Algorithmic Trading in Volatile Markets

ABSTRACT
Algorithmic trading (AT) is widely adopted by equity investors. In the current paper we investigate whether AT increases stock price volatility in turbulent periods. By exclusively focusing on the volatile days on the Australian Securities Exchange during the period of 27 October 2008 till 23 October 2009, we find a significant negative association between the level of AT activities in a particular (individual) share and the price swing of that stock. This is likely caused by AT tracking Volume-Weighted Average Price (VWAP) since we find that algorithmic traders are more likely to trade when price is close to VWAP. We also provide evidence that the AT’s order imbalances have smaller impact on the abnormal returns of individual stocks compared to order imbalances based on non-algorithmic trading. Moreover, there are significant return reversals in low AT activity stocks after market decline days. Overall, our findings indicate that, in turbulent market conditions, the AT improves market quality by reducing price fluctuation and minimizing price pressure.

Keywords: Algorithmic Trading; Market Microstructure; Volatile Market; Trading Volume

JEL classification: G12, G14, G19
1. Introduction

The technological development over the past decade has substantially increased the use of computer algorithms in financial markets. Researchers, regulators and market participants are keen to understand the implication of this recent development. Hendershott, Jones & Menkveld (2011) find that Algorithmic Trading (AT) overall plays a beneficial role in terms of liquidity and price discovery in rising markets. At the same time, they warn that investigations into the characteristics of AT ‘in turbulent or declining markets’ (p. 31) are equally important. The objective of this paper is to evaluate the characteristics of AT in volatile days, defined as the days when the absolute value of the market return exceeds two percent (Dennis & Strickland, 2002). We first analyze the association between AT and return fluctuation in individual stocks. We then provide explanation by looking into the strategies that algorithmic traders may employ. Next, we investigate the different impact of order imbalances from AT and non-Algorithmic Trading (nonAT) to individual stock returns. Last, we provide evidence of return reversal post volatile days.

While regulatory agencies are expressing concerns about the implication of AT to long-term investors, until recently, most of the AT and High Frequency Trading (HFT) studies focus on ultra-short-term intraday effects ranging from milliseconds to minutes. For instance, Hendershott & Riordan (2012) relate AT to intraday liquidity measures such as bid-ask spread and order book depth. Hasbrouck & Saar (2013) proposed a framework for identifying

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1 Algorithmic trading accounts for the majority of trading volume in developed countries. In our sample of the Australian Securities Exchange (ASX) stocks, more than two thirds of the trades are initiated by algorithms.

2 ASX (2010) mention that bringing in new algorithmic traders ‘raises some important public policy issues about balancing the interests of short-term traders with long-term investors’ (p. 4). SEC (2010) indicate that whether the market structural changes due to the algorithmic traders is better or worse for long-term investors is ‘an important issue on which comment is requested’.

3 HFT, as a subset of AT, is generally distinguished from AT by its clear emphasis on the speed of trading.
HFT and assessed the intraday effects of HFT. Brogaard et al. (2012) assess the impact of HFT on market qualities in second-by-second context, and more specifically report the effect of HFT 20 seconds around public announcements. It is intuitive to analyze automated trading in ultra-high frequency since many of the proprietary trading strategies emphasis on exploiting small and fleeing opportunities in the market. However, there are reasons suggesting longer-term implications from AT. Note that, some algorithmic traders follow an extension of the traditional trading strategies such as value, momentum, and pairs trading. These strategies often involve holding positions over days and longer horizons. Moreover, unlike HFT, execution algorithms make up a significant portion of AT. These execution algorithms are services provided to buy side clients to minimize the price impact of trading, and therefore the general intention to trade is initially expressed by human traders. As a result, the inference from these trades can be studied over longer horizons. We differ from previous studies\textsuperscript{4} by describing daily effects of AT. To the best of our knowledge, this is the first study to investigate the impact of AT on the daily stock returns.

Our paper contributes to the literature in the following ways. First, we provide empirical evidence on the characteristics of AT in relation to daily price movement and discuss its implication on longer-term price fluctuations. Many existing studies rely on proxies such as message traffic to model algorithmic trades. Consequently, one cannot distinguish buy and sell trades. In absence of trade direction information, inferences about stock returns may be difficult\textsuperscript{5}. We differ from previous studies by decomposing algorithmic trades into buy and

\textsuperscript{4} More recently, longer term effects from AT are documented in the literature. For instance, Boehmer, Fong & Wu (2013) find that greater AT activity reduce firm’s net equity issues over the next year. Cumming, Zhan & Aitken (2013) relate HFT to end-of-day manipulation on a monthly basis, and argue that HFT curtails the frequency and severity of end-of-day manipulation.

\textsuperscript{5} In the current study, we are unable to find significant relationship between AT and stock returns if we do not disentangle buy and sell algorithmic trades.
sell trades, we discover significant effects of buy (sell) trades on market up (down) days. In particular, we document that the percentage of AT in a stock is positively (negatively) related to the return of that stock on days when market experiences two percent or more declines (increases). Moreover, the resulted price movement reverses within five days after market decline days. This finding implies that, compared to nonAT, AT does not contribute to price deviation from fundamental value among individual stocks. Moreover, our finding is economically significant, in which a ten percent increase in selling by algorithmic traders, on average, corresponds to twelve basis points increase in abnormal return for individual stocks in bear markets.

Second, we provide reasons for the strong relation between AT intensity and individual stock returns. Specifically, we investigate potential algorithmic trading strategies that may affect daily returns. Many agency based algorithms track volume-weighted average price (VWAP) as a benchmark to execute transactions. As a result, algorithm generated trades would be closer to the VWAP metric compared to other trades. We employ a probit model similar to Hendershott & Riordan (2012) to assess the trade decisions made by algorithmic traders. We find that algorithms are more likely to initiate trades when the stock price is closer to VWAP metric. This finding suggests that algorithmic traders are more discipline in term of their trading strategy such as VWAP tracking, thus, they are less likely to be affected by overall market pressures and exacerbate the stock price fluctuation by trading in the direction of board market movement.

Next, we contribute to the literature by empirically documenting the difference between AT and nonAT order imbalances. Rich literature exists on the impact of order imbalances on stock markets (see among others, Chordia, Roll & Subrahmanyam, 2002; Chordia & Subrahmanyam, 2004; Hasbrouck & Seppi, 2001). We highlight the heterogeneity in the effect of order imbalances from different investor groups. We find that nonAT order
imbalances are more persistent compared to AT order imbalances, however, AT order imbalances have significantly less impact to stock returns. After controlling for trade size and total level of trading activity, we find that, ceteris paribus, the impact of order imbalances by nonAT is 50 percent larger than the impact of those by AT.

Our study is also related to AT and stock return volatility literature. The findings in this area are divided. On one hand, AT could reduce volatility by mitigating market frictions, imperfect information, and transient liquidity mismatches. Theoretical work by Biais, Foucault & Moinas (2011) predicts that due to the faster reaction and transaction speed HFT may facilitate faster price discovery process and enhance liquidity. This would in turn reduce volatility caused by non-informational trades. Hendershott & Riordan (2012) confirm that AT is able to quickly respond to the price changes in the futures market and adjust their positions in the spot market. They also find that algorithmic traders decrease uncertainty in liquidity provision and reduce risks associated with liquidity shortages. Brogaard, Hendershott & Riordan (2012) argue that high frequency traders trade in the direction of permanent price movements and in the opposite direction of transitory pricing errors, and thus contribute to the stability of the price discovery process in the stock market. Brogaard et al. (2013) find that both passive and aggressive HFT decreases volatility.

On the other hand, other studies argue that there is positive association between AT/HFT and volatility. Theoretical work by Martinez & Rosu (2011) models HFTs as informed traders and shows that HFTs generate most of the volatility and trading volume in the market. Boehmer, Fong & Wu (2012) find that AT increases volatility, especially during days when market making is difficult. Similarly, Zhang (2010) argues that HFT is positively correlated with stock price volatility and negatively related to the market’s ability to incorporate new information. However, some of these studies may be inconclusive. First, the extent to what AT is informed remains an open question. For example, Frino et al. (2012) document that
nonAT are more informed than AT prior to earnings announcements and the opposite is true after the release of the announcements. Brogaard et al. (2012) find that HFT has an informational advantage of up to 3 or 4 seconds. Second, proxies and instruments for AT and HFT may be noisy. Aitken, Cumming & Zhan (2012) argue that using co-location as an instrument is highly problematic because many AT and HFT companies started operating and moved next to the exchange long before the co-location event. Proxies such as message traffic (Hendershott et al., 2011) may not be conclusive. Message traffic could potentially cause inaccurate inference due to not being able to identify trade direction. Moreover, an increase in volatility alongside an observed increase in message traffic may only indicate an increase in the intensity of market activities. While we do not directly model volatility, our result support the notion that AT reduces price fluctuations and makes return series more smooth.

