Trading Noise, Adverse Selection, and Intraday Bid–Ask Spreads in Futures Markets

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INTRODUCTION

Financial economists have recently developed a significant body of market microstructure literature regarding the determinants of bid–ask spreads. The relevance of the bid–ask spread is due, in part, to the fact that it represents a significant component of traders' overall execution costs. Many argue that the spread reflects the dealer's inventory cost, thus implying that the spread increases with the price risk of the security and decreases with trading volume [Demsetz (1968); Tinic and West (1987); Ho and Stoll (1981); Stoll (1978, 1987)].

In addition, it can be argued that the magnitude of the bid–ask spread is related to information flows. Copeland and Galai (1983) note that the spread must be wider to protect dealers from the costs of providing liquidity to "informed traders." In this respect, the bid–ask spread may vary with both the timing of information arrival and the uncertainty of the information flow. If information arrives sequentially, the more informed participants will trade first and the less informed participants will trade later. Because informed traders who acquire positive (negative) information are willing to bid (ask) a higher (lower) price to buy (sell), the spread may change according to the trading behavior of the parties who possess private information. Therefore, the possession of private information, while not observable, translates into an imbalance of public orders at the current price and can result in changes in the price level and bid–ask spreads when market makers, who have acquired complementary positions, try to rectify possible inventory imbalances. The implication of information flows for bid–ask spreads is that changes in bid–ask spreads may signal the arrival of new information.

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With regard to the uncertainty of information flows, it has been argued that less informed traders seek protection from the generation and ownership of private information in the market by requiring a higher risk premium [Copeland and Galai (1983); Glosten (1987, 1988); Glosten and Milgrom (1985); Glosten and Harris (1986)]. This "adverse selection hypothesis" suggests that the level of bid–ask spreads should be related to the uncertainty of the information flow in the market. In related work, Venkatesh and Chiang (1986) show that the bid–ask spread in stock prices tends to widen before earnings and dividends releases, when these are announced separately. Their results suggest that the separation of these two announcements causes speculation regarding the extraordinary nature of the second of the two announcements. In another study, Conroy and Niden (1988) demonstrate that bid–ask spreads for prices of target takeover stocks decrease after the announcement of mergers. They conclude that specialists must be uninformed participants in the markets before the announcement, first raising their spreads in response to unusual trading and then reducing the spread after the announcement to reflect the new information impounded in stock prices.

While previous studies have focused primarily on the behavior of bid–ask spreads in equity markets, little attention has been given to futures markets. The purpose of this article is to examine the variation of the implied intraday bid–ask spreads in futures prices. Specifically, two alternative measures of bid–ask spreads are calculated from the tick prices for futures contracts on four commodities: Treasury bonds, silver, corn, and soybeans. The results indicate that, for the contracts considered, the effective bid–ask spread is generally higher in the first and last 30 minutes of each daily trading session than during the rest of the trading day. Many trades in the futures markets are triggered by "stop" orders or technical analysis programs that cause trades to be entered in the same direction as recent price moves. This trading noise affects the frequency of positive sequential price changes and may have an important effect on bid–ask spreads in futures markets. Since trending price movements may make it difficult for market makers to reverse their positions inexpensively, they are likely to increase their bid–ask spreads in response to such trading noise. After controlling for the effect of trading noise on bid–ask spreads, the results of this research indicate that significantly higher bid–ask spreads exist at the beginning and end of the day. This incremental increase in the bid–ask spread can be attributed to the information disparity that is commonly associated with trading at the beginning and end of a session. The presence of a component for information uncertainty in bid–ask spreads is consistent with the adverse selection hypothesis that market makers require a higher risk premium when facing a concentration of informed trading.

The remainder of this article is organized as follows. Hypotheses regarding the determinants of bid–ask spreads are discussed along with alternative models which have been developed to describe intraday trading behavior. Alternative measurements of the bid–ask spread are discussed and the database and methodology are described. The effect that intraday variations in trading noise can have on bid–ask spreads is discussed, and the observed tendency for trading noise to vary systematically throughout the day is examined to determine if it accounts for the observed intraday variations in bid–ask spreads.

DETERMINANTS OF BID–ASK SPREADS: MODELS OF INTRADAY TRADING

Endogenous Trading Models

It is recognized generally that there are at least two motives for the trading of financial assets: information and liquidity. Informed traders act on private information which is not yet available to everyone, while liquidity traders trade to satisfy their unique liquidity demands. Both groups of participants submit market orders to the dealer or market maker who, in turn, sets prices so that in a competitive market his/her expected profits from the total order flow are zero [Glosten and Milgrom (1985); Kyle (1984, 1985)]. Admanti and Pfleiderer (1988), hereafter AP, formalize the interaction between informed and liquidity traders by developing an intraday model which seeks to describe the trading behavior of these parties. In the AP model, trading costs arise because of the activity of the informed traders and the burden of these costs are born ultimately by the nondiscretionary, uninformed traders who must trade at particular times, regardless of the price or cost.

Under the assumptions of the AP model, there is concentrated volume at particular trading times because these periods attract the informed and discretionary liquidity traders. The informed traders trade during these times because the presence of the liquidity traders allow them to disguise their information. Discretionary liquidity traders prefer to trade when the market is "thick" in the hopes of finding lower trading costs. The AP argument makes the most sense if one posits that two classes of discretionary liquidity traders exist—"large" traders and "small" traders. The "large" discretionary liquidity traders must execute large transactions and fear that they will incur large price discounts (on sales) or premia (on purchases) if they trade when the market is "thin." Smaller discretionary traders may choose to execute transactions at any time. Since the beginning or ending of a trading session is the first or the last opportunity that nondiscretionary liquidity traders can transact during the day, that group is likely to concentrate its trading at those two times. On the whole, the AP model predicts that trading is concentrated at the beginning and ending of a trading day. This concentration of trading hypothesis is consistent with previous empirical evidence of intraday U-shaped patterns for trading volume and return variances [Jain and Jon (1986); Wood, McInish, and Ord (1985)].

However, as argued by Brock and Kleidon (1990), Foster and Viswanathan (1989), and Subrahmanyam (1989), the AP model also asserts that lower trading costs and, thus, lower bid–ask price spreads, also occur during these concentrated periods.[1] This assertion is in contradiction with empirical evidence, which shows that bid–ask spreads for stocks are higher during these two periods [Foster and Viswanathan (1989)], relative to the rest of the day. Furthermore, in a study of intraday trading for S&P 500 index futures, Eckman (1990) suggests that informed traders concentrate their transactions at the beginning of a session while liquidity traders accumulate their trades at the close.

