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The Role of Algorithmic Trading in Stock Liquidity and Commonality in Electronic Limit Order Markets

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Abstract

Using the adoption of the Arrowhead trading platform in January 2010 as an exogenous event, we investigate the effects of algorithmic trading on stock market liquidity and commonality in liquidity under different market conditions on the Tokyo Stock Exchange. After controlling for endogeneity, we find algorithmic trading increases stock liquidity by narrowing spreads and increasing market depth. Furthermore, algorithmic trading increases commonality in liquidity at both high and low frequency. These findings appear to arise due to the reduction in monitoring costs. Further analysis reveals that, following large market declines, the effect of algorithmic trading on spreads and market depth weakens while the effect on commonality in stock liquidity intensifies.

Keyword: Algorithmic trading, Liquidity, Commonality in liquidity, Market decline

JEL Classification: G14, G24

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1. INTRODUCTION

Recent technological advancements have led to the proliferation of a new form of trading, algorithmic trading (AT) which relies on computer algorithms to make automatic trading decisions, submit orders, and manage orders after submission. High frequency traders, a subset of algorithmic traders, have a differentiating strategic feature of adopting very short stock holding horizons of as little as a millisecond (for a detailed description, see Hasbrouck and Saar (2009)). In the past decade, AT has come to dominate many developed stock markets, prompting many stock exchanges to upgrade their trading platforms accordingly. In this study, we take an encompassing approach to understand the impact of AT on an electronic limit order market by examining its effects on three dimensions, namely, (1) bid-ask spreads and market depths, (2) commonality in liquidity, and (3) market liquidity after large market declines.

A growing body of literature seeks to understand the impact of AT on markets but these studies provide conflicting results. Some studies argue that AT can benefit market participants and reduce transaction costs by increasing competition among liquidity providers and eliminating information friction (e.g., Hendershott et al., 2011; Riordan and Storkenmaier, 2012). Others emphasize the detrimental effects of AT on market quality, such as the increase in mispricing due to the increase in execution risk (Frino et al., 2016). Algorithmic traders, through their ability to process information rapidly, can also exploit other traders such as those who trade for liquidity reasons (e.g., Cartea and Penalva, 2012). Although insightful, this literature offers little information about the behavior of algorithmic traders in volatile markets, nor does it specify the effects of AT on commonality in liquidity, a form of systematic risk that affects asset pricing and is more intense during large market declines (Hameed et al., 2010).

To mitigate the endogeneity problem as well as to investigate the above issues, we consider an electronic limit order market, the Tokyo Stock Exchange (TSE), using data from 2007 to 2012. The TSE is a specifically suitable setting for this analysis for several reasons. First, it represents a large, well-developed electronic limit order book (LOB) market, comparable to many other international exchanges; it was the second market to adopt electronic trading in 1982, after the Toronto Stock Exchange in 1977 (Jain, 2005). In a limit order market, algorithmic traders can act as either liquidity suppliers or liquidity demanders, so their influence on liquidity may differ compared with that observed in hybrid markets, such as the New York Stock Exchange. More importantly, the TSE adopted a new trading platform, Arrowhead, on 4 January 2010, specifically to cater to the high speed requirements of algorithmic traders, so it provides an ideal experimental setting.

We measure the amount of AT by examining message traffic, obtained from intraday transactions data. Biais and Weill (2009) provide its theoretical support by showing that the ratio of messages to volume increases with the rate at which investors can contact the market. This measurement is first used in Hendershott et al. (2011) as an AT proxy on the U.S. stock market; and Boehmer et al. (2015) apply this measure to the AT activities across 39 international exchanges. In this study, we choose to use this proxy for AT as it enables us to examine the trading by algorithmic traders, a precondition for high frequency trading (HFT), in a wide cross-section of stocks listed on the TSE. This approach enhances the generalizability of our study to the whole market, instead of a selection of stocks. To reflect the full picture of market liquidity, we consider measures that capture both spreads and market depths. These liquidity measures are the quoted bid–ask spread, effective spread, market depth at the best prices, and market depth at five levels of quoted prices.

