Information in Short Selling: Comparing NASDAQ and the NYSE

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Abstract:

This study directly compares the level and return predictability of short selling for NYSE stocks to a matched sample of NASDAQ stocks. When considering trading that executes on all exchanges, we document that the NASDAQ has greater levels of short selling, relative to total trading activity, than the NYSE. However, NASDAQ has less relative short activity than the NYSE when considering short selling that executes on the primary exchange. When comparing the contrarian trading behavior and the return predictability of short sellers, we show that NASDAQ short sellers are more contrarian in contemporaneous and past returns and better at predicting negative returns than NYSE short sellers. These results are robust in each trade-size category.

I. Introduction

Research documents differences in the trading behavior of securities listed on the New York Stock Exchange (NYSE) and those on the National Association of Securities Dealers (NASDAQ), including differences in trading costs between the NYSE and NASDAQ (Huang and Stoll, 1996, in a $1/8^{th}$ environment; Bessembinder, 1999, in a $1/16^{th}$ environment; and Bessembinder, 2003, in a decimal environment). In addition, research shows that there are differences between NYSE and NASDAQ stocks in adverse selection (Affleck-Graves, Hegde, and Miller, 1994), information based trading (Heidle and Huang, 2002), as well as reductions in order flow fragmentation when stocks move from NASDAQ to the NYSE (Bennett and Wei, 2006).

Although not directly compared, research on short selling shows that NASDAQ stocks normally have higher levels of short selling than NYSE stocks (Alexander and Peterson, 2008; Diether, Lee, and Werner, 2007(a); Diether, Lee, and Werner, 2007(b); and Edwards and Hanley, 2008). The purpose of this study is to directly compare short selling of NYSE stocks to NASDAQ stocks using various matched samples in order to document any differences in short-selling behavior between the major exchanges. This investigation is warranted by recent findings in two streams of literature. First, Diether, Lee, and Werner (2007a) and Boehmer and Wu (2008) find that short sellers add to the informational efficiency in prices. Second, Theissen (2000) reports that prices are more informationally efficient on call and continuous auction markets than on dealer markets. We explore the level of short selling on the NYSE and NASDAQ in order to bridge these two streams of literature. Further, we examine differences in the contrarian trading behavior and return predictability of short sellers on the major exchanges.

Diether, Lee, and Werner (2007a) report that short volume relative to total trade volume, (short ratio) is 24 percent for NYSE-listed stocks and 31 percent for NASDAQ stocks. In a separate study and a reduced time period (February – July, 2005), Diether, Lee, and Werner (2007b) show similar statistics for their NYSE sample and an even higher short ratio for NASDAQ stocks. Edwards and Hanley (2008) document a positive coefficient for a NASDAQ dummy variable when investigating relative short sales around initial public offerings. Alexander and Peterson (2008), while analyzing the impact of Reg SHO on market liquidity, report higher short sales, relative to long sales, for their NASDAQ sample compared to their NYSE sample.

Many short-sale studies either examine NYSE and NASDAQ stocks separately or pool the different listed stocks and acknowledge the need to control for the influence of exchange listing by, for example, adding an indicator variable. Henry and Koski (2008) do not explicitly divide their sample of seasoned equity offerings (SEO) into NYSE and NASDAQ stocks, but control for the influence of exchange listing on SEO discount by inclusion of a dummy variable. Diether, Lee, and Werner (2007a) not only report their empirical results for NYSE and NASDAQ stocks separately, but argue that it is important to consider trading outside the primary listing market.

In this study, we match NYSE-listed stocks to NASDAQ-listed stocks based on several factors that influence short selling following Huang and Stoll (1996), Bessembinder and Kaufman (1997a, 1997b), and Chung, Van Ness, and Van Ness (2001). We calculate the short ratio for each listed stock using executions on all exchanges and using only executions on the primary listing exchange. When including short-sale and trade activity of all exchanges, we confirm that short selling of NASDAQ stocks is significantly greater than short selling of NYSE stocks, which is consistent with Diether, Lee, and Werner (2007a) and Edwards and Hanley (2008). When examining short activity from only the primary exchange, we find that relative short selling is higher on the NYSE than on NASDAQ. After controlling for factors that influence the level of short selling in a particular stock, the short ratio is greater on the NYSE than on NASDAQ.

Prior research documents that short sellers are informed and able to predict negative returns (Diamond and Verrecchia, 1987; Senchack and Starks, 1993; Aitken et al., 1999; Desai et al., 2002; Christophe, Ferri, and Angel, 2004; Boehmer, Jones, and Zhang, 2008). Diether, Lee, and Werner (2007a) examine the relation between returns and daily short activity. They document that short selling relates directly with contemporaneous and past returns, suggesting that short sellers are contrarian traders. While Diether, Lee, and Werner do not directly compare short sellers of NYSE stocks and short sellers of NASDAQ stocks, the magnitude of the coefficients from panel regressions suggests that NYSE short sellers are slightly more contrarian than NASDAQ short sellers.

We find that both NYSE and NASDAQ short sellers are contrarian in contemporaneous and past returns and are able to predict future negative returns. These results are consistent with the idea that short sellers correct short-term overreactions of stock prices and are able to target stocks that become overvalued (Diether, Lee, and Werner, 2007a), thus adding to the informational efficiency in prices (Boehmer and Wu, 2008). After matching NYSE stocks to NASDAQ stocks, we find new evidence that short sellers of NASDAQ stocks are more contrarian in contemporaneous returns. However, we do not show a significant difference in the contrarian behavior of short sellers in past returns when considering short activity executed on all exchanges. When examining the short activity on the primary exchange, we find that short sellers who trade on NASDAQ are more contrarian in *both* contemporaneous and past returns than short sellers who trade on the NYSE. Further, when comparing the information contained in NYSE and NASDAQ short selling, we show that short sellers on NASDAQ are better at predicting negative next-day returns than short sellers on the NYSE. Our findings that short sellers on NASDAQ are more contrarian and better able to predict negative returns than short sellers on the NYSE is consistent with the findings of Theissen (2000), who documents that prices in auction markets are more efficient than prices in dealer markets. The greater market efficiency on the NYSE makes it more difficult for NYSE short sellers to predict negative returns and allows informed short sellers to target stocks with prices that are out of line with their fundamental values, which occurs more frequently on NASDAQ.

