Odd-Lot Order Imbalance and Returns

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ABSTRACT

This study investigates the explanatory power of odd-lot order imbalances (OI) over returns. We find that models relating OIs to returns improve when odd-lot trades are included in the analysis. However, odd-lot OIs do not hold more explanatory power than 100+ share OIs. Odd-lot trades resulting from odd-lot marketable orders carry more explanatory power than those resulting from 100+ share orders. Odd-lot OIs are positively correlated with lagged and contemporaneous returns. There is no evidence to suggest that it is possible to build a profitable trading strategy around odd-lot OIs.

JEL Classifications: G10, G14

Keywords: Odd-lot trading, order imbalance, returns

INTRODUCTION

Recent research shows that odd-lot trades—those executing in denominations of less than 100 shares—have a disproportionate contribution to price discovery, and the contribution is above what would be predicted by the proportion of volume transacted in odd-lot trades (O'Hara, Yao, & Yea, 2014). Johnson, Van Ness, and Van Ness (2015) similarly found that odd-lot trades that result from at least one party to the transaction submitting an odd-lot order contribute to price formation higher than their proportion of volume. Therefore, models relating price movements to trading may improve with the inclusion of odd-lot trading. This study examines the impact of odd-lot order imbalance (OI hereafter) on individual stock returns.

Precisely, this study draws upon the methods of Chordia and Subrahmanyam (2004) to three ends. First, the study determines whether the inclusion of odd-lot trading better relates order imbalances to lagged, contemporaneous, and future returns. Second, it examines the explanatory power of odd-lot trades relative to 100+ share trades. Finally, the study assesses the characteristics of odd-lot trades as they relate to returns and determines whether their explanatory power derives from odd-lot orders or 100+ share orders being broken up upon execution.

Earlier literature on odd-lot transactions find that uninformed retail traders dominate odd-lot trades (Baker & Wurgler, 2006; Barber & Odean, 2000; Dyl & Maberly, 1992; Odean, 1998). However, technological advances and market innovations that have increased the speed and decreased the cost with which investors can trade have allowed informed investors to trade in smaller denominations in attempts to lessen their market impact (Johnson & Roseman, 2017). Therefore, one can no longer assume odd-lot orders are submitted solely by uninformed retail traders. Also, significant changes in market microstructure have occurred since the period (1988-1998) used by Chordia and Subrahmanyam (2004) to document the relation between order imbalances and returns.[1] The work of Chordia and Subrahmanyam (2004) showed a negative relation between order imbalances and lagged returns. In addition, their research revealed a positive relationship between contemporaneous order imbalances and contemporaneous returns. They found that there is a predictive power of lagged individual stock order imbalance on current stock returns, and a profitable trading strategy is feasible. However, transaction costs will mitigate any profits from such a strategy.

Altogether, this study found that oddlot volume and trade imbalance contributes significantly to the explanation of individual stock returns. The evaluation of order imbalance includes odd-lot transactions, which improves the model fit for lagged and contemporaneous returns, compared to order imbalance evaluated excluding odd-lot transactions. However, when order imbalance is evaluated using only odd-lot trades, the model fit does not increase in most cases. This increase in model fit can be interpreted as the information quality of the order imbalance, indicating that the inclusion of odd lot trades improves the explanatory power of order imbalance. Nevertheless, odd-lot trades do not hold more explanatory power than all trades in aggregate.

[1] For example, decimalization (Bacidore, Battalio, Jennings, & Farkas, 2001; Bessembinder, 2003a; Chakravarty, Panchapagesan, & Wood, 2005; Chung, Van Ness, & Van Ness, 2004; Gibson, Singh, & Yerramilli, 2003), NASDAQ market reforms (Barclay, Christie, Harris, Kandel & Schultz, 1999), increased competition (Battalio, Hatch, & Jennings, 2004; Bessembinder, 2003b; Goldstein, Shkilko, Van Ness, and Van Ness, 2008), the rise of algorithmic trading (Brogaard, 2010), faster trading (Boehmer, 2005; Boehmer, Jennings, & Wei, 2007), and technological advances such as the NYSE Hybrid (Hendershott & Moulton, 2010) each affect equity markets in varying ways.

In addition, this study also examines the initiation mechanism of the odd-lot trade to evaluate the relative impacts of odd-lot transactions resulting from odd-lot denominated orders and odd-lot transactions resulting from 100+ share orders. To illustrate the difference between these two types of trades, one should consider the following example. Let the limit order book contain two resting limit orders of 100 shares each and the same limit price. Next, a 50-share odd-lot trade demanding liquidity submitted followed immediately by a 100-share round lot trade demanding liquidity. This transaction will result in the NASDAQ Historical Totalview ITCH (ITCH [note: according to NASDAQ, ITCH does not stand anything]) data recording three 50 shares odd-lot trades. The first trade for 50 shares is defined as an 'Odd Order' odd-lot trade. Two '100+ Order' odd-lot transactions are created from the 100 share order split into two 50 share trades. In this study's sample, roughly 55% of odd-lot trades are 'Odd Order' while the remaining 45% are '100+ Order.' Importantly the current research found that 'Odd Order' imbalance is more accretive to model fit and holds more explanatory power than '100+ Order' imbalance.