The rest of the study is organized as follows. Section 2 describes our data. Section 3 presents the evidence on AT volume ratios. Section 4 contains the evidence from order imbalances. Finally, Section 5 concludes.

2. Data and Research Design

We employ a special dataset on AT provided by the ASX, the dataset contains all algorithmic trades between 27 October 2008 and 23 October 2009. The sample period is approximately one calendar year covering the Australian stock market around the peak of the global financial crisis. We believe it is an ideal sample to study the trading characteristics in volatile markets since the majority days in sample are within high volatility regime. Each trade contains the company code, trade price, trade volume, buy/sell indicator, time stamp to the nearest millisecond and a special indicator for both sides of the transaction showing whether they are from algorithmic traders or non-algorithmic traders. Similar to Hendershott
& Riordan (2012), we merge AT dataset with order level data provided by Securities Industry Research Centre of Asia-Pacific (SIRCA). SIRCA data enables the accurate identification of buy/sell trade. This combination allows us to identify whether a trade is initiated by a buyer or a seller as well as whether the trade is algorithm driven. The return of the All Ords index is acquired from Thompson Reuters Tick history.

Besides the ability to differentiate AT from non-AT for each transaction, Australian data provides some additional benefits. First, unlike many of the previous studies (e.g. Chordia et al., 2002) that rely on Lee & Ready’s Algorithm (1991) we use the ‘true\(^6\)’ classification of buys and sells from order level data provided by SIRCA. Ellis et al. (2000) and Chakrabarty, Moulton & Shkilko (2012) find that Lee and Ready Algorithm’s accuracy to be 81.05 percent and 69 percent respectively. In the ASX, Aitken & Frino (1996) find the accuracy to be 74 percent. Therefore, there is significant benefit in identifying trade initiator with greater precision. Our data monitors every order in the limit order book and identifies trade initiator based on their time priorities. Additionally, previous study (Dennis & Strickland, 2002) uses quarterly sampled corporate filing data to identify the participation rate of each investor group, we improve the data quality by using real time transaction level data. This enables us to better analyze the time-series of investor participations and account for potential autoregressive properties.

We analyze how individual stock returns correlates with the level of AT activity in volatile days. Similar to Dennis & Strickland (2002), we define volatile days as the days

\(^6\) Our data monitors every order in the limit order book and give each order a unique ID. Therefore, the time stamp of each order can be dynamically updated upon submission, revision, cancellation and execution. Consequently, trade initiator can be identified by comparing the time stamps of ask and bid side orders. Trade is identified as buy (sell) initiated when the time stamp of the ask (bid) side order is older.
when the absolute values of the returns on the market are greater than two percent\(^7\). We use Australian All Ordinaries (All Ords) Index as our proxy for market returns. The All Ords contains the top 500 Australian ordinary stocks and amounts to over 95 percent of the value of all stocks listed in the Australian Securities Exchange. To avoid too many zero observations in any given stock, we limit the sample stocks from the index that were present at the beginning and at the end of the sample period. We further delete the stocks that are being traded on less than 200 days over the 252 trading days in our sample. On each event-day, we delete stocks that did not have both AT and non-AT trades. The final sample contains 9896 stock-trading days across 384 stocks. Table 1 contains the event days, number of stocks in each event day and returns of the All Ords index.

A potential concern for value-weighted days\(^8\) is outliers. Since the top 20 stocks by market capitalization account for more than 55 percent of the market, large movement in the market index could be caused by a few of the largest firms. Consequently, the selected days may contain days when the index change does not represent price shift among a wide range of stocks. To eliminate this possibility, we calculate the percentage firms with positive returns, zero returns, and negative returns. Furthermore, we calculate the ratio of stocks with positive returns (negative returns) over negative returns (positive returns for the positive (negative) market return days. The event-days are presented in Table 1. For market up days, the mean percentage of positive return stocks is 72.40 percent with maximum of 81.47 percent on 14 July 2009 and minimum of 57.45 percent on 27 January 2009. The ratio of

\(^7\) We provide sensitivity analysis in Section 3.3 using alternative event-day selection based on market return threshold from 1% to 2.25%. The results are qualitatively and quantitatively similar.

\(^8\) The All Ords index, similar to the S&P500 index in the U.S., weights the returns of its constituent stocks by their market capitalization.
stocks with positive returns over stocks with negative return indicates that there are, on average, 2.75 times more positive return stocks than negative return stocks over our sample period. The findings for market down days are qualitatively and quantitatively similar to those for market up days. Overall, the results imply that the market portfolio returns on the selected days are not driven by outliers.

Although the number of stocks included on each event-day is not identical, the sample size for each event-day is sufficiently large. The minimum is 205 on January 15, 2009 and the maximum is 340 on 14 August 2009 and 17 September 2009. The distribution of market up days is relatively spread out throughout the year. For market down days, however, there is a cluster of event-days in November 2008.

3. Empirical Results on the AT and Abnormal Return

We hypothesize that, in volatile markets, AT do not increase volatility and cause prices to deviate from their fundamental values by abnormally trade in the direction of the broad market movement. Therefore, the cross-sectional distribution of individual stock returns will be a function of the level of AT activity. We first analyze the univariate properties of AT on stock level and then report the multivariate regression results.

3.1 Univariate Analysis

To highlight the cross-sectional variation in AT and nonAT activity sorted by size, we form quartiles based on the market capitalizations of the 384 stocks with the largest as the first quartile. Summary statistics for trading volume between 27 October 2008 and 23 October 2009 (in millions of shares) and on event-days by AT and nonAT in each of the quartiles are presented in Table 2.

[Insert Table 2 about here]
Consistent with empirical findings by Hendershott et al. (2011), AT is more prevalent in larger stocks. AT accounts for 75.20 percent of volume traded in the largest quartile stocks. However AT remains dominant throughout the four quartiles with 59.36 percent of volume traded in the smallest quartile. On event-days, AT trade slightly more than nonAT with an average increase of 2.70 percent. There are more increases in smaller stocks than larger stocks with 4.63 percent in the smallest quartile and 1.51 percent in the largest quartile. The finding supports our premise that algorithmic traders do not drastically change their trading behaviour compared to non-algorithmic traders in light of extreme market movements.

Similar to Dennis & Strickland (2002), we assess the characteristics of one particular trading group (AT) by measuring the relative trading intensity of this group compared to the overall market. Thus, our main variable of interest is the level of AT activity in proportion to the total trading activity. We measure trading activities by volume traded and number of transactions. We then separate buy initiated trades from sell initiated trades to identify additional information from trade directions. Our measures are aggregated to daily frequency. We consider this frequency as a good compromise between the richness of transactions data and a more comprehensive panel that represents some of the more thinly traded stocks.

Table 3 contains some descriptive statistics. Panel A presents the cross-sectional averages of volume, number of transactions, and various AT volume (number of trades) ratios measured by algorithmic traders initiated volume (number of trades) over total volume (number of trades). The daily statistics are reported for all 252 trading days, 19 up days and 20 down days identified in Table 1. In line with Chordia & Subrahmanyam (2004), the number of buy trades are slightly more than the number of sell trades with mean of 257 and 234 respectively. The up days are more likely to be driven by trading given the average volume is 110,000 more on up days compared all days, whereas we do not observe the same volume increase during the down days. Overall, algorithmic traders initiate 68.25 percent
volume and 80.84 percent trades respectively, implying that the trade size is much smaller for AT compared to nonAT. This is consistent with Hendershott & Riordan (2012) in that AT break their orders into smaller packets to achieve best prices. Since our premise is that higher level of AT relates negatively to price fluctuation, we use ratio between AT volume over all trading volume as our main variables in regression analysis to control for the trade size differences between AT and nonAT.

