The Accuracy of Trade Classification Rules: Evidence from Nasdaq

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The Accuracy of Trade Classification Rules: Evidence from Nasdaq

Katrina Ellis, Roni Michaely, and Maureen O'Hara*

Abstract

Researchers are increasingly using data from the Nasdaq market to examine pricing behavior, market design, and other microstructure phenomena. The validity of any study that classifies trades as buys or sells depends on the accuracy of the classification method. Using a Nasdaq proprietary data set that identifies trade direction, we examine the validity of several trade classification algorithms. We find that the quote rule, the tick rule, and the Lee and Ready (1991) rule correctly classify 76.4%, 77.66%, and 81.05% of the trades, respectively. However, all classification rules have only a very limited success in classifying trades executed inside the quotes, introducing a bias in the accuracy of classifying large trades, trades during high volume periods, and ECN trades. We also find that extant algorithms do a mediocre job when used for calculating effective spreads. For Nasdaq trades, we propose a new and simple classification algorithm that improves over extant algorithms.

I. Introduction

The availability of intraday trade and quote data has allowed research into a wide variety of issues in securities markets. A critical factor for many of these studies is the ability to determine trade direction. Who is buying and who is selling are important elements in determining the information content of trades, the order imbalance and inventory accumulation of liquidity providers, the price impact of large trades, the effective spread, and many other related questions. Unfortunately, commonly available high frequency databases do not provide information on trade direction. Consequently, empirical researchers have relied on trade direction algorithms to classify trades as buyer or seller motivated.

Three trade classification algorithms have been extensively used in microstructure studies: i) the quote rule, ii) the tick rule, and iii) Lee and Ready's (LR here-
after) (1991) rule. The quote rule classifies a transaction as a buy if the associated trade price is above the midpoint of the bid and the ask; it is classified as a sell if the trade price is below the midpoint quote. Trades executed at the midpoint are not classified. The tick rule classification is based on price movements relative to previous trades. If the transaction is above (below) the previous price, then it is a buy (sell). If there is no price change but the previous tick change was up (down), then the trade is classified as a buy (sell). LR’s procedure is essentially a combination of these two rules: first, classify a trade according to the quote rule (above or below the midpoint), and then classify the midpoint transaction using the tick rule. Given the reporting procedure on the NYSE, LR also suggest comparing transaction prices to quotes reported at least five seconds before the transaction was reported.

How well do these algorithms work? This is difficult to determine without information on the source of the original order. What little evidence exists is virtually all based on NYSE data. Using the TORQ database, Lee and Radhakrishna (1996) report an overall 93% agreement between the actual order and LR’s algorithmic inference. Using the same data source, but a different selection criterion, Odders-White (2000) reports a success rate of 85% for the LR algorithm. In a paper in this issue, Finucane (2000), pp. 553–576, uses the TORQ database to test the accuracy of several classification algorithms (tick, quote, and LR). He concludes that for NYSE firms, the tick test and the LR method have very similar performance accuracy in classifying trades. He also shows that the tick rule provides a better estimate of the effective spread than LR’s procedure. The one study done with non-NYSE data, Aitken and Frino’s (1996) examination of the success of tick rules on Australian data, finds only a 75% success rate. There has been, to date, no study of the accuracy of trade algorithms using Nasdaq data. Given the increasing interest in, and analysis of, the Nasdaq market, the ability to adequately interpret Nasdaq data has obvious importance.

In this paper, we investigate the applicability and accuracy of trade direction algorithms to Nasdaq data. What facilitates our analysis is a unique data set containing Nasdaq trades identified with respect to trader identity and direction, as well as complete data on Nasdaq quotes. These data allow us to investigate the accuracy of standard classification techniques, as well as to assess the performance of alternative approaches. Our analysis focuses on four questions: First, how successful are the classification rules for Nasdaq stocks? Second, what type of transactions or market conditions are more likely to result in erroneous classifications? Third, what difficulties arise in applying trade algorithms to publicly available data such as the TAQ (trades and quotes) database? Fourth, is there a more accurate algorithm that would improve upon classifications for Nasdaq stocks?

Our findings are both reassuring and cautionary. We find that the standard classification rules for sorting trades into buys and sells are comparably as accurate for Nasdaq trades as for NYSE trades. The quote rule successfully classifies 76.4% of the trades, the tick rule successfully classifies 77.66% of the trades, and the combination of the two (labeled the LR classification) is successful in 81.05%.

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1For the derivation of these approaches, see Hashbrouck (1988); Blurne, Mackinlay, and Terker (1989), and Lee and Ready (1991).
of the cases. (Odders-White reports success rates of 75%, 79%, and 85%, respectively for NYSE stocks.) The success rate for classifying trades inside the quotes, however, is substantially lower, falling to approximately 60% for midpoint trades and to only 55% for trades that are inside the quotes but not at the midpoint.

Examining further the misclassification of trades reveals a number of regularities. Large trades are less accurately classified as are trades in periods of rapid trading. These findings can be almost entirely attributed to the fact that large trades and trades during high volume periods are more frequently executed in between the quotes. We also find that trades executed on Electronic Communications Networks (ECNs) may be particularly prone to miscalculation for the very same reason: a much larger portion of those trades executes in between the quote. We also find that over 4% of trades are executed outside the quotes, and that as much as 35% of the trades above (below) the ask (bid) are seller- (buyer-) initiated trades. These trades pose severe problems for any trade classification algorithm. Finally, we show that, given Nasdaq reporting and trading procedures, there is a substantial delay in the reporting of Nasdaq trades on the standard TAQ database. This delay, however, does not substantially degrade the ability of extant algorithms to accurately classify Nasdaq trades as buys or sells.

Based on these findings, we develop a new trade classification algorithm that improves upon classification of trades away from the quotes, resulting in an improvement over existing algorithms when applied to Nasdaq data. For sorting trades into buys and sells, our proposed algorithm achieves an overall success rate of 81.9%, a modest improvement compared to the LR value of 81.0%. A more substantial improvement arises when our algorithm is used for calculating effective spreads. In particular, we find that using the LR algorithm significantly overstates the size of the effective spread in the Nasdaq market. Using the correct buy/sell indicator from the Nasdaq audit data, we calculate an average effective spread of 1.34%, whereas using the LR classifications results in an effective spread of 1.96%. Alternatively, our proposed algorithm shows a 10% improvement over the LR approach in calculating effective spreads. Given the greater accuracy and reliability of our classification algorithm, we believe it is a better approach for research involving Nasdaq trades.

The paper is organized as follows. In the next section, we describe the data used in our analysis. In Section III, we test the accuracy of several alternative trade classification algorithms for Nasdaq trades. Section IV then investigates when the algorithms fail, with particular attention given to the types of orders and to features of the trading process. In Section V, we propose an alternative algorithm for analyses of Nasdaq data. In Section VI, we analyze the robustness of our proposed algorithm and explore several possible explanations for the seemingly anomalous behavior of trades executed outside the quotes. We then integrate our analysis of Nasdaq data with the TAQ database to examine reporting delays. In the paper's final section, we summarize our findings, discuss their implications for trade classification, and raise concerns regarding the future ability to classify trades given the increasing propensity for trades to arise between the quotes and from ECNs.

2Using NYSE data, Finucane (2000), pp. 553–576 in this issue, also reports a large overestimate of the effective bid-ask spread when using the LR method.
II. Data

The sample contains 313 Nasdaq stocks traded between September 27, 1996, and September 29, 1997. These stocks began trading following their IPO sometime during this period. Consequently, for each stock, the time series of data varies from three months to 12 months. The transactions data are provided by the NASD and taken from their Market Data Server (MDS). Overall, the sample contains 2,433,019 trades and 627,370 quotes.

Because the sample contains newly traded firms, it is worth comparing its characteristics to those of Nasdaq stocks as a whole. Using information from the CRSP tapes, we compared our sample to the Nasdaq universe (4700 stocks) in terms of market capitalization and trading volume. While the sample firms have a lower market capitalization than the average Nasdaq stock during this period ($172m and $322m, respectively), the median firm in the sample has a larger market value than the median Nasdaq stock ($112m and $56m, respectively). This suggests that the sample has stocks of greater uniformity, and does not have extreme stocks in terms of size. Also, the turnover rate of the sample stocks is 0.83% per day, which is larger than is typical for a stock traded on Nasdaq (0.60%). This is not surprising given the very high trading volume immediately after the IPO. When we eliminate the first month of trading for each firm, the turnover mean (and median) of the sample is 0.60% (0.49%), which is not different from those for Nasdaq as a whole. Overall, at least in terms of market value and turnover, our sample stocks seem to be quite representative of Nasdaq stocks.

