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Evaluation of the biases in execution cost estimation using trade and quote data☆

Mark Peterson[a,*], Erik Sirri[b]

[a] Department of Finance, Southern Illinois University, Carbondale, IL 62901-4626, USA
[b] Finance Department, Babson College, Wellesley, MA 02157, USA

Abstract

We use order data to assess the accuracy of execution cost estimation with trade and quote data. For our sample, estimates of the effective spread overstate actual execution costs by up to 17%. The biases result from errors in the inference of the trade direction and errors in the assignment of the benchmark quote. We find the accuracy of two popular trade direction algorithms improve marginally when trades are not lagged 5 seconds. Evaluation of the biases in execution cost measurement reveal the Ellis et al. (Journal of Financial and Quantitative Analysis (2000) 529) trade direction algorithm, combined with assigning benchmark quotes contemporaneous with trades, provides the least amount of bias. In general, biases are lower for relative effective spread estimates than effective spread estimates.

JEL classification: G10

Keywords: Lee and Ready algorithm; Effective spread; Trade direction

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*Corresponding author. Tel.: +1618-453-1426; fax: +1618-453-5626.
E-mail address: map1@cba.siu.edu (M. Peterson).

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1. Introduction

Researchers in the field of financial economics have access to large amounts of machine-readable data on the trades and quotes of individual stocks. These data have many useful purposes. Two uses of trade and quote (TAQ) data are the assessment of market quality and the measurement of execution costs. Studies in this area are important as the results provide an in-depth examination of the stock trading process. However, publicly available trade and quote databases do not include all of the information necessary to precisely calculate execution costs. Bessembinder (2000) addresses this issue by assessing the sensitivity of trading cost estimates to the time adjustment made before comparing trades to quotes, and the procedure used to designate trades as buyer or seller-initiated. His conclusions are that no allowance for trade reporting lags is optimal when assigning trade direction, and that trades should be lagged to estimated benchmark quotes to capture the effect of quotations systematically moving prior to trades.

Existing studies use datasets with more complete information than the NYSE's TAQ database to address the success of trade side classification algorithms. Finucane (2000), Lee and Radhakrishna (2000), and Odders-White (2000) evaluate the Lee and Ready (1991) trade signing algorithm using the TORQ dataset. The TORQ dataset includes trading information of 144 NYSE stocks for a three-month period beginning in November 1990. The results indicate the accuracy of the Lee-Ready algorithm is between 85% and 93%, depending on the definition of a trade initiator (discussed below). These studies also indicate the algorithm biases are systematic. That is, trades in more liquid stocks, and for smaller amounts, tend to be misclassified more frequently. The Lee-Ready algorithm has also been evaluated on the Nasdaq (Ellis et al., 2000), the Australian Stock Exchange (Aitken and Frino, 1996), and the Frankfort Stock Exchange (Theissen, 2000). The results from these studies are similar to the three studies using NYSE data.

We contribute to the current research in market microstructure in several ways. First, order data are used to calculate the biases in trading cost estimators resulting from the inferences TAQ users must make. While biases in trading costs have been noted elsewhere, e.g., Petersen and Fialkowski (1994), the data used in this study are more recent. On average, estimates of execution costs using TAQ data overstate trading costs by up to 17%. These biases are both statistically and economically significant. Consistent with research such as Odders-White (2000), the biases are systematic. For example, biases are largest for small trades in large stocks.

Second, the robustness of the trade initiator classification scheme put forth by Lee and Ready (1991) (LR) and Ellis et al. (2000) (EMO) is assessed using more recent data. The evidence indicates the algorithms perform similarly and that the accuracy of the algorithms increase as the difference in the time trades are lagged relative to quotes decreases. This result confirms Bessembinder's (2000) conjectures regarding trade direction algorithms and provides support for his contention that the trading cost comparison between the NYSE and Nasdaq is insensitive to the biases documented in this paper.

Third, guidance is provided for researchers estimating trading costs using trades and quotes, absent order data. The results suggest trades should not be lagged relative to quotes for trade direction algorithms, and there should be no lag when assigning the benchmark quote. These suggestions are consistent with Bessembinder (2000). Further, the data reveal that the EMO methodology is superior to the LR methodology when measuring execution costs.

Notably, the sample period covered includes two periods that straddle the NYSE's change in tick size from \$1/8 to \$1/16. This allows an examination to what, if any, impact tick size has on the estimation of execution costs. In the Harris (1994) model, spreads and depths are predicted to decrease with a reduction in tick size. Empirical support for this model is found in Ahn et al. (1996, 1998), Goldstein and Kavajecz (2000), and Porter and Weaver (1997). Jones and Lipson (2000) estimate the effect of the change in tick size on execution costs for institutional trades. They find trading costs increase most for orders that aggressively demand liquidity, suggesting the bias in trading cost measurement may change systematically with a change in tick size. We find after the reduction in tick size, orders took slightly longer to execute, quotes were updated more frequently, and biases, depending on the measurement technique, stayed the same or increased.

2. Examples of errors in trading cost estimates

The trading cost measures considered here are the effective spread and the relative effective spread. The effective spread, which represents the round trip execution costs, less commissions, is calculated as:

$$\text{Effective spread} = 2 \times D \times (\text{Price} - \text{midpoint})$$

where D is the trade direction, $+1$ for a buy, and -1 for a sell. Using only TAQ data, one must infer D. The midpoint must also be estimated because the TAQ data report the trade time, not the order submission time. As noted in Bacidore et al. (1999), execution quality is most appropriately measured setting the benchmark quote to that prevailing at order submission time.

The relative effective spread is calculated as

$$\text{Relative effective spread} = \text{Effective spread}/\text{price}.$$

Next, we demonstrate the possible limitations of trade and quote data in estimating trading costs by providing two specific examples—price improvement in minimum variation markets and quote changes prior to trade execution.

2.1. Price improvement in minimum variation markets

Angel (1994), Edwards (1997), Ready (1999), and Ross et al. (1996), have all reported significant rates of price improvement in minimum variation markets, i.e., when the bid-ask spread is equal to 1 tick. When price improvement occurs in minimum variation markets, the researcher using TAQ data will err in trade side assignment. To illustrate the potential magnitude of this type of error, suppose the market is quoted \$50 bid and \$50 1/16 offered at order submission time and a buy order is executed at \$50. The midpoint is \$50 1/32, so the effective spread is $(2)(1)(-\$1/32)$ or $-\$1/16$. The estimated effective spread is $(2)(-1)(-\$1/32)$ or \$1/16. If a significant number of trades execute in minimum variation markets, then the occurrence of price improvement will result in a significant overstatement of execution costs. Bacidore et al. (1999) report approximately 40% of NYSE market orders in their sample arrived when the bid-ask spread was \$1/16. Of these orders, approximately 10% received price improvement. A back of the envelope estimate of execution cost estimation biases in minimum variation markets then is 25%.[1]

2.2. Quote movement prior to execution

The problem of quotes recorded ahead of trades has always existed, but has increased substantially with the widespread use of "electronic books" by specialists (Lee and Ready, 1991, p. 734). If quotes move between order submission time and the time of execution, the benchmark quote will be estimated with error. In addition to the algorithm used to infer trade direction, Lee and Ready (1991) provide guidance on the estimation of the benchmark quote. They suggest trades be compared to quotes in effect 5 seconds earlier.