[Insert Table 3 about here]

In Panel B of Table 3, we present the cross-sectional means of the individual stock time-series correlations and autocorrelations between AT all trades, AT buys, and AT sells ratios measured by number of trades and volume. Corresponding ratios measured by number of trades and volume are highly correlated, with correlation of 0.672, 0.666, and 0.680 for AT all trades, AT buys, and AT sells respectively. The correlations between AT buys and AT sells measured by number of trades and volume are 0.093 and 0.110 respectively. Panel C contains the cross-sectional average autocorrelations of AT ratios measured by volume and number of trades. The autocorrelation of AT all trades ratio is substantially high; the first-lag autocorrelation is 0.211. The autocorrelation of AT buys and AT sells are smaller but also significant: 0.167 and 0.176 respectively. The autocorrelations decay at a moderate speed. This finding suggests that algorithmic traders have sustained preference towards certain stocks. Therefore, raw AT ratios would not be suitable to disentangle the incremental differences in the level of AT on volatile days. AT ratios measured by number of trades have higher autocorrelations across the board compared to volume ratios. This difference may imply that market participants are splitting their orders to minimize their price impact (see e.g. Chan & Fong, 2000).
3.2 Multivariate Results

To assess how the trading activities of different investor groups correlate to individual stock returns under volatile market, we model the market adjusted return on each event-day as a function of the AT volume ratio and control variables. The most efficient estimation method for our panel data would be a pooled OLS estimator. However, possible cross-sectional correlations in the error terms might be a problem. To mitigate this issue, we follow Dennis & Strickland (2002) and use Fama-MacBeth (1973) regression on each event-day:

\[ ar_i = \alpha_i + \beta_1 abvol_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 variance_i + \beta_5 beta_i + \epsilon_i, \]  

(1)

where \( ar_i \) is the market-adjusted return for stock \( i \) on the event-day. In Panel A of Table 4 \( abvol_i \) is the abnormal volume ratio between AT volume and the overall volume on the event day less the mean volume ratio over the past 5 days. The decision to use abnormal volume ratios as opposed to raw volume ratio is based on the autoregressive properties reported in Table 3. Specifically, algorithmic traders are found to consistently prefer certain stocks over others. Applying the raw ratios on the event-day for the cross-section of stocks would incorporate the information about these preferences, whereas the purpose of our study is to analyze algorithmic traders’ response to the extreme market movement on the event-days and its implications. Moreover, the decision of 5 lags is determined by autocorrelation analysis, wherein the coefficients of the partial autocorrelation function quickly revert back to zero before 5 lags for most stocks.

In Panel B \( abvol_i \) is further segregated into \( abbuyVol_i \) and \( absellVol_i \) corresponding to abnormal buy volume ratio and abnormal sell volume ratio respectively:
\[ ar_i = \alpha_i + \beta_1 abbuyVol_i + \beta_2 absellVol_i + \beta_3 size_i \]

\[ + \beta_4 turnover_i + \beta_5 variance_i + \beta_6 beta_i + \epsilon_i. \] ~ (2) ~

We included beta as an independent variable because it is a classical risk measure. The magnitude of beta is directly associated with market adjusted return and volatility. Omitting beta from the regression is likely to cause biases. There are two reasons to include turnover in our regression. First, previous studies have established the link between stock trades and stock price changes (see Karpoﬀ, 1987, for a detailed survey). Although our main variables capture the trading effects from AT/nonAT, we include turnover to account for the overall liquidity effects. Second, theoretical model by Foucault, Kadan & Kandel (2013) predicts strong association between AT and trading rate. Empirically, AT is reported to follow a liquidity driven strategy (Hendershott & Riordan, 2012). If AT is correlated with liquidity in our sample, omitting turnover would be likely to force our main ratios to become proxies for liquidity effects. Therefore, we include turnover to ensure that the estimated relationship between AT ratios and returns is robust to pricing and proxy effects.

Similar to turnover, we include size in the regression to account for its possible association with return and AT ratios. Banz (1981) find size to be a significant factor of stock return. Moreover, All Ords index as a value weighted index places more weights to larger stocks, including size could alleviate possible biases of returns towards larger stocks. Alternatively, based on our finding in Table 2, algorithmic traders prefer to trade larger stocks. We control for the preference of algorithmic traders by including size factor. Lastly, we include idiosyncratic variance in our regression. Dierkens (1991) suggests using idiosyncratic volatility as a measure of informational effects. If AT has an informational
advantage as argued by Biais, Foucault & Moinas (2011), AT would correlate with idiosyncratic variance.

Our main variable of interest is the level of AT in individual stocks in light of large market movements. We measure the association between AT ratios and market adjusted returns in each stock. When market suffers from more than two percent price decline, further decline in a given stock represented by a decrease in market adjusted return would indicate higher volatility for this stock. If we find more AT in stocks that have less market adjusted return, then AT is likely to cause price fluctuations by exerting further downward pressure in individual stocks. Alternatively, if the level of AT is positively associated with market adjusted return on market decline days, then AT is suggested to have a beneficial effect on abnormal return in individual stocks. Based on the discussion before, we expect the latter of the two possibilities. To emphasize the importance of trade directions, we then segregate trading volume into buy volume and sell volume. We expect buy (sell) volume to be more essential than sell (buy) volume on market up (down) days.

Table 4 presents the results from the estimation. Regression estimations with unsigned AT volume ratio are reported in Panel A. The signs of the coefficients for AT volume ratio \( abvol \) are expected: negative for market up days and positive for market down days. The coefficients suggest that nonAT are creating price pressures in the direction of the market. However, AT volume ratio \( abvol \) is marginally insignificant (p-value of 11.3 percent) on market up days and insignificant (p-value of 18.1 percent) on market down days. To further disentangle the informativeness in trade signals, we report the estimations for AT buy volume ratio \( abbuyvol \) and AT sell volume ratio \( absellvol \) in Panel B. On market up days, AT buy volume ratio is significant and AT sell volume ratio is highly insignificant, whereas the distribution of significance revert on market down days. This suggests that the predictive power of buy (sell) volume on up (down) days is diluted by not assigning trade direction in
Panel A. Taken together, AT buy ratio is negatively correlated with market adjusted return on up days, whereas AT sell ratio is positively correlated with market adjusted return on down days. This supports the notion that stocks with less AT buying (selling) would incur more upward (downward) price swing on up (down) days. As a result, stocks with higher level of trading by algorithmic traders would reduce volatility on event-days.

[Economically, the effects of AT volume ratios on market adjusted returns are substantial. The economic significance is most pronounced when we segregate each trade into buy and sell initiated. The coefficient for AT buy ratio on market up days is 1.61 that implies a 16 basis point decrease in predicted abnormal market return for a 10 percent increase in abnormal AT buy ratio. The coefficients for control variables in the two panels are similar in their magnitude and significance. Beta is significantly related to market adjusted return: larger beta stocks have higher market adjusted return on market up days and lower market adjusted return on market down days. As expected, turnover is positively (negatively) related to market adjusted return on market up (down) days. However, the association on market down days is not significant, implying that market up days are more likely to be liquidity driven compared to market down days. Size and idiosyncratic variance are not significantly related to market adjusted return.

3.3 Robustness Tests

The main results are both statistically and economically significant, we nevertheless perform alternative tests to assess the robustness of our estimation. We first test alternative construction of abnormal AT volume ratios. Madhavan, Richardson & Roomans (1997) argue that innovation in the order flow is more indicative to security prices if the order flow is correlated. Innovation is modeled as the ‘surprise’ component: the raw value less the
expected value from previous period. We follow the methodology similar to Brogaard et al. (2012) and model the innovation in AT volume ratio ($i_{vol}$) as the residual of a five lag autoregressive model. Innovations in AT buy ratio ($i_{buyvol}$) and AT sell ratio ($i_{sellvol}$) are obtained analogously. Table 5 presents the results using innovation in AT volume ratios.

[Insert Table 5 about here]

The re-estimation results in Table 5 is quantitatively and qualitatively similar to the original result in Table 4: AT volume ratio is statistically insignificant when we do not distinguish buy initiated trades from sell initiated trades, and AT buy (sell) ratio is significantly related to abnormal return on market up (down) days with similar coefficients. The re-estimation confirms that our finding is robust with regard to the measurement of AT volume ratios.

We also provide a sensitivity analysis on the event-day selection criteria. In Table 6, we relax the event-day absolute value of market return threshold from two percent to a range between one and a half to two and a half percent. Furthermore, if the market moves during the day but reverse to the initial value at closing, daily market return would not capture these days. Therefore, we replace daily market return with daily high (low) to open price return to capture the extreme price increase (decline) in the intraday.

