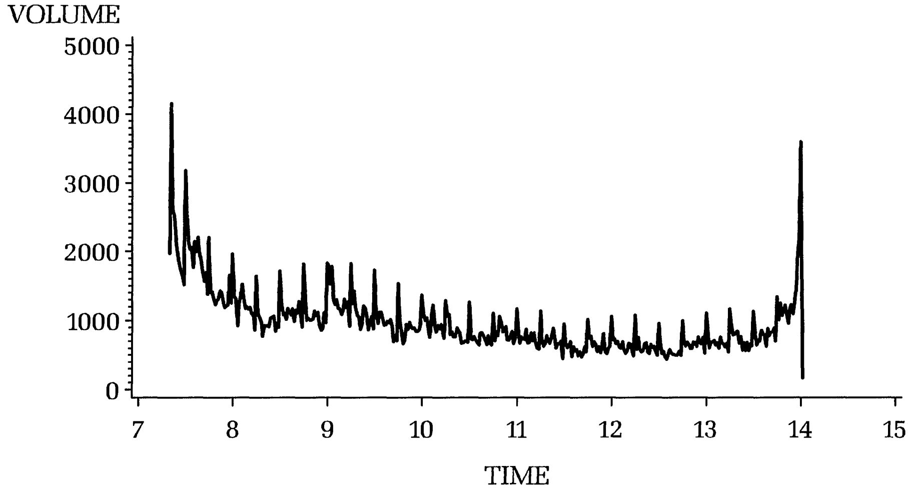

Figure 3. Daily pattern in volume per minute. This plots the pattern of trading volume per minute over the typical trading day. The volume plotted is the average volume per minute taken each minute across the 46 days of the sample.

To be certain that our results are not qualitatively changed by including either more or less lags of any of these information variables, we estimate, but do not report, each of our models with several different lag structures. The results are quite robust to the number of lags chosen. Even when as many as 60 lags of each of the information variables is included in the regressions, the inferences are unchanged. Moreover, we search for an optimal number of lags with the Akaike Information Criterion and find again that our results are unchanged by picking an optimal number of lags. Since we estimate each of our models with a number of lag structures, the results reported should be considered representative of the results obtained when the number of lags is varied.

A. Hypothesis 1: Sound Levels Forecast Volatility

Our first set of tests focus on the ability of sound levels to account for future changes in volatility. Since price changes are highly skewed (for over 60 percent of our observations, there are no net price changes), we estimate an ordered logit model in which the dependent variable is the magnitude of the one-minute net price change in ticks. We use this specification to model our discrete, nonnegative dependent variable and appropriately incorporate differences in magnitudes.[10] This is regressed on past changes in the sound level. We also include independent variables that control for past price changes, trading volumes, changes in the Dow Jones futures price, and time-of-day

[10] We achieve similar results employing probit and linear probability specifications.

effects. Defining $p = \Pr(Y \leq i|x)$ as the probability that a given minute's price change is no more than i ticks, the ordered logit regression equation has the following form:

$$\log\left(\frac{p}{1-p}\right) = \alpha_i + \beta' x, \quad 1 \leq i \leq k \tag{1}$$

where α_i ($i = 1,\ldots,k$) are k intercept parameters and β is the vector of slope parameters. The regression parameters are Maximum Likelihood Estimates computed using an Iteratively Reweighted Least Squares algorithm.

The results of our regression are reported in Table II. As expected, many of the control variables are important in accounting for future price changes. Past price changes, even with up to a 10-minute lag, indicate greater potential for future price movements. Trading volumes with a lag of up to 4 minutes are important as well. Concurrent changes in the Dow are important; however, those with a lag are not. Time-of-day dummy variables confirm the seasonality in intraday price volatility depicted in Figure 2.

However, even after controlling for the above factors, increased sound levels are highly significant in forecasting increased price volatility several minutes into the future. Coefficients on sound-level changes with a lag of one and two minutes are highly significant. Both coefficients are significant at the one percent confidence level. The coefficients are also highly significant in economic terms. For instance, a one standard deviation increase in sound level one minute ago of 37.92 increases the probability of observing a price change of at least two ticks from 3.70 percent to 4.33 percent—a 17 percent increase in probability. These results are strongly consistent with Hypothesis 1. Increases in sound level presage greater future market volatility. They appear to reflect heightened trader eagerness to execute trades in advance of anticipated rises in uncertainty.