To illustrate the magnitude of the error due to quote/trade mismatches consider the following example. Suppose a buy order executes at \$50 1/16 and the market was quoted at \$50 bid and \$50 1/16 offered at execution, but was \$49 15/16 bid and \$50 1/16 offered at order submission. The actual effective spread in this example is $(2)(1)(\$1/16)$ or \$1/8 and the estimated effective spread is $(2)(1)(\$1/32)$ or \$1/16. In this example the estimated effective spread is lower than the actual effective spread by a factor of two. These two examples illustrate that on a trade-by-trade basis, the errors in the estimation of trading costs may be substantial.

3. Sample and data description

The data used in this analysis include SuperDOT system orders sent to the NYSE during two separate two-week periods around the NYSE's change to a tick size of \$1/16. These data are contained in the NYSE's System Order Database Daily File (SOD file).[2] The first period begins on 6/9/97 and ends on 6/20/97. During this time the NYSE priced most stocks using a minimum price variation of \$1/8. The change to 1/16ths occurred on 6/24/97, so the first period begins about three weeks prior to

[1] The estimated effective spread in minimum variation markets is \$1/16. The true effective spread in minimum variation markets is a weighted average of \$1/16 and $-\$1/16$. Using a 10% price improvement rate, the approximate true effective spread is $(90\%)(\$1/16) + (10\%)(-\$1/16)$, or \$0.05. Thus, in minimum variation markets, estimated effective spreads are potentially overstated by $(6.25/5) - 1 = 25\%$.

[2] Hasbrouck (1992) describes the SOD file.

the change in tick size. The second period begins on 6/30/97 and ends on 7/11/97. In this period the NYSE priced most stocks using a minimum price variation of \$1/16.

The set of observations retained for analyses initially includes orders from all NYSE issues of ordinary common shares with corresponding CRSP data. Orders from stocks when the bid-ask spread at order submission time is less than \$1/16 or greater than \$1/4 are excluded as these observations are relatively uncommon and may skew the results. Following Bacidore et al. (1999) we consider the national best bid and offer (NBBO) as the bid and ask quotes observed at order submission time. The NBBO is defined as the highest bid and lowest ask across all markets for an individual stock. In cases when multiple markets are at the best price, the market with the maximum depth is used to represent the quoted depth.

The SOD file is valuable because it includes data on order submission time, trade direction, type of order (market or limit), trade price, and report time, as well as other conditions such as whether the order is tick sensitive. While the SOD file is rather comprehensive, it does not represent the entire picture of trading on the NYSE. Sofianos and Werner (2000) examine trading activity of NYSE floor brokers and find floor broker participation is as high as 44%. They conclude it is misleading to make inferences concerning liquidity using only SOD and TAQ data. Ross et al. (1996) have reported over 80% of the NYSE orders, accounting for 30–40% of the volume are executed through SuperDOT. Hence, an important caveat should be considered at this point. That is, the biases of execution cost estimators presented here apply to mostly retail orders sent to an auction market, not necessarily to orders or trades made by floor brokers, or orders sent to a dealer market such as Nasdaq.

To make appropriate comparisons between the NYSE order data and TAQ data, only those SOD file orders likely to be found in the TAQ database are included. Therefore, we exclude odd-lots (orders for less than 100 shares) because these orders are executed automatically against the specialist inventory at the quote and are not disseminated to the tape (Hasbrouck et al., 1993). Further, only those SOD orders considered to initiate a trade are retained. Hasbrouck and Schwartz (1988) define active traders, or trade initiators, as those who incur execution costs. Any order that we do not consider an initiator is excluded from analysis.

In the literature, researchers use different definitions of trade initiators based presumably on data availability. Odders-White (2000) considers the last arriving order to be the trade initiator. She can make this determination because the TORQ database includes the NYSE audit file, which contains order-entry time for both sides of the trade. Papers such as Lee (1992) and Petersen and Fialkowski (1994) consider the active side to be market orders. Kraus and Stoll (1972) consider the active side to be the side with fewer parties. Finucane (2000) and Lee and Radhakrishna (2000) note many orders cannot be unambiguously defined as buyer- or seller-initiated. Finucane (2000) finds that nearly one-fourth of all trades do not occur as the result of the arrival of a market order. In his final analysis, Finucane (2000) examines trades with at least one standard non-tick sensitive buy or sell market order in the trade. Ellis et al. (2000) and Theissen (2000) take the approach of inferring trade direction from the side contra to the dealer.

Because we do not have access to the NYSE audit file, we cannot define a trade initiator in the same way as those who have used TORQ data. Therefore, our approach will be to begin with all regular-way orders and exclude orders that are most likely not initiators. The following orders are excluded: (a.) limit orders that are not 'marketable', that is buy orders with limit price less than the ask or sell orders with limit price greater than the bid, (b.) tick sensitive orders because they usually do not initiate trades, (c.) stopped,[3] or guaranteed orders, because these orders tend to be more like limit orders, and (d.) partial executions of marketable limit orders for more shares than are at the best quote and execute in multiple parts. For example, suppose an order for 7,500 shares to buy at \$20 1/8 is entered when the quotes are \$20-\$20 1/8, with bid and ask sizes of 1,000 and 4,000 shares, respectively. Suppose further 4,000 shares are executed at \$20 1/8; the market is re-quoted to \$20 1/8-\$20 3/16 with 3,500 shares at the bid and 5,000 shares at the ask; and the remaining 3,500 shares are executed at \$20 1/8 some time later. In the present analysis the first fill will be included, but subsequent fills of this order will be excluded.

A summary of the trades in both sample periods is reported in Table 1. The data are categorized by market capitalization quartile of the underlying stock and the pricing regime under which the order is submitted. We categorize by market capitalization based on observations by Berkowitz et al. (1988), Holthausen et al. (1987, 1990), Keim and Madhavan (1997), Ross et al. (1996), and others who find trading costs decrease with market capitalization. Table 1 indicates market capitalization proxies for liquidity, as trading volume increases with increases in market capitalization. In all, there are 3,355,690 trades, with slightly more trades in the sub-sample with tick size of \$1/8. (Note there are 10 trading days in the earlier sub-sample and 9 trading days in the later sub-sample.) As expected, most trades occur in the quartile with the largest stocks (72% during the \$1/8ths pricing regime and 74% during the \$1/16ths pricing regime). Slightly less than 60% of the trades are for 100–500 shares, slightly less than 40% of the trades are for 501–5,000 shares, and approximately 3% of the trades are for more than 5,000 shares.