Boehmer, Jones, and Zhang (2008) and Blau, Van Ness, and Van Ness (2008) find that larger short sales are more informed than smaller short sales. In our study of the return predictability of short activity on the NYSE and NASDAQ, we compare the frequency of various short-sale sizes on the exchanges. We calculate the proportion of volume from the small trade-size category (less than 500 shares) that is made up by small short sales. Similarly, we determine the proportion of medium-sized-trade volume (500 to 5,000 shares) and large-sized-trade volume (greater than 5,000 shares) that is made up from medium-sized and large-sized short sales, respectively. We find that short volume relative to total trade volume in the small trade-size category is more frequent on the NYSE. Further, large short volume relative to large trade volume is greater on NASDAQ. Our results are robust to both short selling on the primary exchange and all exchanges.

Consistent with Boehmer, Jones, and Zhang (2008) and Blau, Van Ness, and Van Ness (2008), we find that larger short sales are better able to predict negative returns than smaller short sales. We also show that the short ratio on NASDAQ is better at predicting negative returns than the short ratio on the NYSE in each trade-size category. However, our finding that NASDAQ short sellers are better at predicting negative returns than NYSE short sellers is driven by larger short sales (relative to larger trades). Again, these results are robust to both short selling on primary exchanges and short selling on all exchanges.

Boehmer (2005) finds that informed trading is greater on the NYSE than on NASDAQ while Affleck-Graves, Hedge, and Miller (1994) find that asymmetric information is greater on the NYSE. However, Heidle and Huang (2002) find that the probability of informed trading decreases when stocks move from NASDAQ to the NYSE. Our results suggest that, while more short selling, relative to total trade volume, is executed on the NYSE, more informed short selling occurs on NASDAQ; a result consistent with Theissen (2000).

The rest of the paper follows: Section II describes the data and presents the results of our different matching procedures. Section III reports the results of our empirical analysis. Our exchange comparisons of short-selling activity, return predictability, short activity in various size categories, and the information contained in different-sized short sales are reported in subsections in Section III. We offer a summary of our findings in Section IV.

II. Data

In our analyses, we use data that is made available by the Securities and Exchange Commission's Regulation SHO and trade transactions from the Trade and Quotes (TAQ) data base. Our initial sample includes all NYSE- and NASDAQ-listed common stocks (CRSP share code 10 or 11) that trade everyday of 2006 and have a price greater than $5. After these restrictions, there are 1,251 NYSE-listed stocks and 1,588 NASDAQ-listed stocks. Similar to

Diether, Lee, and Werner (2007a), we calculate the short ratio, which is the daily short volume divided by the daily trade volume. Before obtaining our matched samples, we find that the short ratio for NASDAQ-listed stocks is over three percent greater than the short ratio for NYSE-listed stocks, which is significant at the one percent level (*t*-statistic = 15.83). The result of this simple comparison is similar Diether, Lee, and Werner (2007a). From the initial sample, we match stocks based on characteristics in order to isolate the difference between short selling on the NYSE and short selling on NASDAQ.

NYSE-listed stocks and NASDAQ-listed stocks are matched following Huang and Stoll (1996), Bessembinder (1999), Bessembinder and Kaufman (1997a, 1997b), and Chung, Van Ness, and Van Ness (2001). The level of short-selling activity in a particular stock is influenced by its size, volatility, and trading activity (Arnold et al., 2005, Diether, Lee, and Werner, 2007(a), and Boehmer, Jones, and Zhang, 2008). When matching NYSE stocks to NASDAQ stocks, we calculate the following score:

$$\sum_k \left[\frac{Z_k^N - Z_k^D}{\left\{\left(Z_k^N + Z_k^D\right)/2\right\}} \right]^2 \qquad (1)$$

The score estimates the squared deviation between stock characteristics contained in Z_k. For robustness, we match NYSE (N) stocks to NASDAQ (D) stocks using three different groups of stock characteristics. Our first match is based on the stock's market capitalization, k = 1. We calculate the score for each NYSE-NASDAQ pair and choose the unique pair of NYSE and NASDAQ stocks with the smallest score. If the minimum score is greater than 1.5, that match is not included in the sample. In our second match, we include in Z, the stock price, daily volume, and market capitalization, $k = 3$. In our third match, we use the stock's daily volume, market capitalization, and the price volatility, which are considered important determinant in the level of short selling for a particular stock (Diether, Lee, and Werner, 2007a, and Boehmer, Jones, and Zhang, 2008). Price volatility is defined as the difference between the daily high price and the daily low price divided by the daily high price.

Our first match yields 530 pairs of the NYSE and NASDAQ stocks while the second match yields 535 pairs. The third match, based on determinants of short-selling activity described in the literature, results in 505 pairs of NYSE and NASDAQ stocks.

The statistics summarizing our matches are reported in Table 1. The statistics are equally-weighted means. Panel A shows that when matching NYSE stocks to NASDAQ stocks based on market capitalization, volume and price volatility vary between the samples while the average market capitalization and the average daily price are statistically similar. The average stock in all three samples has a price near $30 and a market capitalization of $4 billion. Panel B shows that when matching on market capitalization, price, and volume, only price volatility is varies between the two samples. Panel C shows that when matching on market capitalization, price volatility, and volume, price volatility is still higher for NASDAQ stocks although the difference is not economically significant.

III. Empirical Results

III.A Short Selling Comparison

As the matched samples appear to be reasonably similar, we look to see if shorting is higher on the NASDAQ as in previous literature. Similar to past research (Diether, Lee, and Werner, 2007(a), Boehmer, Jones, and Zhang, 2008), we analyze short-selling activity by examining the short ratio, which is the daily short volume divided by the daily trade volume. First, we calculate the *sh_ratio* using only short sales and trades that execute on the primary-listing exchange. Second, we calculate *sh_ratio_all* using trading data from all venues. We compare the short ratios for NYSE and NASDAQ and report the results in Table 2. Panel A reports statistics using our first matching procedure while Panels B and C show the findings using our second and third matches of NYSE and NASDAQ stocks. Although the average statistics vary across the three matches, the overall conclusion is the same. When considering only the primary exchange, the short ratio is higher for the NYSE, with a primary short ratio slightly greater than 38 percent. However, when all trading venues are included, NASDAQ stocks have significantly higher short ratios, with a short ratio of almost 24 percent. The univariate results suggest that while short selling is generally higher for NASDAQ-listed stocks, proportionately more short-selling activity occurs on the NYSE compared to NASDAQ.