Our proprietary data provide the bid quote, the ask quote, the transaction price, the trade volume, a trader identity code, and a buy/sell indicator. The buy/sell indicator specifies the direction of the reporting party. If the seller reported the trade, then the trade would be called a sale regardless of the price at which it occurred. Thus, this indicator tells us the buyer and the seller in the transaction, but not the trade direction per se. We can determine whether the trade was a buy or a sale by using the trader identity code in conjunction with the buy/sell indicator. The trader identity code is a four-letter code for every NASD member. When a non-NASD member trades (e.g., a customer trading with his NASD member broker), the trader identity code is blank. Thus, we can identify market makers and brokers by name, while the blank identity code merely tells us that a customer is trading. We use three broad categories of trades: transactions between market makers, between market makers and brokers, and between market makers or brokers and customers.

\[1\] A detailed description of NASD data is provided in Smith et al. (1997).

\[2\] As reported in Section VI, we have repeated the entire experiment excluding the first month of trading for each stock. None of our results materially changes.

\[3\] The full MDS database has other fields, including which system was used for the transaction, e.g., whether it was a small order execution system (SOES) trade or via an electronic communications network (ECN). However, we did not obtain these fields with our data.

\[4\] There are three levels of access to the NASD trading screen: market makers who enter and revise quotes, and execute and report trades, order-entry brokers, who see, but cannot change, all the quotes. Order-entry brokers can enter orders to trade directly to a market maker or trade via electronic communications networks (ECNs); and regional brokers who only see the best quotes and cannot directly enter orders. We have the identity of parties in the first two levels.
We are not able to directly sign trades between two market makers (16.6% of the trades), or two brokers (4.5%). For 3.5% of the sample, we know that the trade took place on an ECN because one of the trader identities attached to the trade is the ECN identity code. We cannot sign the ECN trades as we do not have the time the orders were placed with the ECN. Because ECNs function as limit order books, we would need to know the time each order was placed and then use time priority to infer trade direction, with the later order being the trade motivator. (This is how Odders-White infers trade direction using the TORQ database.) Similarly, for the market maker-market maker and broker-broker trades, we do not know which party initiated the trade. In total, we exclude 24.6% of the sample that we cannot accurately sign.

For the remaining 75.4% of the sample, knowing the identity of the trader and whether he was buying or selling allows us to determine directly whether the trade was buy- or sell-initiated. These are market maker-customer or broker-customer trades (26.2%) and market maker-broker trades (49.2%). For example, suppose that a trade is recorded as a sell by the market maker and the other party is a customer. This trade only occurs because the customer wants to trade: the market maker is the liquidity provider, and we categorize such a trade as a buy-initiated trade.\footnote{Since our time period straddles the new SEC-mandated order handling rules, we need to consider orders clearing against limits directly placed by customers. The SEC rules were introduced during 1997. Stocks were phased into compliance via an implementation schedule of 22 waves that started on January 20, 1997 and ended October 13, 1997. Initially, stocks were drawn from the top 1000 stocks ranked on median daily dollar volume. All other stocks were phased into compliance starting August 4, 1997, with the majority being phased in during September 1997. The impact of including customer limit orders in the quotes is a reduction in the inside quote size (see Barclay, Christie, Harris, and Kandel (1999)). Thus, we may see a reduction in the number of trades that occur inside the spread as the order handling rules are introduced. In Section VI, we examine the impact of order handling rules on the success of the trade classification algorithms.}

In the main part of our analysis, we use the market maker-customer and market maker-broker sample. This sample contains 1,833,729 trades that we use to directly test the success of the trading algorithms. We also repeated all of the tests using only an even smaller sample of broker or market maker to customer trades (26.2% of all trades), and these results (reported in Section VI) are virtually identical.

Trade algorithms also typically use quote information. Our data provide the inside quotes (the highest bid and the lowest ask), and we have filtered this data to remove any obvious discrepancies (for example, crossed quotes where the ask is lower than or equal to the bid). After excluding 235 crossed quotes, we are left with 627,135 inside quote revisions.

Table 1 gives the distribution of all trades with respect to the prevailing quote. This table suggests that the market maker-broker sample trades (49.2% of the sample) are, in fact, not different from the market maker-customer (and broker-customer) sample trades (26.2% of the sample). These trades occur at all prices with a frequency very similar to the customer trades: about 72.5%–76% of trades in both samples execute at the quotes, 12%–14.5% execute inside the quote, and approximately 5%–6% execute outside the quote.

By contrast, we find that ECN trades (3.54% of the sample) have a different distribution: 34.62% of ECN trades execute inside the quotes, compared with
### Distribution of Trading Prices and Trading Parties

<table>
<thead>
<tr>
<th>Trading Price</th>
<th>Cust.-Broker</th>
<th>Cust.-Mkt.</th>
<th>Minkr.-Broker</th>
<th>Broker-Broker</th>
<th>Minkr.-Mkt.</th>
<th>ECN</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outside Quotes</td>
<td>815</td>
<td>31061</td>
<td>56672</td>
<td>6577</td>
<td>17401</td>
<td>3017</td>
<td>117433</td>
</tr>
<tr>
<td></td>
<td>5.67%</td>
<td>4.99%</td>
<td>4.83%</td>
<td>5.95%</td>
<td>4.92%</td>
<td>3.51%</td>
<td>4.82%</td>
</tr>
<tr>
<td>At Quotes</td>
<td>10248</td>
<td>45129</td>
<td>90765</td>
<td>79655</td>
<td>224353</td>
<td>26884</td>
<td>1700629</td>
</tr>
<tr>
<td></td>
<td>73.83%</td>
<td>72.47%</td>
<td>76.81%</td>
<td>72.03%</td>
<td>55.65%</td>
<td>31.25%</td>
<td>69.83%</td>
</tr>
<tr>
<td>Inside Quotes</td>
<td>2014</td>
<td>88666</td>
<td>141453</td>
<td>15487</td>
<td>93470</td>
<td>29778</td>
<td>379767</td>
</tr>
<tr>
<td></td>
<td>14.51%</td>
<td>14.24%</td>
<td>11.82%</td>
<td>14.03%</td>
<td>13.21%</td>
<td>34.62%</td>
<td>15.24%</td>
</tr>
<tr>
<td>At Midpoint</td>
<td>795</td>
<td>51379</td>
<td>88669</td>
<td>8771</td>
<td>66519</td>
<td>26444</td>
<td>242577</td>
</tr>
<tr>
<td></td>
<td>5.73%</td>
<td>8.25%</td>
<td>7.42%</td>
<td>7.94%</td>
<td>16.51%</td>
<td>30.51%</td>
<td>10.17%</td>
</tr>
<tr>
<td>Unclassified</td>
<td>0</td>
<td>366</td>
<td>633</td>
<td>59</td>
<td>439</td>
<td>97</td>
<td>1602</td>
</tr>
<tr>
<td>(No Quote)</td>
<td>0.06%</td>
<td>0.05%</td>
<td>0.05%</td>
<td>0.06%</td>
<td>0.11%</td>
<td>0.11%</td>
<td>0.07%</td>
</tr>
</tbody>
</table>

This table shows the distribution of trades relative to the current quotes and by trading party. The sample of 2,433,019 trades is all trades timestamps between 9:30 a.m. and 4:00 p.m. on the NASDAQ audit trail. The quotes are the inside bid and ask revisions from the NASDAQ audit trail. Trades take place at the quotes (the bid or the ask), outside the quotes (above or below the bid), at the midprice quote (the average of the bid and ask price), or outside the quotes but not at the midpoint. Unclassified trades are trades that occur at the beginning of the day before the first quote. The trading parties are identified by four-letter identifiers and come in three categories: market makers who set quotes in the stock, brokers who are NASD members but do not set quotes, and customers who are non-NASD members. Trades are split into three groups: market maker-customer or broker-customer trades, market maker-market maker or market maker-broker trades, and trades via an ECN. Transaction and quote times come from the NASDAQ audit trail.  

14.24% for the customer-based sample, while 30.51% execute at the midpoint, compared to 8.25% for the market maker-customer sample. Thus, 68.75% of ECN trades are not at the quote compared with 27.53% for the customer-based sample. Trades between two market makers appear to have some similarity to the ECN trades, with 40% of trades occurring at the midpoint or inside the spread. These data suggest that our sampling approach of using the subsample of 76% of all trades is reasonable. However, we may introduce noise because of trade that occurs on an ECN between a market maker and a broker. We return to this issue in Section VI.  

### III. Success of Trade Classification Rules

We now examine the accuracy of three trading rules: i) the quote rule, ii) the tick rule, and iii) the LR procedure (i.e., first classify by the quote rule and then by the tick rule).  