The percentage of trades in the sample that were stopped is approximately 5–10% and decreased after the tick size change. Bacidore et al. (1999) report a 'stopping' rate of 2.6% for their data taken from August 1999. In contrast, Ready (1999) reports a 'stopping' rate of 30% for data taken from the TORQ data base (November 1990–January 1991). Therefore, it seems the practice of stopping has diminished over time. Stopped orders are excluded from the analysis from this point forward as we do not consider these orders to be trade initiators when viewed from

[3] Stopped orders may become part of the quote and may trade with incoming market orders. Lee and Radhakrishna (2000) categorize stopped orders as 'clearly passive', and therefore exclude them in their analysis. Bacidore et al. (1999) find that the average stopped order takes 250 seconds to execute, suggesting it has characteristics of a limit order. For a comprehensive description of 'stopped' orders see Ready (1999). See also Finucane (2000), Handa et al. (1999), Harris and Hasbrouck (1996), Odders-White (2000), Petersen and Fialkowski (1994), and Ross et al. (1996). Note Finucane (2000) retains stopped orders in the analysis of effective spreads.

Table 1
Sample means and trades summary

	Market capitalization quartile							
	Quartile 1 (Largest stocks)		Quartile 2		Quartile 3		Quartile 4 (Smaller stocks)	
Stock characteristics								
Market capitalization	\$11,930.0		\$1,188.7		\$416.3		\$109.7	
Trading volume	162.20		34.84		18.15		9.32	
Trade characteristics	Tick = \$1/8	Tick = \$1/16	Tick = \$1/8	Tick = \$1/16	Tick = \$1/8	Tick = \$1/16	Tick = \$1/8	Tick = \$1/16
Number of trades	1,254,328	1,198,332	271,313	225,190	141,099	131,885	69,853	63,690
Small (100–500)	759,021	691,548	169,318	132,982	82,609	73,626	34,711	32,299
Medium (501–5,000)	458,869	474,874	94,779	86,135	54,885	54,494	32,522	29,348
Large (> 5,000)	36,438	31,910	7,216	6,073	3,605	3,765	2,620	2,046
% Stopped	10.1%	6.5%	8.5%	6.3%	6.9%	6.3%	6.4%	5.2%
% Disqualified MLIMs	4.9%	3.8%	4.8%	4.5%	6.0%	5.7%	6.9%	6.7%
Trade location								
Quote	80.6%	69.9%	82.5%	75.9%	87.2%	78.1%	88.7%	81.3%
Midpoint	7.4%	9.5%	8.6%	8.9%	6.5%	8.2%	5.9%	7.4%
Inside	9.1%	13.6%	6.5%	10.6%	4.0%	9.1%	3.3%	6.9%
Outside	2.9%	7.0%	2.4%	4.6%	2.3%	4.6%	2.2%	4.4%
% Trades spread = 1Tick	84.6%	55.4%	79.0%	48.4%	81.4%	49.3%	80.0%	45.1%
Quoted spread	\$0.143	\$0.103	\$0.150	\$0.115	\$0.147	\$0.115	\$0.145	\$0.119
Depth (000s)	12.97	7.06	10.50	6.12	10.60	7.39	12.27	7.87
% Greater than depth	14.7%	18.4%	17.9%	22.5%	21.0%	25.9%	22.9%	28.1%
Price	\$57.70	\$58.42	\$28.95	\$29.13	\$20.29	\$20.38	\$11.98	\$13.66

Market capitalization in millions as of 5/31/97. Volume from 1/1/97 to 5/31/97 in millions. The first sub-sample period begins 6/9/97 and ends 6/20/97 when the tick size was \$1/8. The second sub-sample period begins 6/30/97 and ends 7/11/97 when the tick size was \$1/16. Trades reported in the SOD database and include only regular way trades with valid quotes at the time of order submission. Orders placed when the spread was greater than \$1/4 or less than \$1/16 are excluded. Odd-lot orders are excluded. Tick sensitive orders are excluded. % *Disqualified* MLIMs refers to marketable limit orders for more than the quoted depth that become standing orders after the initial fill is made. Depth refers to the trade-weighted average bid size and ask size and is in multiples of 1,000.

the standpoint of a TAQ user. About 5% of the marketable limit orders become standing limit orders because their size exceeds the depth. As indicated above these orders are excluded.

Table 1 also reports the trade location relative to the quotes at order submission because Ellis et al. (2000), Finucane (2000), and Odders-White (2000) all report trade direction algorithm success rates are sensitive to trade location. The majority (70–89%) of trades execute at the quotes. It is interesting to see there is a significant drop-off of the proportion of trades occurring at the quote after the tick size reduction. This is likely because of a decrease in the percentage of trades in minimum variation markets from approximately 80% when the tick size was \$1/8 to 50% when the tick size was \$1/16. When the spread is greater than 1 tick there is a chance traders can meet inside the quotes. Approximately 6–10% of the trades execute at the midpoint, 3–14% execute inside the quotes, but not at the midpoint, and 2–7% execute outside the quotes.

Consistent with previous empirical work on spreads and depths around the tick size change, the trade-weighted quoted spread and depth both decreased. Quoted spreads declined by 20–25% following the tick reduction and depths declined by 30–40%. There was a corresponding increase in the proportion of orders for more shares than offered at the best quote of approximately 4%.

4. Errors in the inference of trade side and the benchmark quote

In this section the errors in the inferences TAQ users make are analyzed. First, the delay from order time to report time is tabulated. An analysis is performed on the accuracy of estimation of the benchmark quote. Trade side classification success rates are evaluated across several dimensions.

4.1. SOD/TAQ synchronization

Because the data used in this study come from two different sources (SOD file and TAQ files), the differences, if any, in the timing of the systems that report the data must be examined.[4] In the SOD file the RTIME field represents the report time, i.e., the time the order was executed. RTIME is used to estimate when the TAQ user observes a trade. The TAQ trade time (TTIM) reflects the time at which the trade entered CTS. The TAQ manual (v. 3.31) indicates before SuperDOT orders enter CTS, they are first routed through the Post Support System (PSS) and the Market Data System (MDS).[5]

The additional transmission of SuperDOT orders through the PSS and MDS requires the estimation of delay between RTIME and TTIM. Because there is not a one-to-one correspondence of orders on the SOD file and trades on the TAQ file, the

[4] Hasbrouck (1992) suggests that sequencing the data using RTIME from the SOD file and the quote time from the consolidated file can lead to asynchronous prices.