In order to directly compare short selling between NYSE stocks and NASDAQ stocks, we control for other factors that influence the level of short selling in a pooled regression. We estimate the following equation.

$$sh\_ratio_{i,t} = \beta_0 + \beta_1 t\_o_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_vol_{i,t-5,\,t-1} + \beta_8 NY_i + \beta_9 NY \times Ret_t + \beta_{10} NY \times Ret_{t-5,t-1} + \varepsilon_{i,t} \quad (2)$$

where the dependent variable, $sh\_ratio_{i,t}$, is the short ratio, *t_o* is the daily volume divided by the number of shares outstanding while size is the market capitalization (in billions), and p_volt is defined is defined as the difference between the daily high price and the daily low price divided by the daily high price, day_t is a discrete variable numbered 1 to 251 for each day *t* in the sample time period and is included to control for any time trend in short selling that occurs during the time period, and *ret* is the daily return or cumulative return for the specified time period. Diether, Lee, and Werner (2007a) document that short sellers are contrarian in contemporaneous and past returns, therefore, we expect the short ratio to be positively related to both return variables. *sh_vol* is the amount of short volume (in 000,000s) that is executed for a particular stock for the specified time period in order to control for autocorrelation in short-selling activity. As equation (2) is estimated using pooled data, an NY dummy variable, equal to one if stock *i* is listed on the NYSE, is included.[1] We also interact the NY dummy with the *ret* variables. The equation is estimated using OLS with White (1980) robust standard errors and standard errors calculated after controlling for clustering, a Censored (0, 1) regression, and a random effects regression. We tabulate the regression results using our third matched sample, where NYSE and NASDAQ stocks are matched based on volume, market capitalization, and price volatility. Using the other matched samples in the analysis produces qualitatively similar results. In response to a Hausman test, we report the estimates from the random effects model using trades from the primary exchange in Table 3.[2]

When considering only the primary exchange trades (columns 1 through 3), we find that *size*, *p_volt*, and *sh_vol* are positively related to the short ratio, which is consistent with Diether, Lee, and Werner (2007a). We also show that the estimate for *t_o* is negative while the estimate for the trending variable, *day*, is positive suggesting that the short ratio is increasing during 2006. The estimates for the return variables are also positive, supporting the notion that short sellers are contrarian. We also report that the NY dummy variable positively impacts the short ratio, which is consistent with our univariate results and suggests that short selling on the NYSE is greater than short selling on NASDAQ. Interestingly, the interaction variable between the NY dummy and returns produces negative estimates, which implies that, while the NYSE has greater relative short selling, NASDAQ short sellers appear to be more contrarian than NYSE short sellers.

[1] Because the dummy variable NY does not change across the time series, fixed effects estimates are inconsistent. Therefore, we estimate equation (1) using pooled OLS and random effects.
[2] The pooled OLS and censored regression estimates are generally consistent with the random effects estimates.

When trading on all exchanges is considered (columns 4 through 6), the results have different implications. The estimate for the NY dummy variable is not significantly different from zero suggesting that, after controlling for other factors that influence the level of short selling, the proportion of trades on all exchanges that is made up from short sales is similar between the NYSE and NASDAQ. However, when the NY dummy variable is interacted with contemporaneous return and past returns, we find that NASDAQ short sellers are more contrarian in contemporaneous returns than NYSE short sellers, although NASDAQ and NYSE short sellers appear to be similarly contrarian in past returns.

III.B Return Predictability of Short Sales

Previous studies show that short sellers are informed as they are able to predict negative returns. Diamond and Verrecchia (1987) first hypothesized that unanticipated increases in short-selling activity will predict negative price adjustments. Senchack and Starks (1993) and Desai et al. (2002) both find empirical evidence of Diamond and Verrecchia's hypothesis as they document the monthly short interest contains some predictability of future negative returns for NYSE stocks and NASDAQ stocks, respectively. Aitken et al. (1998) find that negative returns on the Australian Stock Exchange generally follow short sales within 15 minutes of execution, which strongly supports Diamond and Verrecchia. At the daily level, Diether, Lee, and Werner (2007a) and Boehmer, Jones, and Zhang (2008) find that short volume, relative to trade volume, predicts negative returns.

In a separate stream of literature, research comparing the level of information-based trading on each exchange suggests that the NYSE has more informed traders than NASDAQ. Affleck-Graves, Hedge, and Miller (1994) finds that more asymmetric information exists on the

NYSE than on NASDAQ while Boehmer (2005) finds that trades of NASDAQ stocks have less price impact than trades of NYSE stocks, suggesting that the NYSE has more informed trading. Similar results are found by Easley, Kiefer, and O'Hara (1996), who document that NYSE tends to execute more informed trades. Contrary to the previous studies, Heidle and Huang (2002) finds that the probability of informed trading declines when stocks move from NASDAQ to the NYSE, suggesting that the likelihood of an informed trade occurring is higher on NASDAQ than on the NYSE. Because short sellers are generally informed (Boehmer, Jones, and Zhang, 2008) and the literature is not entirely definitive when comparing the level of informed trading between the two exchanges, we seek to determine which short sellers are better able to predict negative returns. We estimate the following equation:

$$Ret_{i,t+1,t+s} = \beta_0 + \beta_1 T\_O_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_ratio_{i,t} + \beta_8 NY_i + \beta_9 NY \times sh\_ratio_t + \varepsilon_{i,t+1,t+s} \quad (3)$$

The dependent variable is the cumulative return from day $t+1$ to day $t+s$, where s = {1, 2, or 3}. The independent variables are previously defined with the exception of an interaction term. We interact the *NY* dummy variable with the contemporaneous short ratio in order to test whether NYSE short-selling activity is more informed than NASDAQ short-selling activity. A negative estimate for the interaction variable suggests that NYSE short sellers are better at predicting negative returns than NASDAQ short sellers. The equation is estimated using a random effects model.[3,4]

Table 4 Panel A shows the results from estimating equation (3) using the short ratio from the primary exchange. In column (1) we find that next day returns are positively related to

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[3] We also estimate equation (2) using pooled OLS with White (1980) robust standard errors. The results are qualitatively similar to the random effects estimation, which a Hausman test prefers.
[4] Equation (2) is estimated again using the matching criteria of volume, market capitalization, and price volatility although the regression results are qualitatively similar when using the other matched samples.

turnover and negatively related to size, price volatility, and the cumulative return from day *t-5* to day *t-1*. The positive estimate for the day variable suggests that returns are increasing during the time period. The negative estimate for the short ratio suggests that relative short selling predicts negative next day returns. In column (2), we document that interaction estimate is positive, which suggests that the NYSE short selling is less able to predict negative returns when compared to NASDAQ short selling. That is, we show that NYSE short sellers are less informed or less able to predict negative returns than NASDAQ short sellers. The results appear consistent for two-day and three-day cumulative returns (columns (3) through (6)).