Using the quote rule, a trade is classified as a buy trade if the transaction price is above the midpoint. Trades are classified as sells if they occur below the midpoint. Trades executed at the midpoint cannot be classified by the quote rule. Using the tick rule, trades are classified using the price movement prior to the trade. If the transaction price is above the previous price, then the trade is classified as a buy. If it is below the previous price, then it is a sell. If there is

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8This may be due to the anonymity of trading via an ECN, which results in a lower price impact and lower execution costs (see Huang and Steil (1996)).
no price change, but the previous tick change was up (down), then the trade is a buy (sell). The difficulty of the tick rule as a stand-alone method is that it does not take into account the quoted prices. By only using the tick rule for midpoint transactions, we get the LR algorithm. Thus, the LR procedure (absent the five seconds rule, which we address later) simply combines the quote rule and the tick rule by first classifying all trades by the quote rule; then classifying the midpoint trades by the tick rule.

Table 2 gives the success rates of the classification rules. The quote rule correctly classifies 76.4% of all trades; the tick rule correctly classifies 77.66% of all trades; and the success rate for LR's algorithm on our data is 81.05% of all trades. Of the three candidate algorithms, therefore, LR is the most successful, yielding an improvement of 3.4% over the tick rule alone and an improvement of 4.65% over the quote rule alone. These differences are statistically significant.

<table>
<thead>
<tr>
<th>Table 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Success Rates for Different Trade Classification Algorithms</td>
</tr>
<tr>
<td><strong>Price Range</strong></td>
</tr>
<tr>
<td><strong>Quote Rule</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Tick Rule</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Lee &amp; Ready</strong></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

This table compares different trade classification algorithms. The sample of trades is 1,833,729 classifiable trades, which are trades between a market maker and a customer, a market maker and a broker, or a broker and a customer. The three trade classification algorithms are the quote rule, the tick rule, and the Lee and Ready (1991) rule. For each algorithm, we give the frequency of trades in each category and the percent that agree with the true trade classification. The categories are total (all trades) and four price categories. Midpoint trades occur at the average of the current bid and ask quote prices. Inside spread trades occur within the midpoint, but not at the midpoint. At Quotes trades occur at the bid or the ask, and Outside Quotes trades occur below the bid or above the ask.

These results suggest that trade classification schemes, on average, provide reasonably accurate determinations for Nasdaq trades. The error rate of even the best scheme is sufficiently high, however, to introduce substantial noise into empirical analyses. This suggests determining more precisely when trade algorithms fail. In Section IV, we address this issue by considering several potential factors: the proximity to the bid or ask, the trade size, time to previous quote update, and firm size. We focus our attention on LR's algorithm since it is the most successful and widely used.

IV. When Do the Trade Algorithms Fail?

A. Proximity to the Bid and Ask

The quote rule (and, by extension, LR's algorithm) is very successful in correctly classifying trades executed at the bid and ask prices. As Table 2 indicates, 74.66% of all trades in our sample occurred at either the bid quote or the ask
quote. The quote rule correctly classifies 88.68% of these trades. Because the quotes represent dealers' offers to buy or sell at these prices, this high success rate should not be surprising.

A more interesting question is how well do classification rules work for trades that are not at the quotes. Our sample has 20.4% of all trades that occur inside the spread and 4.93% of trades that occur outside the quotes. By comparison, on the NYSE, LR (1991) find 31.2% of trades occur inside the spread and Oders-White (2000) finds 18.9% of such trades use the TORQ database. Trades that occur at the midpoint of the spread cannot be signed using the quote rule, but rely instead on the tick rule. Here, we find that the algorithm correctly classifies 60.52% of all trades. Trades can also occur within the quotes but not at the midpoint. Using LR's algorithm, the success rate of classifying these trades is a surprisingly low 55.23%. Finally, the success rate of classifying trades that occur outside the spread is only 64.77%. This is surprising since we would expect those trades to be even more easily classifiable than trades occurring at the quotes. (We elaborate further in Section VI.D.)

In the remainder of this section, we examine several situations that may lead to this lower success rate, but we note, at this point, that trades not executing at the prevailing quotes reveal serious deficiencies with extant algorithms.

B. Trade Size

Does the size of a trade affect the likelihood of correctly classifying it as a buy or sell? Table 3 shows the relationship between correct classification and trade size. Overall, there is a monotonic relationship: better classification for smaller trades. For example, trades of less than 200 shares are correctly classified 81.73% of the time compared with 77.85% for trades over 10,000 shares. This is in contrast to Oders-White's (2000) finding that accuracy is lower for smaller NYSE trades. However, a closer examination shows that the better classification of Nasdaq small trades is due to their being more likely to execute at either the bid or the ask quote. Only 51.7% of the largest trades execute at the quotes, compared to 80.31% of the smallest trades. Looking inside the quote, we find 9.3% of the small trades (less than 200 shares) executing there compared with 23.85% of the largest trades (more than 10,000 shares). Likewise, while 10.16% of the large trades occur outside the quote, only 4.94% of the small trades are executed outside the quote. Conditioning on the location of the trade, we find trade classification accuracy increases for larger trades, but overall accuracy is lower.

C. Slow vs. Rapid Trading Times

Table 4 shows that classification success falls during rapid trading (Panel A), and following a quote change (Panel B). When trades occur less than five seconds apart, 72.58% of the trades are correctly classified compared to 88.77% of the trades that occur more than five minutes apart.\(^9\) Interestingly, there is not

\(^9\) Oders-White has noted the higher rate of errors for trade algorithms during heavy trading for NYSE data.
### TABLE 3
Classification Success by Trade Size

<table>
<thead>
<tr>
<th>Trade Size</th>
<th>Total</th>
<th>Midpoint</th>
<th>Inside Spread</th>
<th>At Quotes</th>
<th>Outside Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 200 shs</td>
<td>31.44</td>
<td>5.46</td>
<td>9.30</td>
<td>80.31</td>
<td>4.94</td>
</tr>
<tr>
<td>&lt; 500 shs</td>
<td>24.78</td>
<td>8.81</td>
<td>11.26</td>
<td>77.77</td>
<td>4.18</td>
</tr>
<tr>
<td>&lt; 1,000 shs</td>
<td>20.85</td>
<td>8.15</td>
<td>13.67</td>
<td>74.38</td>
<td>4.42</td>
</tr>
<tr>
<td>&lt; 5,000 shs</td>
<td>17.39</td>
<td>10.56</td>
<td>17.15</td>
<td>66.68</td>
<td>5.61</td>
</tr>
<tr>
<td>&lt; 10,000 shs</td>
<td>3.20</td>
<td>13.14</td>
<td>21.58</td>
<td>58.19</td>
<td>7.10</td>
</tr>
<tr>
<td>&gt; 10,000 shs</td>
<td>2.29</td>
<td>14.29</td>
<td>23.85</td>
<td>51.70</td>
<td>10.18</td>
</tr>
</tbody>
</table>

This table shows the variation in success rate of the Lee and Ready (1991) algorithm across different trade sizes. The trades are grouped by the number of shares in the trade and, for each size category, the total success as well as the success at each price category is reported. The price categories group the trades based on the trade price relative to the current best quotes. The distribution of the trades is given (frequency in each category) and the percentage of trades for which the LR classification agrees with the true trade classification. The sample size is 1,833,728 trades.

much variation in the probability of trades executing inside the quote as a function of the intensity of the trade, but this is not the case for trades executing outside the quotes. We find that 9.26% of trades happen outside the quote in periods of rapid trading compared to 1.3% in periods of slow trading. The opposite picture emerges for trades at the quotes. A trade is more likely to execute at the quote during slow trading periods (8.176%) relative to rapid trading periods (69.56%). This behavior may again reflect features specific to a dealer market. When trading is rapid, dealers may not be able to update quotes as quickly because of arriving orders. As a result, a dealer may be trading at stale prices relative to his updated quote (this phenomenon can also result in a crossed market in which the best bid is above the ask price).

Our findings suggest that the higher success rate in classifying trades during slow trading periods is not due to the speed of trading, but rather to the higher incidence of trades at the quotes. Nonetheless, our findings do suggest caution in interpreting trade data in times of high volume. Likewise, as indicated in Table 4, Panel B, trade classification is more successful the longer the time delay from a quote update. Again, this is due to more trades executing at the quotes as the time grows longer since a quote change. However, trades with five to 90 seconds before a quote change have a lower classification success than trades immediately after a quote, and this is due to lower success for trades at the quote.

