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1-share orders and trades

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ABSTRACT

1-share trades are the most common odd lot trade size, accounting for 9.62% of all odd lot transactions and 3.65% of all trades on NASDAQ in 2012. While 50.41% of 1-share trades result from broken orders, 34.89% of 1-share trades are intentional. We provide substantial evidence that traders use 1-share trades to "ping" for hidden liquidity. In particular, our results indicate that 1-share trades are disproportionately aggressive and also execute against hidden liquidity more than any other odd lot trade size. We also find a relative increase in trading immediately following a 1-share trade. Our results are in line with Clark-Joseph (2014), who suggests that traders may use small, unprofitable trades to detect information from other traders. Specifically, 1-share trades represent the minimum cash outlay necessary to trade, while simultaneously producing the smallest possible effects on a market maker's inventory, and in turn, a security's price.

1. Introduction

1-share trades are the most commonly observed odd lot trade size, accounting for 9.62% of all odd lot transactions and 3.65% of all trades on NASDAQ in 2012. Because odd lots now constitute a significant portion of trading activity (O'Hara et al., 2014),[1] the disproportionate number of 1-share trades observed does not appear to be trivial. Theory suggests that traders may use small trades to hide information and reduce the market impact of their transactions (Admati and Pfeiderer, 1988). However, the persistence of odd lot trades after December 9, 2013 (SEC, 2014), the date on which odd lot trades were first reported to the consolidated tape, suggests that some traders may use small trades for reasons that extend beyond concealing information. Clark-Joseph (2014), for example, suggests that traders may use small trades to detect information from other traders, and provides a model in which high frequency traders place small exploratory orders and observe the resulting changes in market depth. While exploratory orders are unprofitable, the information gathered from such a strategy allows market participants to know when to trade ahead of other orders. 1-share trades are likely to be unprofitable, and are, perhaps, exploratory in nature. Specifically, 1-share trades represent the minimum cash outlay necessary to trade, while simultaneously producing the smallest possible effects on a market maker's inventory, and in turn, a security's price.[2]

Our purpose is to explain the disproportionate number of 1-share transactions. While it may not be surprising to see trades of only 1 share as an investments primer or simply a way to own a small portion of a company, the prevalence of 1-share transactions is unexpected. In this paper, we explore and empirically test three main hypotheses that may explain the large proportions of 1-share trades observed in the data. Specifically, we determine if 1-share trades are (i) intentionally placed or the result of broken orders, (ii) likely to be exploratory trades, or (iii) used by stealth traders to avoid the reporting requirements to the consolidated tape.

Because trade sizes may not reflect the size of incoming market orders or resting limit orders, 1-share trades may simply be the result of broken orders. Based on resting liquidity and the size of incoming market orders, 1-share trades may be a mechanical

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[1] There is a growing literature of odd lot studies. Early researchers use odd lot trading as a proxy for individual trading (see, for instance, Wu, 1972; Ritter, 1988; Dyl and Maberly, 1992; and Lakonishok and Maberly, 1990). More recently, O'Hara, Yao, and Ye (2014) show that odd lot trading is increasing over time. In their sample of 120 stocks with transactions on NASDAQ, O'Hara, Yao, and Ye show that odd lot transactions increase from 14% of trades in January 2008 to 22% in December 2009, while Johnson (2014), with a larger cross section of stocks, shows that odd lot transactions increase from 2005 (16% of trades) to 2012 (approximately 30% of trades).

[2] Easley and O'Hara (1987) investigate the effects of trade sizes on prices and conclude that larger trades are made at less favorable prices due to inventory imbalance.

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consequence of the limit order book queue. For example, if a market order for 99 shares executes against a resting limit order for 100 shares, then 1 share will remain available. A subsequent order for 100 shares will produce a 1-share trade and leave 99 shares available for the next order in the queue. The 1-share trade in this example is not the result of an order for 1 share, but instead the result of a broken order.

Anecdotally, O' Hara, Yao, and Ye report that 60% of 1-share trades are initiated by high-frequency traders. This result is in line with recent literature suggesting that high frequency traders routinely use small trades to hide their information (Hendershott et al., 2011; Hendershott and Riordan, 2013; O'Hara et al., 2014). Additionally, Clark-Joseph (2014) suggests that high frequency traders may place small exploratory trades to detect information. 1-share trades may, thus, be a result of a trader "pinging" a market center, perhaps as part of a liquidity detection strategy. A trader might submit either an aggressive 1-share limit order inside the best displayed bid and ask quote, or a 1-share market order, in order to detect hidden liquidity. A 1-share order that executes would alert a trader that newly discovered liquidity is available at a specific price. Regardless of technique, 1-share trades are likely not used to fill a large position, but rather to learn about market conditions.

During our sample period, odd lot trades are not reported to the consolidated tape. We indirectly test O'Hara et al. (2014) proposition that 1-share trades may be the result of traders breaking up orders to avoid the reporting requirements of trades of 100 shares or more. For example, a trader may break a 100-share order into two orders, one for 1 share and another for 99 shares. Unlike a 100-share trade, a 1-share trade and a 99-share trade will not be reported to the consolidated tape. Support for this hypothesis would suggest that 1-share trades are part of a stealth trading strategy designed to reduce the potential information that can be gleaned from the consolidated tape feed.

Using order-level data provided by NASDAQ, we find that half of all 1-share transactions originate from orders for more than 1 share, while approximately 35% of 1-share trades are intentional (i.e. result from a 1-share liquidity-supplying order).[3] Additionally, we find that almost 25% of 1-share market orders are intentional, that is, the liquidity demanding order is submitted as a 1-share order. We also find that 1-share trades are influenced by firm characteristics. Specifically, 1-share trades fluctuate directly with price and inversely with number of trades, volatility, and firm size. We provide substantial evidence that 1-share trades are used to "ping" hidden liquidity. In particular, our results indicate that 1-share trades are disproportionately aggressive and also execute against hidden liquidity more than any other odd lot trade size. We also find a relative increase in trading immediately after a 1-share trade. We do not find overwhelming evidence that traders split 100-share orders into two trades (one for 1 share and one for 99 shares) in order to avoid reporting the trade to the consolidated tape. In fact, we find that proportions of 1-share trades and 99-share trades increase after odd lot trades are reported to the consolidated tape. In total, our results suggest that while half of 1-share trades are a result of broken orders, many intentional 1-share trades are likely exploratory trades, consistent with theory provided by Clark-Joseph (2014).