Table 4 Panel B shows the results using the short ratio obtained from dividing short sales and trades that are executed on all exchanges. The findings for all exchanges are qualitatively similar to the results for the primary exchange. The short ratio obtained from short sales and trades that are executed on all venues is able to predict next-day returns. Consistent with Panel A, the interaction estimate is positive suggesting that short sellers of NASDAQ stocks are more informed than short sellers of NYSE stocks.

The results of Tables 3 and 4 suggest that NASDAQ short sellers are more contrarian in contemporaneous and past returns and better able to predict future negative returns than NYSE short sellers. Boehmer and Wu (2008) and Diether, Lee, and Werner (2007a) argue that their empirical results support the notion that short sellers add to the informational efficiency in prices. In other words, short sellers short stocks that become out of line with their fundamental values and are able to correct overreaction in stock prices. Our results suggest that informed short sellers are better able to identify NASDAQ stocks that become overvalued. This interpretation is consistent with the findings of Theissen (2000), who documents that prices in call and continuous auction markets are more efficient than prices in dealer markets.

III.C Short-sale Sizes

In order to further investigate the information contained in short sales of stocks that are listed on the NYSE and NASDAQ, we study different short-sale sizes. Boehmer, Jones, and Zhang (2008) report that stocks with the largest proportion of shorting activity in large trade-size category (greater than 5,000 shares) underperform other stocks suggesting that large short sales are most informed. In additional tests, Blau, Van Ness, and Van Ness (2008) find that larger short sales are better able to predict negative intraday and next day returns than smaller short sales. Further, they find that after periods of larger intraday returns, short sellers tend to use larger short sales, suggesting that the contemporaneous correlation between daily returns and daily short activity is driven by the execution of larger short sales.

Because the level of information contained in short sales is a function of trade size, we examine different-sized short sales of both NYSE stocks and NASDAQ stocks. Table 5 reports three different ratios that explain the use of different-sized short sales. The small ratio is the percentage of volume from small trades (less than 500 shares) made up from small short sales. The medium ratio is the proportion of volume from medium-sized trades (500 shares to 5,000 shares) made up from medium-sized short sales. The large ratio is the short volume from large short sales divided by trade volume from large trades. We calculate the three ratios using trades on the primary exchange and trades on all venues. In panel A, we see that the ratios are decreasing across sizes for the NYSE trades and increasing for NASDAQ trades. The results are similar for both trades on the primary exchange and trades on all exchanges. The panel also shows that the difference between the NYSE and NASDAQ is decreasing, suggesting that more large trades on NASDAQ are made up from large short sales while more small trades on the

NYSE are made up from small short sales. The results are consistent across Panels B and C, which report the results using the alternative matched samples.

Similar to Table 3, we regress the short ratio for different trade sizes on several independent variables, including a dummy variable capturing whether the stock is listed on the NYSE or NASDAQ. The following equation is estimated using a random effects regression:

$$size\_sh\_ratio_{i,t} = \beta_0 + \beta_1 t\_o_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_vol_{i,t-5,t-1} + \beta_8 NY_i + \beta_9 NY\times ret_t + \beta_{10} NY\times ret_{t-5,t-1} + \varepsilon_{i,t} \quad (3)$$

where the dependent variable is the short ratio obtained from short sales and trades of different sizes. The independent variables are the same as in equation (1).

Table 6 reports the regression results from estimating equation (3) for stocks included in the third matched sample.[5] Panel A shows the results from estimating equation (3) when including short sales and trades from the primary exchange while Panel B reports the estimates for trades on all exchanges. In Panel A, the coefficients for the small ratio estimation are qualitatively similar to those for the short ratio in Table 3. The only exception is that the coefficient for the interaction between the contemporaneous return and the NY dummy variable is not significantly different from zero, suggesting that short sellers of small sizes on the NYSE and NASDAQ are similarly contrarian in contemporaneous returns. In column (3), we report that NASDAQ short sellers of small sizes are more contrarian in past returns than NYSE short sellers of small sizes. The regression estimates for the medium ratio and the large ratio both show that NASDAQ short sellers are more contrarian in contemporaneous and past returns that NYSE short sellers. Panel B contains the results for short sales and trades on all venues and are similar to those in Panel A. Other broader results suggest that the contemporaneous relation

[5] We estimate equation (3) using pooled OLS and a Censored (0,1) regression and find the results to be similar. Again, the results of a Hausman test reveal the presence of random effects. In addition, we also estimate equation (3) using the other matched samples and find the results to be similar.

between short selling and daily returns (in columns (1), (4), and (7)) is increasing across sizes, which is consistent with the results of Blau, Van Ness, and Van Ness (2008).

III.D Return Predictability of Short Sale Sizes

We continue our comparison of the information in NASDAQ and NYSE short sales by examining the return predictability of different short-sale sizes at the daily level. Boehmer, Jones, and Zhang (2008) and Blau, Van Ness, and Van Ness (2008) document that larger short sales are more informed and better able to predict negative returns. We compare the level of information between NASDAQ short sales of different sizes and NYSE short sales of different sizes by estimating the following equation:

$$Ret_{i,t+1,\,t+s} = \beta_0 + \beta_1 t\_o_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sm\_ratio_{i,t} + \beta_8 med\_ratio_{i,t} + \beta_9 lar\_ratio_{i,t} + \beta_{10} NY_i + \beta_{11} NY\times sm\_ratio_t + \beta_{12} NY\times med\_ratio_t + \beta_{13} NY\times lar\_ratio_t + \varepsilon_{i,t+1,t+s} \quad (4)$$

We estimate equation (4) using ret_{t+1}, $ret_{t+1,\,t+2}$, and $ret_{t+1,\,t+3,}$ as dependent variables. However, as the results are qualitatively similar, we report only the results of estimating the two day cumulative returns, $ret_{t+1,\,t+2}$. All variables are as previously defined, except we interact the size ratio variables with the NY dummy variable to test whether certain sized short sales are more informed on the NYSE than NASDAQ.