[1]Strictly speaking, the AP model predicts the intraday pattern for trading volume and return variances, but not the bid–ask spread. Similar to this study, Foster and Viswanathan (1989), Subrahmanyam (1989), and Brock and Kleidon (1990) relate the implications of the AP model for changes in the bid–ask spread.

Exogenous Demand Shifts and Intraday Trading

An alternative approach to modeling intraday trading is provided by Brock and Kleidon (1990), hereafter BK, who model intraday trading in terms of exogenous factors. Of particular interest are the empirical predictions of their model for volume, return variances, and the determination of bid–ask spreads at the opening and close of the trading day. In the BK model, one factor which is used to explain the high volume observed at the open and close is the inability of traders to transact when the market is closed. Specifically, if traders desire the same position at opening as they would have had if the market were open overnight (thus permitting trades during the night), there will be an accumulation of trades at the opening of each day. The inability to trade overnight could account for the high volume observed during the first hour of trading. Similarly, as BK argue, price changes overnight may alter investors' optimal portfolio positions. In lieu of these undesired effects, traders may be motivated to close out positions at the end of the day, thus avoiding exposure over a period during which trades cannot occur. Hence, volume may also accumulate at the close of each session.

BK also consider the effects that information can have for the variance in prices and its effects on bid–ask spreads. For example, if information production continues during nontrading hours, the accumulation of the information will imply, other things equal, a higher variance in price changes at the opening of each day. Furthermore, because market prices serve to aggregate information across investors, there should be greater divergence of beliefs following nontrading periods in which prices are unobservable. On the whole, because of the increased uncertainty due to these factors, the BK model predicts a widening of bid–ask spreads during the opening and closing of trading on a given day.

As the preceding discussion indicates, at least two types of models have been developed which attempt to explain the empirical results in light of the effects that information can have on bid–ask spreads. Because each model has different predictions for the behavior of intraday bid–ask spreads, the combined impact of these various factors for bid–ask spreads in futures markets is an empirical issue. Thus, this study investigates intraday differences in bid–ask spreads in the futures markets after controlling for the effects of trading noise.

MEASURING BID–ASK SPREADS FOR FUTURES CONTRACTS

Before one can investigate intertemporal differences in bid–ask spreads in futures markets, bid–ask spreads must first be estimated. Estimation techniques are necessary, because, unlike the organized stock market, bid–ask quotes are not always recorded in the futures markets. Because futures contracts are traded at a fast pace on the floor, price reporters generally only record changes in the transaction price.[2] Market makers quote either bid or ask prices at times when trading is slow; consequently, the actual bid or ask price may be recorded independently from the reporting of transaction prices, and is seldom observed for the more frequently traded contracts.[3] Specifically, in the database used in this study, less than 0.1% of all tick

[2]Since only different transaction prices are recorded, the tick sample is only a partial transaction sample. However, this does not pose a problem for this study because the estimate of bid–ask spreads is based only on the change in tick prices.

[3]When market trading slows down, market makers often stand on the sideline and offer either bid or ask prices. The recorded bid and ask prices usually do not come from the same market maker and, most likely, both prices are not quoted at the same time.

prices are recorded as either bid or ask prices. Conversations with exchange price reporters reveal that not all quoted bid and ask prices are recorded.[4] Therefore, spreads computed from such quoted bid and ask prices are often biased, especially bids and asks that are not simultaneously recorded. For these reasons, the actual bid and ask prices are discarded from the sample. Instead, consistent with prior research, several procedures for imputing the implied bid and ask prices are used in this study.

Methods have been developed for imputing bid–ask spreads from observed stock and stock option price data by Roll (1984); Choi, Salandro, and Shastri (1988); and Bhattacharya (1983). This article employs the Bhattacharya (1983) and Thompson–Waller (1988) methods to estimate bid–ask spreads for futures contracts.

The Bhattacharya Measure

In an approach designed to eliminate the influence of price trends from the estimation of bid–ask spreads, Bhattacharya (1983) analyzes only reversing price movements and determines average bid–ask spreads by calculating the mean value for all cases where sequential price changes reverse signs. This procedure, however, requires that data be disregarded if price increases and price decreases do not occur sequentially. That is, only nonoverlapping consecutively reverting stock price record streams of three or more records constitute a valid bid–ask–bid or ask–bid–ask sequence. For these cases, the records are retained for further analysis. The Bhattacharya (1983) methodology, which is used also by Dravid (1987); Madhavan (1987); and Ma and Peterson (1989), assumes that an up-tick (down-tick) transaction price surrounded by down-tick (up-tick) prices represents an ask (bid) price. This is based on the assumption that market makers provide liquidity services by asking a higher selling price and bidding a lower buying price. Therefore, bid and ask prices are identified as that point in time whenever a nonoverlapping consecutive up–down–up or a down–up–down price sequence emerges.

Figure 1 presents an example which illustrates how this method computes bid and ask prices. The Bhattacharya method can identify the transaction type for transactions 4, 5, 7, 8, 9, 11, 14, and 15. Transaction 6 can be either an ask in the 4–5–6 sequence or a bid in the 6–7–8 sequence. Transaction 10 is another case. Whenever such an ambiguity exists, as is the case when the same price is common to two successive price sequences, it is discarded from the sample. Finally, to preserve as much data as possible, note that not all sequential price reversals have to be equal in magnitude. For example, price sequence 14–15–16 generates a 1 1/2-tick "average spread."

Using the above procedure, one can identify a time series of bid and ask prices from which bid–ask spreads can be computed. However, because of substantial positive serial correlation in price changes, using the Bhattacharya measure to estimate bid–ask spreads requires that roughly 50% of the tick prices be dropped from the sample. In addition, because the Bhattacharya measure ignores large price movements that are not matched by an immediate price reversal, it may understate large quoted bid–ask spreads if occasional transactions take place inside the market maker's bid–ask spreads. For example, if the market maker's bid price is P_1 and ask price is P_3, and the price tick moves from P_1 to P_2 to P_1 as two customer trades cross at P_2, where $P_1 < P_2 < P_3$, the market maker's bid–ask spread will be understated by the Bhattacharya measure. Thus, in cases where quoted bid–ask spreads are wide, the

[4]On the floor of Chicago Board of Trade, there are separate groups of exchange employees to record the transaction prices and the bid and ask prices.