2. Data & sample

Our primary data source in this study is the NASDAQ TotalView-ITCH. NASDAQ TotalView-ITCH provides order level data—orders added, removed, and executed on NASDAQ. We examine all firms in ITCH on all trading days during the second half of 2012 (July 2nd through December 31st). We require that each stock close above $5, trade at least five times a day, and have a minimum volume of 1000 shares every trading day in the sample.[4] We also examine 1-share trades in the month surrounding December 9th, 2013, using data from NASDAQ TotalView-ITCH.[5] We obtain shares outstanding and closing share prices for each stock from CRSP in order to calculate market capitalization. This market capitalization measure is the average of a firm's size on the first and last trading day of the sample period. Last, we use NYSE's Trade and Quote (TAQ) data to determine a firm's average daily spread as well as the average number of shares available at the top of the limit order book.

Descriptive statistics for the sample, consisting of 2901 stocks, are shown in Table 1. The average firm in our sample has a share price of $35.90 and a market capitalization of $6.6 billion. Securities trade almost 1800 times per day. When considering averages by firm, 1-share trades comprise 3.65% of these transactions. However, 1-share trades tend to be more heavily concentrated in certain securities, as evidenced by a median daily number of 1-share trades (7.71) which is smaller than the mean number of 1-share transactions (18.65). Additionally, some firms have almost 1300 1-share trades in a single trading day.

Fig. 1 provides the relative frequencies of all odd lot transactions in the latter half of 2012. 1-share trades are the most common odd lot trade size, accounting for 9.62% of all odd lot transactions. Given the range of all possible order sizes available, along with the array of potential execution sizes, these results are surprising. O'Hara et al. (2014) find that 1-share trades are the second (third) most common odd lot trade size class in 2008–2009 (2010–2011). Similar to that documented by O' Hara, Yao, and Ye, our results show that trade sizes cluster on multiples of 10 s and 25 s. However, in sharp contrast to their results, we find that 1-share trades are at the top of the odd lot hierarchy.

Table 1
Summary Statistics.

	Mean	Median	Std. Dev.	Min	Max
Price	35.90	26.23	41.22	5.54	861.63
Trades	1789	634	3399	3	95,992
Volume	475,430	110,067	1827,415	757	66,461,886
Volatility (%)	17.84	11.68	28.04	0.00	2626.39
#1Trades	18.65	7.71	40.31	0.08	1344.46
%1Trades	3.65%	1.11%	9.91%	0.01%	58.24%
#1Orders	65.21	15.26	208.93	0.00	5241.58
%1Orders	0.38%	0.07%	1.87%	0.00%	48.70%
MktCap (000 s)	6633,411	1529,547	22,321,059	4429	572,021,587
# of Firms	2901	2901	2901	2901	2901

Table 1 provides summary statistics for firms in our study. All variables, with the exception of firm size, are recorded by firm by day. The sample includes data for all firms in the NASDAQ TotalView-ITCH database from July 2012 to December 2012. Firms with stock prices that close below $5, trade less than five times a day, and have less than 1000 shares of daily trading volume are filtered from the sample. The summary statistics below are for trades on NASDAQ. *Price* is the daily closing price. *Trades* is the number of trades. *Volume* is the number of shares traded. *Volatility* is the standard deviation of daily trade prices. *#1Trades* is the number of 1-share trades. *%1Trades* is the number of 1-share trades divided by total number of trades for the day. *#1Orders* is the number of 1-share orders. *%1Orders* is the number of 1-share orders divided by total orders for the stock day. *MktCap* is a firm's market capitalization (in 000 s) which is a firm's price multiplied by shares outstanding.

[3] The remaining 15% of 1-share trades are executions against hidden-liquidity and cannot be definitively classified as intentional or broken.

[4] These filters are applied to aggregate numbers from all exchanges reported in CRSP, not trades executing only on NASDAQ. The summary statistics provided in Table 1 are for trades on NASDAQ.

[5] Prior to December 9, 2013 odd lot transactions were not reported to the consolidated tape.

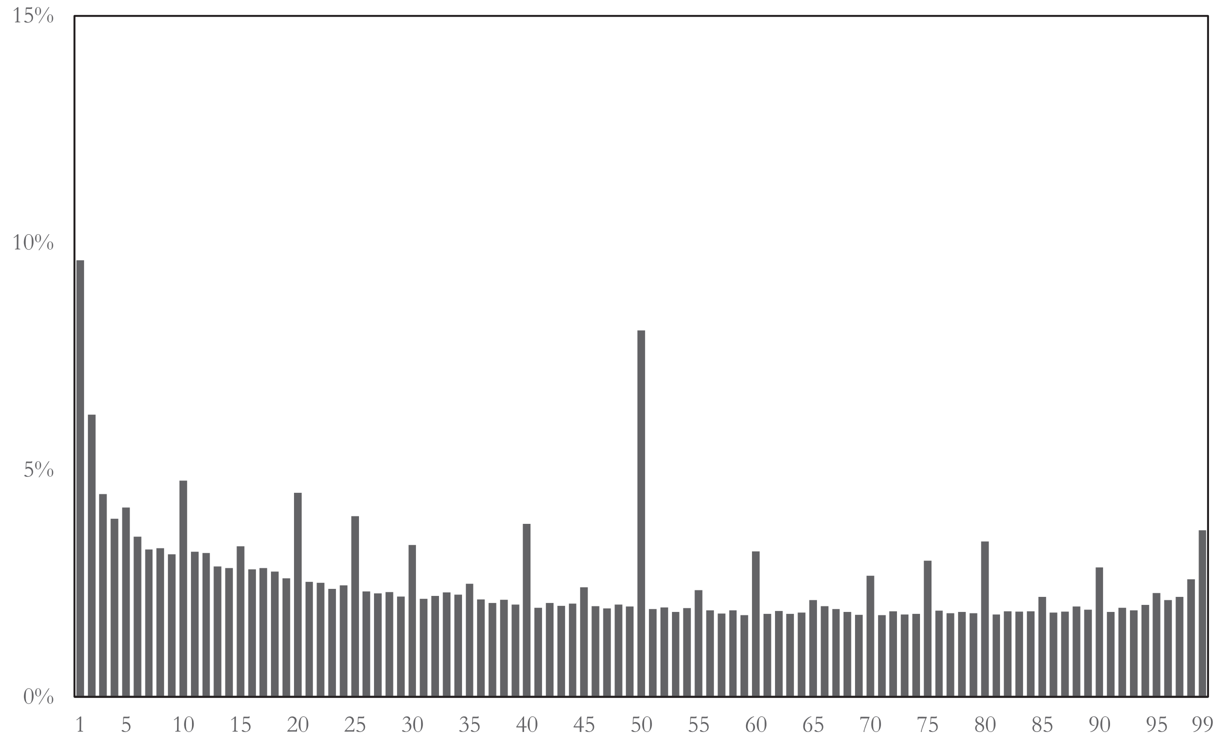

Fig. 1. Relative frequencies of odd lot trades from July 2012 through December 2012.

