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Are Market Center Trading Cost Measures Reliable?*

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Abstract
The cost of trading in securities markets is often estimated on the basis of: 1. the number of shares executed rather than the number of shares in the original order; and 2. the quote midpoint at the time of trade execution rather than at the time of order submission. In our paper, we obtain data from a U.S. brokerage firm to examine the severity of these two problems. We find that the quote midpoint and order size at submission differ from that at execution approximately 40% of the time. These differences are economically important and are more likely to occur when the market is less liquid. Our results highlight the need for caution when inferring trading costs from market center data sources.

1. Introduction

The cost of transacting in securities markets is important to many people and, as such, is a widely studied issue.[1] Although an extensive literature on trading costs exists, a major limitation of most studies is that the cost of trading is not measured from an investor order submission decision (see Perold, 1988). For example, researchers often estimate trading costs on the basis of a trade execution rather than on an investor's original order. Moreover, the national best bid and offer (NBBO) quote midpoint at the time of trade execution is often used as a benchmark price for measuring trading costs rather than the quote midpoint at the time an investor submits an order. These two adjustments are made because of data constraints. Most studies compute trading costs via publicly available market center data sources, which lack any information regarding investor order submission decision. Such information can only be obtained through a broker, and brokerage firms are often reluctant to release it.

In our study, we request and obtain proprietary order-level data from a U.S. brokerage firm. Our motivation is to provide some insight into: 1. how accurate quote midpoint and trade sizes observed in market center databases are for measuring trading costs; 2. what the economic implications of measuring trading costs are at the trade level rather than at the order level; and 3. when market center data sources are more (less) reliable for measuring trading costs. Examining these three issues is important not only to academic researchers, but also to market participants in order to facilitate a better understanding of the costs involved with trading.

We examine the order submission decisions and subsequent trade executions of more than three thousand investors who conducted their trading through a U.S. broker-dealer over an approximate six and one-half year period ending May 2006.

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[1] Trading costs can be either explicit, such as commissions paid to a broker, or implicit, such as the bid-ask spread charged by liquidity providers. Our focus is on implicit trading costs.

Overall, the sample investors executed more than 6 million orders (9 million trades) and 11.5 billion U.S. equity shares. We find that, for marketable orders, the quote midpoint changes more than 40% of the time from order submission to trade execution. Order size equals trade execution size less than 60% of the time. The order size and quote midpoint changes that occur from order submission to trade execution are economically important. For example, the average effective spread based on the quote midpoint at order submission is significantly higher than the average effective spread at trade execution ($0.085 vs. $0.055). Using the quote midpoint at trade execution understates the overall round-trip dollar cost of trading by more than $45 million in our sample data alone.

Market participants will never be able to execute their orders without delay and, consequently, they will always be prone to measurement error if transaction costs are measured at execution rather than at submission. We conduct probit regressions in order to understand better when market center data sources are more (less) reliable for estimating trading costs. This issue is of interest to the numerous researchers examining market center data sources as well to the readers of their research. We find, among other things, that, when the market is more liquid at the time of an order submission decision, or, when the quoted spread is smaller, the quoted depth is greater, the overall trading activity is higher, and the quote midpoint at order submission is more likely to equal that at trade execution. A similar result occurs with respect to order versus trade size; that is, when market liquidity is greater, submitted order size is more likely to equal executed trade size.

The remainder of our paper proceeds as follows. In Section 1, we provide a discussion of related literature. Section 2 describes the sample data used for analyses. Section 3 provides empirical results, and the concluding remarks are provided in Section 4.

2. Common Data Sources Used in Trading Cost Studies

Most research on trading costs is based on transaction-level data sources (see, among others, Bessembinder and Kaufman, 1997; Huang and Stoll, 1996). A commonly used transaction-level database is the New York Stock Exchange (NYSE) Trade and Quote (TAQ) database, which contains historical intraday trade prices and quotations across all U.S. equity market centers that publicly display their quotes. Bessembinder (2003a) provides a discussion on some of the issues involved in accurately assessing trading costs from TAQ data. In general, there are three major problems. First, TAQ data do not identify buyer or seller initiated trades. This identification is critical for measuring trading costs. In order to try and correct this deficiency, researchers often use trade-signing algorithms developed by Lee and Ready (1991) or Ellis et al. (2000).