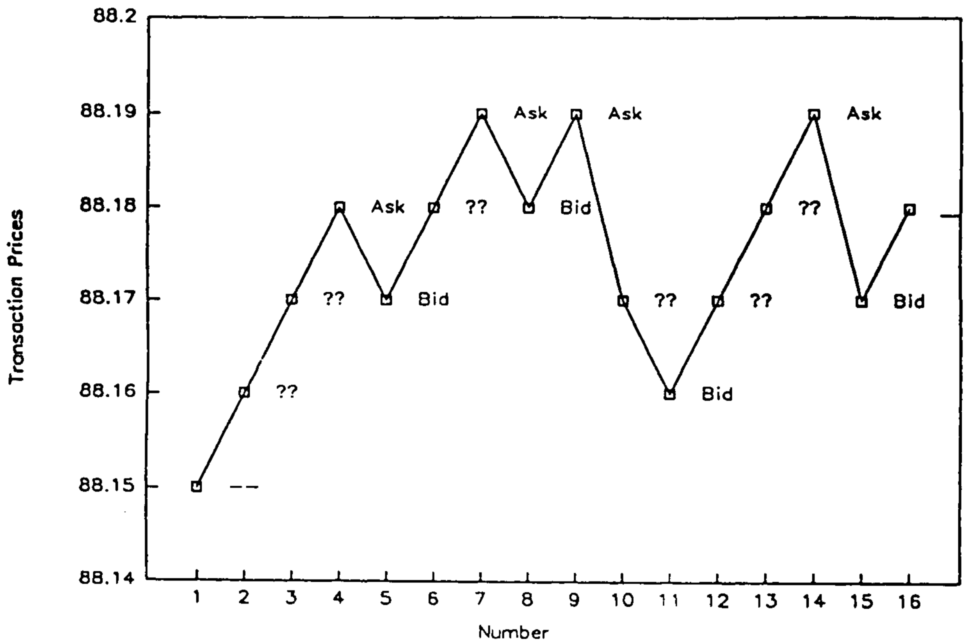

Figure 1
Illustrations of the Bhattacharya method to impute bid and ask prices and bid–ask spreads.

Bhattacharya measure may understate bid–ask spreads to the extent that it measures intermediate reversing price transactions and ignores the true spread if intervening transactions occur. Conversely, the inclusion of price jumps of unequal magnitude in computing average spreads may overstate market maker's spread quotes to some degree if the larger price jump in such a price reversal sequence reflects the entry of new information into the market rather than a movement between market maker's bid and ask prices. Such information events cause an upward bias in spread estimates if they cause prices to move in the *opposite* direction from the last tick and if they are not manifested in trending-price sequences.

The Thompson–Waller Measure

An alternative to the Bhattacharya method for estimating bid–ask spreads that does not discard data is a method developed by Thompson and Waller (1988). Thompson and Waller estimate bid–ask spreads as the average of absolute price changes from tick to tick over a specified time interval, n:

$$\text{Spread} = \sum_{t=1}^{n} |P_t - P_{t-1}|/n \qquad (1)$$

However, because the absolute value of successive price changes may well be increased by large changes in the underlying prices whenever new information arrives in the market, a dramatic change in prices may reflect new information rather than a large bid–ask spread. Since the Thompson–Waller method includes all information events, it probably provides an upwardly biased measure of bid–ask spreads.

Limitations of Bid–Ask Spread Measures

The bid–ask spread estimation techniques discussed above have some limitations. The Bhattacharya measure can result in the elimination of a substantial amount of data, and may cause wide bid–ask spreads to be understated if intermediate reversing transactions occur. The Thompson–Waller measure may overstate true bid–ask spreads as it systematically fails to differentiate between price changes resulting from information arrival and price changes that occur between bid and ask prices. Finally, both bid–ask spreads based on tick data may be biased to the extent that they omit zero-price change data. On this point, the evidence presented in the Appendix suggests that the use of tick data will tend to bias upward spread measurements at certain times of the day, e.g., midday, when trades are relatively more likely to occur at unchanged prices than during opening and close periods of changing prices.

Bid–Ask Spread Measures Used in this Study

The preceding discussion suggests that the Bhattacharya and Thompson–Waller measures may provide upper and lower bound estimates of the true bid–ask price spread. Accordingly, both measures are employed in this study to estimate bid–ask price spreads for futures contracts. In addition to these two measures of the bid–ask spread, a variable called "noise" is estimated as well. The variable "noise" measures the decimal probability that a price change will be followed by another price change of the same sign during any given trading interval. This variable is designed to estimate differences in trading noise; i.e., sequential price movements in the same direction, for different time intervals.

DATA SAMPLE AND THE SCREENING PROCEDURE

The sample used in this study includes tick data for Treasury bond, silver, soybeans, and corn futures contracts. Table I, panels A and B, presents details for the sample as well as some institutional specifications for the four contracts. While the selection of these four futures contracts and the sample periods represent only a sample of commodities, these contracts cover a wide range of commodities, including financial, metal, oilseed, and grain. Because procedures for computing effective bid–ask spreads can be biased if infrequent trading occurs (resulting in information effects having proportionately greater effects on sequential price changes than liquidity effects), the original sample is screened to minimize any measurement errors resulting from infrequent trading[5] Specifically:

1. To further control for possible bias caused by large price jumps that might occur if trading is infrequent, a minimum number of 30 tick prices is required in each 30-minute session for which a bid–ask spread is estimated.
2. Once the spreads are estimated for every half-hour interval, an average spread across days is computed for each measure. Because the Bhattacharya measure requires the elimination of certain data, a minimum of five spreads is used in

[5]The problem associated with using discrete prices is well recognized in the technology of estimating bid–ask prices. Also, thin trading of an asset may create long time intervals between two successive transaction prices, and equilibrium prices may change over those intervals. Current methods used to measure spreads often suffer from the problem of noncontinuous price movements caused by discrete trading. Thus, the spread may be significantly overestimated if larger price changes reflect additional new information released during the longer time intervals between transactions.

Table I
PANEL A: SAMPLE DESCRIPTION

Original Sample	T-Bond	Silver	Soybeans	Corn
Sample period	1980–1983	1984–1986	1984–1986	1980–1985
No. of trading days	1042	754	771	1298
No. of transaction records	1,395,284	987,253	1,004,157	1,286,123

Testing Sample	T-Bond	Silver	Soybean	Corn
No. of trading days	1009	729	750	1237
No. of bid–ask spreads				
Bhattacharya measure	17,785	6517	16,694	26,829
Thompson–Waller measure	22,651	10,742	20,916	44,315

A few days were eliminated from the original sample periods for each of the four futures contracts considered because of infrequent trading or irregular price jumps that resulted in insufficient data to compute reliable bid–ask spreads using the Battacharya technique.