HYPOTHESIS DEVELOPMENT

Hypothesis 1

Regression model fit will improve with the inclusion of odd-lot order imbalance.

Chordia and Subrahmanyam (2004) developed a model based on the effect of inventory accumulation of market makers. The model (Proposition 1, item 3) indicated that the contemporaneous order imbalance will have a positive correlation with the expectation of the contemporaneous returns. They also document a negative relation between contemporaneous order imbalance and lagged returns and a slight positive correlation between order imbalance and future returns. However, the research by O'Hara, Yao, and Ye (2014) revealed that odd-lot trades, which are not contained in the Trade and Quote (TAQ) database used in Chordia and Subrahmanyam (2004), have a substantial impact on the price discovery process. Here, the expectation is that using a dataset that contains all transactions, including odd-lot transactions, can better explain individual equity returns since the dataset allows one to incorporate the impact of both odd-lot and 100+ share transactions. As a result, this study expects to see higher explanatory power reflected in more significant coefficients of determination in regressions relating to returns and order imbalance when using a dataset containing odd-lot transactions relative to the coefficients of determination in the regressions, which use only 100+ share transactions.

Hypothesis 2

Regression model fit will improve when only odd-lot order imbalance, excluding all trades over 100+ shares, is included in the model.

Glosten and Milgrom (1985) proposed a sequential trading model that indicates trade imbalance affects price changes. Especially, the model indicates that when informed traders enter the market and trade on one side of the market, this will lead to higher trade imbalances and more significant price reaction from market makers. If odd-lot trades are favored by informed traders, as found in O'Hara, Yao, and Ye (2014), then the price reaction of odd-lot trade imbalance will have higher explanatory power compared to trade imbalances that include trades of 100+ shares. This transaction implies the second testable hypothesis.

Hypothesis 3

Odd Order imbalance will have higher explanatory power than 100+ Order imbalance.

Odd-lot trades can be initiated by two different mechanisms. First, an Odd Order trade is a trade that results from liquidity demanding order for under 100 shares. Second, when an odd-lot order executes against a resting 100+ share order, and the balance of the resting order is not immediately canceled, the remaining fraction of the 100+ share order will create new odd-lot trades even if the incoming orders are in 100+ share increments. These additional odd-lot trades are termed 100+ Order odd-lot transactions. O'Hara, Yao, and Ye (2014) state that one reason informed traders use odd-lot trades are because they are not printed to the consolidated tape, hiding the trade from exposure. Clearly, 100+ Order odd lot trades are not obvious attempts to 'hide' from the consolidated tape. The third hypothesis is:

[Per the Journal's editor, you need to provide and explanation here as you did for the previous two hypotheses.]

DATA

Here, the sample consists of trade and order data contained in the NASDAQ Historical TotalView ITCH, which includes all submissions to the NASDAQ exchange. This study randomly selected 600 stocks (200 from each market capitalization tercile) and performed an analysis on the sample period July 1, 2015 through September 30, 2015, the most recent period for which all necessary variables are available in the researchers' databases. The universe was filtered of potential equities to include only NASDAQ-listed stocks that trade at least 100 times a day for all 64 trading days within the sample. The researchers restricted the sample to stocks that never closed below $5 or above $300.[2] Moreover, only trades that were executed during regular market hours were used. Trades executing for less than 100 shares are denoted as odd-lot trades. Odd-lot trades that result from the submission of odd-lot denominated marketable orders are denoted as Odd Order odd-lot trades. Odd-lot trades that result from the submission of a 100+ share order that is subsequently divided into smaller executions, at least one of which is an odd-lot trade, are termed 100+ Order odd-lot trades.[3] As a result, data from the Center for Research in Security Prices (CRSP) for daily stock and market returns, and market capitalization calculations is utilized.

[2] Stock price has been found to be a prime determinant of odd-lot trading (Johnson, 2014; Johnson, Van Ness, & Van Ness, 2015; O'Hara, Yao, & Ye, 2014). Therefore, the study excluded very high priced securities from the analysis to prevent any bias that otherwise might be induced by odd-lot trading occurring due to abnormally high priced shares.

[3] To infer the size of the incoming marketable order, all of the executions that occur for the stock during the same nanosecond at the same price are aggregated. Specifically, Upson, Johnson, and McInish (2015) show this methodology is sound with the probability of aggregating two independent marketable orders to be 8.5×10^{-5} at a maximum.