B. Hypothesis 2: Sound Levels Forecast Market Depth

Next, we investigate whether sound levels help predict changes in future market depth. Our initial specification follows Manaster and Mann (1996) in regressing the net price change each minute on the net customer trading volume (measured in thousands of contracts) during that minute.[11] To measure the ability of the sound level to forecast changes in market depth, we include lagged sound level interacted with customer volume as well as lagged sound level on its own. Specifically, our version of the Manaster and Mann depth regression that includes sound levels has the following form:

$$P_t - P_{t-1} = \alpha + \beta_C C_t + \beta_L L_{t-1} + \beta_{CL} C_t L_{t-1} + \epsilon_t, \tag{2}$$

[11] Net customer trading volume reflects the net purchase—the difference between the number bought and sold—of front month contracts by customers. Price changes are those for the corresponding front month contract.

Table II

Price Change Ordered Logit

Table II presents the results of estimating an ordered probit model in which the dependent variable is the number of ticks that the futures price moves in one minute ($|P_t - P_{t-1}|$). Specifically, defining $p = \Pr(Y \leq i|x)$ as the probability that a given minute's price change is no more than i ticks, the ordered logit regression equation has the following form:

$$\log\left(\frac{p}{1-p}\right) = \alpha_i + \beta' x, \quad 1 \leq i \leq k$$

where α_i ($i = 1,\ldots,k$) are k intercept parameters and β is the vector of slope parameters. Independent variables include previous price changes, volume (Q), changes in the sound level (L), absolute changes in the Dow Jones futures price (DJ), and a set of dummy variables that control for time-of-day effects. The model is estimated with 17,590 observations. The regression parameters are Maximum Likelihood Estimates computed using an Iteratively Reweighted Least Squares algorithm. In an analogous linear regression model, the adjusted R^2 is 8.2 percent and tests for autocorrelation of the error term indicate no autocorrelation.

Variable	Coefficient	Std. Error	χ^2	p-Value
α_1	1.3423	0.0827	63.63	0.0001
α_2	4.1488	0.0928	1998.48	0.0001
α_3	6.4168	0.1445	1971.28	0.0001
α_4	7.9482	0.2614	924.78	0.0001
α_6	9.3406	0.4985	351.03	0.0001
$L_{t-1} - L_{t-2}$	−0.0043	0.0007	34.81	0.0001
$L_{t-2} - L_{t-3}$	−0.0022	0.0008	7.55	0.0060
$L_{t-3} - L_{t-4}$	−0.0009	0.0008	1.29	0.2553
$L_{t-4} - L_{t-5}$	−0.0007	0.0008	0.85	0.3544
$L_{t-5} - L_{t-6}$	0.0004	0.0007	0.29	0.5855
$\|P_{t-1} - P_{t-2}\|$	−0.1047	0.0301	12.09	0.0005
$\|P_{t-2} - P_{t-3}\|$	−0.2049	0.0301	46.41	0.0001
$\|P_{t-3} - P_{t-4}\|$	−0.1478	0.0302	23.93	0.0001
$\|P_{t-4} - P_{t-5}\|$	−0.1144	0.0303	14.29	0.0002
$\|P_{t-5} - P_{t-6}\|$	−0.0915	0.0302	9.17	0.0024
$\|P_{t-6} - P_{t-7}\|$	−0.1206	0.0292	17.10	0.0001
$\|P_{t-7} - P_{t-8}\|$	−0.1206	0.0282	18.23	0.0001
$\|P_{t-8} - P_{t-9}\|$	−0.1369	0.0279	24.07	0.0001
$\|P_{t-9} - P_{t-10}\|$	−0.1520	0.0278	29.98	0.0001
$\|P_{t-10} - P_{t-11}\|$	−0.0990	0.0277	12.82	0.0003
Q_{t-1}	−0.0467	0.0222	4.43	0.0352
Q_{t-2}	−0.0588	0.0224	6.86	0.0088
Q_{t-3}	−0.0627	0.0225	7.77	0.0053
Q_{t-4}	−0.0684	0.0224	9.31	0.0023
Q_{t-5}	−0.0319	0.0222	2.06	0.1510
$\|DJ_t - DJ_{t-1}\|$	−0.0053	0.0015	11.75	0.0006
$\|DJ_{t-1} - DJ_{t-2}\|$	−0.0018	0.0017	1.01	0.3141
$\|DJ_{t-2} - DJ_{t-3}\|$	−0.0034	0.0018	3.53	0.0601
$\|DJ_{t-3} - DJ_{t-4}\|$	0.0013	0.0018	0.49	0.4810
$\|DJ_{t-4} - DJ_{t-5}\|$	−0.0020	0.0018	1.25	0.2621
$\|DJ_{t-5} - DJ_{t-6}\|$	−0.0022	0.0016	1.86	0.1721
Dummy (7:30–8:00)	−0.0138	0.0971	0.02	0.8873
Dummy (8:00–9:00)	0.1387	0.0870	2.54	0.1109
Dummy (9:00–10:00)	0.1374	0.0867	2.51	0.1129
Dummy (10:00–11:00)	0.1821	0.0873	4.34	0.0371
Dummy (11:00–12:00)	0.2045	0.0878	5.42	0.0198
Dummy (12:00–13:00)	0.1059	0.0877	1.45	0.2273
Dummy (13:00–13:45)	−0.0359	0.0899	0.15	0.6894