As with the previous regression analyses, we estimate the equations using short sales and trades from the primary exchange (Panel A) and then short sales and trades that execute on all exchanges (Panel B).[6] Again, we report the results from estimating equation (4) using our third match although the other matches produce qualitatively similar findings. In Table 7 Panel A, we use five different specifications. In order to confirm earlier empirical results (Boehmer, Jones,

[6] As before, we report the results of the two-way random effects estimation in response to the Hausman test, although pooled OLS results are qualitatively similar.

and Zhang, 2008), we conduct an *F*-test to determine if large short sales are better able to predict negative returns than small and medium-sized short sales. In Panel A Column (1), we find that the small ratio and the large ratio are able to predict negative next (two-) day cumulative returns. The results of the *F*-test support earlier research and suggest that more information is contained in large short sales than in small short sales as the negative estimate for the large ratio is significantly lower than the negative estimate for the small ratio.[7]

Columns (2) through (4) show that that in each case, NASDAQ short sellers are better able to predict negative returns than NYSE short sellers as the interaction between the NYSE dummy and the short ratio of different sizes produces estimates that are positive and significant. The interaction estimates are increasing across specifications suggesting that the ability of NASDAQ short sellers to predict negative returns better than NYSE short sellers is driven by short selling in larger sizes, which research documents are the most informed short sales (Boehmer, Jones, and Zhang, 2008). Column (5) shows that NASDAQ short sellers of large sizes are better able to predict negative returns than NYSE short sellers of large sizes as the *F*-test, testing the equality of β_{11} and β_{13}, is significant at the one percent level. Panel B, which reports the results of estimating equation (4) using short sales and trades executed on all venues, shows evidence consistent with Panel A.

IV. Conclusion

Research comparing securities trading on the NYSE and NASDAQ documents important differences in trading costs (Christie and Schultz, 1994, Christie, Harris, and Schultz, 1994, Bessembinder, 1999, Bessembinder, 2003), asymmetric information (Affleck-Graves, Hedge,

[7] The medium ratio produces a positive estimate, suggesting that short sales of medium sizes are unable to predict negative returns.

and Miller, 1994), information based trading (Heidle and Huang, 2002), and order flow fragmentation (Bennett and Wei, 2006). Although not directly compared, research examining short selling of NASDAQ stocks and NYSE stocks generally shows higher levels of short selling for NASDAQ stocks (Alexander and Peterson, 2008; Diether, Lee, and Werner, 2007(a); Diether, Lee, and Werner, 2007(b); and Edwards and Hanley, 2008). This paper directly compares short selling on NASDAQ and the NYSE by matching stocks following methods of Huang (1996), Bessembinder and Kaufman (1997a), Bessembinder and Kaufmann (1997b), and Chung, Van Ness, and Van Ness (2001). Our major findings are: (1) the NYSE has greater levels of short selling than NASDAQ, when considering short selling (daily short volume divided by daily trade volume) that executes on the primary exchange; (2) NASDAQ has more short activity than the NYSE when considering short selling on all venues, which is consistent with prior research (Alexander and Peterson, 2008; Diether, Lee, and Werner, 2007(a); Diether, Lee, and Werner, 2007(b); and Edwards and Hanley, 2008); (3) short sellers are generally contrarian in contemporaneous and past returns and NASDAQ short sellers appear to be more contrarian than NYSE short sellers, which is robust across different trade sizes; (4) NASDAQ short sellers (in general and in all size categories) are better able to predict future negative returns than NYSE short sellers; and (5) NASDAQ (NYSE) has a greater proportion of trade volume from large (small) sizes made up from large (small) short sales.

The implications of our study suggest that, while more short selling occurs on the NYSE, short selling on NASDAQ is more informed. Boehmer and Wu (2008) find evidence that short sellers add to the informational efficiency in prices. Diether, Lee, and Werner (2007a) argue that short sellers assist in correcting short-term overreaction of stock prices that are out of line with their fundamental value. Our results that short sellers on NASDAQ are more contrarian in past returns and better able to predict negative future returns, suggest that NASDAQ stocks become more out of line with their fundamental value than NYSE stocks (Theissen, 2000).

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Table 1
Descriptive Statistics
The table reports statistics that describe the samples. After matching NYSE stocks to Nasdaq stocks using different characteristics, we calculate the cross-sectional mean of market capitalization (size) in 000s, price, and volume. Price volatility (p_volt) is defined as the difference between the daily high price and the daily low price divided by the daily high price. The difference between the NYSE and Nasdaq is reported with the corresponding p-value. The score obtained from estimating equation (1) is also reported. Each panel shows the results for the different matched used in the analysis.

Panel A. Stock Characteristics using the Market Cap Match (n=530)				
	NYSE Stocks	NASDAQ Stocks	Difference	Score
size	4,474,557	4,529,324	-54,767	0.0000234
			(0.196)	
price	32.52	30.82	1.70	
			(0.192)	
volume	760,884	1,770,818	-1,009,933**	
			(0.000)	
p_volt	0.0249	0.0296	-0.0048**	
			(0.000)	
Panel B. Stock Characteristics using Price, Volume, and Market Cap Match (n=535)				
size	4,111,590	3,735,352	376,236	0.0328
			(0.072)	
price	30.13	29.75	0.38	
			(0.156)	
volume	1,070,304	1,237,663	-167,362	
			(0.072)	
p_volt	0.0262	0.0292	-0.0030**	
			(0.000)	
Panel C. Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)				
size	4,335,504	4,017,996	317,509	0.0226
			(0.144)	
price	29.64	31.54	-1.89	
			(0.084)	
volume	1,124,040	1,286,588	-162,548	
			(0.097)	
p_volt	0.0270	0.0274	-0.0004**	
			(0.000)	

**,* Statistically significant at the 0.01 and 0.05 levels

Table 2
Differences in shorting
The table reports differences in shorting for the three matched samples of NYSE and NASDAQ samples. Sh_ratio is the daily short volume executed on the specified exchange divided by the daily trade volume executed on the specified exchange. Sh_ratio_all is the daily short volume executed on all exchanges divided by the daily volume executed on all exchanges. The difference between the NYSE and NASDAQ is reported with the corresponding p-value.