Secondly, TAQ data do not reveal the size of an investor's order. A trade printed on transaction-level data might represent a mere fraction of an investor's original order size, which is problematic for assessing the true cost of executing from the perspective of an investor. We are not aware of any systematic approach used in financial studies to correct for this deficiency. However, Alexander and Peterson (2007) examine the NYSE Trades, Orders, Reports, and Quotes (TORQ) database and find that orders arriving at the NYSE are not significantly different from subsequent trade executions for various size categories.

Finally, TAQ data do not provide any information related to an investor's order submission decision, which results in misclassification when identifying the quote midpoint used in common trading cost computations, such as the effective spread. In order to try and correct for quotation movements during the order submission to trade execution time period, Bessembinder (2003a) recommends using the quote midpoint five seconds prior to the reported trade execution time.

Various types of market center data sources have been used in financial studies to measure trading costs, and some of these data sources do provide added benefits by comparison with TAQ for accurately measuring trading costs. For example, the TORQ database, Dash 5 data,[2] etc., classify buy-sell trades along with information about the time when an order *arrives* at the NYSE for execution, but they still do not identify investor-level order submission information, which is needed to measure trading costs properly.[3] Nevertheless, researchers have found evidence of systematic (and adverse) quote midpoint movement from the time when an order arrives at an exchange to the time of execution (see, for example, Bessembinder, 2003a; Peterson and Sirri, 2003; Werner, 2003).

Proprietary databases have been used to study trading costs as well. However, most of these studies are limited to institutional investment managers who do not execute their own orders. The intraday time when an order is submitted/executed is not identified (e.g., Conrad et al., 2003) and the data often lack information about either the original order (e.g., Chan and Lakonishok, 1997) or about how various parts of the order are executed by the firm's broker in the marketplace (e.g., Keim and Madhaven, 1997). The omission of this information precludes researchers from computing common microstructure cost measures such as effective spreads, realized spreads, etc. More recently, Garvey and Wu (2009) obtained data from a U.S. broker-dealer to examine intraday order execution quality patterns. Our data most closely resemble their data in that: 1. our data originate from a broker not a market center, and 2. investors execute their own orders. These two features allow for complete analysis of the order execution process beginning from the order submission decision to trade execution(s). Unlike that of Garvey and Wu (2009), our present focus is not on examining intraday order execution quality patterns, but on examining the accuracy of measuring trading costs with transaction-level data.

3. Data

To conduct our study, we obtained three data sources. The most important involves proprietary data obtained from a U.S. broker-dealer. These proprietary data allow us to examine trader order submission decisions and subsequent trade executions. We then obtained historical intraday pricing data from Thomson Reuters in order to examine the frequency of quote midpoint changes from investor order submission decisions to execution. We also used the Thomson Reuters tick data to examine market conditions (or market liquidity proxies), such as the quoted spread, quoted depth, and trading volume at order submission time. Because these factors

[2] See Boehmer et al. (2007) for a description of Dash 5 data.

[3] There are other limitations as well. For example, TORQ data are limited to 144 NYSE stocks in a three-month sample period during 1990 and 1991; Dash 5 data aggregate trades into four size categories: 100–499, 500–1,999, 2,000–4,999, and 5,000–9,999 shares, etc.

may affect the accuracy of measuring trading costs with transaction-level data, in this paper we are interested in examining the issue in greater detail. The third data source obtained is The Center for Research and Security Price (CRSP) database. CRSP is used to analyze summary trading information regarding the stocks being traded, such as a stock's market capitalization, price, and trading activity. Because trading costs vary across stocks, we are interested in examining the correlation between stock characteristics and trading cost measurement error.

The U.S. broker-dealer has clients and branch office locations nationwide. The firm also has multiple trading operations. The data used in this study originate from the firm's brokerage operation, which provided their clients with direct market access (DMA) order execution and administrative trading support. DMA brokers cater to a wide variety of retail and institutional clients with different trading styles. Unlike traditional brokerage firms, which take care of their client order execution process, DMA brokers allow their clients to choose where and how their order is routed for execution. Firms providing DMA do tend to attract more sophisticated market participants who trade often. Consequently, a sizeable portion of U.S. equity market trading volume flows through these brokerage firms.[4] The importance of DMA brokers in the overall marketplace, the wide variety of market participants who use these brokers, and the ability of investors to exert sole control over their order execution process is what motivates us to study data from a DMA broker.