PANEL B: SUMMARY OF CURRENT CONTRACT SPECIFICATIONS

Chicago Board of Trade Contract	Contract Months	Trading Hours (Chicago Time)	Contract Size	Minimum Price Fluctuation	Outstanding Contracts (Aug. 31, 1990)
T-bond	3, 6, 9, 12	7:20–2:00 Mon.–Fri. 5:00–8:30 PM Sun.–Thurs.	$100,000 8% coupon	1/32 pt. = $31.25	286,142
Silver	2, 3, 6, 8, 12	7:25–1:25	1000 troy oz.	1/10¢/oz. = $1	11,249
Soybeans	1, 3, 5, 7, 8, 9, 11	9:30–1:15	5000 bu.	1/4¢/bu. = $12.50	89,817
Corn	3, 5, 7, 9, 12	9:30–1:15	5000 bu.	1/4¢/bu. = $12.50	203,639

All CBOT futures contracts are the most actively traded futures contracts for each future except silver [where the Commodity Exchange (COMEX) contract is more actively traded].

the computation of average spreads. Any 30-minute interval which does not meet requirements (1) and (2) is dropped from the original sample.

3. A univariate test on the distributions of various bid–ask measures is performed to check for any "unusually high" estimates, which may be caused by infrequent trading or drastic short-term price trends. Any estimates lying outside the 95% confidence interval are considered "outliers" and are deleted from the sample.
4. If, after applying the screening procedures in (1)–(4), during any particular day, three or more half-hour sessions do not have "valid" estimates of bid–ask spreads, the entire trading day is dropped from the sample.

The sample screening procedure described above eliminates any outlier estimates of spreads due to infrequent trading or substantial price changes due to new information arrival, thus reducing the potential bias in spread estimates which can result from measurement errors. Furthermore, these screening procedures, (1)–(4), select a highly liquid sample. In fact, the final sample consists primarily of prices for nearby contracts, while the remaining contracts are predominantly the next contract out. While the use of just the nearby contract might result in a cleaner sample, all contracts satisfying the above screens are included to obtain as large a data base as possible, and in recognition of the practice by hedgers to switch to the next contract out at some point prior to the expiration of the nearby contract. In Table I, panel A, the final test sample, in terms of the number of half-hour spread observations, is summarized.

Since this screening process eliminates some data, imputed spreads from the remaining prices may be biased. In particular, some observations may be lost at the beginning and end of the day when sequential price movements are more likely to be trending than at other times of day. On the other hand, price observations may be lost also at midday when total trading volume is likely to be reduced, resulting in fewer measured price reversals during this time. If the data omissions cause an intraday bias, one should find systematic intraday divergences between the Thompson–Waller and Bhattacharya spread results, because the screening procedure applies to the Bhattacharya but not the Thompson–Waller spread measure. However, the results presented in Table II indicate no such patterns.

Empirical Results

Using the procedures described above, an average bid–ask spread is estimated for every 30-minute interval for each of the four futures contracts for the time periods covered. Summary statistics of the average bid–ask spreads are reported for the four contracts in Table II. As the results in panel A of Table II indicates,

Table II

PANEL A: SUMMARY STATISTICS FOR MEAN BID–ASK SPREAD ESTIMATES FOR T-BOND (IN 1/32 OF A POINT), SILVER (IN 1/10¢/OZ.), SOYBEAN, AND CORN FUTURES (IN CENTS/BU.)[a]

30-Minute Time Intervals	T-Bond		Silver		Soybeans		Corn	
	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
First half hour	1.143	1.280	1.148	1.249	0.454	0.467	0.280	0.309
2nd "	1.050	1.080	1.114	1.196	0.410	0.426	0.263	0.296
3rd "	1.049	1.088	1.098	1.223	0.399	0.413	0.261	0.297
4th "	1.037	1.081	1.100	1.199	0.397	0.410	0.260	0.299
5th "	1.030	1.074	1.101	1.182	0.405	0.423	0.258	0.299
6th "	1.042	1.085	1.087	1.194	0.405	0.425	0.258	0.299
7th "	1.039	1.071	1.069	1.208	0.423	0.442	0.260	0.296
8th "	1.038	1.078	1.087	1.216	0.460	0.472	0.262	0.304
9th "	1.035	1.079	1.064	1.196				
10th "	1.045	1.085	1.105	1.226				
11th "	1.042	1.085	1.128	1.277				
12th "	1.069	1.101						
N	17,785	22,651	6517	10,742	16,694	20,916	26,827	44,315
F-value	42.9[a]	138.0[a]	2.7[a]	3.5[a]	29.8[a]	32.5[a]	27.4[a]	11.3[a]
Chi-square	689.7[a]	805.8[a]	28.4[a]	8.1[a]	226.1[a]	301.3[a]	258.3[a]	50.9[a]

[a]Significant at the 1% level.

Table II (continued)
PANEL B: t-VALUES TO TEST FOR SIGNIFICANT DIFFERENCES IN MEAN BID–ASK SPREADS BETWEEN THE FIRST (S_F), THE LAST (S_L) HALF-HOUR, AND THE REST OF THE DAY (S_r) USING THE BHATTACHARYA (S_1) AND THOMPSON–WALLER (S_2) SPREAD MEASURES

	T-Bonds		Silver		Soybeans		Corn	
Hypothesis	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
H_1: $S_F = S_r$	470.0[a]	1482.0[a]	14.9[a]	8.7[a]	113.0[a]	109.0[a]	187.0[a]	65.2[a]
H_2: $S_L = S_r$	44.0[a]	22.0[a]	6.5[a]	24.0[a]	120.0[a]	123.0[a]	1.9[a]	21.5[a]

[a]Significant at the 1% level.