3. 1-Share relations

As a precursor to our results in the next section, we first introduce factors that affect a trader's decision to place an order for a single share of stock. By construction, liquidity providers and liquidity demanders have different trading preferences. Because of these differences, we also consider the effect of stock and firm characteristics on 1-share limit orders and 1-share market orders. In particular, we examine the relation between common microstructure trading determinants, namely, price, number of trades, volatility, and firm size, on the ratio of 1-share trades to total trades. We also include the bid-ask spread as well as market depth at the time of the trade. Since NYSE-listed securities can trade on NASDAQ, we include a NYSE/NASDAQ dummy to determine if any listing-exchange differences exist. The results of our OLS regression estimations are presented in Table 2, with test statistics reported using robust standard errors clustered by firm and time. We report the results specific to 1-share trades in the first column of Table 2. The estimated coefficients indicate that the use of 1-share trades increases with stock price and decreases with trades, volatility, and firm size. While higher priced stocks have more 1-share trades, traders frequently use 1-share trades in stocks with smaller market capitalizations. Traders may use 1-share trades in inactive stocks as well, as indicated by the negative coefficient of *Trades*. Securities with greater daily price volatility have fewer 1-share trades. Last, 1-share trades are used more frequently when bid-ask spreads are tighter, yet have no relation to *Depth*.

We next consider 1-share orders as 1-share transactions may be 1-share trades executing from larger orders. We relate the same stock characteristics to 1-share orders. Because not all orders execute, we show results for all 1-share orders (1-share orders that execute) in the second (third) column of Table 2. The dependent variable used in the second (third) column is the ratio of 1-share orders (1-share orders that execute) to total orders (total orders that execute), by firm, by day. The estimated coefficients in the regression containing all 1-share limit orders are similar to those reported for 1-share trades in the first column, with three exceptions. First, we find no relation between 1-share limit orders and *Trades*. Second, 1-share limit orders are unrelated to the bid-ask spread. Unlike all 1-share trades, 1-share limit orders are not necessarily placed in stocks with tighter spreads. Third, while we find a positive coefficient on the NASDAQ dummy variable when considering all 1-share trades, the coefficient of the NASDAQ indicator variable is negative when considering 1-share limit orders. The disparate coefficients between these regressions suggest that there are differences in 1-share limit orders between exchanges, particularly that NASDAQ-listed stocks have fewer 1-share orders on the NASDAQ exchange than do NYSE stocks that trade on NASDAQ. The results surrounding 1-share limit orders that execute, reported in column 3 of Table 2, are similar to the results reported for all 1-share trades in the first column.

As previously discussed, NASDAQ TotalView-ITCH provides order level data—orders added, removed, and executed on NASDAQ. Each liquidity-supplying order is assigned a unique order reference number. If multiple trades execute against a resting liquidity-supplying order, then all trades will have the same order reference number. We are thus unable to view market orders in the ITCH data. However, using the method of Johnson et al. (2015), we estimate market orders by summing all trades in the same stock at the same price with identical timestamps. This method of extracting market order sizes is highly accurate.[6] If there is an order for only 1 share in a particular stock at a unique timestamp, we assume that a trader placed a market order for only 1 share. The Johnson, McInish, and Upson method provides a lower bound and most likely underestimates the number of 1-share market orders. In the last column in Table 2, we use the estimated number of 1-share market orders expressed as a proportion of all market orders

[6] Johnson, McInish, and Upson (2015) find that the probability of two independent, marketable orders reaching the exchange at the same nanosecond is 2.05×10^{-21}.

Table 2
Characteristics of 1-share orders and trades.

	(1) 1-Share trades	(2) All 1-share limit orders	(3) 1-share limit orders that execute	(4) 1-share market orders
Intercept	0.0909***	0.0147***	0.0170***	0.0714***
	(16.336)	(3.882)	(4.212)	(18.743)
Price	0.0145***	0.0030***	0.0069***	0.0110***
	(10.326)	(3.256)	(5.547)	(11.044)
Trades	−0.0192***	−0.0014	−0.0068***	−0.0162***
	(−3.753)	(−1.132)	(−4.483)	(−3.210)
Volatility	−0.0017**	−0.0010***	−0.0018***	−0.0021***
	(−2.152)	(−2.851)	(−3.717)	(−3.005)
Spread	−0.0000***	−0.0000	−0.0000***	−0.0000***
	(−4.566)	(−0.924)	(−2.852)	(−3.391)
Depth	0.0000	0.0000	−0.0000	0.0000
	(0.478)	(0.964)	(−0.052)	(1.007)
Mkt Cap	−0.0086***	−0.0015***	−0.0024***	−0.0064***
	(−14.807)	(−3.636)	(−4.896)	(−16.242)
NASDAQ	0.0043***	−0.0017***	0.0015**	0.0001
	(4.894)	(−2.846)	(2.179)	(0.237)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	228,175	213,990	259,579	259,579
N	2285	2285	2285	2285
Adj. R^2	0.0889	0.0249	0.0276	0.0585

This table presents the characteristics of 1-share orders and trades. We regress stock and exchange characteristics against 1-share trades, 1-share limit orders, 1-share limit orders that execute, and 1-share marketable orders. In the first model the dependent variable is the number of 1-share trades expressed as a percentage of all trades. In the second model the dependent variable is the number of 1-share limit orders, expressed as a percentage of all limit orders. The dependent variable in the third model is the number of 1-share limit orders that execute, divided by the total number of limit orders that execute. In the fourth model, the dependent variable is the number of 1-share marketable orders, divided by the total number of marketable orders. We estimate market orders by summing all trades in the same stock at the same price in the same nanosecond. The sample comprises data from July 2012 through December 2012. The data comes from the NASDAQ TotalView-ITCH database and CRSP. All variables, with the exception of market capitalization, are recorded by firm by day. *Price* is the log of stock price. *Trades* is the number of trades divided by shares outstanding. *Volatility* is the standard deviation of daily trade prices. *Spread* is the daily average spread, and *Depth* is the average number of shares at the top of the limit order book. *MktCap* is the log of a firm's market capitalization (a firm's price multiplied by shares outstanding). *NASDAQ* is a dummy variable if a firm is listed on *NASDAQ*. All specifications include firm and day fixed effects.