[5] Hasbrouck et al. (1993) provide a useful resource on the NYSE system, trading rules, and procedures.

estimation procedure becomes complicated. The following approach is taken to estimate the delay. First, stocks are ranked by the number of orders in the SOD file. Forty stocks are chosen randomly, 10 from each quartile. One stock from each quartile is then examined on one of the days in the sample period. Although not reported in a table, the median timing delay is 2 seconds. Interestingly, there are some cases with TTIM earlier than RTIME. However, this happens less than 5% of the time. Based on our observations, it is our view that the unadjusted RTIME most accurately reflects the time that trades are recorded in the TAQ database.

4.2. Trade delay analysis

Ideally, execution costs would be based on market conditions observed at the time the trading decision is made. As a practical matter, not all of this information is available. The SOD database does include an order arrival time (OTIME). We follow Bacidore et al. (1999), and use OTIME as the time to assign the benchmark quotes.

Table 2 reports the distribution of trade delay, defined as the elapsed time between order submission (OTIME) and report time (RTIME). The median trade delay is 13 seconds when the tick size was \$1/8 and 17 seconds when the tick size was \$1/16. Noticeable trends in delay occur when controlling for trade size. Smaller trades (100–500 shares) tend to have the shortest delay, followed by medium trades (501–5,000 shares), then large trades ($> 5,000$ shares). Additionally, trade delays are longer for smaller stocks than larger stocks. The implication for trade delay in the context of this paper is that as trade delay increases, the likelihood trades and quotes will be mismatched also increases. If the benchmark quotes are incorrect, then the confidence in the trade direction inference, and confidence in the estimation of the benchmark quote will be lower.

4.3. Quote/trade mismatch analysis

Table 3 reports the percentage of trades with errors in the estimation of the benchmark quote midpoint. Panel A shows 7.2% (2.1%) of buy orders under the \$1/8ths pricing regime are preceded by increases (decreases) in the quote midpoint. For sell orders the numbers are approximately the same, except the quote midpoint tends to decrease more frequently than increase. Errors in estimating the quote midpoint tend to be more frequent when the tick size was \$1/16. This is not surprising as other studies have reported an increase in quoting activity following the tick size reduction.

Panel B indicates the likelihood of a quote change increases with trade size. This observation is consistent with the data in Table 2 assuming quotes are more likely to change for longer delays, which typically occur for larger trades. With regard to quote changes and market capitalization, there clearly is an increase in midpoint estimation errors as market capitalization increases. This observation suggests the errors in trading cost estimation may be larger for larger stocks.

Table 2
Distribution of trade delay (in seconds)

	Tick = $1/8			Tick = $1/16		
	25	50	75%ile	25%ile	50	75
All						
All	7	13	26	9	17	34
Small trades	7	12	24	8	16	32
Medium trades	8	14	27	10	18	34
Large trades	11	21	39	13	24	46
Quartile 1 (largest stocks)						
All	7	12	24	8	16	32
Small trades	6	11	22	8	15	31
Medium trades	8	13	25	9	17	33
Large trades	11	20	37	12	23	44
Quartile 2						
All	9	15	29	10	19	37
Small trades	8	14	27	10	17	35
Medium trades	9	16	31	11	20	38
Large trades	13	24	50	14	28	56
Quartile 3						
All	9	15	29	11	19	38
Small trades	8	14	27	10	18	36
Medium trades	10	17	31	11	21	40
Large trades	13	23	45	13	26	55
Quartile 4 (smallest stocks)						
All	9	16	30	11	19	38
Small trades	9	15	28	10	18	37
Medium trades	9	16	31	11	20	39
Large trades	11	21	45	13	33	46

Table includes trades described in Table 1. Odd-lots, stopped orders, and subsequent fills from marketable limit orders for more than the quoted depth that become standing limit orders are excluded. Trade delay is measured as the time between order submission (SOD OTIME) and order execution (SOD RTIME). Small trades are for 100–500 shares. Medium trades are for 501–5,000 shares. Large trades are for more than 5,000 shares. Quartile 1 includes trades from the largest stocks and Quartile 4 includes trades from the smallest stocks.

The implication of the results in Table 3 is the quote midpoint is estimated with error approximately 14% of the time for trades in the $1/16ths regime. There also appear to be systematic quote movements before buys and sells. That is, buys tend to be preceded by quote increases and sells preceded by quote decreases. Conditional on making the correct trade side inference, these observations would be consistent with an understatement of execution costs based on the equation used to calculate effective spreads. However, there may be an increased incidence

Table 3
Percentage of trades with midpoint estimation errors

	Tick = $1/8			Tick = $1/16		
Panel A: percent midpoint increase or decrease						
	Buys	Sells	All	Buys	Sells	All
% Increase	7.2%	2.1%	4.9%	10.2%	3.6%	7.1%
% Decrease	2.1	5.7	3.7	3.9	9.5	6.5
Panel B: percent change, either increase or decrease						
	% Change			% Change		
All						
All	8.6%			13.6%		
Small trades	8.0			13.0		
Medium trades	9.2			14.2		
Large trades	10.8			17.7		
Quartile 1 (largest stocks)						
All	9.7			15.9		
Small trades	9.2			15.4		
Medium trades	10.5			16.4		
Large trades	11.4			19.6		
Quartile 2						
All	6.6			7.7		
Small trades	6.1			6.7		
Medium trades	7.1			8.7		
Large trades	11.4			14.0		
Quartile 3						
All	4.5			6.9		
Small trades	4.0			6.0		
Medium trades	5.1			7.7		
Large trades	7.2			11.8		
Quartile 4 (smallest stocks)						
All	4.2			5.8		
Small trades	3.5			5.0		
Medium trades	4.6			6.5		
Large trades	6.2			7.9		

Table includes trades described in Table 1. Odd-lots, stopped orders and subsequent fills from marketable limit orders for more than the quoted depth that become standing limit orders are excluded. Quotes at order submission are compared to quotes at 5 seconds prior to order execution. Panel A categorizes by whether the midpoint increased or decreased. Panel B reports the percentage of trades with the midpoint either increasing or decreasing. Small trades are for 100 to 500 shares. Medium trades are for 501 to 5,000 shares. Large trades are for more than 5,000 shares. Quartile 1 includes trades from the largest stocks and Quartile 4 includes trades from the smallest stocks.

of trade side classification error as the reference quotes will have changed. The net effect of the quote changes, then, becomes an empirical question. We note that the delays reported in Table 2 and the percentage of quote changes reported in Table 3 are unknown to the TAQ user. So these results only indicate some of the limitations of TAQ data. Our analysis below documents implications of changing the trade lag to improve the estimation of execution costs.