We use two-stage least squares regression models (2SLS) in our empirical analysis, using the adoption of Arrowhead trading platform as an exogenous shock to AT. The first stage regression results across all model specifications consistently show an increase in AT following the adoption of Arrowhead. Moreover, after controlling for the endogeneity issue, we observe that AT is associated with lower quoted and effective bid–ask spreads and higher market depth. Although AT is associated with reductions in both realized spread (revenues for liquidity provision) and adverse selection cost (revenues for informed trading), the AT effect is economically stronger on realized spread. Using the adoption of Arrowhead as an instrumental variable in the 2SLS analysis, we also find that AT is positively correlated with low- and high-frequency commonality in stock liquidity across all liquidity measures. Furthermore, we explore the reduction of monitoring costs as one potential mechanism for the liquidity effects of AT. We find supporting evidence that the effects of AT are most pronounced among stocks with high monitoring costs proxied by small firm size, low levels of analyst and media coverage.

In our final analysis, we examine whether algorithmic traders behave differently during periods associated with high levels of market uncertainty. Contrary to the results related to normal market conditions, AT widens spreads in the aftermath of stock market declines. Moreover, AT increases commonality in liquidity to a greater extent following stressful market episodes. These findings are particularly worrisome because AT appears to consume liquidity and increases liquidity commonality in down markets where liquidity is needed the most.

Our research adds to a fast growing body of literature on AT, including studies focusing on HFT. Several studies analyze the effects of AT on market liquidity using data from U.S.

equity markets (e.g., Hasbrouck and Saar, 2009; Hendershott et al., 2011), international foreign exchange markets (e.g., Chaboud et al., 2011; Jovanovic and Menkveld, 2012), or futures markets (Kirilenko et al., 2011). Notably, Hendershott et al. (2011) is the pioneering study in this line of research that first documents the positive effects of AT on liquidity and informativeness of quotes on a sample of New York Stock Exchange common stocks. Although comprehensive, this sample of the study ends in 2005 which precedes the steep growth of AT and their findings may not be generalizable to other markets under different structures such as the TSE where the LOB system is used. Subsequently, several studies (Hendershott and Riordan (2013) in Germany; Anand and Venkataraman (2016) in Canada) attempt to examine the AT effects outside the US but most only use a selection of stocks or a brief sample period due to the lack of data.

Our study fills the gap in the literature by looking at the effects of AT on liquidity and commonality in the largest LOB market in Asia - TSE (World Federation of Exchanges, 2012), using the full sample of TSE stocks. In this context, two studies are particularly relevant to our research. Using a comprehensive international sample of 42 equity markets, Boehmer et al. (2015) document an improvement in liquidity but worsening in volatility with the increase in AT; AT is proxied by the same measure adopted in this study. While insightful, many important market-specific peculiarities could be confounded in a large international sample wherein markets with distinct progressions in AT are aggregated. Two specific aspects set our study apart from theirs: (1) Instead of using the co-location event that occurred on TSE in May 2009, we use the Arrowhead adoption as the exogenous shock to AT. As clearly evidenced in Figure 1, this is a more appropriate event to examine than the co-location event for stocks on TSE. There is no discernable change in AT activity around May 2009 but Figure 1 clearly shows a steady surge post January 2010; (2) Their study examines the impact of AT on various conventional market quality measures including liquidity and volatility cross-sectionally and across time, whereas we conduct a nuanced analysis of two important dimensions of market liquidity (Hameed et al., 2010), that is, stock-level liquidity and commonality in liquidity based on the 2SLS approach using the Arrowhead adoption as the natural AT event.