*** represents test statistics, in parentheses, include robust standard errors clustered by firm and time, with significance at the 1 percent level.

** represents test statistics, in parentheses, include robust standard errors clustered by firm and time, with significance at the 5 percent level.

as the dependent variable. Again, we find that 1-share marketable orders are directly related to price and inversely related to trades, volatility, firm size, and spread. In total, our results indicate that 1-share trades respond similarly to stock and firm characteristics regardless of the original order type. However, we document differences in determinants between 1-share limit orders and 1-share trades. We attribute the differences between 1-share orders and 1-share trades to the fact that there is no cost associated with submitting a limit order (far) outside of the spread, whereas there is a cost of immediacy for executed orders.

4. Results

In this section, we explore three primary hypotheses that may explain the disproportionate number of 1-share transactions observed in the data. The broken order hypothesis states that 1-share trades may not be intentional, but instead a trivial byproduct of the intersection of a specific market order with a particular limit order. The exploratory trading hypothesis states that 1-share trades may be the result of a trader placing aggressive orders to "ping" a market for hidden liquidity. According to Clark-Joseph (2014), traders may place small, unprofitable trades in order to learn about market conditions, only to follow with larger, more profitable orders immediately after. Lastly, the stealth trading hypothesis states that 1-share trades may result from traders splitting round lot orders into two orders, one for 1 share and the other for 99 shares, for example, in order to avoid reporting the trade to the consolidated tape.

4.1. Are 1-share trades intentional?

In this section of our analysis, we determine if 1-share trades are intentional or the result of a broken order. Because a 1-share trade can result from a market order or limit order of any size, it is important to consider the order from which the trade originated. The Securities and Exchange Commission (SEC, 2014) describes broken 1-share trades as follows:

> In any analyses of the size of reported trade executions it is important to recognize that execution sizes for on-exchange trades do not necessarily reflect the actual size of an incoming marketable order, nor the original size of any existing resting order. For example, a marketable odd lot order for 1 share may interact with a resting order for 100 shares. This results in a 1-share odd lot execution reported to the public tape as expected. However, in this instance a subsequent marketable order for a full 100 shares would first lift the remaining 99 shares from the existing resting order and then lift 1 share for the next resting order in the queue. As such, the execution of this original round lot would be reported as one odd lot trade of 99 shares, and one odd lot trade for 1 share.

We begin this portion of our analysis by considering 1-share limit orders. In Panel A of Table 3, we report that 50.41% of 1-share trades originate from resting orders for more than 1 share, whereas 34.89% are intentional 1-share trades, which originate from liquidity supplying orders of 1 share. Almost 15% of 1-share trades execute against hidden liquidity. Since NASDAQ does not report the original order size of hidden liquidity-supplying orders, we are unable to classify these trades as either broken or intentional. The statistics in Panel A, alone, indicate that many 1-share trades are intentional.

We consider market orders in Panel B and find that almost 25% of these 1-share trades are intentional, resulting from a liquidity-demanding order for 1 share. The remaining 75.18% of 1-share trades are broken, resulting from a market order for more than 1 share. In total, the results in Table 3 suggest that the number and proportion of intentional 1-share trades are not inconsequential on either side of the trade (i.e. liquidity-supplying or liquidity-demanding). We conclude that 1-share trades are not simply a result of broken orders, but instead, are a deliberate trade-size choice used by investors.

4.2. Are 1-share orders pinging?

In this subsection we determine to what extent 1-share trades are used as exploratory trades, rather than trades designed to assume a position. In the exploratory trading model of Clark-Joseph (2014), high frequency traders place small exploratory orders and observe the market response to gain insights regarding current market conditions. In this context, 1-share trades are natural candidates to be exploratory trades because they represent the minimum cash outlay necessary to trade, while simultaneously producing the smallest possible effects on a market maker's inventory, and in turn, a security's price.

Many market microstructure studies examine intraday trading patterns. Intraday patterns are documented for returns, trading characteristics, and bid-ask spreads (Wood et al., 1985;

Table 3
Are 1-share trades intentional or the result of broken orders?

Panel A: Intentional 1-share Limit Orders	Observations	Percent
Total 1-share trades	6692,482	(100%)
1-share trades that result from intentional 1-share limit orders	2334,822	(34.89%)
1-share trades that result from broken 1-share limit orders	3373,477	(50.41%)
1-share limit orders that are hidden (may be broken or intentional)	984,183	(14.70%)
Avg. Size of order for broken 1-share trades	220.68	

Panel B: Intentional 1-share Marketable Orders	Observations	Percent
Total 1-share trades	6692,482	(100%)
1-share trades that result from intentional 1-share market order	1661,193	(24.82%)
1-share trades that result from broken 1-share market orders	5031,289	(75.18%)
Order size for broken 1-share market orders	467.23	

We explore whether 1-share trades are intentional or a result of broken orders. NASDAQ TotalView-ITCH data displays orders with a unique order number, number of shares available, and the price to trade. It is possible that multiple trades execute against one limit order, depending on the size of the limit order as well as the size of incoming marketable orders. Intentional 1-share trades may result from a 1-share limit order or a 1-share marketable order. Broken orders may originate from two non-1-share orders that are mismatched. In Panel A, we report 1-share trades resulting from limit-orders, whereas in Panel B we report 1-share trades resulting from marketable orders. Hidden orders do not display the size of the limit order, making it unknown whether hidden limit orders are intentional or broken. We estimate market orders by summing all trades in the same stock at the same price with identical timestamps.