4.4. Trade side classification analysis

Results from the Lee and Ready (1991) study suggest the tick rule is 90% accurate when used to classify trades which occur exactly at the bid or the ask as buyer or seller initiated. We consider the effect of using different lags (0–30 seconds) on trade report times to best estimate the trade direction using the Lee-Ready (LR) algorithm and the Ellis-Michaely-O'Hara (EMO) algorithm. Table 4 reports the classification success rates and is partitioned by tick size, trade size, firm size, and trade location at report time. Panel A reports the LR results and Panel B reports the EMO results. Consistent with prior research on the trade direction algorithms, the trade size, firm size, and trade location categories strongly influence trade side classification success. In general, there tend to be greater error rates for small trades, trades from larger stocks, and trades occurring at the quote midpoint. However, the most important observation from Table 4 is that, aside from a few exceptions, each algorithm performs best when the trades are not lagged. (We have bolded, for each row, the cell with highest success rate.) This result holds across tick sizes and classification algorithms and is consistent with Bessembinder (2000) who also suggests TAQ users do not lag quotes when estimating trade direction.

Overall, the success rate in the 1/16ths regime is lower than in the 1/8ths regime. The LR algorithm performs marginally better than the EMO algorithm when the tick size is \$1/8. The EMO algorithm performs better when the tick size is \$1/16. This observation may indicate the EMO algorithm is superior as tick size decreases.

The classification success rate from research using TORQ data varies from approximately 85% (Odders-White, 2000; Finucane, 2000) to 93% (Lee and Radhakrishna, 2000). Thus, it appears the accuracy of Lee and Ready algorithm has remained consistent across time despite a tick size change. Using data from other markets, Ellis et al. (2000) report a classification success rate of 83% for Nasdaq data and Aitken and Frino (1996) report a classification success rate of 74% using data from the Australian Stock Exchange.

While it appears that the error rates of trades occurring at the midpoint may be problematic when measuring trading costs, the execution cost estimation errors should be small, because trades executing at the midpoint, by definition, have an effective spread of \$0. Beyond the recognition that a lag should not be used in trade side algorithms, the table also illustrates considerable variation across categories (trade size, firm size, and trade location). This result suggests classification accuracy may be sample specific.

4.5. Benchmark quote analysis

To estimate trading costs TAQ users must also infer the benchmark quotes. Table 5 analyzes errors in assigning the benchmark quote. We calculate errors as $\log(\mathrm{Midpoint}_t/\mathrm{Midpoint}_{\text{order submission}})$ and average the errors across lags of $t = 0$–30 seconds. Panel A reports the results for trades identified by the EMO algorithm as buyer-initiated. In general, the errors are negative. Recalling the equation of effective spread above, the data indicate that this type of error results in an overstatement of execution costs. The errors are largest for smaller stocks, and are especially large for trades occurring at locations other than at the report time quote. The results for EMO-indicated sells in Panel B have, in general, the opposite sign to the those in Panel A. The results do not give clear guidance to TAQ users on how much to lag trades when assigning the benchmark quotes. However, it does appear that shorter lags of 0 to 5 seconds minimize errors associated with the assignment of the benchmark quote.

4.6. Trade size and order size

Larger orders are sometimes broken up into smaller orders for execution. This may be problematic for the researcher using TAQ data, as trades from larger orders will be pooled with trades from smaller orders (Walsh, 1997, p. 60). The set of orders used in this study were examined to ascertain the number of fills per order. About 94% of all orders are executed with one fill. About 2/3 of the large orders are executed with one fill. Our sample of orders are similar to Bacidore et al. (1999) who find approximately 96% of all orders without multiple execution reports, and Lee and Radhakrishna (2000) who find 94% of market orders filled in a single execution. These results indicate if there is a bias because of trade size and order size differences, it is small.

5. Effective spread estimation, biases, and adjustments

In this section we report the estimates and the biases of the effective spread and the relative effective spread. We also suggest some adjustments based on the observations in Tables 4 and 5. We estimate spreads five different ways using TAQ data only. The first measure uses traditional methods, which we refer to as the Lee/Ready spread. This measure lags trades 5 seconds for trade signing and assignment of benchmark quotes. We also estimate two measures each using the LR method and EMO method to assign trades using the report time quotes (i.e., no lag). With each signing algorithm we lag trades 0 and 5 seconds for the benchmark quote assignment. Actual spreads are calculated using SOD and TAQ data. For the actual measure, quotes at the time of order submission serve as the benchmark quotes and the trade side in the SOD file is used. Results are categorized as in Tables 4 and 5.

Panel A of Table 6 reports the average actual and estimated effective spreads. When the tick size was equal to \$1/8, the actual effective spread averaged 11.99¢. For the largest stocks, the average actual effective spread was 11.71¢, and for the smallest stocks the average actual effective spread was 13.16¢. Trading costs increase as the size of the trade increases. Based on previous research these results are expected. The grand average estimated Lee/Ready effective spread during the period when the tick size was \$1/8 was 13.05¢. As with the actual effective spread, the estimated effective spread increases with trade size (12.64–14.55¢) and decreases with market capitalization (13.39–12.93¢). As reported in other studies, spread estimation is

Table 4
Lee and Ready (1991) and Ellis et al. (2000) trade signing success rates

				Lag						
Tick size	Trade size	Firm size	Location	0	5 sec	10 sec	15 sec	20 sec	25 sec	30 sec
Panel A: Lee and Ready (1991) success rates										
$1/8	*	*	*	**90.99%**	90.81%	90.73%	90.61%	90.46%	90.30%	88.99%
$1/8	Small	*	*	**89.69**	89.54	89.44	89.32	89.17	89.02	88.85
$1/8	Medium	*	*	**92.76**	92.58	92.52	92.39	92.23	92.05	91.86
$1/8	Large	*	*	**93.69**	93.20	93.19	93.14	93.01	92.93	92.74
$1/8	*	Quartile 1	*	**89.90**	89.72	89.62	89.48	89.31	89.12	88.90
$1/8	*	Quartile 2	*	**92.53**	92.35	92.27	92.18	92.08	91.98	91.87
$1/8	*	Quartile 3	*	**95.08**	94.99	94.98	94.93	94.85	94.79	94.73
$1/8	*	Quartile 4	*	**95.79**	95.60	95.58	95.57	95.52	95.49	95.42
$1/8	*	*	At quote	**93.20**	93.02	92.92	92.76	92.59	92.41	92.21
$1/8	*	*	Inside	76.64	77.31	78.37	79.18	79.83	80.77	**81.13**
$1/8	*	*	Midpoint	**71.10**	70.80	70.88	71.03	71.06	71.08	71.04
$1/8	*	*	Outside	86.44	86.47	**86.49**	86.45	86.41	86.41	86.37
$1/16	*	*	*	**87.44**	87.35	87.31	87.21	87.08	86.93	86.76
$1/16	Small	*	*	**85.18**	85.06	84.99	84.87	84.75	84.61	84.43
$1/16	Medium	*	*	**90.28**	90.25	90.25	90.16	90.03	89.87	89.69
$1/16	Large	*	*	**91.97**	91.84	91.82	91.80	91.70	91.55	91.44
$1/16	*	Quartile 1	*	**85.83**	85.74	85.70	85.58	85.43	85.26	85.06
$1/16	*	Quartile 2	*	**91.29**	91.16	91.11	91.04	90.99	90.88	90.79
$1/16	*	Quartile 3	*	**92.37**	92.30	92.26	92.23	92.14	92.05	91.93
$1/16	*	Quartile 4	*	**94.30**	94.26	94.27	94.28	94.26	94.22	94.13
$1/16	*	*	At quote	**91.48**	91.29	91.15	90.96	90.75	90.52	90.28
$1/16	*	*	Inside	65.03	66.66	67.84	68.70	69.38	69.94	**70.31**
$1/16	*	*	Midpoint	**72.95**	72.53	72.44	72.39	72.32	72.25	72.16
$1/16	*	*	Outside	84.22	84.24	84.32	84.34	84.38	**84.39**	84.39