This study calculated order imbalance (OI) as the buy volume less the sell volume as a percent of the total volume in trade category j (total, odd lot, odd order, or 100+ order), for stock i, on day t. Should there be more buy (sell) volume than sell (buy) volume, the OI metric will be positive (negative), which Chordia and Subrahmanyam (2004) determined to be positively correlated with contemporaneous returns.

$$Order\ Imbalance_{i,j,t} = \frac{Buy\ Volume_{i,j,t} - Sell\ Volume_{i,j,t}}{Total\ Volume_{i,j,t}} \tag{1}$$

Table 1 lists the descriptive statistics for the sample of 38,400 stock days with order imbalance statistics calculated using the trading volume listed in Panel A and order imbalance calculated using the number of trades listed in Panel B.[4] The average stock has a mean of 245,079 shares traded in 2,104 executions, of which 25,939 shares are traded in 657 odd-lot transactions. Consistent with Johnson, Van Ness, and Van Ness (2015) and Upson and Johnson (2016), a little more than half of the odd-lot transactions are made up of orders submitted for less than 100 shares. Across both panels and all trade classifications, there is, on average, more sell volume than buy volume during the sample period, as evidenced by negative mean OIs ranging from -13.70% to -19.57%. The OIs in the sample period is considerably more negative than the 0.54% to -1.72% OIs calculated by Chordia and Subrahmanyam (2004) during the1988 to 1998 sample period. However, the 3rd quarter of 2015 saw considerable volatility and declining market prices on domestic exchanges. On July 1, the NASDAQ Composite opened at 4,958 and reached a quarterly high of 5,219 before dropping to a quarterly low of 4,506 and closing on September 30 at 4,620, for a quarterly return of -6.82% and a -13.66% drop from its quarterly high to its quarterly low.[5] As expected, the average daily return for sample stocks is -0.15% (Panel C), which would equate to a -9.16% effective quarterly return. The average daily excess return over the CRSP Equal-Weighted Index is not significantly different from zero. This study does not focus on returns per se, but rather the relation between order imbalances and returns. Therefore, conclusions should not be affected by negative market performance.

RESULTS

Chordia and Subrahmanyam [3] purported that traders tend to act in a contrarian manner by documenting a negative relation between lagged returns and contemporaneous OI. Supporting their inventory model, they found a positive relationship between contemporaneous OI and contemporaneous returns. They also concluded that there is a slight positive correlation between daily OI and future returns; however, a profitable trading strategy is likely not possible due to associated trading costs. The researchers drew their conclusions with regressions, including lagged order OIs to control for autocorrelations of daily OIs. Therefore, in response, this study adopted methods similar to those used by Chordia and Subrahmanyam (2004) in the testing of the following hypotheses.

Hypothesis 1 Test

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[4] This study conducted tests on a larger sample size (1,200 stocks equaling 76,800 stock days) and found that results were very similar to those found on the smaller dataset. For brevity, only the smaller sample results are reported.

[5] The NASDAQ large-cap, mid-cap, and small-cap indexes experienced similar volatility and negative returns during these months.

Hypothesis 1 postulates that by including odd-lot transactions in the calculations of order imbalance, order imbalance will be better able to explain returns than if odd-lot transactions are not included. Here, Hypothesis 1 is tested by comparing regressions using two subsamples: the first excludes odd-lot transactions in the calculation of OI, similar to date reported to the consolidated tape, and the second includes odd-lot transactions. Using both samples, regressions of order imbalance on lagged returns are run (Model 1). This study also regress contemporaneous returns (Model 2), future returns (Model 3) on contemporaneous, and order imbalance, controlling for OIs lagged four days (Chordia and Subrahmanyam, 2004).

Model 1: $$OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (2)$$

Model 2: $$Return_t = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (3)$$

Model 3: $$Return_{t+1} = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (4)$$

Furthermore, the present study ran the regressions by stock and reported the mean adjusted r-squared's from the regressions in Table 2.[6] Panels A, B, and C list mean r-squared's from Models 1, 2, and 3, respectively. In each model, OI is calculated using volume and number of trades, and use raw returns, returns in excess of the CRSP Value-Weighted, and returns in excess of the CRSP Equal-Weighted Indexes. The differences column reports the difference between the r-squared from the dataset, excluding odd-lot trades relative to the r-squared from the dataset, including odd-lot trades.

In Panel A relating OI to lagged returns, and in Panel B relating OI to contemporaneous returns, the model fit is significantly better when odd-lot trades are included for both OI calculations and all measures of returns. The improvement in model fit (i.e., increasing r-squareds) ranges from 0.55% (volume imbalance using excess returns over the value-weighted index in Model 2) to 2.00% (trade imbalance using returns in Model 2). In both Panel A and Panel B, the model fit improves with the inclusion of odd-lot trades, and the improvement is highly significant. The improvement in r-squareds supports the first hypothesis that the relation between OI and returns is better explained when odd-lot transactions are included in the analysis, at least when lagged and contemporaneous returns are considered.

However, Panel C does not report any significant improvement in r-squareds when odd-lot trades are included. This finding is supported by Chordia and Subrahmanyam (2004), who found only a slight positive relation between OI and future returns and find that a profitable trading strategy most likely is not possible. Coupled with the conclusion adopted by Upson and Johnson (2016) that identified that odd-lot orders are not more informed than 100+ share orders, this most likely explains the insignificant results in Panel C. Regardless of odd-lot trades' price contribution, the inclusion of odd-lot trades does not provide any predictive power of order imbalance over future returns.

Hypothesis 2 Test

To test if odd-lot trades carry more explanatory power than 100+ share trades, a comparison was made between a data subsample that included only 100+ share trades to a dataset that included only odd-lot trades. Subsequently, a regression was run of Models 1, 2, and 3 on both datasets using OI calculated with volume and trades, and with returns and excess

[6] Henceforth, all mentioned r-squareds are adjusted r-squareds.

returns. Table 3 reports the mean r-squared's from stock regressions and the differences between the r-squareds from the 100+ share trade dataset and the odd-lot trade dataset.