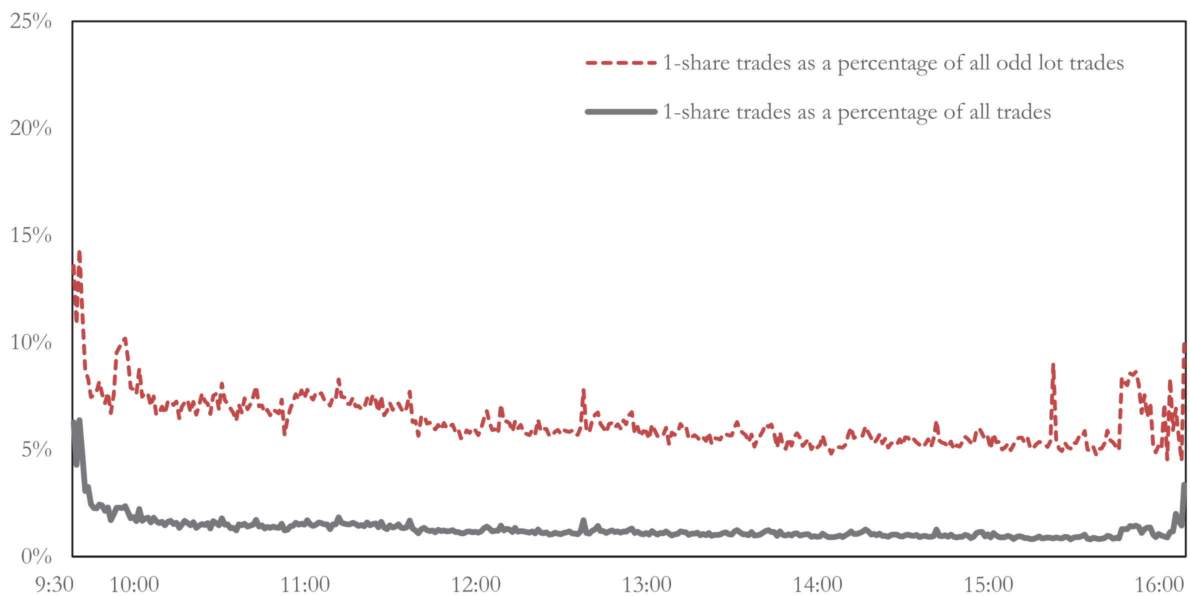

Fig. 2. Intentional 1-share trades by time of day. This figure presents the intraday pattern of intentional 1-share trades. An intentional 1-share trade results from liquidity-supplying order for 1 share. The dashed line represents the number of intentional 1-share trades as a proportion of all odd lot trades, whereas the solid line presents the number of intentional 1-share trades as a proportion of all trades.

Chung et al., 1999; Harris, 1986), price discovery (Barclay and Hendershott, 2003), and order type (Bloomfield et al., 2005; Ellul et al., 2007). Fig. 2 presents intraday patterns of intentional 1-share trades, i.e. 1-share trades that result from an order for 1 share. As a percentage of all trades and of all odd lot trades, 1-share trades are frequently observed at the beginning of the trading day. These results are interesting in light of studies showing informed traders are more active in the morning. In particular, Bloomfield et al. (2005) suggest that informed traders tend to demand liquidity at the beginning of the trading day, and Anand et al. (2005) find that informed traders' marketable orders are more aggressive during the morning hours of trading. Additionally, Garvey and Wu (2009) find that information asymmetry is highest, and trading more informative, around the open and close. The results in Fig. 2 are in line with informed traders placing aggressive 1-share orders at the beginning of the trading day.

The pinging hypothesis suggests that a large proportion of 1-share orders are placed aggressively, either as liquidity demanding marketable orders, or as price improving limit orders. A trader may intentionally place a non-aggressive limit order with a price inferior to the current best quotes. Alternatively, a trader may place an aggressive limit order that improves the current best quotes. To explore this idea further, we compare 1-share order aggressiveness to orders from different size classes: those between 2 to 9 shares, orders of 10 to 99 shares, those orders between 100 and 999 shares, and lastly, orders of 1000 or more shares. We classify order aggressiveness similar to Griffiths et al. (2000) and Johnson and Roseman (2016), where order aggressiveness is categorized according to the price of the order relative to the current best bid or offer. Marketable orders, which are liquidity demanding orders that execute immediately, are the most aggressive order class, followed by limit orders that improve the current national best bid or offer (NBBO). Less aggressive limit orders do not impact current prices, and are placed at the NBBO or behind the NBBO.

The results of our investigation are presented in Table 4. In contrast to the sample of 1-share *trades* used in Table 3, we consider all 1-share *orders* in Table 4.[7] Specifically, we consider order prices relative to the current NBBO. The results in Table 4 indicate that

[7] Because many 1-share limit orders do not execute, we are unable to provide meaningful comparisons between the percentages reported in Table 4 with those presented in Table 3.

Table 4
1-share trades as a search for hidden liquidity.

Order Size	Marketable	Improve NBBO	Match NBBO	Behind NBBO
1 share	43.39%***	7.14%***	23.34%***	26.14%***
2–9 share	32.64%	8.92%	25.62%	32.83%
10–99 shares	16.54%	13.67%	20.84%	48.95%
100–999 shares	5.03%	3.30%	22.86%	68.81%
1000 + shares	4.67%	1.32%	19.30%	74.71%
All Orders	16.82%	6.52%	22.07%	54.59%

This table classifies orders according to aggressiveness and size. Order aggressiveness is partitioned into one of four categories. The most aggressive order class includes orders that are marketable, followed by limit orders that are submitted within the NBBO. The third class includes orders that match the current best NBBO. The least aggressive order class includes limit orders that are placed behind the best bid (for buy orders) or best offer (for sell orders). Standard *t*-tests show that 1-share proportions reported in each column are different than all other trade size proportions within the same aggressiveness classification, at the 1% level.

1-share orders are extremely aggressive, as over 50% of 1-share orders are either marketable or improve the NBBO. 43.39% of 1-share orders are marketable, demonstrating that 1-share orders are the most aggressive order-size class. Relative to the other order-size classes, only 26.14% of 1-share trades are submitted behind the NBBO, suggesting that most 1-share limit orders are placed with the intention of almost immediate execution. The results in Table 4 also signify that smaller odd lot trades, in particular 1-share trades, tend to be more aggressive than larger share orders. While order aggressiveness is not sufficient to prove that 1-share trades are used to search for liquidity, order aggressiveness is a necessary condition of an exploratory trading strategy.