We recognize an important limitation in that our sample reflects trading activity originating from one brokerage firm, which may or may not be representative of market-wide occurrences. Despite the limitation, our sample data are fairly extensive. For example, the data consist of 3,010 geographically dispersed market participants who execute 6 million orders (9.1 million trades) and 11.6 billion executed shares (dollar value of $103 billion) through the broker. The brokerage data are matched with intraday and daily transaction records on 4,606 stocks over a six and one-half year period ending May 2006. Also, the trading activity patterns in our sample data mirror trading activity patterns in the overall marketplace. For example, aggregate intraday trading activity follows a similar pattern to that of the general U-shape market volume. Trading volume steadily declines from morning to midday and then increases progressively to the close of day. Moreover, the most actively traded stocks in our sample data are also those most actively traded in the overall marketplace.[5]

The sample period is from October 7, 1999 to May 25, 2006. For every order request, the data include the identity of the investor submitting the order, the stock symbol, the time of submission, the time of execution, the market(s) where the order was sent, the original volume submitted, the executed volume, the execution price, the order type, and various other types of information. Orders often execute with multiple trades. If an order received multiple fills, the information for each fill is listed.

Prior to analysis, we filtered the data in three ways. First, we exclude stocks for which we were unable to retrieve data from the Thomson Reuters tick history

[4] For example, Goldberg and Lupercio (2004) find that approximately 40% of Nasdaq and NYSE-listed trading flows through DMA brokers.

[5] This is observable through volume comparisons of brokerage data with market-wide data. The volume comparisons are omitted for brevity but are available upon request.

database and/or the CRSP database. Then, we match trading information from these two publicly available data sources over the approximate six and one-half year sample period to our proprietary order-level data. We also exclude orders executed outside the main trading hours because trading before the open or after the close occurs in a very different manner. Lastly, we focus on Nasdaq-listed stocks only because these stocks represent a majority of the orders in the data and because different trading protocols existed between NYSE and Nasdaq stocks during the sample period.[6] The filters imposed do not limit the overall data significantly. On the whole, we analyze more than 90% of the trading activity originating from the sample firm's brokerage operation.

4. Empirical Results

Two major problems that exist with inferring (implicit) trading costs from trade and quote databases are that 1. trade executions (prints) are not always representative of investor submitted order sizes, and 2. the quote midpoint at the time of trade execution (or arrival at the exchange) is not always representative of the quote midpoint at the time an investor submits an order. Both of these factors can result in trading cost measurement error for researchers examining market center data sources. For example, if an investor submits a 1,000 share order that executes in four different trades (and prices), then inferring the true cost of executing in the marketplace based on four separate transactions is quite misleading. Furthermore, the cost of transacting is typically assessed based on a benchmark price. Perold (1988) and others recommend using the quote midpoint at the time of an investor order submission decision as the benchmark price. Investors assess the cost of trading based on the time of order submission not on the time when a (single) trade execution occurs. However, most studies (because of data constraints) involve the quote midpoint at trade execution time, which may severely misrepresent the cost of trading. In our empirical analysis, we examine three issues related to trading cost measurement error.

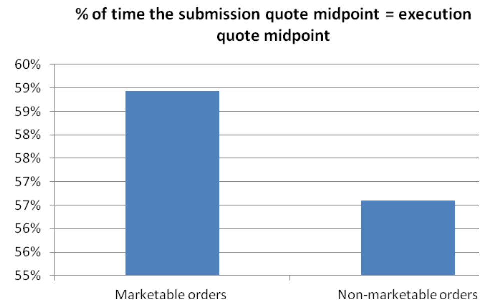
4.1 How Accurate Is Market Center Trading Cost Measurement?