Should odd-lot trades hold more explanatory power over returns as Hypothesis 2 proposes, the differences column should be negative. However, the majority of the differences are positive or are not significantly different from zero. Only Model 2 shows an improvement of fit when using odd-lot trade imbalance to explain contemporaneous returns. The regressions suggest that odd-lot trades do not hold more explanatory power over lagged, contemporaneous, and future returns than 100+ share trades.

Hypothesis 3 Test

The relative contribution of Odd Order and 100+ Order odd-lot trades were evaluated in Tables 4 through 6. Because an odd-lot trade may arise from a 100+ share trade executing against an odd-lot limit order, thereby becoming an odd-lot order without the intent of the liquidity demander. As a result, odd-lot trades were separated into two groups: Odd Order and 100+ Order. The regression equations were similar to those used in earlier sections: OI as calculated using all odd lot trades (Odd Lot), OI as calculated using odd lot trades that were submitted as an odd lot marketable order (Odd Order), and OI as calculated using odd lot trades that were submitted as 100+ share orders (100+ Order). Separating trades into odd-lot types allows us to isolate the effect of odd-lot OIs and returns. Consistent with Chordia and Subrahmanyam (2004), the remainder of the analysis will focus on excess returns as calculated over the CRSP Equal-Weighted Index.

To evaluate the impact of lagged returns on order imbalance, measures of odd-lot OI on lagged daily returns are regressed. Table 4 reports mean regression coefficients from stock day regressions tested to be different from zero with the measures of odd-lot OI as the dependent variable and lagged total OI controls. Panel A reported results using volume imbalance, and Panel B reports results using trade imbalance as the dependent variable.

Model 4:

$$Odd\ OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \tag{5}$$

Table 4 shows positive mean coefficients for lagged returns when the odd-lot OI is the dependent variable. Specifically, this finding means that there is more buying (selling) than selling (buying) in odd-lot denominated transactions on days following positive (negative) stock returns in both the number of shares and trades. Still, not all odd-lot trades are the result of an odd-lot order. Column 2 of Table 4 relates the order imbalance of odd-lot denominated marketable orders to lagged returns. The two regressions show a positive correlation between lagged returns and Odd Order OI, meaning odd-lot liquidity demanders follow a momentum strategy, buying after days with positive returns and selling after days with negative returns.

Results regarding 100+ Order OI are similar. Excess returns hold positive predictive power over 100+ Order imbalance. Since these orders were submitted with the intent to be 100+ share trades, they are grouped into an odd-lot classification because of the size of the order resting at the top of the limit order queue. Therefore 100+ Order OI characteristics are expected to be comparable to 100+ share trades.

To evaluate Hypothesis 3, the regression coefficients and the model fit of the regressions are examined. Since 100+ Order trades were submitted as 100+ share orders, which are not intended to be odd-lot trades, one would expect for 100+ Order coefficients to be insignificant when controlling for total OI. Since 100+ Order coefficients are more significant in magnitude than Odd Order coefficients, this study concludes that 100+ Order explanatory power is more significant than that of Odd Orders, at least in regards to lagged returns. In addition, the r-squareds of the 100+ Order regressions are uniformly more substantial than those of the Odd Order regressions; thus, rejecting Hypothesis 3—that Odd Orders hold more explanatory power than 100+ Orders.

The results in Table 4 differ from that of Chordia and Subrahmanyam (2004), who find a negative relationship between lagged returns and order imbalance. Consistently across all regression equations, contemporaneous total OIs have positive coefficients that are highly economically and statistically significant. Change to market characteristics may explain the differences between the present study's results and the results of Chordia and Subrahmanyam (2004). For example, the precipitous rise of electronic and algorithmic trading, who tend to end the trading day in market-neutral positions, has shortened the average holding period for traders. This finding would influence market participants to trade in the same direction as previous days' returns to take advantage of short-term momentum in stock returns, leading to the positive coefficients for total OI in Table 4.

Next, this study explores the odd-lot order imbalances relative to contemporaneous returns by regressing returns on odd-lot OIs. Mean coefficients for stock regressions are reported in Table 5 by volume imbalance (Panel A) and trade imbalance (Panel B) when using excess returns as the dependent variable.

Model 5:

$$Return_t = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (6)$$

This set of results agrees with the findings of Chordia and Subrahmanyam (2004) as total OI is positively related to contemporaneous returns, further validating their inventory model. Odd-Lot OI and Odd-Order OI are both positive determinants of daily stock returns, meaning odd-lot order submitters are not behaving differently from the market as a whole. When equity prices are increasing (decreasing), odd-lot traders submit buy (sell) orders, and the odd-lot orders are accretive to the buy (sell) pressure that is driving daily returns. These transactions are expected outcomes, as there is no reason to expect odd-lot traders to trade in the opposite direction of the overall market.