1-share trades may be used by traders searching for hidden liquidity. Hidden orders are invisible orders on the limit order book, and are common among all exchanges (Bloomfield et al., 2015). Hasbrouck and Saar (2009) examine 100 NASDAQ stocks on INET and document the widespread use of submissions and cancellations of non-marketable limit orders within two seconds of each other and conclude that some of these “fleeting orders” could be the result of traders searching for hidden liquidity. A trader might submit either a 1-share limit order inside the best displayed bid and ask quote, or a 1-share market order, in order to detect hidden liquidity. An order that executes against a hidden order inside the best displayed bid and ask quotes finds liquidity.

NASDAQ TotalView-ITCH data provides execution details for events involving non-displayed order types (i.e. hidden liquidity). In 2012, the ITCH database provides a null order reference number for all trades against hidden orders, making it impossible to distinguish between different hidden orders. Because of the data limitation, we further explore the pinging hypothesis in an indirect way in order to identify increased executions against hidden liquidity. Our first method, presented in Fig. 3, shows odd lot executions against hidden liquidity. The proportions presented in Fig. 3 represent the percentage of all trades against hidden liquidity by each odd lot order class size. Large orders should increasingly execute against hidden orders. Relative to other odd lot trade sizes, however, 1-share trades execute disproportionately against hidden liquidity. For the average stock day in our sample, 1-share trades represent 3.25% of all executions against hidden orders.

In Fig. 4, we present the intraday pattern of executions against hidden liquidity. Consistent with the distribution of 1-share trades in Fig. 2, we find that both the number of trades executing against hidden liquidity as well as total hidden volume, are highest at the open and close of the trading day. We believe these results, considered together with those presented in Fig. 2 and Fig. 3, add further support for the pinging hypothesis.

The results presented in Fig. 3 do not account for the total number of market orders submitted. If there are only a few 1-share orders placed for a particular stock, and if most of these orders execute against hidden liquidity, the results may tilt towards firms that have few 1-share transactions. While 1-share trades may account for a disproportionate percentage of executions against

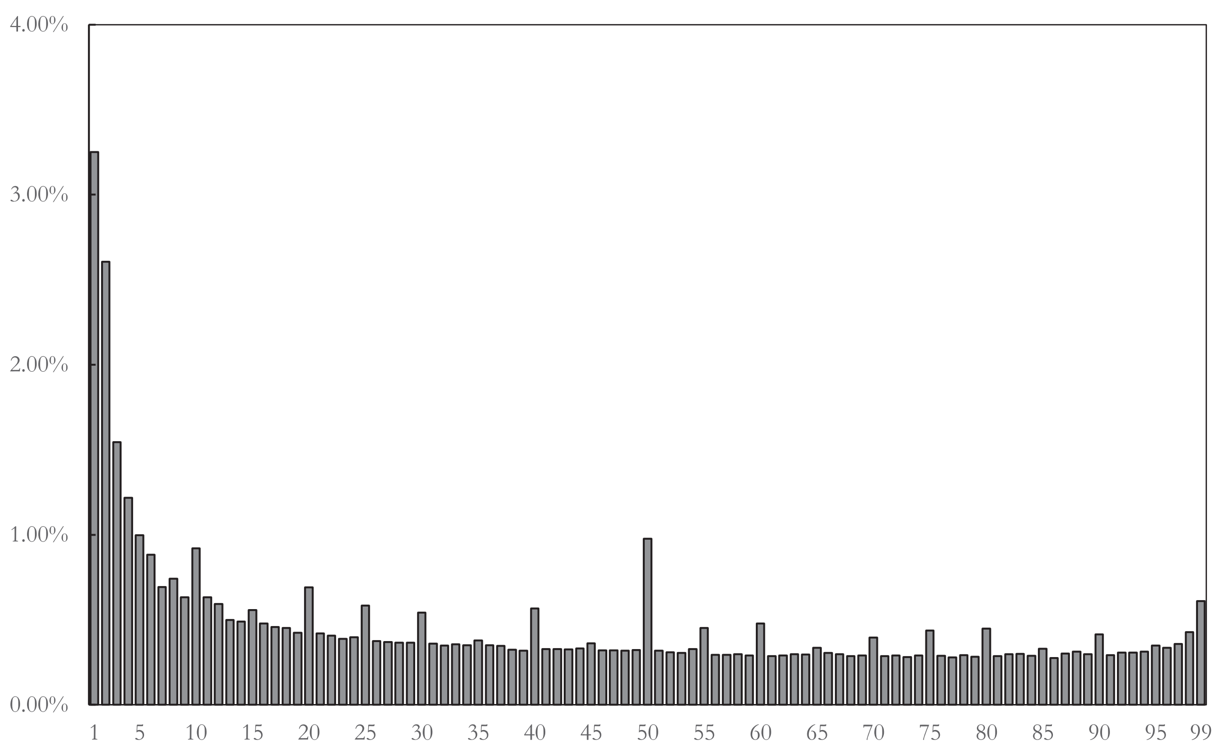

Fig. 3. Proportion of marketable orders executing against hidden liquidity. This figure presents the proportions of all trades against hidden liquidity by each marketable order class size. While we consider all trade size executions against hidden liquidity, we only present the results for odd lot trade sizes against hidden liquidity in the figure below.