[Insert Table 6 about here]

The results from alternative event-day specifications are quantitatively and qualitatively similar to those estimated from the original specifications. Finally, the result is also robust to nonconsecutive event-day selection, firm fixed effects, double cluster of the standard error in stocks and days. For brevity, the results are not reported and available upon request.
4. Difference between AT and nonAT Order Imbalances

The evidence on AT volume ratios supports our premise that the stocks traded more by algorithmic traders have less price fluctuation on event-days. We provide possible explanation for the source of the cross-sectional return difference. One probable reason is that trades from algorithmic traders and non-algorithmic traders exert different level of price pressure. Therefore, the order imbalance\(^9\) from algorithmic traders would have less price pressure compared to order imbalance from non-algorithmic traders. We model market adjusted return as a function of order imbalances from algorithmic traders and non-algorithmic traders and explore our hypothesis.

4.1 Univariate Analysis

Order imbalances are measured as the scaled and unscaled imbalances in number of transactions and in volume. We separately measure each order imbalance metric for algorithmic traders and non-algorithmic traders on a daily basis. The cross-sectional averages of the correlations between various order imbalance metrics are reported in Panel A of Table 6. The correlations between scaled order imbalances and the unscaled order imbalances are high. For example, the correlations between unscaled volume imbalance and scaled volume imbalance for AT and nonAT are 0.705 and 0.730 respectively. The correlations between volume imbalances and number of trades imbalances are lower (0.427 and 0.570 respectively for AT and nonAT). Correlations between AT and nonAT are very small across different metrics. The largest value (in absolute term) of AT versus nonAT correlations is -0.071. This highlights the heterogeneity in trading strategies of algorithmic traders and non-algorithmic traders.

[Insert Table 6 here]

\(^9\) Similar to Chordia et al., (2002), we measure order imbalance metrics using only executed orders.
Panel B of Table 6 presents the cross-sectional averages of the autocorrelation of AT and nonAT order imbalances measured by number of trades and volume. Domowitz & Yegerman (2005) argue that a substantial proportion of buy side AT use a volume weighted average price strategy to execute trades overtime in order to minimize execution costs. Interestingly, among all but one metric, nonAT daily autocorrelations in order imbalance are larger than those by AT. This suggests that AT does not seem to break down orders across days which minimize any potential biases due to autocorrelation.

4.2 Multivariate Results

We model individual stock returns as a function of order imbalances by AT and nonAT. Although our order imbalance metrics have smaller autocorrelation than those in Chordia & Subrahmanyam (2004), we include 4 lags of order imbalance. We also use market adjusted return to mitigate the cross-sectional correlation in error terms. Similar to model (1), we estimate Fama & MacBeth (1973) regression on each event-day:

\[ ar_i = \alpha_i + \beta_{1}\text{atob}_i + \beta_2\text{nonatob}_i + \sum_{k=1}^{4} \beta_{2+k}\text{atob}_{i,t-k} + \sum_{k=1}^{4} \beta_{6+k}\text{nonatob}_{i,t-k} + \beta_{11}\text{size}_i + \beta_{12}\text{turnover}_i + \beta_{13}\text{variance}_i + \beta_{14}\text{beta}_i + \epsilon_i, \tag{3} \]

where \( ar_i \) is the abnormal return for stock \( i \) on the event-day, \( \text{atob}_{i,t} \) is the volume imbalance from AT in stock \( i \) on day \( t \). Day \( t \) is the event-day and day \( t-k \) is \( k \) days prior to the event-day. \( \text{size}_i, \text{turnover}_i, \text{variance}_i \), and \( \text{beta}_i \) are defined identical to those in Section 3.2. The control variables are included to account for risk factors, informational effects, liquidity effects, and potential preference of algorithmic traders. The detailed rationale is discussed in Section 3.2. The regression results are presented in Panel A of Table
7. The results for lagged order imbalances are mostly insignificant and in line with the findings of Chordia & Subrahmanyam (2004). Therefore, the coefficients for lagged metrics are omitted. In Panel B, we replace volume imbalance (atoib and nonatoib) metrics in model (3) with scaled volume imbalance metrics for AT (atoibscel) and (nonatoibscel). The estimation method is the same as in Equation (3).

[Insert Table 7 about here]

The core variable of interest is the order imbalance metrics from both algorithmic traders and non-algorithmic traders. The relationship between market adjusted return and imbalance from the order flow can be expected from previous literature (see, e.g. Chordia et al., 2002): higher order imbalance would create more price pressure on the buy side and cause price to go up. In this regression, however, our objective is to find out whether order imbalances from algorithmic traders and non-algorithmic traders affect abnormal return differently. In other words, if the coefficients for AT imbalances (atoib) are larger than the coefficients for nonAT imbalances (nonatoib), then the implication is that AT exert larger price pressure compared to nonAT and the imbalances from different trading groups are taken differently by the market. We expect, however, that nonAT imbalances would have greater price pressure compared to AT based on the results in Table 4.

As shown in Table 7, all contemporaneous imbalance metrics are significant. The results for market up days and market down days are quantitatively and qualitatively similar. Therefore, we discuss the results on up days and down days together. For unscaled volume imbalance, the average coefficients of imbalances from AT and nonAT are 1.35 and 2.33 respectively, corresponding to a 72.59 percent difference in effects. The results from scaled volume imbalance regression are more modest. The mean coefficients for AT and nonAT imbalances are 4.59 and 5.49 respectively. The impact of nonAT imbalances are 19.61
percent larger than AT imbalances. Overall, the results from the estimation in model (3) are consistent with our expectation that the abnormal return and volatility in individual stock are related to the level of AT activity. One possible reason is that AT executes their trades more intelligently to minimize the price pressure exerted to the traded stock, and AT exert less price pressure to the traded stock than nonAT. As a result, stocks with higher AT trading experience lower volatility on days in volatile markets.

5. Post Event Analysis

The empirical findings on event-days indicate that the absolute value of the individual stock returns with lower AT activity exceeds those with higher AT activity. However, whether the return difference is permanent needs to be addressed. In this section, we document the post event return differences of stocks with high versus low AT activity. The return difference on event-day could be explained by nonAT reacting to information and driving prices to their fundamental value. If this is the case, then we should observe no return reversal during the period immediately after the event-day for lower AT activity stocks compared to higher AT activity stocks. If, however, there are significant return reversals among lower AT activity stocks, then it implies that nonAT increases volatility and causes prices to deviate from their fundamental values.

The time spam of our data dictates that longer-term analysis is not feasible, we nevertheless provide post event cumulative return analysis over the immediate five days after each event-day. We cumulate post event market adjusted returns (CAR) for each stock and partition the CARs into quartiles based on their event-day AT activity. We then calculate the mean difference between higher AT activity CAR and lower AT activity CAR. The intuition is that, if the return effects on event-days are temporary, we will observe significantly higher CAR in low AT stocks compared to high AT stocks immediately after market down days.
Alternatively, if the return effects are fundamental on event-days, we will observe insignificant differences in post event CARs.

[Insert Table 8 about here]

Table 8 contains the results of the post event CAR differences. In Panel A, the first (third) row contains the mean CAR difference between the top fifty (twenty five) percent and the bottom fifty (twenty five) percent based on AT activities. The second and the fourth row report the p-values corresponding to a test of a null hypothesis that the CARs from high/low AT quartiles are identical. On market down days, post event CAR difference is significantly negative. This implies that there are significant return reversals in low AT activity stocks.

6. Conclusion

We provide evidence on the characteristics of AT in volatile times. We find that the level of AT in individual stock is statistically and economically significant related to abnormal return in volatile markets. In particular, stocks with lower level of AT experience greater price swings when the absolute return of the market exceeds two percent. We compliment this finding by showing that the order imbalances from nonAT have, on average, 50 percent more impact to the abnormal returns of individual stocks on event-days. Overall, our results support the premise that AT execute their transactions more intelligently which result in smaller price pressure and lower volatility in the stocks that they trade. Finally, we also highlight the importance in accurately differentiating trade direction in the order flow. We illustrate that identifying trade direction vastly improves the informativeness of our inference.