### D. Multivariate Analysis

Given the influence on trade classification accuracy of the interaction of the proximity of the trade to the quote with trade size, trading speed, and quoting speed, a multivariate analysis may highlight the residual importance of such fac-
TABLE 4
Classification Success by Rapidity of Trading and Quoting

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Midpoint</th>
<th>Inside Quotes</th>
<th>At Quotes</th>
<th>Outside Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Time from Previous Trade</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 5 seconds</td>
<td>25.94</td>
<td>9.39</td>
<td>12.67</td>
<td>69.56</td>
<td>9.26</td>
</tr>
<tr>
<td>5-90 seconds</td>
<td>37.83</td>
<td>8.66</td>
<td>13.80</td>
<td>72.48</td>
<td>5.03</td>
</tr>
<tr>
<td>90-300 seconds</td>
<td>13.02</td>
<td>6.62</td>
<td>12.00</td>
<td>78.72</td>
<td>2.44</td>
</tr>
<tr>
<td>&gt; 300 seconds</td>
<td>22.40</td>
<td>5.78</td>
<td>11.13</td>
<td>81.76</td>
<td>1.30</td>
</tr>
<tr>
<td>% Agree</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 5 seconds</td>
<td>72.58</td>
<td>59.69</td>
<td>50.92</td>
<td>79.50</td>
<td>62.97</td>
</tr>
<tr>
<td>5-90 seconds</td>
<td>80.43</td>
<td>82.58</td>
<td>55.19</td>
<td>88.46</td>
<td>65.25</td>
</tr>
<tr>
<td>90-300 seconds</td>
<td>86.15</td>
<td>60.86</td>
<td>57.54</td>
<td>93.29</td>
<td>57.54</td>
</tr>
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<td>&gt; 300 seconds</td>
<td>88.77</td>
<td>56.68</td>
<td>59.41</td>
<td>95.32</td>
<td>73.24</td>
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<tr>
<td><strong>Panel B. Time from Previous Quote</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 5 seconds</td>
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<td>6.98</td>
<td>13.07</td>
<td>67.97</td>
<td>11.51</td>
</tr>
<tr>
<td>5-90 seconds</td>
<td>22.91</td>
<td>7.51</td>
<td>12.35</td>
<td>70.24</td>
<td>9.84</td>
</tr>
<tr>
<td>90-300 seconds</td>
<td>14.81</td>
<td>7.12</td>
<td>11.03</td>
<td>76.69</td>
<td>5.12</td>
</tr>
<tr>
<td>&gt; 300 seconds</td>
<td>53.25</td>
<td>8.00</td>
<td>13.15</td>
<td>76.76</td>
<td>1.09</td>
</tr>
<tr>
<td>% Agree</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 5 seconds</td>
<td>78.36</td>
<td>59.08</td>
<td>58.46</td>
<td>86.76</td>
<td>64.63</td>
</tr>
<tr>
<td>5-90 seconds</td>
<td>75.24</td>
<td>57.88</td>
<td>56.31</td>
<td>61.99</td>
<td>64.41</td>
</tr>
<tr>
<td>90-300 seconds</td>
<td>81.38</td>
<td>59.75</td>
<td>54.56</td>
<td>86.61</td>
<td>61.53</td>
</tr>
<tr>
<td>&gt; 300 seconds</td>
<td>83.77</td>
<td>62.00</td>
<td>54.60</td>
<td>61.53</td>
<td>67.86</td>
</tr>
</tbody>
</table>

The table examines the relationship between classification success and the speed of trading. Panel A groups trades by the number of seconds between the previous trade and the current trade, as well as the current trade price relative to the quote prices. Panel B groups trades by the time between current trade and previous quote update, and price of current trade relative to quote prices. The frequency of each time delay group is presented, as well as the success rate of the Lee and Ready algorithm (1991) for each group. The sample size is 1,833,729 trades.

We ran a logistic regression where the binary dependent variable, y (1 if successful classification, 0 otherwise), was changed via the logistic transformation,

\[
\log \left( \frac{\Pr(y = 1)}{\Pr(y = 0)} \right) = \beta x + \epsilon.
\]

As independent variables, we included dummy variables representing the location of the trade relative to the quote (at, outside, inside, and midpoint) as well as the trade size (in thousands of shares). Other independent variables we include are firm size (the average market capitalization over the sample period in tens of millions of dollars),\(^\text{10}\) time since the previous trade in minutes; and time since the previous quote in minutes.\(^\text{11}\) The logistic regression gives the relative importance of each variable in classifying trades correctly via the modified LR rule. Because of the logit transformation, the regression coefficients cannot be interpreted in the standard way as the marginal effect of the independent variable.

\(^{10}\)Univariate analysis of market capitalization with trade classification accuracy showed better accuracy for small firms, due to more trades executing at the quote. We also analyzed the effect of time of day, and there was no variation in trade classification accuracy.

\(^{11}\)We performed univariate analyses with these variables, and found the proximity of the trade to the quote dominated the effect of firm size or trading and quoting rapidity.
on the probability of successful classification. Instead, we can calculate this effect via
\[
(2) \quad \frac{\partial \Pr(y = 1)}{\partial x} = \frac{\partial A(\hat{\beta}' \bar{x})}{\partial \hat{\beta}} \frac{\hat{\beta}'}{\partial \bar{x}} = A \left( \hat{\beta}' \bar{x} \right) \left( 1 - A \left( \hat{\beta}' \bar{x} \right) \right) \hat{\beta},
\]
where \( A(\hat{\beta}' \bar{x}) = \exp(\hat{\beta}' \bar{x})/(1 + \exp(\hat{\beta}' \bar{x})) \) is the cumulative logistic distribution function, \( \hat{\beta} \) is the vector of parameter estimates, and \( \bar{x} \) is the vector of the means of the independent variables.

Table 5 reports the results. The regression shows trade size, firm size, trading speed, and quoting speed are each less significant in determining the probability of correct classification than is proximity to the quotes. The probability of correct classification increases with trade size, decreases with firm size, increases with the time between trades (less rapid trading), and increases with the time between a quote update and a trade. However, the relationship is slight: the slope value shows that the marginal effect of these variables is minimal. Proximity to the quotes is the most important factor in affecting classification accuracy. The slope values suggest that trades occurring at the midpoint, the quotes, or outside the quotes result in a 4%, 27%, and 7% respective increase in the probability of being correctly classified over trades inside the quotes. Finally, to check for stability, we also estimated the parameters of the logistic regression using the first half of the data. Our results suggest that the parameters are generally reliable, and that the characteristics that determine correct classification are the same in different samples.\(^{12}\)

V. An Alternative Trade Classification Algorithm

Our analysis has demonstrated a number of empirical regularities with respect to trade classification of Nasdaq trades. While we find that standard algorithms applied to Nasdaq trades compare quite favorably to NYSE-based results, approximately 20% of all trades on Nasdaq are incorrectly classified. This is due to a number of factors, with the most important being the difficulty of assigning direction for trades within the quotes. We have also demonstrated a problem unique to Nasdaq—trades that occur outside of the quotes perform poorly with respect to trade classification.

What, then, is the best trade classification approach for researchers to take when working with Nasdaq trades? Although extant algorithms are adequate to the basic job of sorting trades, our work suggests that a refinement to the extant methods of classifying trades will do even better. Specifically, the difficulties of assigning non-quote trades suggest relying more on tick rules than on quote rules. Hence, we propose the following alternative trading algorithm:

\(^{12}\)With a cutoff value for the estimated probability of 0.5, 80.4% of the trades are correctly classified. The out-of-sample predictive ability of the regression is tested on the remainder of the data by fitting the regression coefficients. Using a cutoff of 0.5 (i.e., if the estimated probability is above 0.5, then the trade is correctly classified), the error rate is 30.9%, indicating that 73.1% of trades are correctly classified.
### TABLE 5
Logistic Regression of Classification Success

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.6662*</td>
<td>0.00657</td>
<td></td>
</tr>
<tr>
<td>Outside</td>
<td>0.4586*</td>
<td>0.0123</td>
<td>0.0718</td>
</tr>
<tr>
<td>Quote</td>
<td>1.6636*</td>
<td>0.03743</td>
<td>0.8740</td>
</tr>
<tr>
<td>Midpoint</td>
<td>0.3774*</td>
<td>0.0145</td>
<td>0.0404</td>
</tr>
<tr>
<td>Trade Size</td>
<td>0.00126</td>
<td>0.000021</td>
<td>0.0008</td>
</tr>
<tr>
<td>Firm Size</td>
<td>-0.00025*</td>
<td>0.000025</td>
<td>-0.0004</td>
</tr>
<tr>
<td>Trade Speed</td>
<td>0.00326*</td>
<td>0.000025</td>
<td>0.0014</td>
</tr>
<tr>
<td>Quote Speed</td>
<td>0.00174*</td>
<td>0.000013</td>
<td>0.0001</td>
</tr>
<tr>
<td>2log L</td>
<td>0.0067*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The table gives the parameter estimates, standard errors, and odds ratios for the following logistic regression:

\[
\log \left( \frac{Pr(\text{correct})}{Pr(\text{incorrect})} \right) = a + b_1 \times \text{outside} + b_2 \times \text{midpoint} + b_3 \times \text{quotes} + b_4 \times \text{trade size} + b_5 \times \text{firm size} + b_6 \times \text{trading speed} + b_7 \times \text{quote speed}. 
\]

The dependent variable is the logistic transformation of a binary variable that is one if the classification via Lee and Reidy's (1991) algorithm is correct, and zero if incorrect. Outside, midpoint, and quote are dummy variables that take the value one if the trade occurs at the named range, and zero otherwise. Trade size is the size of the trade in thousands of shares. Firm size is the average market capitalization of the firm during the trading period in tens of millions of dollars. Trade (quote) speed is the number of minutes since the trade. The slope is the marginal effect of a change in the independent variable on the probability of correct classification, holding all other variables at their mean values. Half of the trade sample was used to estimate the regression; the sample size is 316,864 trades.