LR test that all coefficients = 0 is 1241.7 with 33 d.f. (p = 0.000).

where $P_t - P_{t-1}$ measures the change in price during minute t, C_t measures the net customer trading volume, during minute t, and L_{t-1} measures the sound level during period $t - 1$. The coefficients β_C, β_L, and β_{CL} capture the impact of customer trading volume, lagged sound level, and customer volume times lagged sound level, respectively. Hence, the total effect of net customer volume on price changes is captured by $\beta_C + \beta_{CL} L_{t-1}$. The results from our regression are reported at the top of Table III.

Consistent with Manaster and Mann (1996), we find that net customer orders are positively related to price changes. The coefficient on customer orders is 0.00911, and is significant at the one percent level. This means that a one standard deviation increase in net customer orders (0.3889) will be associated with a concurrent increase in prices of 0.11 ticks. The product of net customer orders and lagged sound level is also important in explaining price changes. The coefficient, which is equal to 0.000085, is significant at the one percent level and is also significant in economic terms. Since a one standard deviation increase in sound level is equal to 37.92, this results in an increase in the total coefficient on concurrent customer volume, $\beta_C + \beta_{CL} L_{t-1}$, from 0.00911 to 0.01233. Now, a one standard deviation increase in net customer orders results in a concurrent increase in price of 0.153 ticks.

To see whether the sound level proxies for other observable variables, and to make the regression specification consistent with those used in the price and customer order regressions, we expand the regression to include the set of lagged control variables described in Section II.A. Each of the variables are interacted with net customer orders and lagged sound levels are differenced to accommodate the five-minute lag structure used earlier. The results are reported in the second panel of Table III. As we can see, including the additional variables maintains the statistical and economic significance of the sound level coefficients. The coefficients are of similar magnitude to those obtained in the above regressions.

These results are highly consistent with Hypothesis 2. Traders appear to have information regarding the nature of future market depth that is not contained in current prices or trading activity. When traders perceive a coming increase in the extent to which prices will move against their trades, they become highly anxious to execute their orders immediately. This anxiousness, which is reflected in a heightened exchange sound level, strongly forecasts the future decline in market depth.

C. Hypothesis 3: Sound Levels Forecast Customer Orders

The sound level may also convey information about the type of trader that market participants can expect to face in subsequent activity. If locals are viewed as competitive market makers, outside orders are likely to be more asymmetrically informed than orders originating within the pit or orders

Table III

Depth Regressions

Table III presents the results of estimating a linear regression model in which the dependent variable is the change in the futures price corrected for second order autocorrelation. We use a regression of the following form:

$$P_t - P_{t-1} = \alpha + \beta_C C_t + \beta_L L_{t-1} + \beta_{CL} C_t L_{t-1} + \varepsilon_t,$$

where $P_t - P_{t-1}$ measures the change in price during minute t, C_t measures the net customer trading volume during minute t, and L_{t-1} measures the sound level during period $t - 1$. The coefficients β_C, β_L, and β_{CL} capture the impact of customer trading volume, lagged sound level, and customer volume times lagged sound level, respectively. Hence, the total effect of net customer volume on price changes is captured by $\beta_C + \beta_{CL} L_{t-1}$.