Column 3 in Panels A and B all report insignificant coefficients for 100+ Order imbalance, meaning that odd-lot trades resulting from 100+ share marketable orders are not accretive to contemporaneous returns over and above total OI. This finding is attributed to 100+ Orders being submitted with the intention of taking 100+ shares worth of liquidity from the market. Therefore, the characteristics of 100+ Orders should closely mimic those of the overall market, of which the vast majority are submitting orders in denominations of 100 shares or more. Intuitively, an order being broken up upon execution to match the size of resting limit orders should not change the market's reaction to the order, as it should carry the same information regardless of the number of transactions in which it executes. Therefore, all the information contained in 100+ Order odd lot trades is already conveyed in the total market OI.

Here, conclusions are drawn about Hypothesis 3 from Table 5 regarding the Odd Order imbalance relative to 100+ Order imbalance. Certainly, a significant variable (Odd-Order OI) carries more explanatory power than an insignificant variable (100+ Order OI), which lends support to Hypothesis 3 that Odd Orders are a more substantial determinant of returns than 100+ share orders.

Table 6 reports results relating odd-lot order imbalances to future returns. Chordia and Subrahmanyam (2004) found a slight predictive power of order imbalances on future stock returns, and we adopt a similar method and regress next-day stock returns on contemporaneous odd-lot order imbalances, controlling for total OI. Although there is no expectation to find evidence of a profitable trading strategy employing order imbalances in our sample, this study believes that thoroughly evaluating relations between OI and all returns (past, contemporaneous, and future) is warranted for complete analysis.

As with previous regressions, Odd OIs are calculated for Odd Orders and 100+ Orders using volume and number of trades. Panel A reported mean coefficients from stock day regressions using volume imbalance, and Panel B reported results using trade imbalance. The results in Table 6 show that there is no predictive power of any OIs, odd or otherwise, over future excess returns, which is consistent with Chordia and Subrahmanyam (2004), who concluded that a profitable trading strategy derived from contemporaneous OIs is not possible.

Model 6:

$$Return_{t+1} = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \qquad (7)$$

Columns 2 and 3 differentiate odd lot trading by order submission size. Odd Orders carry insignificant coefficients when explaining returns, as do 100+ Orders. As with the results in Table 5, the insignificance of 100+ Orders is attributed to the inclusion of total OI in the equation, as their characteristics being similar if not equal. However, traders submitting marketable orders for less than 100 shares are also unable to trade in the same direction of future returns, and excess returns are not achievable. Concerning Hypothesis 3, the slightly larger r-squareds of the regressions containing 100+ Orders than the r-squareds of regressions containing Odd Orders, the results suggest that odd-lot trades generated by 100+ share orders hold only marginally larger explanatory power over future returns than odd-lot trades submitted as marketable orders for less than 100 shares. The slight increase in explanatory power of 5 basis points is deemed to be economically insignificant. Coupled with the insignificant coefficients, this study interprets the results in Table 6 to mean the explanatory power of the two order imbalances to be equal.

Finally, the regression analyses was run on the data subset by stock day returns, either positive or negative. This was done to assess whether the relation between odd-lot order imbalance and daily returns varies on days when stock prices increase or decrease. The regressions used to create Tables 4 through 6 were repeated [Equations 5 through 7]), and those results are reported in Models 4, 5, and 6, respectively, and in Table 7. Results are reported for days with positive returns and negative returns. Listed are the variables of interest for the individual models: $Return_{t-1}$ for Model 1, OI_t for Model 2, and OI_{t-1} for Model 3.[7] As before, we define Odd OI to be either Odd-Lot OI, Odd-Order OI, or 100+ Order OI and report the results from all three in their denoted columns. Panel A contains regression results using volume to create the order imbalance measures, and Panel B contains results using trades to calculate the measures.

This study concludes that the direction of stock day returns does not affect their relationship with odd-lot order imbalance. The results in Table 7 are similar to their counterparts reported in Tables 4 through 6. Odd-lot OI is highly dependent on prior daily returns, although

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[7] This study only reported the variables of interest in Table 7 in the interest of brevity. Coefficients for the control variables in the regressions (lagged OIs) are similar to those listed in Table 4 through 6 and do not affect the interpretation of the results. The full analysis is available upon request.

the magnitude of the dependency is lower on days with negative returns. These results are valid for both volume and trade imbalances. Contemporaneous returns are significantly related to Odd-Lot OI and Odd-Order OI, and not related to 100+ Order OI on both positive and negative days. The differences between the coefficients on positive and negative days hold no economic difference. Finally, there is no predictive power of future returns by odd-lot OIs regardless of the direction of the stock day return. The lack of evidence suggesting a profitable trading strategy is not surprising, as this finding has been widely documented in finance literature.

CONCLUSION

O'Hara, Yao, and Ye (2014) show that odd-lot trades, which are not reported to the consolidated tape, have a disproportionately high price contribution when compared to the proportion of odd lot volume execution.

Using a method similar to Chordia and Subrahmanyam (2004), this study independently tests the explanatory power of odd-lot order imbalances over lagged, contemporaneous, and future returns. Using a sample of 600 NASDAQ-listed firms and the NASDAQ ITCH database from July 1, 2015 to September 30, 2015, which contains odd-lot trades, this study found that models relating order imbalances to returns improve when odd lot trades are included in the calculation of OIs relative to when odd-lot trades are excluded from OI calculations. However, odd-lot OIs do not hold more explanatory power than 100+ share OIs.