*Indicates that the $\chi^2$ statistic of the estimate has a p-value of 0.01.

All trades executed at the ask quote are categorized as buys. All trades executed at the bid quote are categorized as sells. All other trades are categorized by the tick rule.

Table 6 reports the success rate of this alternative classification rule and compares it to LR's algorithm. The classification accuracy for trades executed inside the quotes increases from 55%--61%, a significant improvement. There is also an improvement, but to a lesser extent, for trades outside the quote: from a 64.8% success rate under the LR procedure to 65.8% under the alternative procedure. This improvement translates into an overall success rate of 81.87% for our candidate algorithm, compared to 81.05% for the LR algorithm.

While this may seem a relatively modest improvement, a more compelling case for the proposed algorithm arises in specific applications. An important application of trade classification algorithms is the computation of effective bid-ask spreads, which measure the difference between actual trade prices and quotes (see Petersen and Fialkowski (1994)). When trades routinely transact between the quotes, this measure will give a smaller, and more accurate, estimate of transactions costs than do posted bid-ask spreads. The effective spread is calculated as

\[
\text{Effective spread} = 2f[\text{transaction price} - \text{midpoint price}],
\]

\footnote{Given the logistic regression results, we do not find any reason to adjust the algorithm for time of day issues, nor do we feel it advisable to treat order size differently.}
TABLE 6
Classification Success for Tick-Quote Rule

<table>
<thead>
<tr>
<th>Trading Price</th>
<th>Frequency</th>
<th>Lee &amp; Ready % Agree</th>
<th>Tick-Quote Rule % Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outside Quotes</td>
<td>4.93</td>
<td>64.77</td>
<td>66.82</td>
</tr>
<tr>
<td>At Quotes</td>
<td>74.66</td>
<td>86.69</td>
<td>88.88</td>
</tr>
<tr>
<td>Inside Spread (not at midpoint)</td>
<td>12.66</td>
<td>55.21</td>
<td>61.32</td>
</tr>
<tr>
<td>Midpoint</td>
<td>7.65</td>
<td>60.52</td>
<td>60.52</td>
</tr>
<tr>
<td>Unclassified</td>
<td>0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,833.729</td>
<td>81.05</td>
<td>61.07</td>
</tr>
</tbody>
</table>

This table compares the success of Lee and Ready's (1991) algorithm with a proposed alternative (tick-quote rule). The alternative algorithm uses the quote rule to classify trades at the quote (bid or ask) and the tick rule to classify all other trades. The distribution of trades across the price categories, as well as the success rates of the LR and proposed algorithms, is given.

where $I$ is an indicator variable that equals one for buy trades and negative one for sell trades, and the midpoint is the average of the bid and ask prices. Obviously, correct classification of buy and sell trades is crucial in calculations of the effective spread.\(^{14}\)

For every market maker-customer, broker-customer, and market maker-broker trade in the sample, we calculate the effective spread using the previous quote. Using the correct buy/sell classification from the NASD audit trail, we calculate the average effective spread as $0.1997$, or 1.34% of the price, compared to the average posted bid-ask spread of $0.3363$, or 2.33% of the price. Such dramatic differences between effective and posted spreads testify to the complexity of accurately measuring transactions costs in dealer markets.

Since audit trail data is not typically available to researchers, we now calculate the effective spreads using LR's algorithm. We find an average effective spread of $0.2909$, or 1.96% of the price. The surprisingly high error in this classification mirrors the one Finucane (2000), pp. 553–576, of this issue, found in his analysis of NYSE trades, suggesting that LR's algorithm is inaccurate in measuring effective spreads in both Nasdaq and the NYSE. This is largely due to the poor performance of LR's algorithm in classifying trades between the quotes. Our suggested algorithm performs much better. We find an effective spread of $0.2681$, or 1.80% of the price. While still an overstatement of the actual cost, our measure is a 10% improvement over the estimate found using the LR measure, a direct result of using the tick rule for non-quote trades rather than assuming that every trade above (below) the midpoint is a buy (sell).

Our proposed algorithm thus provides a more accurate method for classifying Nasdaq trades. A natural concern is whether this approach is robust to factors such as different sampling techniques. How reporting delays influence classification accuracy is another concern. Section VI addresses these concerns and the larger question of how well our proposed algorithm works when applied to publicly available databases.

\(^{14}\) Some researchers use a simpler definition of effective spread: twice the absolute difference between the transaction price and the midpoint. Thus, all trades above the midpoint are implicitly assumed to be buys, and all trades below the midpoint are assumed to be sells. When the LR classification is used, the two effective spread measures are identical.
VI. Robustness

A. Trading Beyond the IPO Month

Since our sample consists of stocks entering the market through IPOs, a natural concern is that trading surrounding these events may differ from "normal," thereby biasing our classification results. To test whether trade classification algorithms work differently in initial trading than in normal trading, we repeat the analysis excluding the first month of trading. Restricting the analysis to market maker-customer, broker-customer, or market maker-broker trades after the IPO month yields a sample of 1,380,271 trades.

Table 7 shows that the distribution of trades is not different from the sample including the IPO: 4.9% of the sample is outside the quotes, 74.3% at the quotes, 13.4% within the quotes but not at the midpoint, and 7.4% at the midpoint. Overall the quote rule, tick rule, and LR’s rule correctly classify 75.3%, 76.6%, and 79.8% of the trades. Our new algorithm significantly improves upon these results by correctly classifying 80.8% of the trades. The rate of success is again much higher at the quotes (87.41%), with a 60.56% success rate at the midpoint, and a 61.55% success rate within the spread, but not at the midpoint. We repeated the univariate analyses comparing trade classification success with trade size, time between trades and quotes, and firm size, and we found identical results. The logistic regression reported in Table 7, Panel B supports the better classification at the quotes, midpoint, and outside the quotes. Overall, our conclusions support the hypothesis that trade classification rules work with similar success in normal trading periods.

B. Market Maker-Customer Trades

A possible problem in our data might be that some trades between market makers and brokers actually occurred on an ECN, but were not reported as such. This matters because ECN trading essentially involves limit orders, and the direction of the active party may be difficult to infer: in signing a market maker-broker trade, the broker’s order could have been first on the ECN acting as the liquidity provider, and the market maker hitting the broker’s order initiated the trade. We have excluded ECN trades from our sample, but any erroneous reporting will introduce noise. In general, in a dealer market, we would expect that market makers are the liquidity providers and brokers the liquidity demanders, and that is the intuition underlying our simplifying assumption. Because the market maker-customer trades do not have this potential problem, doing our accuracy results using this restricted sample provides a simple check on our analysis.

This new sample includes 636,637 trades, or approximately 26% of the initial sample. Overall, the success of the trade classification algorithms improves slightly to 77.8%, 80.2%, and 83.0% for the quote, tick, and LR rules. Our new tick rule first-quote rule second algorithm again successfully classifies trades at the rate of 84.2%. The success rate is highest for trades at the quotes (91.2%) with

\[15\text{Including ECN trades should add noise but not bias if the broker is equally likely to make or take trades on an ECN. Over our time period, ECN trades are only a very small part of the market for these stocks (approximately 4%), and so any effect should be small.}\]
TABLE 7
Trade Classification Success: Excluding the First Month of Trading and Market Maker-Broker Trades