Our study is subject to a few caveats, however. While our sample period is rather homogenously distributed in volatile regime, multi-year international studies may be warranted to add further robustness to our findings. Second, our observation of the
association between the level of AT and volatility is strong, with access to more detailed data, further investigation into the causalities and intentions of AT would be fruitful.
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Table 1: Event-Days and Returns

This table contains dates, market returns, number of stocks in sample, and the proportion of stocks that have positive, zero, and negative returns on days when the absolute value of the return of market portfolio exceeds two percent. Sample period is between 27 October 2008 and 23 October 2009. Stocks are included on each event-day if they were traded by both algorithmic traders and non-algorithmic traders on the day. Market portfolio is defined as the Australian All Ordinaries index. Percent positive is the percentage of stocks with returns more than zero. Percent zero is the percentage of stocks with returns equal to zero. Percent negative is the percentage of stocks with returns less than zero. Ratio is the ratio of percent positive (negative) over percent negative (positive) on market up (down) days. There are 19 up days and 20 down days in our sample.

| Date       | Market Return (%) | Number of Stocks | Percent Positive | Percent Zero | Percent Negative | Ratio   |
|------------|-------------------|------------------|------------------|--------------|------------------|---------|
| 05-Nov-08  | 2.82              | 277              | 72.92            | 5.78         | 21.30            | 3.42    |
| 25-Nov-08  | 5.51              | 253              | 73.52            | 7.91         | 18.58            | 3.96    |
| 28-Nov-08  | 4.10              | 244              | 73.77            | 8.61         | 17.62            | 4.19    |
| 08-Dec-08  | 3.69              | 221              | 71.04            | 4.98         | 23.98            | 2.96    |
| 15-Dec-08  | 2.41              | 224              | 72.32            | 4.46         | 23.21            | 3.12    |
| 27-Jan-09  | 2.79              | 235              | 57.45            | 8.94         | 33.62            | 1.71    |
| 13-Mar-09  | 3.27              | 242              | 80.99            | 4.96         | 14.05            | 5.76    |
| 17-Mar-09  | 2.91              | 252              | 75.00            | 5.16         | 19.84            | 3.78    |
| 23-Mar-09  | 2.29              | 241              | 64.73            | 8.30         | 26.97            | 2.40    |
| 02-Apr-09  | 2.69              | 269              | 76.58            | 5.58         | 17.84            | 4.29    |
| 14-Apr-09  | 2.22              | 274              | 75.55            | 5.84         | 18.61            | 4.06    |
| 30-Apr-09  | 2.26              | 265              | 76.98            | 5.28         | 17.74            | 4.34    |
| 04-May-09  | 2.89              | 266              | 73.31            | 5.64         | 21.05            | 3.48    |
| 19-May-09  | 2.12              | 274              | 67.52            | 6.93         | 25.55            | 2.64    |
| 10-Jun-09  | 2.10              | 277              | 67.51            | 10.11        | 22.38            | 3.02    |
| 14-Jul-09  | 3.23              | 259              | 81.47            | 8.11         | 10.42            | 7.81    |
| 13-Aug-09  | 2.74              | 340              | 73.75            | 5.01         | 21.24            | 3.47    |
| 16-Sep-09  | 2.32              | 334              | 71.56            | 8.68         | 19.76            | 3.62    |
| 07-Oct-09  | 2.15              | 330              | 69.70            | 8.48         | 21.82            | 3.19    |
Table 1: Continued

| Date     | Market Return (%) | Number of Stocks | Percent Positive | Percent Zero | Percent Negative | Ratio  |
|----------|-------------------|------------------|------------------|--------------|------------------|--------|
| 06-Nov-08| -4.22             | 233              | 13.30            | 3.00         | 83.69            | 6.29   |
| 07-Nov-08| -2.43             | 236              | 34.75            | 5.51         | 59.75            | 1.72   |
| 11-Nov-08| -3.40             | 224              | 15.18            | 2.68         | 82.14            | 5.41   |
| 13-Nov-08| -5.44             | 220              | 8.64             | 5.00         | 86.36            | 10.00  |
| 17-Nov-08| -2.32             | 225              | 22.67            | 6.22         | 71.11            | 3.14   |
| 18-Nov-08| -3.47             | 238              | 15.13            | 5.88         | 78.99            | 5.22   |
| 20-Nov-08| -4.32             | 266              | 14.29            | 5.64         | 80.08            | 5.61   |
| 26-Nov-08| -2.68             | 225              | 23.56            | 8.44         | 68.00            | 2.89   |
| 02-Dec-08| -4.02             | 217              | 13.82            | 5.35         | 80.65            | 5.83   |
| 12-Dec-08| -2.31             | 211              | 29.38            | 5.21         | 65.40            | 2.23   |
| 08-Jan-09| -2.27             | 220              | 20.91            | 4.55         | 74.55            | 3.57   |
| 15-Jan-09| -4.07             | 205              | 2.93             | 4.39         | 92.68            | 31.67  |
| 20-Jan-09| -3.00             | 223              | 15.25            | 4.04         | 80.72            | 5.29   |
| 23-Jan-09| -3.83             | 216              | 13.43            | 6.48         | 80.09            | 5.97   |
| 02-Mar-09| -2.82             | 225              | 22.22            | 7.11         | 70.67            | 3.18   |
| 08-Apr-09| -2.22             | 255              | 20.78            | 4.71         | 74.51            | 3.58   |
| 21-Apr-09| -2.40             | 265              | 19.25            | 2.64         | 78.11            | 4.06   |
| 14-May-09| -3.43             | 277              | 13.72            | 2.17         | 84.12            | 6.13   |
| 23-Jun-09| -3.01             | 308              | 11.04            | 6.17         | 82.79            | 7.50   |
| 02-Oct-09| -2.04             | 331              | 9.37             | 4.23         | 86.40            | 9.23   |
This table presents the variance to Volume Weighted Average Price (VWAP) from AT and nonAT. VWAP for stock $i$ at time $t$ is defined as:

$$VWAP_{i,t} = \frac{\sum_{j=0}^{t} Vol_{i,j} Price_{i,j}}{\sum_{j=0}^{t} Vol_{i,j}}$$

$Vol_{i,j}$ and $Price_{i,j}$ are volume and price of the trade at time $j$ for stock $i$ respectively. We then calculate variance of each trade relative to VWAP at the time. Panel A contains variance per trade for AT and nonAT on all days, non-event days and event days. In Panel B, variance per trade is replaced by volume weighted variance of which larger trades are given larger weights. The p-values in brackets correspond to a test of a null hypothesis that the variances of AT and nonAT trades have identical means. All coefficients are multiplied by 1,000.

|                    | All Days | non-Event Days | Up Days | Down Days |
|--------------------|----------|----------------|---------|-----------|
| **Panel A: VWAP Variance per Trade** |          |                |         |           |
| AT                 | 0.167    | 0.158          | 0.200   | 0.235     |
| non-AT             | 0.337    | 0.332          | 0.338   | 0.390     |
| AT less non-AT     | -0.170   | -0.174         | -0.138  | -0.154    |
|                    | (0.005)  | (0.015)        | (0.005) | (0.026)   |
| **Panel B: VWAP Variance Volume Weighted** |          |                |         |           |
| AT                 | 0.528    | 0.522          | 0.606   | 0.518     |
| non-AT             | 0.872    | 0.870          | 0.901   | 0.862     |
| AT less non-AT     | -0.343   | -0.348         | -0.295  | -0.345    |
|                    | (0.014)  | (0.035)        | (0.132) | (0.093)   |

|                    | All Days | non-Event Days | Event Days |
|--------------------|----------|----------------|------------|
| **Panel A: VWAP Variance per Trade** |          |                |            |
| AT                 | 0.167    | 0.158          | 0.218      |
| non-AT             | 0.337    | 0.332          | 0.364      |
| AT less non-AT     | -0.170   | -0.174         | -0.146     |
|                    | (0.005)  | (0.015)        | (0.001)    |
| **Panel B: VWAP Variance Volume Weighted** |          |                |            |
| AT                 | 0.528    | 0.522          | 0.562      |
| non-AT             | 0.872    | 0.870          | 0.882      |
| AT less non-AT     | -0.343   | -0.348         | -0.320     |
|                    | (0.014)  | (0.035)        | (0.022)    |
Table 3: Trading Volume of AT versus Non-AT by Stock Size (in Millions of Volume)

This table contains volume statistics for Algorithmic Trading (AT) and non-Algorithmic Trading (nonAT) from 27 October 2008 to 23 October 2009 and on event-days. Sample size is 384 stocks based on the filtering criteria in Data section. The event-days are defined as the days when the absolute values of market returns exceed two percent. Volume from AT and nonAT are partitioned into four quartiles based on stock size. Size is defined as the closing market price multiplied by number of shares outstanding on 23 October 2009. Volume is presented in millions of shares. Volume fraction for each investor group is calculated and presented in brackets.