Panel B: Ellis et al. (2000) success rates

$1/8	*	*	*	**90.81%**	90.65%	90.57%	90.46%	90.32%	90.16%	89.93%
$1/8	Small	*	*	**89.54**	89.39	89.28	89.17	89.03	88.89	88.72
$1/8	Medium	*	*	**92.55**	92.40	92.36	92.23	92.08	91.90	91.73
$1/8	Large	*	*	**93.53**	93.12	93.09	93.07	92.94	92.86	92.70
$1/8	*	Quartile 1	*	**89.72**	89.56	89.47	89.34	89.17	88.98	88.78
$1/8	*	Quartile 2	*	**92.39**	92.21	92.11	92.02	91.93	91.85	91.74
$1/8	*	Quartile 3	*	**94.92**	94.83	94.81	94.74	94.68	94.62	94.56
$1/8	*	Quartile 4	*	**95.59**	95.43	95.41	95.41	95.37	95.35	95.31
$1/8	*	*	At quote	**93.20**	93.00	92.87	92.71	92.53	92.34	92.14
$1/8	*	*	Inside	**83.27**	83.20	**83.27**	82.96	82.89	82.57	82.72
$1/8	*	*	Midpoint	69.17	69.36	69.71	70.04	70.22	70.38	**70.47**
$1/8	*	*	Outside	85.12	85.33	**85.37**	85.35	85.32	**85.37**	**85.37**
$1/16	*	*	*	**88.22**	88.09	88.01	87.90	87.77	87.64	87.48
$1/16	Small	*	*	**86.31**	86.13	86.02	85.90	85.77	85.64	85.48
$1/16	Medium	*	*	**90.64**	90.58	90.53	90.43	90.31	90.16	90.02
$1/16	Large	*	*	**92.01**	91.87	91.82	91.76	91.65	91.50	91.40
$1/16	*	Quartile 1	*	**86.67**	86.54	86.45	86.32	86.17	86.02	85.85
$1/16	*	Quartile 2	*	**92.10**	91.92	91.82	91.75	91.69	91.59	91.49
$1/16	*	Quartile 3	*	**92.87**	92.78	92.74	92.66	92.59	92.50	92.40
$1/16	*	Quartile 4	*	**94.59**	94.48	94.50	94.50	94.47	94.42	94.36
$1/16	*	*	At quote	**91.48**	91.32	91.19	91.02	90.84	90.66	90.47
$1/16	*	*	Inside	**79.15**	78.98	78.92	79.02	79.05	79.11	79.00
$1/16	*	*	Midpoint	71.93	71.96	72.11	72.26	72.36	72.39	**72.40**
$1/16	*	*	Outside	83.88	83.98	83.99	84.07	84.09	84.21	**84.28**

Table includes trades described in Table 1 and reports the success rates of trade signing algorithms of Lee and Ready (1991) and Ellis et al. (2000). Location refers to the trade location relative to the quotes at report time. 'At quote' includes trades that execute at the bid or ask. 'Inside' includes trades that execute between the quotes, but not at the midpoint. 'Midpoint' includes trades that execute at the midpoint. 'Outside' includes orders that execute outside the quotes. A '*' indicates all of category. Bold cells indicate highest success rate for row.

Table 5
Midpoint estimation errors (in basis points) at various trade lags

				Lag						
Tick size	Trade size	Firm size	Location	0	5 sec	10 sec	15 sec	20 sec	25 sec	30 sec
Panel A: Trades identified by Ellis et al. (2000) as buyer-initiated										
\$1/8	*	*	*	−0.21	**−0.08**	−0.12	−0.13	−0.14	−0.16	−0.17
\$1/8	Small	*	*	−0.18	**−0.06**	−0.08	−0.08	−0.08	−0.09	−0.11
\$1/8	Medium	*	*	−0.22	**−0.06**	−0.13	−0.17	−0.19	−0.21	−0.22
\$1/8	Large	*	*	−0.82	**−0.46**	−0.53	−0.58	−0.62	−0.67	−0.67
\$1/8	*	Quartile 1	*	−0.11	**−0.01**	−0.04	−0.05	−0.07	−0.09	−0.13
\$1/8	*	Quartile 2	*	−0.27	**−0.12**	−0.18	−0.18	−0.18	−0.19	−0.16
\$1/8	*	Quartile 3	*	**−0.35**	−0.45	−0.49	−0.50	−0.48	−0.45	−0.39
\$1/8	*	Quartile 4	*	−1.55	**−0.34**	−0.54	−0.59	−0.54	−0.59	−0.53
\$1/8	*	*	At quote	−0.53	−0.31	−0.26	−0.21	−0.16	−0.12	**−0.08**
\$1/8	*	*	Inside	11.77	8.90	6.05	4.35	3.27	2.17	1.49
\$1/8	*	*	Midpoint	3.42	2.52	1.72	1.10	0.56	0.08	−0.39
\$1/8	*	*	Outside	−5.20	**−3.33**	−3.65	−3.74	−4.09	−4.35	−4.53
\$1/16	*	*	*	0.18	**−0.10**	−0.20	−0.28	−0.35	−0.42	−0.49
\$1/16	Small	*	*	0.17	**−0.08**	−0.14	−0.21	−0.27	−0.34	−0.40
\$1/16	Medium	*	*	0.23	**−0.12**	−0.25	−0.35	−0.43	−0.50	−0.58
\$1/16	Large	*	*	**−0.26**	−0.37	−0.54	−0.67	−0.74	−0.84	−0.86
\$1/16	*	Quartile 1	*	0.22	**−0.11**	−0.20	−0.29	−0.37	−0.46	−0.55
\$1/16	*	Quartile 2	*	0.11	**−0.02**	−0.12	−0.16	−0.19	−0.22	−0.24
\$1/16	*	Quartile 3	*	0.17	**−0.02**	−0.11	−0.19	−0.21	−0.25	−0.28
\$1/16	*	Quartile 4	*	**−0.35**	−0.52	−0.64	−0.72	−0.77	−0.76	−0.66
\$1/16	*	*	At quote	**−0.22**	−0.38	−0.38	−0.37	−0.38	−0.38	−0.38
\$1/16	*	*	Inside	3.07	2.12	1.52	0.96	0.56	**0.15**	−0.20
\$1/16	*	*	Midpoint	2.15	1.46	1.02	0.61	0.27	**−0.09**	−0.41
\$1/16	*	*	Outside	**−2.03**	−2.62	−2.90	−3.10	−3.28	−3.42	−3.57