α	β_C	β_L	β_{CL}
0.00034	0.01175		
(2.22)	(27.40)		
	Adjusted R^2 = 4.11%	n = 17,253	
0.00033	0.00911	−0.000003	0.000085
(2.19)	(17.72)	(−0.75)	(9.53)
	Adjusted R^2 = 4.61%	n = 17,247	

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Intercept	0.00032	0.00015	2.08	0.0373
C_t	−0.00007	0.00203	−0.03	0.9710
$C_t * L_{t-1} - L_{t-2}$	0.00004	0.00002	2.39	0.0166
$C_t * L_{t-2} - L_{t-3}$	0.00007	0.00002	3.80	0.0001
$C_t * L_{t-3} - L_{t-4}$	0.00004	0.00002	1.77	0.0765
$C_t * L_{t-4} - L_{t-5}$	0.00004	0.00002	1.86	0.0626
$C_t * L_{t-5} - L_{t-6}$	0.00003	0.00002	1.60	0.1078
$C_t * \lvert P_{t-1} - P_{t-2} \rvert$	0.00069	0.00064	1.07	0.2808
$C_t * \lvert P_{t-2} - P_{t-3} \rvert$	0.00128	0.00069	1.83	0.0659
$C_t * \lvert P_{t-3} - P_{t-4} \rvert$	0.00106	0.00069	1.54	0.1228
$C_t * \lvert P_{t-4} - P_{t-5} \rvert$	0.00197	0.00068	2.86	0.0041
$C_t * \lvert P_{t-5} - P_{t-6} \rvert$	−0.00252	0.00069	−3.65	0.0003
$C_t * Q_{t-1}$	0.00050	0.00036	1.38	0.1677
$C_t * Q_{t-2}$	0.00042	0.00037	1.14	0.2514
$C_t * Q_{t-3}$	−0.00014	0.00039	−0.36	0.7182
$C_t * Q_{t-4}$	−0.00066	0.00040	−1.65	0.0986
$C_t * Q_{t-5}$	0.00040	0.00042	0.93	0.3501
$C_t * \lvert DJ_{t-1} - DJ_{t-2} \rvert$	0.00008	0.00005	1.56	0.1184
$C_t * \lvert DJ_{t-2} - DJ_{t-3} \rvert$	−0.00010	0.00005	−2.06	0.0389
$C_t * \lvert DJ_{t-3} - DJ_{t-4} \rvert$	0.00006	0.00005	1.10	0.2677
$C_t * \lvert DJ_{t-4} - DJ_{t-5} \rvert$	−0.00005	0.00005	−0.97	0.3276
$C_t * \lvert DJ_{t-5} - DJ_{t-6} \rvert$	0.00015	0.00006	2.68	0.0073
$C_t *$ Dummy (7:30–8:00)	0.01026	0.00224	4.58	0.0001
$C_t *$ Dummy (8:00–9:00)	0.00398	0.00216	1.84	0.0649
$C_t *$ Dummy (9:00–10:00)	0.00901	0.00217	4.14	0.0001
$C_t *$ Dummy (10:00–11:00)	0.00698	0.00222	3.14	0.0017
$C_t *$ Dummy (11:00–12:00)	0.00978	0.00236	4.14	0.0001
$C_t *$ Dummy (12:00–13:00)	0.01004	0.00240	4.18	0.0001
$C_t *$ Dummy (13:00–13:45)	0.00942	0.00254	3.70	0.0002

Adjusted R^2 = 4.92%, n = 17,218.

executed for hedging purposes.[12] This possibility, which is outlined in Daigler and Wiley (1999), leads us to our test of Hypothesis 3. Specifically, we examine whether anxiousness to trade, as measured by sound level, increases when traders perceive a coming increase in the degree of information asymmetry (i.e., customer-driven trading) in the pit.

We measure customer-driven trading during a given minute as the percentage of contracts traded by brokers fulfilling customer orders during a given minute.[13] To see whether the sound level conveys information about the participants' expectations of trade composition, we regress the fraction of customer orders on the exchange sound level. We also include lagged values of trader type, lagged price changes, lagged volume, concurrent and lagged changes in the Dow contract price, and dummy variables to account for the time of day in our regression. Since the percentage of volume accounted for by brokers does not have a constant variance throughout the day, we employ weighted least squares in our regression, with an observation's variance assumed proportional to the inverse of total volume. Our trader type regression is of the following form:

$$\frac{Q_t^{cust}}{Q_t} = \alpha + \sum_{j=1}^{j=5} \beta_j (L_{t-j} - L_{t-j-1}) + \gamma' X_t + \epsilon_t, \tag{3}$$

where Q_t^{cust}/Q_t reflects the fraction of trading volume accounted for by customer orders at time t, $L_{t-j} - L_{t-j-1}$ is the change in sound level lagged j periods, and X_t represents a vector of lagged control variables used in earlier regressions, including customer order fraction, absolute price change, trading volume, absolute change in the Dow futures contract, and time-of-day dummy variables. The sound level change and each of the control variables is lagged for up to five minutes. We also include the concurrent change in the Dow futures contract.