Panel A. Stock Characteristics using the Market Cap Match (n=530)			
	NYSE Stocks	NASDAQ Stocks	Difference
sh_ratio	0.3823	0.3658	0.0164**
			(0.000)
sh_ratio_all	0.2150	0.2361	-0.0211**
			(0.000)
Panel B. Stock Characteristics using Price, Volume, and Market Cap Match (n=535)			
sh_ratio	0.3823	0.3653	0.0169**
			(0.000)
sh_ratio_all	0.2146	0.2360	-0.0214**
			(0.000)
Panel C. Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)			
sh_ratio	0.3801	0.3663	0.0137**
			(0.000)
sh_ratio_all	0.2130	0.2359	-0.0229**
			(0.000)

**,* Statistically significant at the 0.01 and 0.05 levels

Table 3
Regression Results – primary exchange
The table reports the results from estimating the following model where the dependent variable is the short ratio, small ratio, medium ratio, and large ratio.

$$Ratio_{i,t} = \beta_0 + \beta_1 T\_O_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_vol_{i,t-5,\,t-1} + \beta_8 NY_i + \beta_9 NY \times Ret_t + \beta_{10} NY \times Ret_{t-5,t-1} + \varepsilon_{i,t}$$

t_o is the daily volume divided by the number of shares outstanding while size is the market capitalization (in billions). P_volt is defined as before and day is the a discrete variable numbered 1 to 251 for each day t in the sample time period. Ret is the daily return (or cumulative return for the specified time period. NY is dummy variable equal to one if stock i is listed on the NYSE. The interaction variables are also defined. The equation is estimated using OLS (with White (1980) robust standard errors and standard errors controlling for clustering), a Censored (0, 1) regression, and a random effects regression. In response to a Hausman test, we report the estimates from the random effects model although the main results in the other specifications are quantitatively similar. P-values are reported in the parentheses. The Panels report the results for different matches.

Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)						
	Primary Exchange $Sh\_ratio_{i,t}$			*All Exchanges* $Sh\_ratio_{i,t}$		
Intercept	0.332**	0.321**	0.305**	0.268*	0.165	0.287*
	(0.000)	(0.000)	(0.000)	(0.019)	(0.154)	(0.015)
T_o_t	-0.706**	-0.733**	-0.701**	2.786**	2.556**	2.781**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.007)	(0.003)
$Size_t$	0.137**	0.196**	0.298**	-1.417	-1.327	-1.435
	(0.001)	(0.001)	(0.000)	(0.689)	(0.708)	(0.685)
P_volt_t	0.638**	0.635**	0.636**	0.443	0.421	0.444
	(0.000)	(0.000)	(0.000)	(0.253)	(0.278)	(0.253)
Day	0.002**	0.002**	0.002**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.076)	(0.095)	(0.074)
Ret_t	0.466**	0.873**	0.472**	-4.481**	-0.830	-4.484**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.368)	(0.000)
$Ret_{t-5,t-1}$	0.091**	0.094**	0.284**	0.677**	0.698**	0.535
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.072)
$Sh\_vol_{t-5,t-1}$	0.006**	0.006**	0.006**	0.003	0.003	0.003
	(0.000)	(0.000)	(0.000)	(0.476)	(0.508)	(0.463)
NY	0.038**	0.060**	0.090**	0.256	0.451**	0.218
	(0.000)	(0.000)	(0.000)	(0.094)	(0.004)	(0.179)
$NY \times Ret_t$		-0.796**			-7.147**	
		(0.000)			(0.000)	
$NY \times Ret_{t-5,t-1}$			-0.378**			0.278
			(0.000)			(0.493)
Adj R^2	0.014	0.015	0.016	0.0002	0.0004	0.0002
RE	Yes	Yes	Yes	Yes	Yes	Yes

**,* Statistically significant at the 0.01 and 0.05 levels

Table 4

Future Return Regressions – Primary Exchange

The table reports the results from estimating the following equation, where the dependent variables are the next day cumulative returns.

$$Ret_{i,t+1,t+s} = \beta_0 + \beta_1 T\_O_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_ratio_{i,t} + \beta_8 NY_i + \beta_9 NY \times sh\_ratio_t + \varepsilon_{i,t+1,t+s}$$

where s = {0, 1, 2}. The independent variables are defined as before, however, we interact the NY dummy variable with the contemporaneous short ratio in order to test whether NYSE short-selling activity is more informed than Nasdaq short-selling activity. The equation is estimated using random effects and p-values are reported in parentheses. Panel A contains the results for trades and shorts that occur on the primary exchange while panel B contains the results using trades and shorts that occur on all exchanges.

Panel A. Primary Exchange - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)

	Ret_{t+1}		$Ret_{t+1,t+2}$		$Ret_{t+1,t+3}$	
Intercept	0.0015**	0.0016**	0.0032**	0.0039**	0.0040**	0.0046**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_O_t	0.0143**	0.0147**	0.0002	0.0020	-0.0129	-0.0114
	(0.003)	(0.002)	(0.974)	(0.767)	(0.115)	(0.167)
$Size_t$	-0.0369**	-0.0372**	-0.1301**	-0.1322**	-0.2576**	-0.2601**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Pvolt_t$	-0.0065	-0.0065*	-0.0132**	-0.0133**	-0.0242**	-0.0243**
	(0.056)	(0.054)	(0.006)	(0.006)	(0.000)	(0.000)
Day	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Ret_t	0.0020*	0.0019	-0.0519**	-0.0523**	-0.0540**	-0.0544**
	(0.315)	(0.342)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	-0.0152**	-0.0152**	-0.0209**	-0.0210**	-0.0325**	-0.0325**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sh_ratio_t	-0.0026**	-0.0030**	-0.0044**	-0.0064**	-0.0034**	-0.0052**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY		-0.0002*		-0.0012*		-0.0009*
		(0.607)		(0.024)		(0.412)
$NY \times sh\_ratio_t$		0.0011*		0.0041**		0.0036**
		(0.014)		(0.000)		(0.000)
Adj R^2	0.0019	0.0019	0.0038	0.0041	0.0041	0.0042
Random Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. All Exchanges - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)						
	Ret_{t+1}		$Ret_{t+1,t+2}$		$Ret_{t+1,t+3}$	
Intercept	0.0024**	0.0028**	0.0048**	0.0059**	0.0059**	0.0069**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_O_t	0.0098*	0.0105**	0.0025	0.0045	-0.0054	-0.0039
	(0.014)	(0.009)	(0.657)	(0.429)	(0.436)	(0.574)
$Size_t$	-0.0410**	-0.0411**	-0.1400**	-0.1421**	-0.2727**	-0.2745**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Pvolt_t$	-0.0044	-0.0048	-0.0159**	-0.0168**	-0.0283**	-0.0289**
	(0.173)	(0.146)	(0.001)	(0.003)	(0.000)	(0.000)
Day	0.0000	0.0000	0.0001*	0.0001*	0.0001**	0.0001**
	(0.567)	(0.862)	(0.003)	(0.037)	(0.000)	(0.000)
Ret_t	0.0025	0.0023	-0.0458**	-0.0466**	-0.0453**	-0.0459**
	(0.184)	(0.232)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	-0.0138**	-0.0139**	-0.0195**	-0.0198**	-0.0308**	-0.0309**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sh_ratio_t	-0.0065**	-0.0077**	-0.0109**	-0.01475**	-0.0102**	-0.0131**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY		-0.0008*		-0.0023**		-0.0018
		(0.041)		(0.001)		(0.075)
$NY \times sh\_ratio_t$		0.0029**		0.0091**		0.0068**
		(0.000)		(0.000)		(0.000)
Adj R^2	0.0022	0.0023	0.0042	0.0045	0.0042	0.0043
Random Effects	Yes	Yes	Yes	Yes	Yes	Yes

**,* Statistically significant at the 0.01 and 0.05 levels

Table 5
Short Sale Sizes

The table shows the different sized ratios. The small ratio is defined as the small short volume divided by the small trade volume where small volume is the daily volume made up from trades or shorts that are less than 500 shares. The medium (500 to 5,000 shares) ratio and large (trades or short greater than 5,000 shares) ratio are similarly defined. The cross-sectional mean for NYSE stocks, Nasdaq stocks, and difference between the two exchanges with the corresponding p-value are reported. The panels show the results for the different matchs.