Panel B: Trades identified by Ellis et al. (2000) as seller-initiated										
$1/8	*	*	*	0.83	0.77	0.75	0.70	0.66	0.62	**0.59**
$1/8	Small	*	*	0.70	0.61	0.57	0.52	0.49	0.46	**0.43**
$1/8	Medium	*	*	0.96	0.96	0.96	0.90	0.85	0.80	**0.77**
$1/8	Large	*	*	1.68	1.50	1.57	1.66	1.69	1.66	1.62
$1/8	*	Quartile 1	*	0.71	0.70	0.67	0.64	0.61	0.58	**0.56**
$1/8	*	Quartile 2	*	0.87	0.59	0.57	0.49	0.45	0.42	**0.39**
$1/8	*	Quartile 3	*	1.02	1.05	1.04	0.99	0.90	0.85	**0.77**
$1/8	*	Quartile 4	*	2.38	2.03	2.12	1.99	1.92	1.78	**1.68**
$1/8	*	*	At quote	1.05	0.90	0.81	0.70	0.61	0.53	**0.45**
$1/8	*	*	Inside	−14.90	−11.42	−8.35	−6.05	−3.37	−2.12	**−0.67**
$1/8	*	*	Midpoint	−1.95	−1.19	−0.70	−0.25	**0.12**	0.43	0.77
$1/8	*	*	Outside	8.61	**7.81**	7.95	7.93	7.84	7.84	7.95
$1/16	*	*	*	0.16	**0.09**	0.16	0.22	0.27	0.32	0.36
$1/16	Small	*	*	0.07	−0.03	**0.02**	0.07	0.13	0.18	0.22
$1/16	Medium	*	*	0.22	**0.20**	0.29	0.36	0.40	0.45	0.48
$1/16	Large	*	*	1.13	**1.09**	1.27	1.35	1.41	1.44	1.40
$1/16	*	Quartile 1	*	0.05	−0.06	**0.02**	0.08	0.14	0.21	0.26
$1/16	*	Quartile 2	*	**0.29**	0.35	0.39	0.43	0.47	0.48	0.50
$1/16	*	Quartile 3	*	**0.55**	0.61	0.68	0.66	0.64	0.61	0.60
$1/16	*	Quartile 4	*	0.96	**0.94**	1.05	1.24	1.29	1.33	1.30
$1/16	*	*	At quote	0.52	0.38	0.36	0.34	0.32	0.31	**0.29**
$1/16	*	*	Inside	−2.87	−2.36	−1.75	−1.25	−0.84	−0.48	**−0.14**
$1/16	*	*	Midpoint	−1.52	−1.41	−1.11	−0.77	−0.46	−0.18	**0.02**
$1/16	*	*	Outside	3.21	**3.12**	3.27	3.39	3.49	3.53	3.69

Table includes trades described in Table 1. Midpoint estimation errors are calculated as $\log(\text{midpoint}_{\text{lag}}/\text{midpoint}_{\text{order submission}})$ and reported in basis points. A '*' indicates all of category. Trade direction algorithm modified using quotes at report time. Location refers to the trade location relative to the quotes at report time. 'At quote' includes trades that execute at the bid or ask. 'Inside' includes trades that execute between the quotes, but not at the midpoint. 'Midpoint' includes trades that execute at the midpoint. 'Outside' includes orders that execute outside the quotes. Bold cells indicate lowest error for row.

Table 6
Actual and estimated effective and relative effective spreads and biases

						Lee and Ready (1991)		EMO (2000)	
Tick size	Trade size	Firm size	Location	Actual Spread	Lee/Ready Spread	0s lag	5s lag	0s lag	5s lag
Panel A: *effective spreads* (*in cents*)									
\$1/8	*	*	*	11.99	13.05	12.82	12.84	**12.78**	12.79
\$1/8	Small	*	*	11.30	12.64	12.43	12.42	12.39	**12.38**
\$1/8	Medium	*	*	12.93	13.56	13.30	13.35	**13.26**	13.31
\$1/8	Large	*	*	13.35	14.55	14.41	14.34	14.39	**14.33**
\$1/8	*	Quartile 1	*	11.71	12.93	12.64	12.67	**12.60**	12.62
\$1/8	*	Quartile 2	*	12.38	13.28	13.23	13.16	13.19	**13.11**
\$1/8	*	Quartile 3	*	13.09	13.48	13.38	13.43	**13.35**	13.40
\$1/8	*	Quartile 4	*	13.16	13.39	13.31	13.31	**13.28**	**13.28**
\$1/8	*	*	At quote	12.67	13.81	13.75	13.67	13.75	**13.67**
\$1/8	*	*	Inside	18.07	**15.87**	13.38	15.16	7.10	10.49
\$1/8	*	*	Midpoint	2.83	**1.89**	0.00	0.96	0.00	0.83
\$1/8	*	*	Outside	27.37	36.37	36.63	36.11	35.30	**34.79**
\$1/16	*	*	*	8.31	9.68	9.26	9.46	**8.82**	8.98
\$1/16	Small	*	*	7.54	9.32	8.88	8.98	**8.33**	8.47
\$1/16	Medium	*	*	9.28	10.11	9.67	9.90	**9.36**	9.57
\$1/16	Large	*	*	9.90	11.02	10.88	10.95	**10.70**	10.78
\$1/16	*	Quartile 1	*	7.89	9.49	8.95	9.14	**8.49**	8.68
\$1/16	*	Quartile 2	*	9.27	10.10	9.98	10.04	**9.55**	9.63
\$1/16	*	Quartile 3	*	9.56	10.25	10.12	10.18	**9.79**	9.86
\$1/16	*	Quartile 4	*	10.36	10.77	10.64	10.72	**10.37**	10.46
\$1/16	*	*	At quote	8.92	10.09	**9.82**	9.89	**9.82**	9.89
\$1/16	*	*	Inside	5.46	9.01	8.21	8.30	2.61	**3.34**
\$1/16	*	*	Midpoint	1.59	**1.23**	0.00	0.69	0.00	0.41
\$1/16	*	*	Outside	20.91	28.18	27.44	27.85	**25.25**	25.65
Panel B: *effective spreads* (*in basic points*)									
\$1/8	*	*	*	40.4	42.9	42.5	42.3	42.4	**42.2**
\$1/8	Small	*	*	35.2	38.3	38.0	37.8	37.9	**37.7**
\$1/8	Medium	*	*	46.7	48.4	47.9	47.7	47.7	**47.6**
\$1/8	Large	*	*	59.5	62.1	62.6	**61.8**	62.4	61.9
\$1/8	*	Quartile 1	*	25.4	27.9	27.4	27.3	27.4	**27.2**