As is evident from Table IV, changes in sound level have a strong ability to forecast customer order flow. Even after controlling for other trading conditions, increases in sound level consistently precede increases in the fraction of customer trades. The coefficients on lagged sound levels are all highly statistically significant. A one standard deviation increase in the sound level results in a 0.0054 increase in the portion of customer-generated volume. Considering that this change represents 4.2 percent of one standard deviation in the dependent variable, the economic significance of the finding is somewhat poor. On the other hand, considering the strong statistical

[12] Roughly three percent of the trades are placed by traders in other pits hedging into the bond pit.

[13] Local traders term this the fraction of "paper" coming into the market at a particular point in time. Most view the nature of outside order flow as—by far—the most important piece of information they look to in setting their market.

Table IV

Customer Order Flow Regression

Table IV presents the results of estimating a linear regression model with gross customer order flow divided by total volume per minute as the dependent variable. Our trader type regression is of the following form:

$$\frac{Q_t^{cust}}{Q_t} = \alpha + \sum_{j=1}^{j=5} \beta_j (L_{t-j} - L_{t-j-1}) + \gamma' X_t + \epsilon_t,$$

where Q_t^{cust}/Q_t reflects the fraction of trading volume accounted for by customer orders at time t, $L_{t-j} - L_{t-j-1}$ is the change in sound level lagged j periods, and X_t represents a vector of lagged control variables used in earlier regressions, including customer order fraction, absolute price change, trading volume, absolute change in the Dow futures contract, and time-of-day dummy variables. We employ weighted least squares with weights equal to 1/volume. No autocorrelation was found in the residuals.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Intercept	0.320609	0.00421495	76.06	0.0001
$L_{t-1} - L_{t-2}$	0.000177	0.00004002	4.42	0.0001
$L_{t-2} - L_{t-3}$	0.000191	0.00004403	4.34	0.0001
$L_{t-3} - L_{t-4}$	0.000196	0.00004481	4.38	0.0001
$L_{t-4} - L_{t-5}$	0.000199	0.00004227	4.70	0.0001
$L_{t-5} - L_{t-6}$	0.000211	0.00003627	5.81	0.0001
Q_{t-1}^{cust}/Q_{t-1}	2.0888377E-8	0.00000001	2.05	0.0398
Q_{t-2}^{cust}/Q_{t-2}	2.7341105E-8	0.00000001	4.71	0.0001
Q_{t-3}^{cust}/Q_{t-3}	1.8678264E-8	0.00000001	3.15	0.0016
Q_{t-4}^{cust}/Q_{t-4}	8.336596E-10	0.00000001	0.13	0.8962
Q_{t-5}^{cust}/Q_{t-5}	1.0548956E-8	0.00000001	1.11	0.2638
$\|P_{t-1} - P_{t-2}\|$	0.005939	0.00146056	4.06	0.0001
$\|P_{t-2} - P_{t-3}\|$	−0.002793	0.00146490	−1.90	0.0566
$\|P_{t-3} - P_{t-4}\|$	−0.004970	0.00150398	−3.30	0.0010
$\|P_{t-4} - P_{t-5}\|$	−0.003785	0.00149634	−2.52	0.0114
$\|P_{t-5} - P_{t-6}\|$	−0.003173	0.00151519	−2.09	0.0363
Q_{t-1}	0.003224	0.00096144	3.35	0.0008
Q_{t-2}	0.001947	0.00096359	2.02	0.0434
Q_{t-3}	0.003004	0.00100185	2.99	0.0027
Q_{t-4}	−0.001204	0.00097693	−1.23	0.2179
Q_{t-5}	0.000618	0.00099815	0.62	0.5355
$\|DJ_t - DJ_{t-1}\|$	0.000013629	0.00006814	0.20	0.8415
$\|DJ_{t-1} - DJ_{t-2}\|$	−0.000027464	0.00008673	−0.31	0.7515
$\|DJ_{t-2} - DJ_{t-3}\|$	−0.000195	0.00009018	−2.15	0.0310
$\|DJ_{t-3} - DJ_{t-4}\|$	0.000047195	0.00009300	0.50	0.6118
$\|DJ_{t-4} - DJ_{t-5}\|$	−0.000083705	0.00009797	−0.85	0.3929
$\|DJ_{t-5} - DJ_{t-6}\|$	−0.000228	0.00010419	−2.18	0.0288
Dummy (7:30–8:00)	−0.056778	0.00471916	−12.03	0.0001
Dummy (8:00–9:00)	−0.047037	0.00450886	−10.43	0.0001
Dummy (9:00–10:00)	−0.043267	0.00450332	−9.60	0.0001
Dummy (10:00–11:00)	−0.031215	0.00463080	−6.74	0.0001
Dummy (11:00–12:00)	−0.007884	0.00482935	−1.63	0.1026
Dummy (12:00–13:00)	−0.021218	0.00494300	−4.29	0.0001
Dummy (13:00–13:45)	−0.040142	0.00508999	−7.88	0.0001