Odd-lot trades can be initiated by two mechanisms. First, there can be an odd-lot denominated marketable order submitted to the exchange, which necessarily results in an odd-lot trade. Second, an odd-lot trade can be the result of a 100+ share marketable order being submitted that executes against one or more odd-lot limit orders resting in the limit order queue. This study defines trades initiated by the first mechanism as Odd-Order trades and hypothesize that these types of odd-lot trades carry more explanatory power than 100+ Order trades. The results regarding this hypothesis are mixed. Specifically, the results show that Odd-Order trades carry more explanatory power over contemporaneous returns relative to 100+ Order trades. However, 100+ Order trades carry more explanatory power over lagged returns than Odd-Order trades, and both odd-lot OIs contribute little if anything to future returns.

This article offers a brief explanation of the results found in a larger study. First, prior research has shown uninformed traders no longer dominate odd-lot trading. Therefore, including odd-lot trading in current analyses, one would most likely improve the model as information is contained in odd-lot denominations. However, some informed traders choose too small orders, and a majority of price moving trades are submitted as 100+ share orders, which explains the more substantial relationship between 100+ share trades and daily stock returns. Finally, when an odd-lot order is submitted, it frequently is executed against a 100+ share order. Still, when both odd-lot orders and 100+ share orders are comingled in a single trade, the explanatory power of resulting daily returns would also be comingled. As a result, this leads to mixed results when trying to determine which type of odd-lot trade is a larger determinant of the returns.

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Table 1

Summary Statistics

Table 1 lists summary statistics for our sample comprised of 600 NASDAQ-listed equities (200 from each market cap tercile: large, medium, and small cap) from July 1, 2015 through September 30, 2015. Listed are the mean daily total, buy, and sell volume and number of trades and the mean order imbalances using stock observations. Means are computed with volume and number of trades for four categories of trades: All Trades, Odd-Lot trades, Odd Orders (odd lot trades resulting from odd lot marketable orders), and 100+ Orders (odd lot trades resulting from 100+ share marketable orders executing against odd-lot limit orders). Mean daily returns and excess returns relative to the CRSP Equal-Weighted Index are also reported.

Panel A: Volume				
	Total	Buy	Sell	OI
All Trades	245,079	103,925	141,154	-0.1957
Odd Lot	25,939	11,287	14,652	-0.1517
Odd Order	13,214	5,630	7,584	-0.1631
100+ Order	12,725	5,659	7,068	-0.1454
Panel B: Trades				
All Trades	2,104	902	1,202	-0.1810
Odd Lot	657	282	376	-0.1586
Odd Order	378	157	221	-0.1757
100+ Order	280	125	155	-0.1370
Panel C: Returns				
Return	-0.0015			
Excess	0.0004			

N=600 stocks and 38,400 stock days

Table 2 lists mean r-squareds from regressions using two subsamples of our data: one that excludes odd lot trades in the calculations of order imbalances and one that includes odd lot trades. We run regressions by stock and report the mean r-squareds from the stock regression observations. The differences column is calculated as the r-squared from the exclusive subsample less the inclusive subsample and is tested to be different from zero using standard t-tests. The regressions are of the forms

Model 1: $$OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (2)$$

Model 2: $$Return_t = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (3)$$

Model 3: $$Return_{t+1} = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (4)$$

where *OI* denotes the order imbalance and *Return* denotes the daily stock return on day *t*. Models 1, 2, and 3 are reported in Panels A, B, and C, respectively. For each of the three models, we report results from regressions with order imbalances calculated using volume and number of trades, as well as from using returns, excess returns over the CRSP Value-Weighted Index, and excess returns over the CRSP Equal-Weighted index in the equations.

	Volume Imbalance			Trades Imbalance		
	Exclusive	Inclusive	Difference	Exclusive	Inclusive	Difference
Panel A: Model 1						
Returns	0.1287	0.1378	-0.0090**	0.1482	0.1549	-0.0067**
Excess, Value	0.1310	0.1404	-0.0094**	0.1516	0.1591	-0.0076**
Excess, Equal	0.1311	0.1404	-0.0093**	0.1516	0.1586	-0.0070**
Panel B: Model 2						
Returns	0.1097	0.1175	-0.0078**	0.1022	0.1222	-0.0200**
Excess, Value	0.1102	0.1157	-0.0055**	0.1049	0.1165	-0.0116**
Excess, Equal	0.1121	0.1182	-0.0062**	0.1062	0.1201	-0.0138**
Panel C: Model 3						
Returns	0.0778	0.0785	-0.0007	0.0802	0.0806	-0.0005
Excess, Value	0.0779	0.0783	-0.0005	0.0797	0.0793	0.0005
Excess, Equal	0.0780	0.0782	-0.0002	0.0797	0.0786	0.0011

** and * denote significance at the 1% and 5% levels, respectively

Table 3 lists mean r-squareds from regressions using two subsamples of our data: one that includes only 100+ share trades in the calculations of order imbalances and one that includes only odd lot trades. We run regressions by stock and report the mean r-squareds from the stock regression observations. The differences column is calculated as the r-squared from the exclusive subsample less the inclusive subsample and is tested to be different from zero using standard t-tests. The regressions are of the forms

Model 1 $$OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (2)$$

Model 2 $$Return_t = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (3)$$

Model 3 $$Return_{t+1} = OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (4)$$

where *OI* denotes the order imbalance and *Return* denotes the daily stock return on day *t*. Models 1, 2, and 3 are reported in Panels A, B, and C, respectively. For each of the three models, we report results from regressions with order imbalances calculated using volume and number of trades, as well as from using returns, excess returns over the CRSP Value-Weighted Index, and excess returns over the CRSP Equal-Weighted index in the equations.