	Primary Exchange			All Exchanges		
	Small Ratio (< 500 shares)	Medium Ratio (500 to 5,000 shares)	Large Ratio (> 5,000 shares)	Small Ratio (< 500 shares)	Medium Ratio (500 to 5,000 shares)	Large Ratio (> 5,000 shares)
Panel A. Stock Characteristics using the Market Cap Match (n=530)						
NYSE Mean	0.4709	0.4197	0.2141	0.3354	0.3574	0.1374
Nasdaq Mean	0.3281	0.4162	0.5343	0.2279	0.3229	0.4004
Difference	0.1428**	0.0028	-0.3202**	0.1075	0.0345	-0.2630
(p-value)	(0.000)	(0.601)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B. Stock Characteristics using Price, Volume, and Market Cap Match (n=535)						
NYSE Mean	0.4762	0.4211	0.2140	0.3291	0.3545	0.1389
Nasdaq Mean	0.3293	0.4229	0.5204	0.2294	0.3288	0.3912
Difference	0.1469**	-0.0019	-0.3064**	0.0997	0.0257	-0.2523
(p-value)	(0.000)	(0.707)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C. Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)						
NYSE Mean	0.4723	0.4192	0.2130	0.3251	0.3528	0.1393
Nasdaq Mean	0.3292	0.4278	0.5230	0.2291	0.3345	0.3906
Difference	0.1431**	-0.0086	-0.3100**	0.0960	0.0183	-0.2513
(p-value)	(0.000)	(0.108)	(0.000)	(0.000)	(0.004)	(0.000)

**,* Statistically significant at the 0.01 and 0.05 levels

Table 6
Size Regression Results

The table reports the results from estimating the following model where the dependent variable is the short ratio, small ratio, medium ratio, and large ratio.

$$Ratio_{i,t} = \beta_0 + \beta_1 T\_O_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sh\_vol_{i,t-5,\,t-1} + \beta_8 NY_i + \beta_9 NY \times Ret_t + \beta_{10} NY \times Ret_{t-5,t-1} + \varepsilon_{i,t}$$

T_O is the daily volume divided by the number of shares outstanding while size is the market capitalization (in billions). P_volt is defined as before and day is the a discrete variable numbered 1 to 251 for each day t in the sample time period. Ret is the daily return (or cumulative return for the specified time period). NY is dummy variable equal to one if stock i is listed on the NYSE. The interaction variables are also defined. The equation is estimated using OLS with White (1980) robust standard errors, a Censored (0, 1) regression, and a random effects regression. We find differences in the relation between the dependent variable and T_O using OLS and random effects so we report the estimates from the random effects model. P-values are reported in the parentheses. The Panels report the results using short sales and trades that execute on the primary exchange and shorts and trades that execute on all exchanges, respectively.

Panel A. Primary Exchange - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)

		$Sm\_Ratio_{i,t}$			$Med\_ratio_{i,t}$			$Lar\_ratio_{i,t}$	
Intercept	0.265**	0.260**	0.242**	0.376**	0.369**	0.353**	0.276**	0.259**	0.246**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_o_t	-0.151**	-0.163**	-0.148**	-1.431**	-1.444**	-1.427**	2.388**	2.355**	2.403**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Size_t$	0.493**	0.534**	0.679**	-0.326	-0.316	0.272	1.928 **	1.906**	1.891**
	(0.000)	(0.000)	(0.000)	(0.093)	(0.104)	(0.168)	(0.000)	(0.000)	(0.000)
P_volt_t	0.721**	0.719**	0.719**	0.438**	0.437**	0.438**	0.506**	0.502**	0.504**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day	0.002**	0.002**	0.002**	0.001**	0.001**	0.001**	-0.003**	-0.003**	-0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ret_t	0.626**	0.797**	0.630**	0.747**	0.954**	0.751**	0.756**	1.337**	0.759**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	0.078**	0.079**	0.231**	0.154**	0.155**	0.316**	0.121**	0.124**	0.332**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Sh\_vol_{t-5,t-1}$	0.006**	0.006**	0.006**	0.006**	0.006**	0.006**	0.007**	0.007**	0.007**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY	0.146**	0.155**	0.187**	0.001	0.012	0.044**	-0.165**	-0.134**	-0.109**
	(0.000)	(0.000)	(0.000)	(0.907)	(0.146)	(0.000)	(0.000)	(0.000)	(0.000)
$NY \times Ret_t$		-0.335			-0.4071			-1.141**	
		(0.349)			(0.000)			(0.000)	
$NY \times Ret_{t-5,t-1}$			-0.301**			-0.316**			-0.413**
			(0.000)			(0.000)			(0.000)
$Adj\ R^2$	0.024	0.024	0.025	0.007	0.008	0.008	0.024	0.024	0.025
RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. All Exchanges - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)									
		Sm_Ratio$_{i,t}$			*Med_ratio*$_{i,t}$			*Lar_ratio*$_{i,t}$	
Intercept	0.218**	0.209**	0.197**	0.299**	0.295**	0.279**	0.283**	0.274**	0.264**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_o_t	-0.691**	-0.710**	-0.686**	-1.267**	-1.278**	-1.265**	1.182**	1.164**	1.192**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Size_t$	-0.582**	-0.520**	-0.432**	-0.285	-0.269	-0.199	2.378**	2.343**	2.306**
	(0.000)	(0.000)	(0.001)	(0.084)	(0.105)	(0.243)	(0.000)	(0.000)	(0.000)
P_volt_t	0.519**	0.517**	0.518**	0.331**	0.329**	0.329**	0.335**	0.333**	0.334**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Day	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ret_t	0.324**	0.627**	0.327**	0.481**	0.643**	0.485**	0.563**	0.894**	0.564**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	0.083**	0.085**	0.228**	0.175**	0.176**	0.321**	0.098**	0.101**	0.239**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Sh\_vol_{t-5,t-1}$	0.004**	0.004**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY	0.097**	0.114**	0.0136**	0.032**	0.041**	0.071**	-0.173**	-0.155**	-0.135**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NY \times Ret_t$		-0.593**			-0.317**			-0.649**	
		(0.000)			(0.000)			(0.000)	
$NY \times Ret_{t-5,t-1}$			-0.283			-0.285**			-0.274**
			(0.000)			(0.000)			(0.000)
Adj R^2	0.0170	0.0179	0.0188	0.0130	0.0131	0.0138	0.0222	0.0225	0.0228
RE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