Adjusted R^2 = 4.04%, n = 14,357.

significance of the coefficients on sound lagged up to five minutes, a change in the sound level is associated with a highly persistent, albeit small, increase in the fraction of customer orders.

Overall, this finding is consistent with Hypothesis 3. If traders pay higher adverse selection costs when trading during periods of high levels of customer-based trades, these results may capture their ability to forecast increases in these costs. An alternative possibility is that traders have some ability to forecast the direction of customer order flow and trade in anticipation of future order flow. Of course, the low economic significance of the results cautions against too strong an interpretation.

D. Hypothesis 4: Sound Levels Identify Inventory Control

Our final set of tests focus on whether sound levels reflect trader eagerness to unwind existing positions. To test this, we measure efforts to control inventory following the procedure used by Manaster and Mann (1996). We use their "execution skill" measure, defined for purchases as

$$\pi^b_{i,t} = \bar{p}^b_t - p^b_{i,t}, \tag{4}$$

where $\bar{p}^b_t$ is the volume-weighted average purchase price of all locals' trades during the five-minute window surrounding minute t, and $p^b_{i,t}$ is local i's purchase price during minute t. Likewise, execution skill for a sale is defined as

$$\pi^s_{i,t} = p^s_{i,t} - \bar{p}^s_t. \tag{5}$$

Hence, $\pi^b_{i,t}$ captures how much less trader i had to pay in executing a purchase than other locals making purchases. Likewise, $\pi^s_{i,t}$ measures how much more trader i was able to obtain in executing a sale than his competitors.

Inventory control models such as Ho and Stoll (1983) and Biais (1993) demonstrate that traders charge a premium on inventory-increasing trades and offer price concessions on trades that reduce inventory exposure. Hence, we should expect execution skill to be good when traders with positive (negative) positions make further purchases (sales) and to be poor when the traders are lowering their inventories. We then regress execution skill on relative inventory, defined for a purchasing trader as the difference between the trader's inventory and the average pit inventory and for a seller as the difference between the average pit inventory and the trader's inventory (see Manaster and Mann (1996) for details).

To allow for execution skill to vary across traders, we conduct a fixed-effects regression of the following form:

$$\pi^j_{i,t} = \alpha_i + \beta_I I^j_{i,t} + \sum_{l=1}^{k} \beta_{Il} X_{l,t} I^j_{i,t} + \varepsilon_{i,t}, \qquad j = \{b, s\} \tag{6}$$

where $\pi_{i,t}^{j}$ is the measure of execution skill of trader i placing trade j, α_i is the trader-specific fixed effect term that captures trader i's average trading skill, $I_{i,t}^{j}$ is trader i's relative inventory position (measured in thousands of contracts) when placing trade j, X_l ($l = 1$ to k) represents lagged control variables used in earlier regressions, and $\varepsilon_{i,t}$ is the error for trader i at time t. If price concessions are important for controlling inventories, we should expect the coefficient on the inventory level, β_I, to be significantly positive. This would reflect that to unwind an outstanding long (short) position, the trader would have to sell (buy) at a lower (higher) price than the average price at which locals were transacting during that period. If the sound level is important in explaining inventory control efforts, we should see a significant coefficient on the product of inventory level and the sound level, β_{LI}. The results are reported in Table V.

As we can see, contrary to Manaster and Mann (1996), we find some evidence that price concessions take place unconditionally. The coefficient on relative inventory of 0.003795 is highly statistically significant. However, in economic terms it is less so. A trader with an inventory of 1,000 will sell at prices which are, on average, \$3.79 lower per contract than those received by other sellers. When we introduce sound levels, the picture changes slightly. The unconditional price concession term remains significant but drops to \$2.01 for a trader with an inventory of 1,000 contracts. However, when we condition on a sound level which is one standard deviation larger (37.92), the trader will make price concessions of \$3.91. In relative terms, this increase appears large since it represents an almost doubling of the inventory effect on trading skill. However, since the overall impact of inventory is not terribly large in economic terms, we view this as only moderate support for Hypothesis 4.