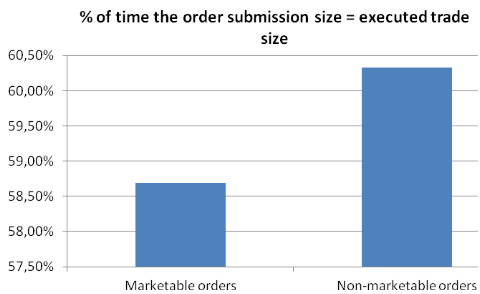
In *Figure 1*, we report how often order size equals the trade execution size reported on transaction-level data and how often the quote midpoint at the time of an order submission decision equals the quote midpoint at the time of trade execution. Results are reported for both marketable and non-marketable orders. Marketable orders are market orders and marketable limit orders with a buy (sell) limit price set greater (less) than or equal to the national best offer (bid). Non-marketable orders are limit orders with a buy (sell) price set lower (higher) than the national best offer (bid) and are not immediately executable. Our focus is on marketable orders as these orders pay the bid-ask spread and are more accurate (common) for estimating trading costs. However, non-marketable orders are of interest. Although non-marketable orders (partially) avoid the spread, they are susceptible to other trading costs such as

[6] Nasdaq stocks trade in multiple trading venues with automated execution. The primary benefit of using a DMA broker is the ability to access liquidity quickly and directly across the multiple electronic markets. By contrast, NYSE-listed trading is mainly confined (approximately 80%) to a single physical trading floor location during the sample period. Trading is much slower (often manual) on the NYSE trading floor than on Nasdaq trading venues, and automated trading is heavily restricted. Consequently, most order executions through DMA brokers occur on Nasdaq-listed stocks.

Figure 1 How Accurate Is Market Center Trading Cost Measurement?

The figures present: 1. the percentage of time the quote midpoint at the time of an order submission decision equals the quote midpoint at the time of trade execution, and 2. the percentage of time the order submission size equals the executed trade size. Marketable orders are market orders and marketable limit orders with a buy (sell) limit price set greater (less) than or equal to the national best offer (bid). Non-marketable orders are limit orders with a buy (sell) price set lower (higher) than the national best offer (bid) and are not immediately executable.





adverse selection costs and (partial) non-execution. In order to estimate adverse selection cost, researchers often compare the quote midpoint or trade execution price with a post-trade price (e.g., 5 minutes in the future). As with marketable orders, measuring from the time of order submission decision rather than from the time of trade execution may be a better approach. Thus, examining the extent of quote midpoint movement from the time of order submission decision to (last) trade execution and the extent to which order size equals trade size with non-marketable orders is also of interest.

For marketable (non-marketable) orders, the quote midpoint at the time an investor submits an order equals the quote midpoint at the time of trade execution approximately 59% (57%) of the time. The original submitted marketable (non-marketable) order size also equals the trade execution size printed on transaction data approximately 59% (61%) of the time. These results highlight the large difference that exists between measuring trading costs at the order level versus the trade level.

4.2 Are Quote Midpoint Changes Economically Important?

Given that the quote midpoint (order size) frequently changes from the time of order submission to that of execution, a natural question arises: what are the economic implications of this occurrence? To provide some insight for answering this

Table 1 Effective Spread Differences at the Order Level vs. Trade Level

This table presents marketable order effective spread measures involving quote midpoints at the time of order submission and at the time of trade execution. For buy orders, the effective spread is calculated as twice the difference between the share-weighted execution price and the quote midpoint at order submission (trade execution). For sell orders, the effective spread is calculated as twice the difference between the quote midpoint at order submission (trade execution) and the share-weighted execution price. The average effective spread across orders is reported. The average dollar trading cost is computed by multiplying the effective spread by the number of shares per order and then averaged across orders. The total dollar trading cost is computed by multiplying the effective spread by the number of shares per order and then adding the sum across orders. The [*] indicates significantly different from zero at the 1% level.