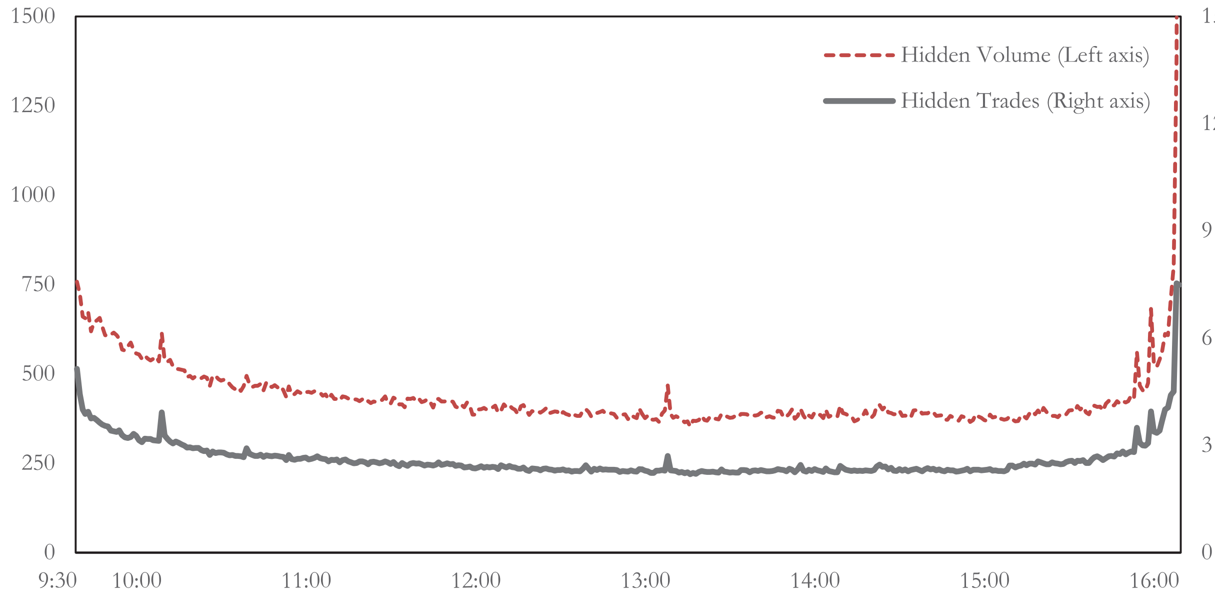

Fig. 4. Executions against hidden orders by time of day. This figure presents the number of executions and volume against hidden liquidity throughout the trading day. The dashed line represents the average volume of hidden orders executed, while the solid line represents the average number of trades against hidden orders.

Table 5
Proportion of hidden orders executed by class size.

	Proportion of Hidden Orders executed by share class		
Intercept	0.0063***	0.0048***	0.0051***
	(35.021)	(32.716)	(33.093)
1 Indicator	0.0017***	0.0010***	0.0012***
	(8.467)	(5.487)	(5.557)
50 Indicator			−0.0049***
			(−40.648)
100 Indicator		−0.0227***	−0.0216***
		(−15.414)	(−14.292)
Marketable Percent	0.9243***	0.9611***	0.9611***
	(626.393)	(448.440)	(448.404)
Controls & Fixed Effects	Yes	Yes	Yes
Observations	49,235,636	49,235,636	49,235,636
N	6783	6783	6783
Adj. R^2	0.6687	0.6683	0.6686

This table reports cross sectional regression estimates for the proportion of hidden orders executed per order class size. The dependent variable is the proportion of hidden orders executed for each order class size. Although the regression includes all class sizes, we report the major clustered proportions. We also include, but do not report, major determinants that impact the proportion of hidden orders executed. These control variables include the number of marketable orders per class size divided by total marketable orders submitted (*Marketable Percent*), the daily closing price, volatility, market capitalization, spread, and depth.

*** represents test statistics, in parentheses, include robust standard errors clustered by firm and time, with significance at the 1 percent level.

hidden liquidity, true disparities in proportions should be weighted by the total number of market orders placed. We address this concern in Table 5 by providing cross sectional regression estimates of the proportion of hidden orders that execute per order class size. The dependent variable is the proportion of hidden orders that execute for each order class size. The primary control variable, *Marketable Percent,* is the number of marketable orders submitted per order size, divided by the total number of marketable orders (from all order sizes) submitted. We include similar control variables from previous tables. The variable of interest is a 1-share indicator variable that identifies whether 1-share trades execute disproportionately against hidden liquidity. In order to provide a meaningful comparison, we include indicator variables for 50-shares, the second most common odd lot trade size, and 100-shares, the most common trade size in our sample.

After controlling for the number of market orders placed, we find a positive coefficient on *1 Indicator* suggesting that 1-share trades execute against hidden liquidity more than what would be expected by the number of 1-share marketable orders submitted. For comparison, the coefficient of *50 Indicator* and *100 Indicator* are negative indicating that, while these trade size classes frequently execute against hidden liquidity, they do so at a lesser proportion than what is expected by the number of 50- and 100-share marketable orders placed. In total, 1-share orders execute against hidden liquidity in larger proportions than all other trade size classes, and also in larger proportions than would be expected by the number of 1-share orders submitted.

In Clark-Joseph's (2014) model, traders place small, unprofitable orders to learn about market conditions, and then follow with larger orders in the direction of future price changes. If 1-share trades are exploratory trades, then we expect 1-share trades to be followed disproportionately by larger, more profitable trades. We identify average trading volume and trade size, as well as the price impact of all trades in one-, five- and thirty-second intervals following a 1-share trade. For comparison, we report these metrics around 2-share trades and 3-share trades.

As reported in Table 6, we find an average volume of 2937 shares and an average order size of 40 shares in the first second after a 1-share trade. Relative to trading activity surrounding 2-share trades and 3-share trades, both volume and order sizes observed in the data are higher after a 1-share trade. This result holds in all three time intervals. The relatively small order sizes in Table 6 are consistent with previous studies stating that odd lots comprise a large percentage of trades (e.g., Hara et al., 2014; Johnson, 2016; Johnson et al., 2016).

We next consider the price impact of trades immediately after a 1-share trade. Following Hendershott et al. (2011), we measure price impact as the difference between the price midpoint five minutes after the trade and the price midpoint at the time of the trade, scaled by the midpoint at the time of the trade. Price impact is signed according to the direction of the trade (i.e. buy or sell), where positive (negative) values indicate that the liquidity demander is able (unable) to extract abnormal profits at the expense of the liquidity supplier. While our results indicate that trades following a 1-share trade and a 2-share trade are similar, we find evidence that trading after a 1-share trade is more profitable

Table 6
Trading activity immediately following a 1-share trade.

	Trading activity following:				
	1-share trades	2-share trades	3-share trades	1-share trades vs. 2-share trades	1-share trades vs. 3-share trades
Panel A: One second					
Volume	2937.58	1867.03	1802.71	1070.60*** (9.34)	1137.90*** (10.15)
Avg. Order Size	40.12	34.59	35.57	5.53*** (26.30)	4.54*** (20.66)
Avg. Price Impact (%)	0.47	0.96	−0.31	0.49 (−1.39)	0.76** (2.35)
Panel B: Five Seconds					
Volume	6661.74	4205.30	3961.52	2456.40*** (12.05)	2700.20*** (13.25)
Avg. Order Size	51.99	46.06	47.28	5.93*** (24.98)	4.71*** (19.01)
Avg. Price Impact (%)	0.41	0.90	−0.11	−0.49 (−1.38)	0.52* (1.67)
Panel C: Thirty Seconds					
Volume	25,075.95	15,404.17	14,244.23	9671.80*** (13.75)	10,831.70*** (14.09)
Avg. Order Size	71.69	65.60	67.53	6.09*** (22.69)	4.16*** (14.97)
Avg. Price Impact (%)	0.35	0.92	−0.05	−0.57 (−1.56)	0.40 (1.35)

This table investigates whether 1-share trades are followed disproportionately by larger, more profitable trades. For each trade class size and time interval we compute the total volume of shares traded, the average order size, and the average price impact of trades *after* a 1-share trade. Because our sample period contains significant levels of high-frequency trading, we compute the above metrics at one-, five- and thirty-second intervals immediately after a 1-share trade. We compare these results to trading after 2-share trades and 3-share trades. Price impact is the difference between the price midpoint five minutes after the trade and the price midpoint at the time of the trade, scaled by the midpoint at the time of the trade. Price impact is signed according to the buy/sell indicator.