<table>
<thead>
<tr>
<th>Panel A. Distribution of Classification Success</th>
<th>Price Range</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td>Excluding the First Month of Trading</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>1,380,271</td>
<td>7.40</td>
<td>13.37</td>
<td>74.29</td>
<td>4.89</td>
</tr>
<tr>
<td>Lee &amp; Ready % Agree</td>
<td>79.86</td>
<td>60.56</td>
<td>54.71</td>
<td>87.41</td>
<td>62.81</td>
</tr>
<tr>
<td>Tick-Quote % Agree</td>
<td>80.66</td>
<td>60.56</td>
<td>61.55</td>
<td>87.41</td>
<td>64.46</td>
</tr>
<tr>
<td>Market Maker-Customer Trades</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>656,637</td>
<td>8.20</td>
<td>14.24</td>
<td>72.50</td>
<td>5.01</td>
</tr>
<tr>
<td>Lee &amp; Ready % Agree</td>
<td>83.01</td>
<td>64.83</td>
<td>57.96</td>
<td>61.19</td>
<td>65.56</td>
</tr>
<tr>
<td>Tick-Quote % Agree</td>
<td>84.24</td>
<td>64.93</td>
<td>66.15</td>
<td>51.19</td>
<td>67.90</td>
</tr>
<tr>
<td>Panel B. Logistic Regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excluding First Month of Trading</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independent Variable</td>
<td>Estimated</td>
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<td>Regression</td>
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</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
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<tr>
<td>Outside</td>
<td>0.413*</td>
<td>0.0645</td>
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<td></td>
</tr>
<tr>
<td>Quote</td>
<td>1.7278*</td>
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<td></td>
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</tr>
<tr>
<td>Midpoint</td>
<td>0.2656*</td>
<td>0.0408</td>
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<tr>
<td>Trade Size</td>
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<td>0.0013</td>
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<tr>
<td>Firm Size</td>
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<td>-0.00032</td>
<td>0.0005</td>
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<tr>
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<td>0.00105*</td>
<td>0.0016</td>
<td></td>
<td></td>
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<tr>
<td>Quote Speed</td>
<td>0.0008*</td>
<td>0.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2log L</td>
<td>12.1316*</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Market Maker-Customer Trades</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Independent Variable</td>
<td>Estimated</td>
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<td></td>
<td>Regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.2417*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outside</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quote</td>
<td>0.2906*</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Midpoint</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trade Size</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm Size</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trade Speed</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quote Speed</td>
<td>0.0001*</td>
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<td></td>
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<td>2log L</td>
<td>66.002*</td>
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</tbody>
</table>

Panel A shows the success rate of the tick-quote rule for two different subsamples: customer trades excluding the first month of trading and market maker-broker trades. The tick-quote rule classifies trades at the bid (ask) as buys (sells) and all other trades by the tick rule. The distribution of the trades with respect to the quote prices is given, as well as the success of the tick-quote rule in each range. Customer trades are all trades between a market maker and customer, or broker and customer that occurred after the first 20 days of trading.

Panel B shows the parameters from a logistic regression where a binary variable denoting correct or incorrect classification is regressed against dummy variables for the trading range (outside, midpoint, at quotes), trade size, trading speed, quoting speed, firm size. The parameters and their marginal effects on the probability of correct classification (slope) are reported.

* signifies the parameter is significant at the 1% level; standard errors are not reported.

Compared to at the midpoint 64.8% (Panel A, Table 7). A logistic regression (reported in Panel B) confirms this pattern: trades at the quotes, midpoint, and outside the quotes are more likely to be correct than trades within the spread. These results suggest little difference in classification accuracy compared with the larger sample including the market maker-broker trades.

C. Reporting Delays for Trades

Reporting conventions may significantly affect the success rates of trade classification rules. On the NYSE, for example, the median delay in reporting trades is five seconds. The incorporation of this five-second delay is one of the distinctive features of LR’s algorithm. How reporting delays affect Nasdaq trades
is not clear, but can be established using our data set. Because our data are drawn from the NASD audit trail, the transaction time given is generally accurate. For users of publicly available Nasdaq trade-by-trade data sets (such as TAQ), however, reporting delays may arise. They could arise, for example, because of the different execution systems available to brokers and market makers, and because of delays between execution time and reporting time. Thus, an important question for users of publicly available databases is how to adjust for any reporting delays.

The transaction times on the NASD audit trail are not perfect. A trade always appears with the time that the trade was entered into the Automatic Confirmation Transaction Service (ACT). In addition, if a trade occurred via an automated trading system such as SOES, SelectNet, or ACES (Advanced Computerized Execution System), then the actual execution time is reported and appears on the NASD audit trail. Also, if a trade is reported later than the allowed 90-second delay, then the actual execution time must be reported, and it also appears on the NASD audit trail. The result is that transaction times on the NASD audit trail are a mix of ACT times (if no alternative execution time is reported) and the more accurate execution times (for automated trades or late reported trades). By contrast, times reported on TAQ are based solely on the ACT times.

To measure the difference between the transaction time and the time reported on the NYSE TAQ database (the most widely used Nasdaq trade-by-trade database), we match trades in our database with trades on TAQ. For the 313 stocks between September 27, 1996 and September 29, 1997, there were 2,479,093 trades on the NASD database and 2,494,926 trades on TAQ. Trades were matched for size and price. If multiple trades match on both size and price, then time priority is used. For example, if there are two trades for 100 shares at $12.50 on TAQ, but only one on NASD, then the one closest in time to the NASD trade is matched. The matching rate is 96.85% for trades and 98.27% for quotes.

Table 8 gives the distribution of reporting delays for trades (Panel A), and for quotes (Panel B). The data clearly show evidence of two trade types: those with a one-second reporting delay (12.4% of trades), and those with a reporting delay of 15–16 seconds (58.6% of trades). In total, 93.2% have a reporting delay of up to 16 seconds: the mean delay is 11 seconds and the median reporting delay is 15 seconds. This is much shorter than Blume and Goldstein's (1997) finding that the median reporting delay for transactions of NYSE stocks on Nasdaq is 31 seconds. By contrast, there does not appear to be a significant time delay in the reporting of quotes. We find that 88% of all quotes are reported within plus or minus one second of the time on the NASD audit trail, with a median report delay of zero seconds.

The reporting delays for trades and quotes suggest that inaccuracies from the TAQ database may be prone to errors due to trades matched with the wrong quote. To measure the extent of this problem, we calculated the number of quote updates between the actual trade time (NASDAQ data) and the reported trade time (TAQ) and report them in Table 8, Panel A, columns 3–5. Overall, only 10.93% of trades have a quote update in this interval, limiting the problem of referring to the wrong quote to, at worst, only a fairly small fraction of all trades.

We can calculate how much the trade reporting delay affects the LR and tick-quote trade classification algorithm by matching trades on the TAQ with our
TABLE 8
Reporting Delays on the TAQ Database

Panel A. Time Delay for Trades

<table>
<thead>
<tr>
<th>Time Delay</th>
<th>Frequency</th>
<th>%</th>
<th># with Quote Update in Between</th>
<th># with Quote Update in Between (as % of trades with this delay)</th>
<th># with Quote Update in Between (as % of all trades)</th>
</tr>
</thead>
<tbody>
<tr>
<td>—10 minutes</td>
<td>1377</td>
<td>0.06</td>
<td>917</td>
<td>66.58</td>
<td>0.04</td>
</tr>
<tr>
<td>—1 minute</td>
<td>1951</td>
<td>0.05</td>
<td>404</td>
<td>20.26</td>
<td>0.22</td>
</tr>
<tr>
<td>&lt; —1 minute</td>
<td>6580</td>
<td>0.28</td>
<td>517</td>
<td>7.87</td>
<td>0.02</td>
</tr>
<tr>
<td>Same time</td>
<td>61098</td>
<td>2.59</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1 second</td>
<td>292280</td>
<td>12.41</td>
<td>14418</td>
<td>4.93</td>
<td>0.61</td>
</tr>
<tr>
<td>2 seconds</td>
<td>146342</td>
<td>6.21</td>
<td>11641</td>
<td>7.95</td>
<td>0.49</td>
</tr>
<tr>
<td>3—14 seconds</td>
<td>315558</td>
<td>13.41</td>
<td>44363</td>
<td>14.05</td>
<td>1.68</td>
</tr>
<tr>
<td>15 seconds</td>
<td>743866</td>
<td>31.58</td>
<td>81967</td>
<td>11.02</td>
<td>5.48</td>
</tr>
<tr>
<td>16 seconds</td>
<td>626192</td>
<td>27.01</td>
<td>76778</td>
<td>12.07</td>
<td>3.26</td>
</tr>
<tr>
<td>17—60 seconds</td>
<td>233335</td>
<td>5.66</td>
<td>20568</td>
<td>8.77</td>
<td>0.87</td>
</tr>
<tr>
<td>1—10 minutes</td>
<td>15896</td>
<td>0.67</td>
<td>5035</td>
<td>31.67</td>
<td>0.21</td>
</tr>
<tr>
<td>More</td>
<td>1720</td>
<td>0.07</td>
<td>1078</td>
<td>62.67</td>
<td>0.05</td>
</tr>
<tr>
<td>Total</td>
<td>2355564</td>
<td>100.00</td>
<td>252516</td>
<td>10.93</td>
<td></td>
</tr>
</tbody>
</table>