	Midpoint quote = = order submission	Midpoint quote = = trade execution	Difference
Average effective spread			
Buy orders	$0.082	$0.053	$0.029*
Sell orders	$0.088	$0.058	$0.030*
All orders	$0.085	$0.055	$0.030*
Average dollar trading cost			
Buy orders	$50.44	$32.68	$17.76*
Sell orders	$51.88	$34.99	$16.89*
All orders	$51.09	$33.72	$17.37*
Total dollar trading cost			
Buy orders	$71,805,674.15	$46,506,998.84	$25,298,675.31
Sell orders	$60,512,267.97	$40,786,320.63	$19,725,947.34
All orders	$132,317,942.12	$87,293,319.47	$45,024,622.25

question, we focus on the effective spread. The effective spread is a commonly reported trading cost measure that is intended to depict the round-trip cost of transacting. We calculate the effective spread at both the trade level and the order level and compare the dollar cost difference between these methods. At the trade level, the effective spread is calculated for marketable buy (sell) orders as twice the difference between the share-weighted execution price (quote midpoint) and the quote midpoint (share-weighted execution price) at the time of trade execution. At the order level, the quote midpoint at the time of order submission is used instead of the quote midpoint at trade execution. The results are reported in *Table 1*.

The average effective spread is $0.085 with the quote midpoint at order submission and $0.055 with the quote midpoint at trade execution. The average round-trip dollar trading cost (effective spread multiplied by the number of shares per order and averaged across orders) is $33.72 with the quote midpoint at trade execution and $51.09 with the quote midpoint at order submission. Both the average effective spread and round-trip dollar trading cost differences are significantly different from zero at the 1% level. The total round-trip dollar trading cost (the effective spread multiplied by the number of shares per order and summed across orders) is $87 million with the quote midpoint at trade execution and $132 million with the quote midpoint at order submission. Overall, on the 2.6 million marketable orders and 4.4 billion shares, the quote midpoint at trade execution understates the round-trip cost of transacting by more than $45 million.

Why is the effective spread, on average, less at execution than at submission? When measured at the order submission decision, higher transaction costs could arise because of persistent order flow patterns. For example, it is well known that, in securities markets, buy orders tend to be followed by buy orders, and sell orders tend to be followed by sell orders (see, for example, Ellul et al., 2007; Biais et al., 1995). Persistent order flow patterns can result in liquidity imbalances, based on supply and demand, thereby leading to worsening prices from order submission to execution. Overall, the adverse price movement we observe from order submission to execution at the trader level corresponds to prior research, which documents adverse price movement from order arrival to execution at the exchange level (see, for example, Bessembinder, 2003a; Peterson and Sirri, 2003; Werner, 2003).

4.3 When Is Market Center Trading Cost Measurement More Accurate?

The difference in trading costs which we observe arises from the delay in time between an order submission decision and trade execution. Although continual advances in trading technology are leading to faster execution, market participants will never be able to execute their orders instantaneously or without delay. Thus, measuring trading costs at the time of execution will never be 100% accurate. There are various factors which may cause the quote midpoint to change from an order submission decision to trade execution and/or for submitted order size not to equal trade execution size. For example, if the market is less liquid at order submission time, the quote midpoint may be more likely to change, thereby leading to trading cost measurement error. Trading cost measurement error might also predictably vary across different order characteristics, stock characteristics, etc. In this section, we examine when market center data sources are likely to be more accurate for measuring trading costs. Understanding this issue is useful for interpreting trading cost studies.

We estimate two separate probit regression models for both marketable and non-marketable orders. For the quote midpoint regression, the dependent variable is equal to one or, otherwise, zero, when the quote midpoint at the time of an order submission decision equals the quote midpoint at the time of trade execution. For the order size regression, the dependent variable is equal to one or, otherwise, zero, when order submission size equals executed trade size. We select various factors that may affect trading cost measurement accuracy, including three market liquidity proxies, two order characteristic variables, a decimal pricing dummy, a limit order aggressiveness variable, and three stock characteristic variables. The independent variables are: the quoted national best bid and offer percentage spread (100*[ask price – bid price]/midpoint price) at the time an investor submits an order; the log quoted depth at the time an investor submits an order, which for buy (sell) orders is the log number of shares quoted at the national best offer (bid); the log total trading volume on the stock within the half-hour interval when an investor submits an order; the log order size (shares); an order direction dummy variable that takes the value of one or, otherwise, zero, if the order is a buy; a dummy variable that takes the value of one or, otherwise, zero, if the order is executed in the decimal pricing environment;[7] limit order aggressiveness, which is computed for buy orders by subtracting the quote midpoint at the time an investor submits an order from the limit price, and for sell orders by subtracting the limit price from the quote midpoint; the prior year-end log

[7] The change to decimal pricing had a dramatic impact on market conditions (see Bessembinder, 2003b).