|                          | q1(large) | q2       | q3       | q4(small) | Total   |
|--------------------------|-----------|----------|----------|-----------|---------|
| **Panel A: AT and non-AT Volume All-Days** |           |          |          |           |         |
| AT                       | 59,143    | 26,083   | 15,036   | 6,459     | 106,721 |
|                          | (75.20%)  | (71.03%) | (58.75%) | (59.36%)  | (70.29%)|
| non-AT                   | 19,501    | 10,636   | 10,557   | 4,423     | 45,117  |
|                          | (24.80%)  | (28.97%) | (41.25%) | (40.64%)  | (29.71%)|
| All                      | 78,644    | 36,720   | 25,593   | 10,882    | 151,838 |
|                          | (100.00%) | (100.00%)| (100.00%)| (100.00%) | (100.00%)|

|                          | q1(large) | q2       | q3       | q4(small) | Total   |
|--------------------------|-----------|----------|----------|-----------|---------|
| **Panel B: AT/non-AT Volume on Event-Days** |           |          |          |           |         |
| AT                       | 9,407     | 3,917    | 2,274    | 1,081     | 16,679  |
|                          | (76.71%)  | (73.23%) | (64.02%) | (63.99%)  | (72.99%)|
| non-AT                   | 2,855     | 1,432    | 1,278    | 608       | 6,173   |
|                          | (23.29%)  | (26.77%) | (35.98%) | (36.01%)  | (27.01%)|
| All                      | 12,262    | 5,349    | 3,552    | 1,689     | 22,852  |
|                          | (100.00%) | (100.00%)| (100.00%)| (100.00%) | (100.00%)|

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Table 4: Descriptive Statistics, Correlations and Autocorrelations for AT Volume Ratios

This table contains summary statistics for daily AT ratios between 27 October 2008 and 23 October 2009. Sample size is 384 stocks based on the filtering criteria in Data section. The event-days are defined as the days when the absolute values of market returns exceed two percent. AT Volume Ratio is defined as the ratio between AT volume and the overall volume daily. Other ratios are defined analogously. Panel A presents the means and the standard deviations of the ratios overall and on event-days. Panels B and C presents the cross-sectional means of the individual stock time-series correlations and autocorrelations. There are 252 trading days, 19 up days, and 20 down days.

Panel A: Descriptive Statistics

|                      | All Days |            | Up Days |            | Down Days |            |
|----------------------|----------|------------|---------|------------|-----------|------------|
|                      | Mean     | Std. dev.  | Mean    | Std. dev.  | Mean      | Std. dev.  |
| Buy Volume (.000)    | 794      | 738        | 904     | 704        | 574       | 424        |
| Sell Volume (.000)   | 775      | 647        | 720     | 548        | 695       | 483        |
| No. of Buy Trades    | 257      | 130        | 295     | 135        | 250       | 123        |
| No. of Sell Trades   | 234      | 114        | 220     | 103        | 238       | 104        |
| AT Volume Ratio (%)  | 68.25    | 17.26      | 69.97   | 16.76      | 71.56     | 15.89      |
| AT Buy Volume Ratio (%) | 68.22   | 18.27      | 69.74   | 17.46      | 69.64     | 16.38      |
| AT Sell Volume Ratio (%) | 67.24   | 19.01      | 67.21   | 18.91      | 69.86     | 17.25      |
| AT No. of Trades Ratio (%) | 80.84   | 11.75      | 81.40   | 11.33      | 81.75     | 10.47      |
| AT No. of Buy Trades Ratio (%) | 79.56   | 12.46      | 80.67   | 11.53      | 80.08     | 10.85      |
| AT No. of Sell Trades Ratio (%) | 79.32   | 12.84      | 79.06   | 12.68      | 80.43     | 11.62      |

Panel B: Correlations

|                      | AT Buy Volume Ratio | AT Sell Volume Ratio | AT No. of Trades Ratio | AT No. of Buy Trades Ratio | AT No. of Sell Trades Ratio |
|----------------------|---------------------|----------------------|------------------------|---------------------------|----------------------------|
| AT Volume Ratio      | 0.622               | 0.678                | 0.672                  | 0.440                     | 0.484                      |
| AT Buy Volume Ratio  | 0.093               | 0.435                | 0.666                  | 0.090                     |                            |
| AT Sell Volume Ratio | 0.441               | 0.090                | 0.680                  |                            |                            |
| AT No. of Trades Ratio | 0.649             | 0.643                |                        |                            |                            |
| AT No. of Buy Trades Ratio | 0.110             |                        |                        |                            |                            |

Panel C: Autocorrelations

|                      | AT Volume Ratios   | AT No. of Trades Ratios |
|----------------------|--------------------|-------------------------|
|                      | All Trades         | Buy Trades              | Sell Trades             | All Trades | Buy Trades | Sell Trades |
| lag                  |                    |                        |                        |            |            |            |
| 1                    | 0.211              | 0.167                  | 0.176                  | 0.254      | 0.211      | 0.204      |
| 2                    | 0.149              | 0.118                  | 0.109                  | 0.191      | 0.150      | 0.142      |
| 3                    | 0.116              | 0.085                  | 0.082                  | 0.159      | 0.117      | 0.113      |
| 4                    | 0.100              | 0.075                  | 0.071                  | 0.140      | 0.102      | 0.093      |
| 5                    | 0.087              | 0.059                  | 0.056                  | 0.127      | 0.086      | 0.085      |
Table 5: Event-Day Market Adjusted Return Regressions on Abnormal AT Ratios

This table presents coefficient estimates from Fama-MacBeth regressions using the following model:

\[ ar_i = \alpha + \beta_1 \text{abvol}_i + \beta_2 \text{size}_i + \beta_3 \text{turnover}_i + \beta_4 \text{idiovar}_i + \beta_5 \text{beta}_i + \epsilon_i. \]

\( ar_i \) is the market-adjusted abnormal return for stock \( i \) on the event-day. The event-days are defined as the days when the absolute values of market returns exceed two percent.

In Panel A \( \text{abvol}_i \) is the abnormal volume ratio between AT volume and the overall volume on the event day less the mean volume ratio over the past 5 days. \( \text{size}_i \) is the logarithm of the market value of stock \( i \) 5 days prior to the event day, \( \text{turnover}_i \) is the ratio of daily volume over number of shares outstanding on the event day. \( \text{idiovar}_i \) is the idiosyncratic variance of the market model residual of stock \( i \) on days \([-125,-5]\). \( \text{beta}_i \) is the beta of stock \( i \) for days \([-125,-5]\). P-value is reported from a t-test of the mean being different from zero. The event-days are segregated into 19 up days and 20 down days.

In Panel B \( \text{abvol}_i \) is further segregated into \( \text{abbuyvol}_i \) and \( \text{absellvol}_i \) corresponding to abnormal buy volume ratio and abnormal sell volume ratio respectively:

\[ ar_i = \alpha + \beta_1 \text{abbuyvol}_i + \beta_2 \text{absellvol}_i + \beta_3 \text{size}_i + \beta_4 \text{turnover}_i + \beta_5 \text{idiovar}_i + \beta_6 \text{beta}_i + \epsilon_i. \]

The control variables are identical to those in Panel A. Coefficients for \( \text{abvol}_i, \text{abbuyvol}_i, \text{absellvol}_i, \) and \( \text{beta}_i \) are multiplied by 100 in both panels. Coefficients for \( \text{size}_i \) are multiplied by 1,000.

|                     | Up Days |                     | Down Days |                     |
|---------------------|---------|---------------------|-----------|---------------------|
|                     | mean    | p-value             | min       | max     | mean    | p-value             | min       | max     |
| Panel A: Aggregated AT Ratio |         |                     |           |         |         |                     |           |         |
| abvol               | -1.01   | 0.113               | -5.22     | 3.98    | 0.73    | 0.181               | -2.83     | 6.47    |
| beta                | 1.86    | <.0001              | -0.12     | 4.74    | -1.93   | <.0001              | -4.66     | 0.29    |
| turnover            | 0.60    | 0.001               | -0.72     | 1.94    | -0.36   | 0.239               | -3.54     | 2.57    |
| size                | -0.19   | 0.838               | -5.10     | 10.49   | 0.09    | 0.889               | -4.42     | 8.40    |
| idiovar             | 0.42    | 0.380               | -3.61     | 4.53    | -0.58   | 0.316               | -3.71     | 5.22    |
| Panel B: Segregated Buy/Sell Ratio |         |                     |           |         |         |                     |           |         |
| abbuyvol            | -1.61   | 0.005               | -6.54     | 1.43    | -0.31   | 0.579               | -3.61     | 6.18    |
| absellvol           | -0.13   | 0.764               | -3.52     | 2.80    | 1.19    | 0.011               | -2.58     | 5.05    |
| beta                | 1.86    | <.0001              | -0.11     | 4.80    | -1.95   | <.0001              | -4.58     | 0.52    |
| turnover            | 0.59    | 0.002               | -0.91     | 1.98    | -0.33   | 0.272               | -3.68     | 2.66    |
| size                | -0.24   | 0.803               | -5.35     | 10.46   | 0.13    | 0.848               | -4.13     | 8.41    |
| idiovar             | 0.39    | 0.427               | -3.69     | 4.57    | -0.61   | 0.300               | -3.63     | 5.20    |
Table 6: Event-Day Market Adjusted Return Regressions on Abnormal AT Ratios (Robustness Test)

This table presents coefficient estimates from Fama-MacBeth regressions using the following model:

$$ar_i = \alpha_i + \beta_1 ivol_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i.$$ 

$ar_i$ is the market-adjusted abnormal return for stock $i$ on the event-day. The event-days are defined as the days when the absolute values of market returns exceed two percent.