S_1: the mean bid–ask spread estimate using the Bhattacharya measure; S_2: the mean bid–ask spread estimate using the Thompson–Waller measure; N: the number of observations in the sample; F-value: the F-test statistic for the equivalence of mean bid–ask spreads across different time intervals; chi-square: Kruskal–Wallis test statistic for the equivalence of mean bid–ask spreads across different time intervals; and H_1H_2: hypothesis for equality of first (S_F) and last (S_L) half-hour mean bid–ask spreads with the mean bid–ask spread during the rest of the day (S_R).

the average bid–ask spread estimates are relatively close in magnitude regardless of the measure used. However, as expected, bid–ask spread estimates based on Bhattacharya's measure are smaller than those generated by the Thompson–Waller measure.[6] Nonetheless, given the theoretical reasons why spread estimates may diverge, it is gratifying that the estimates given by the various measures show little variation.[7]

From panel A of Table II, it appears that there is an intertemporal difference in bid–ask spreads during the day; and, the level of the spread in the first and the last

[6]For purposes of comparison, the Roll (1984) and Choi, Salandro, and Shastri (1983) measures of bid–ask spreads are estimated. Both measures, which are often used in studies of stock market bid–ask spreads, are adjusted for the presence of positive serial correlation. Both techniques produced spread measures that are consistent with the Bhattacharya and Thompson–Waller measures and, as expected, produced values greater (less) than the Bhattacharya (Thompson–Waller) estimates. Because futures tick data prices do not record transactions that occur at unchanged prices, it is probably not appropriate to use the Roll and the Choi et al. measures to estimate futures price bid–ask spreads. With tick prices, the Roll measure overstates spreads [Followill and Helms (1990)]. Also, the Choi et al. modification requires that the probability that sequential bid and ask prices will move in the same direction be known. Consequently, this study uses the Bhattacharya and Thompson–Waller measures since they are more easily adapted to the futures markets. Nonetheless, bid–ask spreads estimated with modification of both the Roll and Choi et al. measures provide similar U-shaped patterns during the day. These results are available upon request from the authors.

[7]An additional bid–ask spread measure for the futures markets has recently been developed by Smith and Whaley (1991). Their "method of moments" approach uses futures market tick data to impute simultaneously (i) the bid–ask spread, and (ii) the underlying variance in the futures price distribution. This method has great promise for providing refined estimates of futures market bid–ask spreads. However, it requires the iterative solution of two simultaneous quadratic equations, one of which contains cumulative normal probabilities, thus making it computationally time consuming. For that reason, the Smith and Whaley technique is not used here. However, in general, methods of moments estimates of bid–ask spreads should be bounded by the Bhattacharya and Thompson–Waller estimates of spreads. The Thompson–Waller measure is automatically overstated by the underlying price variance while the Smith–Whaley method is not. Conversely, because the Bhattacharya method computes the spread based on tick reversals, it will understate the spread to the extent that reversing price transactions occur within the spread. Since both the Bhattacharya and Thompson–Waller measures provide similar intraday results, it is likely, but not certain, that the method of moments estimates would be similar. However, because the method of moments estimates will not increase if spreads remain the same and the underlying futures price variance increases, it is not certain that it will generate results similar to that of Thompson–Waller on an intraday basis. In future research, the authors will investigate this issue using smaller data bases.

half hours is generally higher than the spread for the rest of the day. In panel A, an F-test that compares the mean bid–ask spread across different half-hour trading sessions indicates that the level of the spread is significantly different at the 1% level across half-hour trading sessions. To test the hypothesis that bid–ask spreads are higher in the first and last 30-minute sessions than in the remainder of the day, the mean spreads during each of these two periods are compared with the mean spread during the rest of the day. In panel B of Table II, the statistics for these t-tests are presented. The results of these tests indicate that, across all four futures contracts, the spreads in the first and the last half-hour trading periods are significantly higher than the spreads in the rest of the day. The differences are significant at the 1% level for all cases where the Thompson–Waller spread measure is considered and is significant at the 1% level, with but one exception (the last half hour for corn), when the Bhattacharya measure is considered. Finally, since the omission of no-price change transaction data is more likely to upwardly bias spread estimates during the middle of the day relative to the beginning and end of the day when tick-price changes are more frequent (see Appendix), the finding of wider bid–ask spreads at the beginning and end of the trading session is likely to be even more probable than shown here, done to the use of tick data, which might bias against finding that result.

NOISE, VOLUME, INFORMATION DISPARITY, AND BID–ASK SPREADS

Based on the current understanding regarding the determinants of bid–ask spreads, finding a time-varying intraday bid–ask spread, especially at the beginning and end of a trading session, may suggest that levels of trading noise, trading volume, and information disparity change during the day. Previous studies show that trading volume and return variance increase significantly at the beginning and end of the trading day. The current evidence is inconsistent with the effect expected from higher trading volume per se since the higher liquidity derived from the heavy trading activity should narrow, rather than widen, the spread in these two periods. However, considering that trading noise may generate heavy trading if trades sequentially follow trades in a positively correlated manner, higher trading noise at the beginning and end of the day could conceivably widen spreads (and thus offset the impact of trading volume) as market makers widen their spreads to compensate for the greater risk of being trapped on the wrong side of the market by continually trending price movements.

For each time interval examined in Table II, the corresponding level of trading noise is estimated also. This noise variable is proxied by the proportion of the time that sequential price changes during a particular time interval are of the same, rather than opposite, sign. These estimates, along with their associated statistics, are presented in Table III, panels A and B. As Table III indicates, in nearly all cases, the level of noise is significantly greater during the beginning and end of the day when compared to the rest of the day.

It is likely that trading noise is associated with sequentially positively correlated short-run price movements in the futures markets. A positive sign is assumed to represent noise since very short time intervals are being analyzed. Over longer periods, if noise trading causes futures prices to overshoot their equilibrium values, negative serial correlations should be observed. In the short run, trading noise results from trading that begets additional trading. An example of such activity is the triggering of stop orders that result in additional buy orders when prices are

Table III

PANEL A: SUMMARY STATISTICS FOR MEAN NOISE LEVELS FOR T-BOND, SILVER, SOYBEAN, AND CORN FUTURES

30-Minute Time Interval	T-Bond	Silver	Soybeans	Corn
1st (first)	0.50	0.38	0.45	0.35
2nd	0.43	0.37	0.44	0.29
3rd	0.41	0.39	0.43	0.26
4th	0.39	0.38	0.42	0.27
5th	0.38	0.38	0.44	0.29
6th	0.45	0.42	0.47	0.28
7th	0.42	0.41	0.49	0.31
8th	0.41	0.43	0.49	0.32
9th	0.43	0.43	N/A	N/A
10th	0.45	0.46	N/A	N/A
11th	0.45	0.46	N/A	N/A
12th	0.46	N/A	N/A	N/A
N	22,713	9,443	36,675	27,523
F-value	66.7[a]	54.2[a]	105.0[a]	147.9[a]
Chi-square	705.0[a]	575.6[a]	752.0[a]	1146.8[a]

[a]Significant at the 1% level.