$1/8	*	Quartile 2	*	50.7	54.0	53.8	53.4	53.7	**53.3**
$1/8	*	Quartile 3	*	78.6	80.8	80.3	80.5	**80.2**	80.3
$1/8	*	Quartile 4	*	185.1	188.3	188.0	186.1	187.5	**186.0**
$1/8	*	*	At quote	43.1	45.9	45.9	**45.5**	45.9	45.5
$1/8	*	*	Inside	40.8	**34.4**	29.4	32.8	15.5	21.8
$1/8	*	*	Midpoint	7.4	**4.4**	0.0	1.9	0.0	1.7
$1/8	*	*	Outside	83.7	105.2	107.5	104.5	102.8	**100.1**
$1/16	*	*	*	26.4	29.3	28.6	28.8	**27.6**	27.9
$1/16	Small	*	*	22.3	25.9	25.3	25.4	**24.1**	24.2
$1/16	Medium	*	*	31.1	32.8	32.1	32.5	**31.4**	31.7
$1/16	Large	*	*	43.5	46.6	46.2	46.3	**45.8**	45.8
$1/16	*	Quartile 1	*	16.3	19.1	18.4	18.6	**17.6**	17.8
$1/16	*	Quartile 2	*	36.0	39.0	38.6	38.7	**37.2**	37.4
$1/16	*	Quartile 3	*	55.9	59.3	58.9	59.0	**57.3**	57.5
$1/16	*	Quartile 4	*	125.0	128.1	127.2	127.4	**125.0**	125.2
$1/16	*	*	At quote	29.4	32.0	**31.6**	**31.6**	**31.6**	**31.6**
$1/16	*	*	Inside	13.5	21.1	19.7	20.0	7.1	8.6
$1/16	*	*	Midpoint	4.1	**2.4**	0.0	1.3	0.0	0.8
$1/16	*	*	Outside	53.7	69.2	68.3	68.7	**63.2**	63.7

Table includes trades described in Table 1 and reports the actual effective spreads and estimated effective spreads. The effective spread is calculated as

$$\text{Effective spread} = 2 \times D \times (\text{Price} - \text{midpoint}), \ \text{where } D \text{ is the trade direction.}$$

$$\text{Relative effective spread} = \text{Effective spread}/\text{Price}$$

'Lee/Ready Spread' refers to effective spreads estimated using the Lee and Ready (1991) to estimate D with trades lagged 5 seconds relative to quotes. The midpoint is calculated 5 seconds prior to trade report time. The columns with 'Lee and Ready (1991)' and EMO (2000) refer to spread estimates using quotes at report time to estimate trade direction using either the Lee and Ready (1991) or the Ellis et al. (2000) algorithms respectively. The columns labeled '0s lag' and '5s lag' refer to the time that trades were lagged when calculating the benchmark quote. Odd-lots, stopped orders and subsequent fills from marketable limit orders for more than the quoted depth that become standing limit orders are excluded. Location refers to the trade location relative to the quotes at report time. 'At quote' includes trades that execute at the bid or ask. 'Inside' includes trades that execute between the quotes, but not at the midpoint. 'Midpoint' includes trades that execute at the midpoint. 'Outside' includes orders that execute outside the quotes. A '*' indicates all of category. Bold cells indicate lowest estimated bias for row.

upward biased. Our results indicate the amount of the bias using traditional methods is 8.8% (= 13.05/11.99 − 1).

Panel A indicates improvements can be made when using different quote lags and/or trade direction algorithms. Staying with the 1/8ths pricing regime, we see the EMO algorithm with no lag for benchmark quote assignment reduces biases to 6.6% (= 12.78/11.99 − 1). For most categories, the EMO algorithm outperforms the LR algorithm and the Lee/Ready estimator. (For each row in the table we have bolded the cell with the least bias.)

Examining the results for the case when the tick size is equal to \$1/16 we see trends similar to the \$1/8ths pricing regime. Although the Lee/Ready estimator has a greater bias (16.5% = 9.68/8.31 − 1) in the 16ths regime, there is some reassuring results in that the EMO estimator has a lower bias (6.1% = 8.82/8.31 − 1) in the 16ths regime when the benchmark quote is assigned at report time. Based on this information, we conclude that when estimating effective spreads, the EMO trade signing algorithm, using quotes at report time to classify trades, combined with benchmark quote assignment at report time, gives the smallest bias in execution cost measurement. Biases are reduced from 16.5 to 6.1%, a reduction of more than 10% in the overstatement of execution costs.

Panel B of Table 6 presents the results for the relative effective spread. Patterns in the variation of spread estimates based on the categories of tick size, trade size, firm size, and trade location are similar to those reported in Panel A, except the biases are smaller on a percentage basis. This results from the fact that most of the errors in the estimates occur for larger stocks. Because the relative effective spreads are divided by price, the errors are attenuated because larger stocks tend to have larger prices.[6] The bias of the Lee/Ready relative effective spread estimate when the tick size is equal to \$1/16 is 11.0% (= 29.3/26.4 − 1) and the EMO bias is 4.5% (= 27.6/26.4 − 1). Once again the EMO algorithm with no lags provides the least bias amongst the measures considered here.

6. Conclusion

Using recent data this study documents that TAQ users over-estimate effective spreads by up to 17%. Biases are highest for small trades and trades from larger firms. The errors result because of incorrect inferences regarding the trade side and the quote benchmark. Our data suggest to minimize execution costs estimation errors, researchers use the EMO algorithm without lagging quotes, either for trade side assignment or for assignment of the benchmark quote. Further, biases are shown to be lower for relative effective spreads than effective spreads.

[6] For example, consider a buy order mistaken for a sell order in minimum variation markets with a tick size of \$1/16 for stocks with price of \$20 and \$60. The bias of the estimated effective spread will be the same, but the bias of the estimated relative effective spread will be three times higher for the lower priced stock.

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