In Panel A $ivol_i$ is the volume ratio innovation obtained as the residual of an autoregressive model with 5 lags applied to individual stock volume ratios. $size_i$ is the logarithm of the market value of stock $i$ 5 days prior to the event day, $turnover_i$ is the ratio of daily volume over number of shares outstanding on the event day. $idiovar_i$ is the idiosyncratic variance of the market model residual of stock $i$ on days $[-125,-5]$. $beta_i$ is the beta of stock $i$ for days $[-125,-5]$. P-value is reported from a t-test of the mean being different from zero. The event-days are segregated into 19 up days and 20 down days.

In Panel B $ivol_i$ is further segregated into $ibuyvol_i$ and $isellvol_i$ corresponding to the innovation of buy volume ratio and sell volume ratio respectively:

$$ar_i = \alpha_i + \beta_1 ibuyvol_i + \beta_2 isellvol_i + \beta_3 size_i + \beta_4 turnover_i + \beta_5 idiovar_i + \beta_6 beta_i + \epsilon_i.$$ 

The control variables are identical to those in Panel A. Coefficients for $ivol_i$, $ibuyvol_i$, $isellvol_i$, and $beta_i$ are all multiplied by 100 in both panels. Coefficients for $size_i$ are multiplied by 1,000.

|                  | Up Days | Down Days |
|------------------|---------|-----------|
|                  | mean    | p-value   | min    | max    | mean    | p-value   | min    | max    |
| ivol             | -0.93   | 0.160     | -5.43  | 4.30   | 0.48    | 0.378     | -3.22  | 5.58   |
| beta             | 1.86    | <.0001    | -0.15  | 4.75   | -1.94   | <.0001    | -4.66  | 0.32   |
| turnover         | 0.60    | 0.001     | -0.71  | 1.94   | -0.36   | 0.235     | -3.54  | 2.56   |
| size             | -0.15   | 0.871     | -4.87  | 10.42  | 0.09    | 0.891     | -4.52  | 8.42   |
| idiovar          | 0.42    | 0.391     | -3.74  | 4.54   | -0.56   | 0.338     | -3.65  | 5.28   |

Panel B: Segregated Buy/Sell Ratio

|                  | Up Days | Down Days |
|------------------|---------|-----------|
|                  | mean    | p-value   | min    | max    | mean    | p-value   | min    | max    |
| ibuyvol          | -1.65   | 0.005     | -6.48  | 1.58   | -0.49   | 0.398     | -4.06  | 5.52   |
| isellvol         | 0.10    | 0.820     | -2.98  | 3.57   | 0.94    | 0.059     | -3.44  | 5.17   |
| beta             | 1.87    | <.0001    | -0.12  | 4.80   | -1.95   | <.0001    | -4.64  | 0.59   |
| turnover         | 0.59    | 0.002     | -0.85  | 2.02   | -0.35   | 0.255     | -3.71  | 2.62   |
| size             | -0.11   | 0.902     | -4.91  | 10.49  | 0.11    | 0.871     | -4.34  | 8.38   |
| idiovar          | 0.36    | 0.462     | -3.90  | 4.52   | -0.58   | 0.319     | -3.50  | 5.29   |
Table 7: Sensitivity Test for Event-Day Selection

This table presents coefficient estimates from Fama-MacBeth regressions using the following model:

\[ ar_t = \alpha + \beta_1 \text{ivol}_t + \beta_2 \text{size}_t + \beta_3 \text{turnover}_t + \beta_4 \text{idiovar}_t + \beta_5 \text{beta}_t + \epsilon_i. \]

Sensitivity analysis of the event-days selection method is presented based on the absolute value of market returns exceeds a range from 1.5% to 2.5%. In the last column, we estimate the event-days when the absolute value of the end of day high/low return exceeds 2%.

\( ar_t \) is the market-adjusted abnormal return for stock \( i \) on the event-day. \( \text{abbruy}_t \) (\( \text{absell}_t \)) is the abnormal volume ratio between AT buy (sell) volume and the overall buy (sell) volume on the event day less the mean volume ratio over the past 5 days. \( \text{size}_t \) is the logarithm of the market value of stock \( i \) 5 days prior to the event day, \( \text{turnover}_t \) is the ratio of daily volume over number of shares outstanding on the event day. \( \text{idiovar}_t \) is the idiosyncratic variance of the market model residual of stock \( i \) on days \([-125,-5]\). \( \text{beta}_t \) is the beta of stock \( i \) for days \([-125,-5]\). P-value is reported in brackets. Coefficients for \( \text{abbruy}_t \), \( \text{absell}_t \), and \( \text{beta}_t \) are multiplied by 100 in both panels. Coefficients for \( \text{size}_t \) are multiplied by 1,000.

| | 1.50% | 1.75% | 2% | 2.25% | 2.50% | high/low |
|---|---|---|---|---|---|---|
| No. of up days | 32 | 25 | 19 | 14 | 10 | 23 |
| No. of down days | 29 | 24 | 20 | 18 | 13 | 31 |

**Panel A Market Up Days**

| | abbuy | absell | beta | turnover | size | idiovar |
|---|---|---|---|---|---|---|
| abbuy | -1.199 | -2.02 | 1.527 | 0.475 | -0.800 | 0.163 |
| (0.012) | (0.494) | (0.000) | (0.000) | (0.000) | (0.313) | (0.663) |
| absell | -1.528 | -0.104 | 1.664 | 0.539 | 0.000 | 0.194 |
| (0.008) | (0.772) | (0.000) | (0.000) | (0.000) | (0.142) | (0.645) |
| beta | -1.606 | -0.128 | 1.865 | 0.587 | -0.236 | 0.387 |
| (0.005) | (0.764) | (0.000) | (0.000) | (0.002) | (0.803) | (0.427) |
| turnover | -1.834 | -0.137 | 1.901 | 0.642 | 0.105 | 0.334 |
| (0.016) | (0.775) | (0.000) | (0.000) | (0.008) | (0.929) | (0.601) |
| size | -1.592 | 0.064 | 1.705 | 0.611 | 0.746 | 0.565 |
| (0.101) | (0.923) | (0.902) | (0.920) | (0.646) | (0.929) | (0.897) |
| idiovar | -1.510 | 0.041 | 1.632 | 0.461 | 0.721 | 0.645 |
| (0.002) | (0.041) | (0.000) | (0.000) | (0.007) | (0.003) | (0.000) |

**Panel B Market Down Days**

| | abbuy | absell | beta | turnover | size | idiovar |
|---|---|---|---|---|---|---|
| abbuy | -0.485 | 0.829 | -1.719 | -0.315 | -0.884 | -0.663 |
| (0.246) | (0.057) | (0.000) | (0.239) | (0.218) | (0.155) | (0.298) |
| absell | -0.475 | 0.790 | -1.796 | -0.426 | 0.047 | -0.531 |
| (0.345) | (0.579) | (0.000) | (0.272) | (0.937) | (0.175) | (0.300) |
| beta | -0.313 | 1.194 | -1.953 | 0.330 | 0.130 | -0.610 |
| (0.532) | (0.011) | (0.277) | (0.848) | (0.988) | (0.272) | (0.411) |
| turnover | -0.416 | 1.117 | -2.004 | -0.368 | -0.012 | -0.526 |
| (0.532) | (0.027) | (0.396) | (0.701) | (0.375) | (0.772) | (0.084) |
| size | -0.854 | 1.260 | -2.126 | -0.394 | 0.375 | -1.205 |
| (0.300) | (0.926) | (0.000) | (0.000) | (0.000) | (0.300) | (0.000) |
| idiovar | -0.301 | 0.827 | 1.447 | -0.434 | 0.398 | 0.417 |
| (0.495) | (0.396) | (0.124) | (0.036) | (0.532) | (0.396) | (0.451) |
Table 8: Correlations and Autocorrelations for Order Imbalances

This table contains summary statistics for daily AT and nonAT order imbalances between 27 October 2008 and 23 October 2009. Sample size is 384 stocks based on the filtering criteria in Data section. AT volume imbalance is defined as daily AT buy volume less daily AT sell volume. Other imbalances are defined analogously. Panel A presents the cross-sectional means of the individual stock time-series correlations, and Panel B contains the autocorrelations.