Panel B. Time Delay for Quotes

<table>
<thead>
<tr>
<th>Time Delay</th>
<th>Frequency</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than —10 minutes</td>
<td>420</td>
<td>0.1</td>
</tr>
<tr>
<td>—10 minutes to —31 seconds</td>
<td>167</td>
<td>0.0</td>
</tr>
<tr>
<td>—5 to —30 seconds</td>
<td>120</td>
<td>0.0</td>
</tr>
<tr>
<td>—2 to —4 seconds</td>
<td>14061</td>
<td>2.4</td>
</tr>
<tr>
<td>—1 second</td>
<td>66990</td>
<td>11.8</td>
</tr>
<tr>
<td>Same time</td>
<td>381431</td>
<td>86.0</td>
</tr>
<tr>
<td>1 second</td>
<td>66635</td>
<td>12.2</td>
</tr>
<tr>
<td>2—4 seconds</td>
<td>51255</td>
<td>8.6</td>
</tr>
<tr>
<td>5—30 seconds</td>
<td>4021</td>
<td>0.7</td>
</tr>
<tr>
<td>31 seconds to 10 minutes</td>
<td>1038</td>
<td>2.2</td>
</tr>
<tr>
<td>More</td>
<td>202</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td>933344</td>
<td>100.0</td>
</tr>
</tbody>
</table>

This table examines reporting delays for trades and quotes on the NYSE TAQ database. Trades are matched for each day using the trading price, volume, and time proximity if there are multiple trades at the same price and for the same volume. The reporting delay is the time between the TAQ timestamp and the NASD audit trail timestamp. As well as the frequency of each time delay, the table reports the occurrence of a quote update between the NASD time and the TAQ time. Trades with a quote update between the true time and the reported time will use the wrong quote in the trade classification algorithm. Panel B shows the difference in the timestamp for inside quote revisions on TAQ and the NASD audit trail.

market maker-customer sample trades. Of these trades, we matched 1,751,792 of 1,833,729, or 95.5%. Table 9 reports the success of LR’s algorithm and tick-quote rule for these trades. Overall, the classification success increases from 82.74% to 83.74% when the TAQ trade times are used instead of the actual trade times. If trades are advanced by 15 seconds (adjusting for the median reporting delay), then we correctly classify 82.73% of the sample. We conclude that incorporating reporting delays into the classification algorithm does not improve their accuracy for Nasdaq data. Consequently, we recommend using the TAQ time with no delay when classifying Nasdaq trades from TAQ data.

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\[\text{This overall success rate differs from the previous rate (81.8\%) as we are only using the subsample of matched trades.}\]
D. Classifications of Trades Executed Outside the Quotes

A feature peculiar to dealer markets in general and to Nasdaq in particular is the large fraction of trades occurring outside of the posted quotes. We find 4.93% of the trades in the sample execute outside the spread, a figure nine times greater than the 0.5% of NYSE trades reported in LR (1991).

Surprisingly, the classification success for trades outside the quotes is significantly lower than it is for trades inside the quotes. One expects that trades above the ask (below the bid) will almost always be initiated by a buyer (seller), reflecting, for example, the premium that a large buyer is willing to pay for liquidity. We find, however, that the success rate of classifying trades that occur outside the spread is only 65.8%, implying that a large portion of these trades actually is buyers buying below the bid and sellers selling above the ask. This result mirrors the findings of Bernhardt, Dvoracek, Hughson, and Werner (1999) that large trades on the London Stock Exchange actually receive better execution than small trades. Why this occurs on the Nasdaq is not obvious, but four hypotheses seem most relevant.

The first hypothesis is simply that this divergence is specific to our data sample: 11.52% of the trades outside the quotes occurred on the IPO day, which may be a unique event. Second, reporting rules may introduce technical problems in interpreting data. Third, the Nasdaq market structure of multiple dealers creates situations of multiple effective bids and asks at times of rapid and large volume. Fourth, features specific to a dealer market may result in trades outside the spread representing significant price improvement for the trader.

The unique feature of our data sample is that it includes trading around the IPO. As noted earlier, a significant portion of outside trades occurs on the IPO date. In fact, 6.5% of all trades on the offer day fall into this category. But what is so unique about the first day of trading? Two features seem most important. First, there is an extremely high volume of trade (Ellis, Michaela, and O'Hara (2000) report an average 60% first day turnover for the stocks in this sample). Second, the trading frequency is intense; over 50% of all trades on the first day occur within five seconds of the previous trade. Difficulties with order executions on Nasdaq on IPO days are not uncommon, with some traders buying above the
inside quotes and others selling below. These execution problems largely reflect logistical difficulties when large volumes are handled by multiple dealers in newly issued securities.\textsuperscript{17}

However, even excluding the first month of trading (see Table 7), 4.89% of the trades occur outside the quote and the classification success of these trades is not any better: only 64.48% are correctly classified. Overall, this suggests that the IPO day is not the reason for either the large number of trades outside the quotes, or the lack of success in classifying outside-the-quote trades.

We now consider the issue of technical or reporting problems. Porter and Weaver (1998) present evidence that late reporting of trades is a more common occurrence on the Nasdaq than it is on the NYSE. We do not have a condition code for late trades in our data set, but we can investigate this issue by matching our trades with trades in the TAQ data, which does indicate a flag for late reports. We find 13.7% of the trades outside the quotes match a late reported trade on TAQ.\textsuperscript{18} Thus, late reporting is a significant factor in explaining the prevalence of trades outside the quotes.

Even the comparison to the late reported trades may not indicate the full extent of the problem. As previously noted, a trade may be reported up to 90 seconds after the transaction time without being regarded as a late reported trade. If a quote change occurs between the execution time and the reporting time, then we may be overstating the fraction of trades that occur outside the spread. For the whole sample, 29.93% of all trades occur within 90 seconds of the previous quote and thus can be labeled ambiguous trades. However, for trades outside the quote, 62.26% are ambiguous. Therefore, it is possible that these trades are reported with a delay and if quotes have moved during this time period, then what is recorded as an outside-the-quote trade is simply misclassified.\textsuperscript{19}

To examine the extent of this potential problem, we compare the trade price to all the quotes in the 90 seconds prior to the trade and examine whether the trade price was at or within any of the prior quotes. We find that 67% of the ambiguous trades occurred outside the spread for all of the quotes within a 90-second time frame. This suggests that for 33% of the ambiguous outside-the-quote trades, the current quote is incorrect. However, most ambiguous outside-the-quote trades simply occur outside the spread.

Although these technical issues do explain a fraction of the outside-the-quote trades, they are not the full explanation. If we exclude all the late reported trades and 33% of the ambiguous trades that would be reclassified if we used a quote different from the current quote, we are still left with 3.38% (instead of 4.93%) of the whole sample being outside-the-quote trades. This is still six times the

\textsuperscript{17}Such difficulties are the subject of "Nasdaq's Problems with Trading Snags May Make it Vulnerable to Competition," Wall Street Journal, June 10, 1999. The article focuses on a recent IPO (theGlobe.com) in which some investors bought at the opening from Meyers & Schweitzer at $95, while other traders were simultaneously selling to Bear Stearns at $90. The article notes that "the controversial opening illustrates the structural problems plaguing Nasdaq."

\textsuperscript{18}Just under a quarter of these trades (24%) occurred on the IPO day, a finding consistent with our earlier discussion of the relatively chaotic trading conditions often found on the offer day.

\textsuperscript{19}However, 90 seconds can be a considerable delay, and we find that 62% of the ambiguous trades have at least two quotes within the preceding 90 seconds, and 25% have at least five quote updates during this time. Thus, we cannot easily identify the correct quote.
frequency reported on the NYSE in LR (1991). Furthermore, only 67.28% of these trades are correctly classified with our algorithm compared to 65.82% for the whole sample. Thus, although correcting for technical issues may reduce the frequency of outside-the-quote trades, the lack of success in classifying these trades remains a puzzle.

The third possible explanation for outside-the-quote trades and the mediocre classification of these trades is that, in times of rapid trading, multiple effective bids and asks may prevail in a multiple dealer market. Indeed, the evidence in Table 4 indicates that whenever trading is rapid, the frequency of outside-the-spread trades is much higher and the classification success is lower. For example, when trades occur less than five seconds apart, 9.26% of the trades are outside the spread and only 62.97% of these are correctly classified (last column, Table 4). Conversely, when trades occur more than 300 seconds apart, outside-the-spread trades occur only 1.3% of the time, and 73.24% of these are classified correctly. In a multiple market maker system like Nasdaq, it is possible that, in times of high volume, information is fragmented across dealers, and multiple effective bids and asks can prevail. Unlike a NYSE specialist, a Nasdaq market maker cannot see all the order flow in periods of rapid trading, but only his own orders. This can result in market makers relying on (and trading at) their quote rather than the inside quote during fast trading and, thus, many more trades occur outside the spread.