PANEL B: t-VALUES TO TEST FOR SIGNIFICANT DIFFERENCES IN MEAN NOISE LEVELS BETWEEN THE FIRST (S_F), THE LAST (S_L) HALF-HOUR, AND THE REST OF THE DAY (S_R)

Hypotheses	T-Bonds	Silver	Soybeans	Corn
H_1: $S_F = S_R$	380.0[a]	29.9[a]	0.11	757.0[a]
H_2: $S_L = S_R$	95.0[a]	159.8[a]	198.0[a]	137.9[a]

[a]Significant at the 1% level.

Noise: the mean proportion of successive price moves that were in the same direction during a given time interval; N: the number of observations used to measure noise; F-value: the F-test statistic for the equivalence of mean noise levels across different time intervals; chi-square: Kruskal–Wallis test statistics for the equivalence of mean noise levels across different time intervals; and H_1,H_2: hypotheses for equality of first (S_F) and last (S_L) half-hour mean noise levels with the mean noise level during the rest of the day (S_R).

moving up or additional sell orders when prices are moving down. Another form of sequentially trending price movement is generated by technical trading procedures that call for purchases when resistance lines, moving averages, or price channels, are penetrated by price increases or sales when support lines, moving averages, or price channels are penetrated by downward price movements. Almost all technical trading systems for futures markets try to identify trends because futures traders usually trade with the trend ("the trend is your friend" is often stated by technical analysts). Thus, such systems, as well as the common use of stop orders in futures markets, tens to exaggerate any substantive positive or negative price movements that occur in those markets. It is assumed here that trading noise over a given time interval can be measured by the proportion of time that a change in price is followed by another price change of the same sign (i.e., in the same direction). As shown in Table II, these trend proportions are greater at the beginning and end of the day. One reason for this may be that many technical traders enter "stop" orders based on the previous day's closing prices at the open, and many traders enter new positions based on the closing price for the day by using "stop-on-close only" orders.

It should be noted, however, that the sequential release of private or public information can also generate price trends. To the extent that all positive serial correlation is ascribed to trading noise rather than to positively correlated sequential information arrival, the results may understate the effect that information arrival per se has on the market. The first and last 30 minutes of trading within a day may also be characterized by higher information disparity in the market. Market makers realize that most informed traders and liquidity traders concentrate their trading in these two sessions. At the beginning of a trading session, informed traders prefer to trade on their private information produced in the previous nontrading period, which is not yet known to the market. At the end of a trading session, informed traders are also more motivated to trade, since they can take advantage of less informed traders' inability to rebalance their portfolios in the following nontrading period when the information becomes more widely disseminated. Therefore, in these two periods there is a significantly higher information disparity among traders in the market and the process of adverse selection is most profound. To achieve a nonnegative marginal profit, market makers would require a wider spread from liquidity traders to offset the loss to informed traders at such times. This effect is aggravated if some local market makers square their positions and leave the trading pit at the end of the day. In that case there are fewer people to take the other side of a transaction and bid–ask spreads may increase because of reduced competition. However, it is unlikely that small reductions in competition have a substantial effect per se on spreads in actively traded futures contracts, such as the contracts studied here.

In short, the higher spreads in the first and the last half hours may be attributed to higher trading noise or to information asymmetry. Changes in the competitive structure of the market also could affect spreads, but are unlikely to have much independent effect in actively traded markets. In assessing the impact of adverse information on the level of bid–ask spreads, it is desirable to remove the effect of trading noise. French and Roll (1986) note that trading noise over short time intervals should cause positively correlated price movements. However, over longer intervals, trading noise should cause negative serial correlations in price changes as short-term overreactions are "unwound" as prices return toward their equilibrium levels. The observation that trading noise over short time intervals can cause positive serially correlated price movements is consistent with the "stop-order" and "technical-trading" comments made earlier. Thus, Jordan et al. (1988) use the level of positive serial correlation of successive returns as their measure of trading noise. If trading noise is primarily caused by trades following previous trades, this can result in positive serial correlation of returns. While there also may be a positive serial correlation of returns if information arrives sequentially at any time of the day, the resulting bias on this proxy should not affect intraday comparisons, since there is no evidence that sequential information releases concentrate in the first and the last half hours of trading.

Positive serial correlations in returns are indicated by positive covariances in price movements, or, as in this study, by an elevated probability (NOISE) that price changes of similar sign follow each other. To identify the possible impact of trading noise on bid–ask spreads, the following equation is estimated:

$$\text{Spread}_t = a + b\,\text{NOISE}_t + e_t \qquad (2)$$

If $NOISE_t$ is a proper measure for trading noise, e_t should be the component of the bid–ask spread, independent from trading noise, which is associated with information uncertainty. To the extent that $NOISE_t$ also captures the effect of serially correlated information releases, e_t will understate the effect of information on bid–ask spreads. However, as long as the bias does not vary systematically throughout the trading day, this will, if anything, make it less likely that the subsequent tests will find that information has a significant effect on bid–ask spreads. Thus, any positive information effect found in e_t will be stronger than indicated. In Table IV, statistics obtained from estimating eq. (2) for the Bhattacharya and Thompson–Waller measures of bid–ask spreads are reported. As the results show, with the sole exception of the Bhattacharya measure of silver, there is a significant positive relationship between the level of bid–ask spreads and the proxy for trading noise. This result is consistent with the hypothesis that the bid–ask spread will increase with the level of trading noise in the market. Even so, the low R^2 values indicate that while NOISE is a significant variable in explaining the bid–ask spread, there are clearly other explanators [Madhavan (1987); Thompson and Waller (1988)].

The average residual levels from eq. (2) estimated for each half-hour interval in the trading day are reported in panel A of Table V. Consistent with the above findings, even after controlling for trading noise, adjusted estimates of average residual bid–ask spreads generally are higher at the beginning and the end of trading sessions. As shown in panel B of Table V, the mean residual bid–ask spreads are significantly higher at the beginning and end of each trading session than during the middle of the day for every futures contract except corn. While the mean residual bid–ask spreads for corn are positive both at the beginning and end of the day, they are significantly elevated only at the beginning of the day. Both the F- and t-tests in Tables III and IV indicate that the null hypothesis of equal mean levels of trading noise and residual spreads across different half-hour trading sessions can be rejected at the 1% level.