IV. Robustness Checks

Although the results presented above are quite strong, the variety of data problems confronted in Section III, ranging from synchronizing time stamps, to deseasonalizing sound levels, to adjusting for abnormalities in volume levels, justify remaining skepticism. To address these concerns, we examine a wide variety of alternative specifications to check for robustness.

The first possibility is that our results are driven by sound level increases that simply announce the arrival of publicly observable news. For example, if everyone knows an important announcement by the Federal Reserve will take place shortly, and the sound level increases as traders prepare to take positions, it would be unsurprising to find that this precedes periods of increased volume and volatility. To allow for this possibility, we ran our tests on a sample that excluded two minutes before and five minutes after all 148 scheduled news announcements listed by CBOT on their financial calendar during the two-month study.[14] This led to no discernable effect, as all results remained virtually unchanged.

[14] The CBOT's financial calendar is available at http://www.cbot.com.

Table V

Price Concessions Regressions

Table V presents the results of estimating fixed-effects regression models in which the dependent variable is the Manaster and Mann (1996) "execution skill" measure. The regression is of the following form:

$$\pi_{i,t}^{j} = \alpha_i + \beta_I I_{i,t}^{j} + \sum_{l=1}^{k} \beta_{Il} X_{l,t} I_{i,t}^{j} + \varepsilon_{i,t}, \qquad j = \{b,s\}$$

where $\pi_{i,t}^{j}$ is the execution skill of trader i placing trade j, α_i is the trader-specific fixed effect term that captures trader i's average trading skill, $I_{i,t}^{j}$ is trader i's relative inventory position (measured in thousands of contracts) when placing trade j, X_l (l = 1 to k) represents lagged control variables used in earlier regressions, and $\varepsilon_{i,t}$ is the error for trader i at time t, where $\pi_{i,t}^{j}$ is the execution skill of trader i placing trade j, α_i is the trader-specific fixed effect term that captures trader i's average trading skill, $I_{i,t}$ is trader i's relative inventory position (measured in thousands of contracts) when placing trade j, L_t is the sound level, and $\varepsilon_{i,t}$ is the error for trader i at time t.

β_I	β_{IL}
0.00388	
(18.65)	
$\bar{R}^2$ = 0.02%, n = 1,443,013	
0.00198	0.000052
(7.53)	(11.28)
$\bar{R}^2$ = 0.03%, n = 1,337,853	