	Volume Imbalance			Trades Imbalance		
	100+ Shares	Odd Lot	Difference	100+ Shares	Odd Lot	Difference
Panel A: Model 1						
Returns	0.1287	0.1292	-0.0005	0.1482	0.1293	0.0188**
Excess, Value	0.1310	0.1317	-0.0008	0.1516	0.1326	0.0189**
Excess, Equal	0.1311	0.1315	-0.0003	0.1516	0.1319	0.0197**
Panel B: Model 2						
Returns	0.1097	0.1196	-0.0098**	0.1022	0.1272	-0.0250**
Excess, Value	0.1102	0.1080	0.0022	0.1049	0.1125	-0.0076*
Excess, Equal	0.1121	0.1118	0.0002	0.1062	0.1173	-0.0111**
Panel C: Model 3						
Returns	0.0778	0.0806	-0.0027	0.0802	0.0790	0.0012
Excess, Value	0.0779	0.0782	-0.0003	0.0797	0.0775	0.0023
Excess, Equal	0.0780	0.0770	0.0010	0.0797	0.0759	0.0038

** and * denote significance at the 1% and 5% levels, respectively

Table 4

Odd Lot Order Imbalance and Lagged Returns

Table 4 reports mean coefficients from regressions of the form

$$Odd\ OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (5)$$

where *Odd OI* denotes odd-lot order imbalance calculated with odd-lot trades (Odd Lot), odd lot trades resulting from odd-lot marketable orders (Odd Order), and odd-lot trades resulting from a 100+ share order executing against odd-lot limit orders (100+ Order), *OI* denotes the order imbalance and *Return* denotes the daily excess stock returns over the CRSP Equal-Weighted Index on day *t*. Regressions were run by stock and report the mean coefficients from the stock regressions, tested to be different from zero using standard t-tests. This study reported results from regressions with order imbalances calculated using volume in Panel A and the number of trades in Panel B.

Panel A: Volume Imbalance

	Odd Lot	Odd Order	100+ Order
Intercept	-0.0975**	-0.1213**	-0.0815**
$Return_{t-1}$	0.6272**	0.4356**	0.7537**
OI_{t-1}	0.2115**	0.1484**	0.2699**
OI_{t-2}	0.0465**	0.0322**	0.0603**
OI_{t-3}	0.0153*	0.0112	0.0164
OI_{t-4}	-0.0108	0.0012	-0.0216*
R-squared	0.1295	0.1140	0.1241

Panel B: Trade Imbalance

	Odd Lot	Odd Order	100+ Order
Intercept	-0.0976**	-0.1279**	-0.0617**
$Return_{t-1}$	0.7256**	0.5513**	0.8678**
OI_{t-1}	0.2474**	0.1757**	0.3316**
OI_{t-2}	0.0457**	0.0284**	0.0663**
OI_{t-3}	0.0368**	0.0361**	0.0354**
OI_{t-4}	-0.0138	-0.0038	-0.0262**
R-squared	0.1371	0.1190	0.1365

** and * denote significance at the 1% and 5% levels, respectively

Table 5

Odd Lot Order Imbalance and Contemporaneous Returns

Table 5 reports mean coefficients from regressions of the form

$$Return_t = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \qquad (6)$$

where *Odd OI* denotes odd-lot order imbalance calculated with odd lot trades (Odd Lot), odd lot trades resulting from odd lot marketable orders (Odd Order), and odd lot trades resulting from a 100+ share order executing against odd-lot limit orders (100+ Order), *OI* denotes the order imbalance and *Return* denotes the daily excess stock returns over the CRSP Equal-Weighted Index on day *t*. Regressions were run by stock and reported the mean coefficients from the stock regressions, tested to be different from zero using standard t-tests. Results from regressions were reported with order imbalances calculated using volume in Panel A and the number of trades in Panel B.