* represents test statistics in parentheses, with significance at the 10 percent level.

*** represents test statistics in parentheses, with significance at the 1 percent level.

than trading after a 3-share trade. Our results are similar, regardless of the time interval.[8] Given the above results, along with the aggressiveness of 1-share orders and the disproportionate number of 1-share executions against hidden liquidity, we conclude that 1-share trades are likely to be exploratory trades as modeled by Clark-Joseph (2014).

4.3. Are 1-share trades used to avoid reporting to the consolidated tape?

O'Hara et al. (2014) suggest that odd lot trades below 50 shares typically fall into the 1- to 5-share trade group, while trades above 50 shares are typically 95- to 99-share trades. We indirectly test O'Hara et al. (2014) proposition that 1-share trades may be the result of traders breaking up orders to avoid the reporting requirements of trades of 100 shares or more by examining 1-share trades (99-share trades) immediately followed by a 99-share trade (1-share trade). We find that 9.84% of all 1-share trades are followed by a 99-share trade within 1 s. We also find that 32.51% of 99-share trades are followed by a 1-share trade within 1 s. These results provide mild support for the notion that traders may break larger orders into smaller trades using 1-share trades. We further analyze the use of 1-share trades and 99-share trades around December 9th, 2013, the date on which the consolidated tape feed first began reporting odd lot transactions. If traders are indeed splitting larger orders into smaller slices in order to avoid reporting to the consolidated tape feed, then we expect to find a decrease in the use of 1-share trades and 99-share trades after the reporting change. In Panel A (Panel B) of Table 7, we show that the number of 1-share and 99-share trades as a percentage of all odd lot trades

Table 7
Are 1-share trades a result of traders attempting to avoid the tape?

	Pre-Dec 9	Post-Dec 9	Post minus Pre
Panel A: As a percent of odd lots			
1-share trade proportion	0.0968	0.1130	0.0163*** (17.89)
99-share trade proportion	0.0391	0.0415	0.0024*** (4.90)
Panel B: As a percent of all trades			
All odd lot trade proportion	0.3135	0.3262	0.0127*** (10.45)
1-share trade proportion	0.0359	0.0417	0.0058*** (10.77)
99-share trade proportion	0.0113	0.0123	0.0010*** (4.96)

This table presents the analysis of the number of 1-share trades and 99-share trades prior to and after the December 9th, 2013, reporting change. Prior to December 9th, odd lot trades were omitted from the consolidated tape feed. Following December 9th the ticker tape printed trades of all sizes. In this analysis we study the number of 1-share trades and 99-share trades in the two week periods prior to and following the transparency change. Panel A reports the number of 1-share and 99-share trades as a percentage of all odd lot trades. Panel B reports the number of odd lot, 1-share trades, and 99-share trades expressed as a percentage of all trades. Data for the analysis comes from the NASDAQ TotalView-ITCH database which includes odd lot trades before the reporting change.

*** report test-statistics in parentheses, with significance at the 1% level.

(all trades) does not decrease after the change in odd lot transparency. Results from both panels indicate that 1-share trades and 99-share trades as a proportion of odd lot trades and all trades increase after December 9th, 2013. The increase in 1-share trades and 99-share trades after December 9th, 2013, suggests that stealth trading does not explain the large number of 1-share transactions observed in the data. Additionally, our results are in line with Roseman et al. (2016) and the SEC (2014), who do not find a decrease in odd lot trading after the transparency change.

[8] In untabulated results, we also examine the trade-weighted price impact of 1-share trades, as opposed to the price impact of trading *after* 1-share trades, and do not find any significant impact of these trades on prices. The lack of price impact on 1-share trades suggests that 1-share trades have little effect on inventory.

5. Conclusion

1-share trades account for almost 10% of all odd lot transactions and 3.65% of all trades on NASDAQ. Although trading costs have substantially decreased since decimalization, 1-share trades completely forgo the economies of scale of larger share orders. It is difficult to reconcile the prevalence of 1-share trades with the notion that 1-share trades are likely to be unprofitable. However, we explain the persistence of 1-share trades through an exploratory trading model presented by Clark-Joseph (2014). Clark-Joseph suggests that high frequency traders place small aggressive orders to identify current market conditions. The information gathered from these small, unprofitable orders subsequently leads to larger, more profitable orders. We identify a large portion of intentional 1-share trades are aggressively priced, as over 50% of 1-share orders are either marketable or submitted inside the NBBO. We also find that 1-share trades execute against 3.25% of all hidden orders. This percentage is higher than all other odd lot trade sizes.

We show that 50% of 1-share trades are the result of broken orders, while 35% are deliberate orders for 1 share. We also study the effect of stock and firm characteristics on 1-share trades and 1-share orders and find that 1-share trades are directly (inversely) related to stock price (number of trades, volatility, and firm size). Finally, we study the possibility that 1-share trades are the result of traders splitting orders to avoid having transactions print on the consolidated tape. We fail to find a decrease in the proportional use of 1-share trades and 99-share trades after odd lots became visible to all traders. In total, we find that the majority of 1-share trades are the result of broken orders, while a large proportion of 1-share orders are consistent with pinging. Our results are in line with Clark-Joseph (2014), who suggests that traders may use small trades to detect information from other traders. Although 1-share trades may not be profitable, they provide important information to traders regarding the current state of the market. 1-share trades, the smallest trade size available, represent the minimum cash outlay necessary to trade, while simultaneously producing the smallest possible effects on a market maker's inventory, and in turn, a security's price.

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