Table 2 When Is Market Center Trading Cost Measurement More Accurate?

The results indicate when market center data are more likely to depict trading costs accurately. For both marketable orders and non-marketable orders, two separate probit regression models are estimated. For the quote midpoint regression, the dependent variable is equal to one or, otherwise, zero, when the quote midpoint at the time of an order submission decision equals the quote midpoint at the time of trade execution. For the order size regression, the dependent variable is equal to one or, otherwise, zero, when the order submission size equals the executed trade size. Independent variables include three market liquidity proxies, two order characteristics, a decimal pricing dummy, a limit order aggressiveness variable, and three stock characteristics. *P*-values are reported below coefficient estimates in parentheses.

	Marketable orders		Non-marketable orders	
	Quote midpoint	**Order size**	**Quote midpoint**	**Order size**
Intercept	-0.4736 (<.0001)	-0.0299 (<.0001)	0.0460 (<.0001)	0.4460 (<.0001)
Quoted spread	-0.0389 (<.0001)	-0.0073 (<.0001)	-0.0292 (<.0001)	0.0106 (<.0001)
Log quoted depth	0.1610 (<.0001)	0.0281 (<.0001)	0.1386 (<.0001)	0.0607 (<.0001)
Log half-hour volume	0.0061 (<.0001)	0.0102 (<.0001)	0.0018 (<.0001)	0.0072 (<.0001)
Log order size	0.0242 (.0001)	0.0309 (<.0001)	-0.0038 (<.0001)	-0.0853 (<.0001)
Buy order dummy	0.0148 (<.0001)	0.0548 (<.0001)	-0.0199 (<.0001)	0.0125 (<.0001)
Decimal pricing dummy	0.0478 (<.0001)	-0.1903 (<.0001)	-0.3858 (<.0001)	0.2104 (<.0001)
Limit order aggressiveness			3.1198 (<.0001)	-0.2231 (<.0001)
Log market capitalization	0.0045 (<.0001)	-0.0021 (<.0001)	-0.0006 (<.0001)	-0.0014 (<.0001)
Turnover ratio	-2.7493 (<.0001)	-1.8360 (<.0001)	0.2057 (<.0001)	-0.1232 (0.0012)
1/Price	-0.0862 (<.0001)	-0.0252 (<.0001)	-0.0312 (<.0001)	-0.0348 (<.0001)
Log likelihood	-1668385	-1744592	-2188910	-2295946
Number of observations	2589936	2589936	3458086	3458086

market capitalization of the stock; the prior year average daily turnover (volume/ /shares outstanding) of the stock; and the prior year-end price of the stock.[8]

The probit results are reported in *Table 2.*[9] The coefficients reveal how various factors affect trading cost measurement accuracy with transaction-level data. The results indicate that, when the market is more liquid, trading cost measurement error is less likely to occur. For example, consider the quote midpoint marketable

[8] See Harris (2003) for a more in-depth discussion of these and other variables involved in the trading process.

[9] We also investigate determinants of the (dollar) change in the quote midpoint from order submission to execution. For this, we estimate an ordinary least squares regression and a tobit regression for (non)marketable orders. In both estimations, the dependent variable for buy (sell) orders is the quote midpoint at execution (submission) minus the quote midpoint at submission (execution). The independent variables are the same as the probit regression. With regard to the liquidity proxy variables, the quoted spread (depth) variable is consistently negative (positive) across regressions, indicating that, when the quoted spread (depth) widens (declines), the quote midpoint change becomes smaller. The half-hour volume results are mixed across regressions. More information on these results can be obtained by contacting the authors.

order regression: the quoted spread coefficient is negative, the quoted depth coefficient is positive, and the overall trading activity coefficient is positive. All three coefficients are highly significant. Thus, when the quoted spread is smaller, the quoted depth is greater, and the overall trading activity in the market is higher, the quote midpoint at the time of investor order submission decision is more likely to equal the quote midpoint at the time of trade execution, maintaining all other variables constant. The results indicate a similar occurrence with order size regression. For example, the quoted spread coefficient is negative, the quoted depth coefficient is positive, and the trading activity coefficient is positive. All three coefficients are statistically significant at the 1% level. Thus, when the market is more liquid, order size is more likely to equal trade size.