Overall, even after adjusting for differences in trading noise, bid–ask spreads are generally higher in the first and last half hours of each trading day. Since elevated trading volume in those periods should, if anything, cause bid–ask spreads to be smaller at those times, the increase in mean residual spreads at those times probably

Table IV
REGRESSION ESTIMATES FOR EQ. (2):
Spread Measure = $a+b$ $NOISE_t+e_t$

Parameter Estimates	T-Bond		Silver		Soybeans		Corn	
	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
$\hat{a}$	0.942	0.968	1.085	1.023	0.218	0.298	0.240	0.259
	(218)[a]	(225)[a]	(76.3)[a]	(71.9)[a]	(35.6)[a]	(48.0)[a]	(214)[a]	(290)[a]
$\hat{b}$	0.302	0.315	0.544	0.478	0.498	0.457	0.092	0.116
	(27.8)[a]	(34.5)[a]	(1.43)	(14.6)[a]	(34.7)[a]	(45.5)[a]	(23.9)[a]	(53.8)[a]
F-value	773[a]	1190[a]	2.04	213[a]	1204[a]	2065[a]	571[a]	2890[a]
R^2	0.042	0.05	0.00	0.02	0.07	0.09	0.02	0.06
N	17,785	22,649	6517	10,743	16,694	20,914	26,827	44,583

[a]Significant at the 1% level.

t Values are in parentheses; S_1: Bhattacharya measure; and S_2: Thompson–Waller measure.

Table V

PANEL A: SUMMARY STATISTICS FOR MEAN RESIDUAL BID–ASK SPREAD ESTIMATES FOR THE BHATTACHARYA AND THOMPSON–WALLER MEASURES

30-Minute Time Interval	T-Bond		Silver		Soybeans		Corn	
	RS_1	RS_2	RS_1	RS_2	RS_1	RS_2	RS_1	RS_2
1st (first)	0.072	0.157	0.045	0.043	0.029	0.032	0.010	0.004
2nd	−0.005	−0.023	−0.012	−0.005	−0.005	−0.003	−0.000	0.004
3rd	−0.002	−0.010	−0.005	−0.016	−0.010	−0.012	−0.001	−0.000
4th	−0.006	−0.009	−0.003	−0.006	−0.007	−0.011	0.001	0.003
5th	−0.012	−0.014	−0.002	−0.023	−0.006	−0.007	−0.002	−0.003
6th	−0.017	−0.025	−0.017	−0.028	−0.019	−0.019	−0.004	−0.000
7th	−0.014	−0.030	−0.034	−0.010	−0.016	−0.013	−0.005	−0.005
8th	−0.011	−0.020	−0.018	−0.012	0.018	0.018	−0.003	0.001
9th	−0.016	−0.023	−0.042	−0.034	N/A	N/A	N/A	N/A
10th	−0.011	−0.024	−0.003	−0.015	N/A	N/A	N/A	N/A
11th	−0.014	−0.023	0.021	0.035	N/A	N/A	N/A	N/A
12th	0.008	−0.012	N/A	N/A	N/A	N/A	N/A	N/A
N	17785	22649	6517	10743	16694	20914	26827	44583
F-value	29.1[a]	114.5[a]	2.8[a]	2.7[a]	15.6[a]	21.8[a]	12.1[a]	5.8[a]
Chi-square	104.9[a]	370.9[a]	65.1[a]	130.2[a]	111[a]	176[a]	59.2[a]	54.1[a]

[a]Significant at the 1% level.

Residual spreads were calculated from eq. (2). The two alternative spread measures used as dependent variables were the Bhattacharya measure (used to generate RS_1) and the Thompson–Waller measure (used to calculate RS_2).

PANEL B: *T*-VALUES TO TEST FOR SIGNIFICANT DIFFERENCES BETWEEN MEAN RESIDUAL SPREADS IN THE FIRST (S_F), THE LAST (S_L) HALF-HOUR, AND THE REST OF THE DAY (S_R)

Hypothesis Testing	T-Bond		Silver		Soybeans		Corn	
	RS_1	RS_2	RS_1	RS_2	RS_1	RS_2	RS_1	RS_2
H_1: $S_F = S_r$	322[a]	1210[a]	15.5[a]	13.6[a]	85.9[a]	121[a]	70.4[a]	10.8[a]
H_2: $S_L = S_r$	21.1[a]	3.9[a]	5.4[a]	10.4[a]	36.3[a]	49.8[a]	1.4	1.0

[a]Significant at the 1% level.

N: the number of the observations in the sample; RS_1: residual bid–ask spread for eq. (2) for the Bhattacharya spread; RS_2: residual bid–ask spread from eq. (2) for the Thompson–Waller spread; F-value: the F-statistic tests for the equivalence of mean residual bid–ask spreads; chi-square: Kruskal–Wallis test statistics for the equivalence of mean residual spreads across different time intervals; and H_1,H_2: hypotheses for equality of first (S_F) and last (S_L) half-hour mean residual spreads with the mean residual spread during the rest of the day (S_R).

reflects an independent component of information flow which is unique to these two periods. This evidence is consistent with the hypothesis that the varying level of the spread may have reflected wider information disparity among traders in these two trading periods.

CONCLUSIONS

In this article, intraday bid–ask spreads are examined for prices of four widely diverse futures contracts. Using alternative measures, it is shown that the bid–ask spread is significantly higher in the first and last 30 minutes of each trading session. While the bid–ask spreads are related to higher levels of trading noise in the same periods, changes in the level of trading noise do not fully account for the intraday changes in bid–ask spreads. Thus, the significantly higher spreads in the first and last half hours of trading may be attributed to the higher degree of information uncertainty unique to these periods. This evidence is consistent with the adverse selection hypothesis that market makers protect themselves from the activities of informed trading and the generation of overnight private information by requiring a higher risk premium at the beginning and the ending of a trading session. Market makers also appear to play a smaller role in the market, at least in the T-bond market, at the beginning and end of the day while "outside traders" who are more likely to possess private information play a relatively larger role.

The implication of these findings is that the market has, as would be predicted by efficient market theories, priced the changing level and nature of information flows among trading agents within the day. Intertemporal differences in bid–ask spreads suggest a nonuniform cost of executing orders for traders. Therefore, a wealth-maximizing, information-based trader should determine the optimal timing of trading by comparing the tradeoff between the benefit of trading on private information at the start of the trading day, while the information is not yet well disseminated, with higher transaction costs, in the form of bid–ask spreads, that may result from trading small volumes at these times. An increase in spreads caused by greater information asymmetries at the beginning and end of the trading day does not necessarily suggest, however, that liquidity-based traders should always avoid trading at the beginning and the ending of a session. Nondiscretionary liquidity traders may be forced to trade at those times. Also, the tradeoff from trading in these two periods for liquidity traders is between the benefit of trading in a thick market (particularly for large discretionary liquidity traders who can trade large volumes at lower incremental costs) and the higher information-based spread paid to the market makers. Thus, large-volume liquidity traders may be more likely to trade at the beginning and end of the day. This unique concentration of nondiscretionary liquidity trading and large-volume discretionary liquidity trading will motivate the informed traders to participate and lead to more concentrated trading. The equilibrium clearing condition for the market is that market makers seek protection from the information disparity of informed traders by requiring a higher bid–ask spread at those times.