### Panel A: Correlations

|                     | nonAT Volume Imbalance | AT Volume Imbalance | nonAT Volume Imbalance Scaled | AT No. of Trades Imbalance | nonAT No. of Trades Imbalance | AT No. of Trades Imbalance Scaled | nonAT No. of Trades Imbalance Scaled |
|---------------------|------------------------|---------------------|-------------------------------|-----------------------------|--------------------------------|-----------------------------------|--------------------------------------|
| AT Volume Imbalance | -0.071                 | 0.705               | -0.062                        | 0.427                       | -0.061                         | 0.430                             | -0.058                               |
| nonAT Volume Imbalance | -0.055               | 0.730               | -0.019                        | 0.570                       | -0.024                         | 0.503                             |                                      |
| AT Volume Imbalance Scaled | -0.057           | 0.401               | -0.055                        | 0.641                       | -0.016                         | 0.726                             |                                      |
| nonAT Volume Imbalance Scaled | -0.019           | 0.520               | -0.018                        | 0.756                       | -0.020                         | 0.738                             |                                      |
| AT No. of Trades Imbalance | -0.018            | 0.756               |                               |                             |                                |                                   |                                      |
| nonAT No. of Trades Imbalance | -0.027            |                     |                               |                             |                                |                                   | -0.021                               |

### Panel B: Autocorrelations

| lag | AT Volume Imbalances | No. of Trades Imbalances |
|-----|----------------------|--------------------------|
|     |                      |                          |
|     |                      |                          |
|     |                      |                          |
|     |                      |                          |
|     |                      |                          |
| 1   | 0.122                | 0.182                    |
| 2   | 0.059                | 0.097                    |
| 3   | 0.033                | 0.074                    |
| 4   | 0.017                | 0.043                    |
| 5   | 0.015                | 0.049                    |
Table 9: Event-Day Market Adjusted Return Regressions on Order Imbalances

This table reports coefficient estimates from Fama-MacBeth regressions using the following model:

\[
ar_i = \alpha_i + \beta_1 atoiib_{it} + \beta_2 nonatoib_{it} + \sum_{k=1}^{4} \beta_{2+k} atoiib_{it-k} + \sum_{k=1}^{4} \beta_{6+k} nonatoib_{it-k} \\
+ \beta_{11} size_i + \beta_{12} turnover_i + \beta_{13} variance_i + \beta_{14} beta_i + \epsilon_i.
\]

$ar_i$ is the market-adjusted abnormal return for stock $i$ on the event-day. The event-days are defined as the days when the absolute values of market returns exceed two percent.

In Panel A $atoiib_i$ is the order imbalance in volume traded by AT. $nonatoib_i$ is the order imbalance in volume traded by nonAT. $size_i$ is the logarithm of the market value of stock $i$ 5 days prior to the event day. $turnover_i$ is the ratio of daily volume over number of shares outstanding on the event day. $idiovar_i$ is the idiosyncratic variance of the market model residual of stock $i$ on days $[-125,-5]$. $beta_i$ is the beta of stock $i$ for days $[-125,-5]$. P-value is reported from a t-test of the mean being different from zero. The event-days are segregated into 19 up days and 20 down days. $atoiib_i$ and $nonatoib_i$ are scaled by 100,000,000.

In Panel B $atoiib_i$ and $nonatoib_i$ are replaced by $atobsc_i$ and $nonatoibsc_i$ corresponding to order imbalance in volume traded divided by total volume for stock $i$ on the event-day for AT and nonAT respectively. The coefficients for $atobsc_i$ and $nonatoibsc_i$ are multiplied by 100. The control variables are identical to those in Panel A. Coefficients for $beta_i$ ($size_i$) are multiplied by 100 (1,000).

|                  | Up Days |          |          |          | Down Days |          |          |          |
|------------------|---------|----------|----------|----------|-----------|----------|----------|----------|
|                  | mean    | p-value  | min      | max      | mean      | p-value  | min      | max      |
| Panel A: Volume Imbalance |         |          |          |          |           |          |          |          |
| atvoib           | 1.43    | 0.001    | 0.12     | 5.22     | 1.28      | 0.000    | -0.33    | 4.87     |
| natvoib          | 2.13    | <.0001   | 0.25     | 8.15     | 2.53      | <.0001   | 0.42     | 7.76     |
| beta             | 1.71    | <.0001   | -0.02    | 4.52     | -1.79     | <.0001   | -4.34    | 0.65     |
| turnover         | 0.36    | 0.001    | -0.15    | 1.23     | -0.76     | 0.147    | -8.16    | 1.36     |
| size             | -0.55   | 0.590    | -6.50    | 9.75     | 0.25      | 0.701    | -4.25    | 7.99     |
| idiovar          | 0.49    | 0.307    | -3.57    | 4.42     | -0.01     | 0.984    | -4.72    | 4.78     |
| Panel B: Volume Imbalance Scaled |         |          |          |          |           |          |          |          |
| atvoibs          | 4.86    | <.0001   | 0.95     | 9.19     | 4.33      | <.0001   | 0.37     | 10.05    |
| natvoibs         | 5.86    | <.0001   | 1.81     | 12.35    | 5.13      | <.0001   | 1.45     | 11.76    |
| beta             | 1.54    | 0.000    | -0.20    | 4.35     | -1.83     | <.0001   | -4.20    | 0.93     |
| turnover         | 0.52    | 0.001    | -0.58    | 1.55     | -0.37     | 0.209    | -3.16    | 2.78     |
| size             | -0.60   | 0.458    | -5.65    | 7.98     | -1.18     | 0.108    | -7.05    | 4.57     |
| idiovar          | 0.66    | 0.161    | -3.46    | 4.81     | -0.81     | 0.164    | -4.07    | 6.32     |
Table 10: Post Event Cumulative Abnormal Returns

This table presents post event cumulative abnormal return analysis for stocks ranked by AT activity quartiles. The event-days are defined as the days when the absolute values of market returns exceed two percent. In Panel A, cumulative abnormal return (CAR) for stock $i$ is the market adjusted return over 5 days after each event-day. The CARs for individual stocks are partitioned into quartiles based on the AT buy (sell) volume market share on each up (down) days. The mean CAR difference between high and low AT stocks are presented. The p-values in brackets correspond to a test of a null hypothesis that the CARs from high/low AT quartiles have identical means. In Panel B, CAR for stock $i$ is calculated as the 5-day post event return for stock $i$ less the mean 5-day returns for all stocks in the same beta quartile as stock $i$ on the event-day.

|                      | Up Days | Down Days |
|----------------------|---------|-----------|
|                      | 5 Days  | 5 Days (Indep) | 5 Days  | 5 Days (Indep) |
| **Panel A: Post Event CAR Partitioned by AT Activities** |         |           |         |           |
| Top less Bottom Half (%) | -0.201  | -0.249    | -0.690  | -1.000    |
|                      | (0.595) | (0.446)   | (0.027) | (0.017)   |
| Top less Bottom Quartile (%) | -0.095  | 0.348     | -0.775  | -1.380    |
|                      | (0.817) | (0.607)   | (0.084) | (0.024)   |
| **Panel B: Post Event CAR Partitioned by AT Activities (Robustness)** |         |           |         |           |
| Top less Bottom Half (%) | -0.364  | -0.227    | -0.775  | -1.080    |
|                      | (0.182) | (0.480)   | (0.011) | (0.009)   |
| Top less Bottom Quartile (%) | -0.091  | -0.180    | -0.832  | -1.420    |
|                      | (0.820) | (0.700)   | (0.058) | (0.018)   |