In addition to the liquidity proxy variables, other factors are highly correlated with trading cost measurement error. For example, consider the quote midpoint marketable order regression. The buy order dummy, decimal pricing dummy, and market capitalization coefficients (to name a few) are all positive and highly significant. The positive buy order dummy coefficient may result from the overall trend in the market. For example, when a pre-trade benchmark measure of transaction costs is used (e.g., the midpoint quote at order submission), buy orders will experience higher trading costs during bullish markets and sell orders will experience higher trading costs during bearish markets (see Hu, 2009). Given the overall downward market trend during our sample period, we would, on average, expect more (less) liquidity in the market when a trader submits a buy (sell) order. Thus, for buy orders the quote midpoint at order submission is more likely to equal the quote midpoint at trade execution. The positive decimal pricing dummy coefficient may result from changes in execution speed over time. For example, it is well known that, during our sample period, continual advances in technology enabled market participants to execute their orders more quickly (especially for those who use sophisticated DMA trading software). If traders are able to execute their orders more quickly, they will be less prone to price movement from order submission to execution. Finally, the positive market capitalization coefficient may result from differences in liquidity across stocks. For example, the market for larger (smaller) capitalization stocks tends to be more (less) liquid and, thus, when traders transact on these stocks, they will be less (more) prone to price movement from order submission to execution.

Because multiple stocks are included in our analysis, the data are not homoscedastic. Problems arising from heteroscedasticity can weaken the validity of the results. In order to control for the unique characteristics of individual stocks, we introduced three (continuous) stock characteristic controls into the probit regressions. For robustness, we re-examine the results by means of two alternative approaches (instead of the three right-hand side continuous stock characteristic control variables). First, we narrow our sample to trading occurring on the 200 most actively traded stocks. Approximately 86% of orders are executed on these stocks. Then, separate dummies (200) for individual stocks are used in probit regressions. In addition, we estimate probit regressions separately for each individual stock and then test whether the average coefficients across individual stock regressions are significantly different from zero. The results are reported in *Table 3*. The two alternative approaches show little change in sign and significance among the variables. Overall, the results continue to indicate that, when the market is more liquid: 1. the quote

Table 3 Robustness Results

This table reports probit regressions by means of two alternative methods to control for individual stock characteristics. The sample is narrowed down to the 200 most actively traded stocks, which account for 86% of orders. Panel A reports probit regression results with dummies for individual stocks. *P*-values are reported below the coefficient estimates in parentheses. Panel B reports the results of running the probit regressions on an individual stock basis and then averaging the coefficients across the individual probit regressions. *P*-values, which are reported below the coefficient estimates, indicate whether the average coefficient across the individual regressions is significant from zero.

Panel A Probit Regressions with Stock Dummies

	Marketable orders		Non-marketable orders	
	Quote midpoint	Order size	Quote midpoint	Order size
Intercept	-0.1377 (<.0001)	0.3579 (<.0001)	0.3713 (<.0001)	0.4710 (<.0001)
Quoted spread	-0.0080 (<.0001)	-0.0103 (<.0001)	-0.0119 (<.0001)	0.0269 (<.0001)
Log quoted depth	0.1182 (<.0001)	0.0098 (<.0001)	0.0792 (<.0001)	0.0515 (<.0001)
Log half-hour volume	0.0072 (<.0001)	0.0056 (<.0001)	0.0011 (<.0001)	0.0033 (<.0001)
Log order size	-0.0120 (<.0001)	0.0066 (<.0001)	-0.0198 (<.0001)	-0.0944 (<.0001)
Buy order dummy	0.0136 (<.0001)	0.0620 (<.0001)	-0.0111 (<.0001)	0.0090 (<.0001)
Decimal pricing dummy	0.0706 (<.0001)	-0.1575 (<.0001)	-0.4152 (<.0001)	0.1843 (<.0001)
Limit order aggressiveness			3.6148 (<.0001)	-0.2876 (<.0001)
Log likelihood	-1310030	-1403235	-1895861	-2012884
Number of observations	2123321	2123321	3065937	3065937