Panel A: Volume Imbalance

Variable	(1)	(2)	(3)
Intercept	0.0035**	0.0040**	0.0034**
Odd Lot OI_t	0.0055**		
Odd Order OI_t		0.0108**	
100+ Order OI_t			0.0001
OI_t	0.0184**	0.0174**	0.0228**
OI_{t-1}	-0.0096**	-0.0095**	-0.0094**
OI_{t-2}	0.0020	0.0020	0.0020
OI_{t-3}	-0.0001	-0.0002	-0.0002
OI_{t-4}	0.0002	0.0001	0.0001
R-squared	0.1401	0.1403	0.1371

Panel B: Trade Imbalance

Variable	(1)	(2)	(3)
Intercept	0.0036**	0.0039**	0.0038**
Odd Lot OI_t	0.0114**		
Odd Order OI_t		0.0129**	
100+ Order OI_t			-0.0013
OI_t	0.0106**	0.0111**	0.0234**
OI_{t-1}	0.0007	0.0007	0.0006
OI_{t-2}	-0.0058	-0.0058	-0.0059
OI_{t-3}	0.0048	0.0046	0.0047
OI_{t-4}	-0.0021	-0.0022	-0.0021
R-squared	0.1412	0.1442	0.1384

** and * denote significance at the 1% and 5% levels, respectively

Table 6

Odd Lot Order Imbalance and Future Returns

Table 6 reports mean coefficients from regressions of the form

$$Return_{t+1} = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \quad (7)$$

where *Odd OI* denotes odd-lot order imbalance calculated with odd-lot trades (Odd Lot), odd-lot trades resulting from odd-lot marketable orders (Odd Order), and odd-lot trades resulting from a 100+ share order executing against odd-lot limit orders (100+ Order), *OI* denotes the daily excess stock returns over the CRSP Equal-Weighted Index on day *t*. This study ran regressions by stock and report the mean coefficients from the stock regressions, tested to be different from zero using standard t-tests. Results were reported from regressions with order imbalances calculated using volume in Panel A and the number of trades in Panel B.

Panel A: Volume Imbalance

Variable	(1)	(2)	(3)
Intercept	0.0007	0.0005	0.0007
Odd Lot OI_t	0.0010		
Odd Order OI_t		-0.0001	
100+ Order OI_t			0.0000
OI_t	-0.0009	-0.0012	-0.0007
OI_{t-1}	0.0029	0.0028	0.0027
OI_{t-2}	0.0000	0.0002	0.0001
OI_{t-3}	-0.0008	-0.0007	-0.0008
OI_{t-4}	0.0010	0.0008	0.0010
R-squared	0.0916	0.0920	0.0925

Panel B: Trade Imbalance

Variable	(1)	(2)	(3)
Intercept	-0.0001	0.0001	-0.0001
Odd Lot OI_t	0.0016		
Odd Order OI_t		0.0020	
100+ Order OI_t			0.0003
OI_t	-0.0021	-0.0017	-0.0009
OI_{t-1}	-0.0059	-0.0058	-0.0058
OI_{t-2}	0.0057	0.0059	0.0057
OI_{t-3}	-0.0037	-0.0035	-0.0039
OI_{t-4}	0.0012	0.0010	0.0012
R-squared	0.0916	0.0920	0.0925

** and * denote significance at the 1% and 5% levels, respectively

Table 7. Odd Lot Order Imbalance on Stock Days with Positive and Negative Returns

Table 7 lists the results from regressions relating stock returns to odd lot order imbalances for stock days with positive returns and for stock days with negative returns. The regressions are of the forms

$$\textit{Model 4} \qquad Odd\ OI_t = Return_{t-1} + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \qquad (5)$$

$$\textit{Model 5} \qquad Return_t = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \qquad (6)$$

$$\textit{Model 6} \qquad Return_{t+1} = Odd\ OI_t + OI_t + OI_{t-1} + OI_{t-2} + OI_{t-3} + OI_{t-4} \qquad (7)$$

where *Odd OI* denotes odd lot order imbalance calculated with odd lot trades (Odd Lot), odd lot trades resulting from odd lot marketable orders (Odd Order), and odd lot trades resulting from a 100+ share order executing against odd lot limit orders (100+ Order), *OI* denotes the order imbalance and *Return* denotes the daily excess stock returns over the CRSP Equal-Weighted Index on day *t*. For each of the models, we report the variable of interest: $Return_{t-1}$ for Model 1, OI_t for Model 2, and OI_{t-1} for Model 3. We report results from regressions with order imbalances calculated using volume in Panel A and number of trades in Panel B. Results for stock days with positive returns are reported in columns 1 through 3, and results for stock days with negative returns are reported in columns 4 through 6.

Panel A: Volume Imbalance

	Positive Returns				Negative Returns		
	Odd Lot OI_t	Odd Order OI_t	100+ Order OI_t		Odd Lot OI_t	Odd Order OI_t	100+ Order OI_t
Model 1	1.0152**	0.7926**	1.1871**	Model 1	0.7030**	0.4079**	0.8413**
Model 2	0.0102**	0.0106**	0.0006	Model 2	0.0109**	0.0097**	0.0004
Model 3	-0.0020	-0.0032	0.0003	Model 3	0.0031	0.0036	0.0000

Panel B: Trade Imbalance

	Positive Returns				Negative Returns		
	Odd Lot OI_t	Odd Order OI_t	100+ Order OI_t		Odd Lot OI_t	Odd Order OI_t	100+ Order OI_t
Model 1	1.1174**	0.8585**	1.3760**	Model 1	0.8205**	0.5915**	0.9303**
Model 2	0.0112**	0.0131**	0.0018	Model 2	0.0099**	0.0078**	-0.0022
Model 3	-0.0018	-0.0028	0.0019	Model 3	0.0006	0.0017	-0.0006

** and * denote significance at the 1% and 5% levels, respectively