**,* Statistically significant at the 0.01 and 0.05 levels

Table 7
Information in Different Sized Short Sales – Primary Exchange
The table reports the results of estimating the next (two) day cumulative returns on several independent variable defined as before.

$$Ret_{i,t+1,\,t+s} = \beta_0 + \beta_1 t\_o_{i,t} + \beta_2 size_{i,t} + \beta_3 p\_volt_{i,t} + \beta_4 day_t + \beta_5 ret_{i,t} + \beta_6 ret_{i,t-5,t-1} + \beta_7 sm\_ratio_{i,t} + \beta_8 med\_ratio_{i,t} + \beta_9 lar\_ratio_{i,t} + \beta_{10} NY_i + \beta_{11} NY{\times}sm\_ratio_t + \beta_{12} NY{\times}med\_ratio_t + \beta_{13} NY{\times}lar\_ratio_t + \varepsilon_{i,t+1,t+s}$$

We also used ret_{t+1} and $ret_{t+1,\,t+3}$ as dependent variables and the results are qualitatively similar. We test which sized-short sales contain more information. Sm_ratio is the daily short volume from small trades made up from small short sales divded by the total trade volume. Med_ratio and Lar_ratio are similarly defined. We interact the new ratio variables with the NY dummy variable to test whether certain sized short sales are more informed on the NYSE than on Nasdaq. Panel A reports the results where the ratios are obtained by using short sales and trades that execute on the primary exchange. Panel B reports the results using short sales and trades that execute on all venues. Our third matched sample is tabulated although the other matched samples are qualitatively similar. The estimates are obtained using a random effects regression and p-values are reported in parentheses.

Panel A. Primary Exchange - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)

	[1]	[2]	[3]	[4]	[5]
Intercept	0.0024**	0.0030**	0.0030**	0.0029**	0.0035**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_O_t	0.0075	0.0078	0.0083	0.0071	0.0077
	(0.282)	(0.261)	(0.237)	(0.307)	(0.267)
$Size_t$	-0.1258**	-0.1265**	-0.1270**	-0.1306**	-0.1316**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Pvolt_t$	-0.0173**	-0.0165**	-0.0172**	-0.0177**	-0.0169**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Day	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ret_t	-0.0533**	-0.0531**	-0.0532**	-0.0539**	-0.0537**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	-0.0213**	-0.0212**	-0.0213**	-0.0214**	-0.0212**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sm_ratio_t	-0.0034**	-0.0052**	-0.0036**	-0.0035**	-0.0048**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Med_ratiot	0.0024**	0.0017**	-0.0015	0.0015*	-0.0008
	(0.000)	(0.001)	(0.205)	(0.020)	(0.508)
Lar_ratiot	-0.0082**	-0.0083**	-0.0083**	-0.0106**	-0.0107**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY		-0.0009	-0.0008	-0.0006	-0.0013**
		(0.240)	(0.302)	(0.446)	(0.086)
$NY{\times}sm\_ratio_t$		0.0032**			0.0025**
		(0.000)			(0.011)
$NY{\times}med\_ratio_t$			0.0051**		0.0022
			(0.000)		(0.119)
$NY{\times}lar\_ratio_t$				0.0114**	0.0110**
				(0.000)	(0.000)
F-test($\beta_7 = \beta_9$)	38.09**				
(p-value)	(0.000)				
F-test($\beta_{11} = \beta_{13}$)					25.63**
(p-value)					(0.000)
Adj R^2	0.0041	0.0041	0.0041	0.0043	0.0044
Random Effects	Yes	Yes	Yes	Yes	Yes

Panel B. All Exchanges - Stock Characteristics using Volume, Market Cap, and Price Volatility Match (n=505)					
	[1]	[2]	[3]	[4]	[5]
Intercept	0.0041**	0.0046**	0.0045**	0.0044**	0.0048**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_O_t	0.0005	0.0011	0.0008	-0.0001	0.0007
	(0.946)	(0.876)	(0.904)	(0.993)	(0.916)
$Size_t$	-0.1315**	-0.1313**	-0.1316**	-0.1321**	-0.1321**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Pvolt_t$	-0.0108*	-0.0105*	-0.0110*	-0.0112*	-0.0110*
	(0.025)	(0.031)	(0.023)	(0.021)	(0.023)
Day	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Ret_t	-0.0508**	-0.0509**	-0.0509**	-0.0513**	-0.0515**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ret_{t-5,t-1}$	-0.0217**	-0.0218**	-0.0218**	-0.0219**	-0.0219**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sm_ratio_t	-0.0119**	-0.0138**	-0.0119**	-0.0119**	-0.0135**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Med_ratiot	-0.0010	-0.0014	-0.0155**	-0.0016	-0.0046*
	(0.426)	(0.259)	(0.006)	(0.192)	(0.016)
Lar_ratiot	-0.0154**	-0.0156**	-0.0155**	-0.0172**	-0.0174**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NY		-0.0010	-0.0008	-0.0006	-0.0014
		(0.225)	(0.270)	(0.427)	(0.076)
$NY \times sm\_ratio_t$		0.0048**			0.0042*
		(0.009)			(0.031)
$NY \times med\_ratio_t$			0.0070**		0.0043
			(0.003)		(0.086)
$NY \times lar\_ratio_t$				0.0134**	0.0132**
				(0.000)	(0.000)
F-test($\beta_7 = \beta_9$)	6.98**				
(p-value)	(0.008)				
F-test($\beta_{11} = \beta_{13}$)					7.64**
(p-value)					(0.006)
Adj R^2	0.0047	0.0047	0.0047	0.0048	0.0048
Random Effects	Yes	Yes	Yes	Yes	Yes

**,* Statistically significant at the 0.01 and 0.05 levels