The fourth factor accounting for outside-the-quote trades may be related to inventory consideration by market makers. One explanation that immediately comes to mind is trade size. However, only 20.1% of the trades outside the quotes are for between 1,000 and 10,000 shares, and 6.4% are for amounts greater than 10,000 shares. Thus, the vast majority (74%) of trades outside the quotes are actually small trades. The success rate of the LR algorithm is highest for trades over 10,000 shares (71.74%), suggesting that customers are paying for liquidity when they transact large amounts. For trades between 1,000 and 10,000 shares, however, the trade classification success drops between 60%–67%, suggesting that market makers are giving these customers better prices than the prevailing quotes. This price behavior may reflect features specific to a dealer market. In particular, Bernhardt, Dvoracek, Hughson, and Werner (1999) suggest that dealer markets relationships between traders and dealers can result in dealers providing their regular customers with "better deals." When such enduring relationships are important, these authors argue that trades will tend to be larger, resulting in larger traders garnering better price execution. Such behavior is not observed on specialist markets or in open limit order markets, which, by definition, lack the relationship feature common to dealer markets.

On the other hand, for small trades outside the spread, the trade classification success of 64%–67% suggests that although 33%–36% receive executing at prices better than the inside quotes, most execute at worse prices.20 This seems at odds with best execution requirements, but cannot be explained away by data errors such as late reported trades or by comparison to other quotes that fall within 90 seconds prior to the trade. However, over 55% of these small outside-the-spread trades occur within five seconds of the previous trade (and 80% occur within 30

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20We thank the referee for pointing this out.
TABLE 10

Estimate of the Impact of 1987 Order Handling Rules on Trade Classification

<table>
<thead>
<tr>
<th></th>
<th>Average Percentage Spread</th>
<th>Trades</th>
<th>Total</th>
<th>Midpoint</th>
<th>Inside Spread</th>
<th>At Quotes</th>
<th>Outside Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pre-Order</strong></td>
<td>3.61</td>
<td>Frequency</td>
<td>30821</td>
<td>7.57</td>
<td>12.87</td>
<td>77.13</td>
<td>2.96</td>
</tr>
<tr>
<td><strong>Handling</strong></td>
<td></td>
<td>Tick-Quote % Agree</td>
<td>66.28%</td>
<td>63.03</td>
<td>64.90</td>
<td>92.66</td>
<td>69.47</td>
</tr>
<tr>
<td><strong>Rules</strong></td>
<td></td>
<td>Lee &amp; Pressy % Agree</td>
<td>64.86%</td>
<td>63.03</td>
<td>54.86</td>
<td>92.66</td>
<td>67.45</td>
</tr>
<tr>
<td><strong>Post-Order</strong></td>
<td>2.96</td>
<td>Frequency</td>
<td>53946</td>
<td>5.79</td>
<td>8.50</td>
<td>79.70</td>
<td>5.97</td>
</tr>
<tr>
<td><strong>Handling</strong></td>
<td></td>
<td>Tick-Quote % Agree</td>
<td>76.67%</td>
<td>58.41</td>
<td>60.79</td>
<td>80.95</td>
<td>64.54</td>
</tr>
<tr>
<td><strong>Rules</strong></td>
<td></td>
<td>Lee &amp; Pressy % Agree</td>
<td>76.16%</td>
<td>58.41</td>
<td>55.06</td>
<td>80.95</td>
<td>64.11</td>
</tr>
</tbody>
</table>

This table compares two samples: market maker-customer trades from Sept. 17 to Sept. 30, 1987, and market maker-customer trades from Jan. 6 to Jan. 17, 1997. Only stocks that traded in both periods are included (156 stocks). The first sample proxies for trades after the introduction of the order handling rules, and the second sample is before the implementation of the order handling rules. We do not know the exact date of implementation for each stock. The table gives the daily average time-weighted percentage spread for each period, and the proportion of trades that occur at the midpoint, within the spread, at the quotes and outside the quotes, and the success of the tick-quote rule in classifying the direction of these trades. A t-test was performed to test the difference in spreads and Pearson's x² test was done to test for differences in the success rate of pre- and post-order handling rules.

seconds of the previous trade), which again suggests that, in times of rapid trading, the multiple market maker system may create situations of multiple effective bids and asks.

Whatever the explanation, from the perspective of trade classification, these results suggest that trades outside the quotes are likely to degrade the accuracy of any trade classification algorithm. In particular, for 36.2% of trades outside the quotes, trades are sells above the ask and buys below the bid, the opposite of what would be expected (or predicted by a trade direction algorithm). Our results suggest that trade classification during periods of active trading, particularly on IPO days, will be prone to greater error.

E. Impact of the Order Handling Rules

Our sample period includes the introduction of the new SEC order handling rules. Did the changes in trade handling rules affect the distribution of trade execution relative to the quotes and the accuracy of classification rules? Although we do not know the specific date of compliance for the individual stocks in our sample, we can separate the stocks into pre-compliance and post-compliance periods. We do this by looking at a subsample of 156 stocks that traded before and after the implementation of the order handling rules. The period used as the pre-compliance period is the 10 trading days from January 6, 1997–January 17, 1997, and the post-compliance period is the last 10 trading days in our sample for each stock (September 17, 1997–September 30, 1997).

Table 10 shows that spreads fell sharply after the order handling rules were implemented, dropping from 3.61%–2.96%. A natural consequence of narrowing the spread is that fewer trades occur within the spread. Indeed, in the post-compliance period, only 14.29% of trades occur inside the spread (compared to 20.44% prior to the implementation of the order handling rules). After the order
handling rules, the classification success is lower within the spread and at the midpoint. Classification success decreased at the quotes (the difference is significant at the 1% level) and outside the quotes (significant at the 10% level). Overall, the success rate of the tick-quote classification rule is somewhat lower after the implementation of the order handling rules.

VII. Summary

We have documented the success of various trade classification algorithms on a sample of Nasdaq data. Overall, we find that extant trade classification algorithms perform adequately in sorting buy and sell trades, with approximately 81% of all trades correctly classified by LR’s (1991) algorithm. The results also indicate that, despite the median delay of 15 seconds in Nasdaq trades, incorporating those delays into the trade direction algorithm does not improve its accuracy. For researchers using publicly available data sets (such as TAQ) to investigate Nasdaq trades, we recommend using a simple algorithm relying more on tick rules than quote rules. This improves the accuracy of classifying trades in general, and it is substantially more accurate when classifying trades for the purpose of calculating effective spreads.

While our results suggest a reasonable level of accuracy in classifying trade direction, we raise two cautionary issues for consideration by empirical researchers. A sobering aspect of our findings is the difficulty of classifying trades both inside and outside the spread. Trades outside the spread are more likely in times of greater trade intensity, but these times also correspond to the events (such as earnings announcements, takeovers, and equity issuances) that are of greatest interest to researchers. Consequently, trade classification errors may arise non-uniformly over a sample period.

Although this outside-the-spread problem appears specific to Nasdaq data, another difficulty may be more universal. It is generally true that trades at prices other than quotes are increasingly common on all markets. ECN trades are a case in point. We found that only 32% of ECN trades take place at the quotes compared to over 72% of customer trades on Nasdaq. For our sample, ECN trades are only a small fraction of trades, but for Nasdaq as a whole, recent data show that ECNs account for more than 30% of trades.21

We found that the tick rule performs more reliably than the quote rule for trades away from the quotes, and that using the tick rule for all trades away from the quotes and the quote rule for trades at the quotes provides an improvement over Lee and Ready’s algorithm. This improvement arises primarily because the new algorithm is better at classifying trades between quotes. However, trades between the quotes only accounted for 12.7% of our test sample. For trades excluded from our test sample (24% of all trades), occurrence within the quotes was much higher (23.2%) suggesting that, overall, use of the tick-quote rule instead of the LR algorithm may be more reliable for Nasdaq data.

These findings indicate that empirical researchers will face increasing difficulty in accurately classifying trade direction and in accurately calculating ef-

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ffective spreads, a common measure of transaction costs. Using our trade classification rule, we show that the average effective spread is much lower than the effective spread calculated using LR's algorithm. However, all classification algorithms overstate the true effective spread, suggesting that researchers generally overstate the estimated cost of trading Nasdaq stocks.

As trading fragments, it will be more difficult to infer the underlying order, particularly if trades take place inside the spread. Although the development of more complete data sources and changes in market reporting rules may alleviate this difficulty, it is unlikely that complete data or order transparency will be available for all markets. Consequently, the study of trading algorithms is of increasing importance for empirical research.

References


22Changes to trade reporting on Nasdaq, including the move to include whether the trade came from a limit or market order (NASDAQ Rules 6930-6957 and Order Audit Trail System (OATS) Rules adopted March 1998) will allow better determination of the origin of trades.