Panel B Stock by stock probit regressions

	Marketable orders		Non-marketable orders	
	Quote midpoint	Order size	Quote midpoint	Order size
Intercept	-0.3957 (<.0001)	-0.0243 (0.7381)	0.4307 (0.0001)	0.8329 (<.0001)
Quoted spread	-0.3754 (<.0001)	-0.1191 (<.0001)	-0.5332 (<.0001)	0.0369 (0.0158)
Log quoted depth	0.2122 (<.0001)	0.1141 (<.0001)	0.1181 (<.0001)	0.0351 (<.0001)
Log half-hour volume	0.0016 (0.2110)	0.0038 (0.0288)	-0.0107 (0.0096)	0.0031 (0.0032)
Log order size	-0.0011 (0.8275)	-0.0004 (0.9747)	-0.0405 (<.0001)	-0.1300 (<.0001)
Buy order dummy	0.0071 (0.3708)	0.0191 (0.0225)	-0.0425 (0.0003)	0.0288 (0.0001)
Decimal pricing dummy	0.1099 (0.0002)	-0.2364 (<.0001)	-0.4110 (0.0002)	0.0702 (0.4310)
Limit order aggressiveness			-0.8066 (<.0001)	-0.7504 (<.0001)

midpoint at order submission is more likely to equal the quote midpoint at trade execution, and 2. order size is more likely to equal trade size.

5. Conclusion

Investors assess the cost of trading in securities markets when they submit an order for execution. However, trading costs are often measured according to the time when a trade execution occurs or according to the time when an (partial) order arrives at an exchange for execution. Thus, the discrepancy between how trading costs should be measured and how they are actually measured raises some important issues related to the reliability of publicly reported trading cost measures derived from market center data sources. In our paper, we obtain proprietary data from a U.S. broker-dealer and examine the relative accuracy of measuring trading costs at trade execution rather than at order submission. We also analyze whether or not the difference is economically important and when differences are more likely to arise.

Two of the major problems with estimating trading costs from market center data sources are that 1. trade executions (prints) are not always representative of investor submitted order size, and 2. the quote midpoint at the time of trade execution (or arrival at the exchange) is not always representative of the quote midpoint at the time an investor submits an order. The quote midpoint is used as a benchmark price to compute common trading cost measures such as the effective spread. Our analysis demonstrates that the quote midpoint at order submission often differs from the quote midpoint at trade execution. Furthermore, order size often differs from trade execution size. For example, we find that both the quote midpoint and order size at submission differ from that at execution approximately 40% of the time. The differences have important implications for those trying to assess (measure) the true cost of trading in securities markets. In our sample data alone, the effective spread or round-trip cost of trading on 2.6 million marketable orders is understated by more than $45 million. Investors should expect publicly reported measures of trading costs (derived from market center data sources) to be less reliable during times when the market is less liquid. For example, we find that trading cost measurement error is greater when the quoted spread is wider, the quoted depth is smaller, and the overall trading activity in the market is lower.

One potential way the government could lead the way and provide a more accurate depiction of the cost of trading in U.S. securities markets is to exercise its right (more often) under SEC Rule 17a-25, which requires brokers and dealers to submit electronically to the Commission, upon request, information about customer and firm securities trading.[10] Such data could then be used regularly to compute trading costs (anonymously) on the basis of market participant order submission decisions. It would be interesting to compare these trading cost statistics at the order level with those at the trade level, which the government currently requires market centers to report under SEC Rule 605 (e.g., average effective and realized spread measures). While our study provides some initial insight into the extent to which differences exist between measuring trading costs at the order level rather than at the trade level, our results are limited to trading activity flowing though one

[10] See http://www.sec.gov/rules/final/34-44494.htm. Soliciting such information is typically referred to as "blue sheet" requests. For several decades, the SEC requested this information by mailing questionnaire forms (known as "blue sheets" because of the color of the paper used to print these forms) to broker-dealers to be manually completed and returned to the Commission.

brokerage firm. An ongoing and more comprehensive analysis of trading cost measurement at the order level, across brokerage firms, would be valuable for understanding the true cost of market-wide trading better.

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