Variable	Coefficient	Std. Error	t-Statistic	p-Value
$I_{i,t}^{a}$	0.012716	0.000912	13.94	0.0001
$I_{i,t}^{a} * (L_t - L_{t-1})$	0.000063	0.000008	7.90	0.0001
$I_{i,t}^{a} * (L_{t-1} - L_{t-2})$	0.000046	0.000010	4.75	0.0001
$I_{i,t}^{a} * (L_{t-2} - L_{t-3})$	0.000058	0.000010	5.86	0.0001
$I_{i,t}^{a} * (L_{t-3} - L_{t-4})$	0.000066	0.000010	6.73	0.0001
$I_{i,t}^{a} * (L_{t-4} - L_{t-5})$	0.000130	0.000009	14.04	0.0001
$I_{i,t}^{a} * (L_{t-5} - L_{t-6})$	0.000071	0.000008	8.57	0.0001
$I_{i,t}^{a} * \lvert P_{t-1} - P_{t-2}\rvert$	0.000823	0.000307	2.67	0.0075
$I_{i,t}^{a} * \lvert P_{t-2} - P_{t-3}\rvert$	0.002019	0.000313	6.45	0.0001
$I_{i,t}^{a} * \lvert P_{t-3} - P_{t-4}\rvert$	0.000108	0.000320	0.33	0.7351
$I_{i,t}^{a} * \lvert P_{t-4} - P_{t-5}\rvert$	−0.000921	0.000317	−2.90	0.0037
$I_{i,t}^{a} * \lvert P_{t-5} - P_{t-6}\rvert$	−0.001070	0.000319	−3.35	0.0008
$I_{i,t}^{a} * Q_{t-1}$	0.000615	0.000187	3.29	0.0010
$I_{i,t}^{a} * Q_{t-2}$	−0.001387	0.000179	−7.72	0.0001
$I_{i,t}^{a} * Q_{t-3}$	0.000261	0.000197	1.32	0.1849
$I_{i,t}^{a} * Q_{t-4}$	−0.000454	0.000178	−2.55	0.0107
$I_{i,t}^{a} * Q_{t-5}$	0.001522	0.000199	7.63	0.0001
$I_{i,t}^{a} * \lvert DJ_t - DJ_{t-1}\rvert$	0.000001	0.000018	0.06	0.9476
$I_{i,t}^{a} * \lvert DJ_{t-1} - DJ_{t-2}\rvert$	−0.000063	0.000021	−2.95	0.0031
$I_{i,t}^{a} * \lvert DJ_{t-2} - DJ_{t-3}\rvert$	0.000032	0.000021	1.55	0.1200
$I_{i,t}^{a} * \lvert DJ_{t-3} - DJ_{t-4}\rvert$	−0.000095	0.000019	−5.06	0.0001
$I_{i,t}^{a} * \lvert DJ_{t-4} - DJ_{t-5}\rvert$	0.000035	0.000020	1.74	0.0818
$I_{i,t}^{a} * \lvert DJ_{t-5} - DJ_{t-6}\rvert$	0.000121	0.000021	5.76	0.0001
$I_{i,t}^{a}$ * Dummy (7:30–8:00)	−0.012437	0.001131	−10.99	0.0001
$I_{i,t}^{a}$ * Dummy (8:00–9:00)	−0.013458	0.000984	−13.66	0.0001
$I_{i,t}^{a}$ * Dummy (9:00–10:00)	−0.010865	0.000960	−11.31	0.0001
$I_{i,t}^{a}$ * Dummy (10:00–11:00)	−0.012093	0.000980	−12.33	0.0001
$I_{i,t}^{a}$ * Dummy (11:00–12:00)	−0.008640	0.001019	−8.47	0.0001
$I_{i,t}^{a}$ * Dummy (12:00–13:00)	−0.014548	0.001050	−13.85	0.0001
$I_{i,t}^{a}$ * Dummy (13:00–13:45)	−0.014397	0.001067	−13.49	0.0001

$\bar{R}^2$ = 0.08%, n = 1,333,030.

A second possibility is that timing problems still pervade our data. Although we are highly confident that we have fitted our sound time stamps to within a second of those of the time and sales data, it is still conceivable that inaccuracies remain. For example, there may be more of a delay between the time a trade takes place and the time the price is actually recorded than the CBOT recognizes. Additionally, as mentioned earlier, it is possible that the volume spikes that occur on the minute and one second after the minute are not a result of rounding of some transaction time stamps but are due to truncation. To accommodate these possibilities, we ran our tests after lagging the sound level an additional minute. Again, no substantial changes in the results could be detected.

We conducted a number of additional checks. We ran our tests on the pre- and post-July subsamples. Although the coefficients were slightly higher during the second period, they were still significant and qualitatively similar across the two subsamples. To ensure the results were not driven by peculiarities surrounding the open and close, we ran the tests on a sample that excluded observations before 7:45 a.m. and after 1:45 p.m. The resulting coefficients were largely unchanged and remained highly significant.

For all of our results, we tried a number of different variations in the test specification, including altering the lag structures, changing frequencies, and including and omitting different explanatory variables. We choose to report the particular results in Tables II through V because they are relatively easy to interpret, but the results of each test that we ran were the same as those we report. In summary, our robustness checks leave us fairly confident that the conclusions we are drawing from the data are not an artifact of the sample period, the specification, or a failure to control for important omitted factors.

V. Conclusion

This paper has studied an unusual time series, the ambient noise level of a trading pit, to help improve our understanding of an important issue in financial economics: how markets process information in reaching equilibrium. This paper supports the claim that market participants are not relying solely on easily observable data, such as past prices, trading volumes, or news announcements, in determining their supply and demand schedules. The evidence presented herein suggests that the communication and processing of highly subtle and complex nontransaction signals by traders plays a central role in determining equilibrium supply and demand conditions.

A key implication of this research is that in the trading arena, machine may not be a perfect substitute for man. Current electronic trading mechanisms are clearly not equipped to convey the kinds of signals for which a sound level is likely to proxy. Certainly computer terminals can be outfitted to offer some conveyance of nonmarket signals. But their ability to replicate the variety of signals that can be communicated in a face-to-face setting—for example, fear in a trader's voice—is likely to be limited. As a result, as trading volumes migrate to electronic exchanges, much of this information will be lost. The welfare implications of losing this information merit further study.

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