Appendix

INTRADAY TRADING PATTERNS FOR TREASURY BOND FUTURES

The validation of some of the assumptions made in the text requires further analysis. Such analysis requires the use of trading volume data to supplement the CBOT tick data which were used in the analysis. Trading data for Treasury-bonds, which was available to the authors, are used. Treasury-bond trading volume data from 1983 until November 1987 are used in detailed tests of several assumptions made in the text.

First, the article points out that large-volume discretionary liquidity traders prefer to trade at the open and close if they are able to transact at those times without incurring substantial trading costs for their large-volume trades. If their cost savings are sufficient, they may offset higher trading costs caused by the greater relative activity of informed traders at the same time. Consequently, the ratios of volume per price tick are analyzed. It is posited that this ratio should be higher at the beginning and end of the day, thereby allowing large discretionary liquidity traders to trade in higher volumes at such times with smaller price concessions. The results of that analysis are shown in column 1 of Table AI. The associated t-test and chi-square test statistics indicate that trading volume per tick varies significantly throughout the trading day for T-bond futures, and is significantly greater at the beginning and end of the day than during the rest of the day.

The second test analyzes the intraday frequency of zero price-change ticks. Recognizing that futures transaction price data omit zero price-change ticks, this implies that the bid–ask spread measures derived from tick price data could be biased if sequential trades occur at unchanged prices with varying frequency throughout the day. In particular, the omission of zero price changes from the tick data sample could cause average price changes and average bid–ask spreads to be overestimated to the extent that market makers offset part or all of their positions with flat trades at the same price at which they just acquired positions. The overestimates would be greater whenever flat trades and zero price change trades represent a greater proportion of total trades.

Thus, the second test on the T-bond data analyzes the relative frequency of tick price changes in each half-hour trading interval throughout the day. The results of these tests are presented in column 2 of Table AI. The results indicate that significantly more price changes occur in the first and last hours of trading than during the rest of the trading day. Because of the relatively greater frequency of price changes in the first and last trading hours, it is likely that the relative incidence of flat-price trading is reduced at such times. If so, measured bid–ask spreads would be likely to be overstated by a greater amount at midday (if relatively more zero-tick trades were ignored) than at the beginning and end of the day (when price changes are more frequent). Thus, this bias, if present, should make it more difficult to observe an intraday U-shape in bid–ask spreads if one, in fact, exists. Therefore, this finding reinforces the conclusions.

A third test of assumptions use 1983–1987 data for Treasury-bond trades classed according to the "Customer Trade Indicator (CTI)" designation for the individual making the trade. Trades for nonexchange members are included in CTI class 4. That class should include "outsiders" who may possess private information not available to local traders. The percentage of trades executed for such customers, not surprisingly, tends to be higher at the beginning and end of the day than at other times (see column 3 of Table AI). Because "local" traders and market members are most exposed to risk if they take the opposite sides of trades from holders of private information, one would expect such traders to be more reluctant to trade and to widen their bid–ask spreads when outside traders are most active. This study documents the fact that bid–ask spreads are wider at the beginning and end of the day, while the data in column 4 indicate that local traders (CTI 1) are proportionally least active at those times. Because it is hard to identify the exact composition of the remaining classes (2 and 3) they are combined. In many respects, trades made by others for the accounts of exchange members (classes 2 and 3) behave much like trades personally made by exchange members for their own accounts (class 1). Thus, it appears that exchange outsiders (class 4) account for proportionally more trades at the beginning

Table AI
THE NUMBER OF DIFFERENT PRICE TICKS AND VOLUME PER TICK IN EACH HALF-HOUR INTERVAL FOR THE TREASURY-BOND FUTURES CONTRACTS

Half-Hour Interval	Average Trading Volume Per Different Price Tick[b]	Average Number of Price Ticks[c]	Percentage of Trades by Types of Traders[d]		
			Outsiders (CTI 4) (%)	Locals (CTI 1) (%)	Other (CBOT) Members' Trades (CTI 2 or 3) (%)
1	540.9	8.51	29.47	57.97	12.56
2	399.3	7.88	26.61	59.62	13.77
3	310.0	7.84	28.37	57.49	14.14
4	243.9	8.01	30.04	55.10	14.86
5	239.0	7.64	29.71	55.30	14.99
6	266.8	7.62	27.72	58.38	13.88
7	245.4	7.47	28.68	56.69	14.64
8	231.9	7.76	29.30	55.55	15.15
9	241.9	7.38	27.91	58.10	13.98
10	250.6	7.72	29.33	57.77	12.90
11	276.5	8.10	29.07	58.16	12.77
12	395.7	7.93	32.23	54.50	13.27
Mean first and last half hour	468.3	8.22	30.85	56.23	12.20
Mean, other times	270.5	8.53	28.67	57.22	14.11
t-test[e]	16.71[a]	9.30[a]			
Chi-square[f]	42.94[a]	23.10[a]			

[a]Significant at the 1% level.

[b]The average volume per tick is computed by the trading volume divided by the number of different price changes.

[c]The number of different ticks is calculated by the average of the number of different price changes within every half-hour time interval.

[d]The classification of traders is based on "Customer Trade Indication" definitions where (1)–(4) are defined as follows: (1) the person executing this trade was trading for his/her own account or an account which he controlled; (2) the person executing this trade was trading for his/her clearing member's house account; (3) the person executing this trade was trading for another member present on the exchange floor, or an account controlled by other such member; (4) the person executing this trade was trading for any other type of customer.

[e]The t-test statistics evaluate differences in the mean level during the first and last half hours with the mean level during the rest of the day.

[f]The chi-square statistics employ the Kruskal–Wallis procedure to evaluate the difference between the mean level during the first and last half hour with the mean level during the rest of the day.

and end of the day while trades made by or on behalf of exchange members are relatively less important at those times.

Overall, the statistics for T-bond futures trading presented in Table AI are consistent with the hypotheses advanced in the text to explain U-shaped intraday variations in bid–ask spreads. They suggest that information-based traders are likely to be more active at the beginning and end of the trading day and that volume per price tick is greater at such times (thereby letting new information enter the market in quantity more easily at those times). In addition, the data suggest that, if anything, because of more frequent price changes, computed bid–ask spreads are less likely to be overstated at the beginning and end of the day than during midday trading periods.

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