Similar to our study, Jain et al. (2012) utilize the Arrowhead event in their study. They find that the LOB liquidity measured by the cost of immediacy (COI) and LOB slope improves, and auto correlation and cross correlation in order flow increase in their sample period which is one year after the adoption of the Arrowhead system. While both studies are complementary, they differ substantially from ours in a number of ways. Jain et al. (2012) use liquidity measures (COI and LOB slope) to capture the liquidity in the full LOB whereas our measures reflect the liquidity on the top of LOB which have been found to be more informative of the offsetting social benefits (Hasbrouck and Saar, 2013; Gai, Yao and Ye, 2013).[1] Further, Jain et al. (2013) focus on intraday commonality in liquidity gauged by cross-correlation in order flow using only three months of trading data in the pre-crisis, post-crisis and post-Arrowhead periods, respectively. Our work looks into the AT effect on commonality in liquidity at both high and low frequency using four alternative liquidity measures for a longer sample period from 2007 to 2012. A much longer sample allows for time series variations in the AT effect and indeed we show an intensified AT effect on liquidity commonality during market downturns. The last differentiation lies in the research design. Jain et al. (2013) does not measure AT activity

[1] Hasbrouck and Saar (2013) argue that active quoting behaviour of AT may arise as a consequence of quote-stuffing. Quote-stuffing refers to a particular strategic AT that attempts to conceal trading strategies by submitting a large volume of messages. Gai, Yao, and Ye (2013) suggest that quote stuffing induced by AT only transfers wealth among traders but has no offsetting social benefits.

explicitly but infers this from the Arrowhead adoption. We clearly address the endogeneity concern by measuring AT using message traffic and instrument the AT variable with the Arrowhead adoption as well as include firm fixed effects in the 2SLS regression framework.

In Section 2, we outline some existing literature and discuss our research questions. Section 3 contains a description of our data and research methods. In Section 4, we analyze the effect of AT on stock liquidity and commonality in stock liquidity in normal and extreme market conditions. In Section 5, we conclude with a discussion of implications.

2. RELATED LITERATURE

The global proliferation of AT has prompted a rapidly growing number of studies that analyze the impacts of AT and HFT on market environments. Although this literature remains in its infancy, it already is marked by controversy about how AT affects market quality. We discuss, in detail, both theoretical and empirical findings in this realm.

2.1 EFFECT OF ALGORITHMIC TRADING ON MARKET QUALITY

Computerized AT and HFT have shortened the time the market takes to respond to news events and dramatically increased the speed of transactions. Considering this faster response to news events, there are good reasons to think that AT improves market quality. Unlike their human counterparts, machines can process vast amounts of information in a fraction of the time that humans would require. Thus AT can considerably reduce the monitoring costs of market makers and enhance liquidity (Foucault et al., 2013).[2] In addition, algorithmic traders gather information

[2] In their model, Foucault et al. (2013) show that the effect of ATs on liquidity depends on whether the reduction in monitoring costs mainly affects liquidity providers or suppliers. When ATs mainly reduce monitoring costs for liquidity demanders, the rate at which liquidity gets consumed is higher than the rate at which it is supplied.

simultaneously across different exchanges and in different but related securities, which helps them set more efficient prices and therefore decreases the transaction costs of liquidity traders (Gerig and Michayluk, 2016; Jovanovic and Menkveld, 2012). Even if algorithmic traders are uninformed, their automated liquidity provision likely increases competition among liquidity suppliers and reduces transaction costs.

However, some theories highlight the negative externalities of AT. For example, Cartea and Penalva (2012) model the intermediating role of high frequency traders between liquidity traders and market makers, such that traders exacerbate the price impact of liquidity traders by extracting trading surplus with their speed advantage. Biais et al. (2012) analyze the trading equilibrium when high frequency traders are present and find that HFT enables fast traders to process information before slow traders, giving rise to adverse selection costs. Using an arbitrage-free pricing approach, Jarrow and Protter (2011) arrive at a similar conclusion: The speed advantage of high frequency traders creates arbitrage opportunities at the expense of ordinary traders and thus makes the market less efficient. Yet theoretical studies are inconclusive thus far about the relationship between AT and market liquidity, with different conclusions drawn depending on the strategies and market environments assumed.

Despite the theoretical debate, most empirical findings that identify particular groups of algorithmic traders or construct proxies for AT (using intraday transactions data) suggest that AT actually increases market quality. For example, Hendershott and Riordan (2013) examine algorithmic trades on 30 DAX stocks traded on the Deutsche Boerse in January 2008 and find that the efficient quotes that algorithmic traders place lead to efficient market prices. Brogaard (2010) analyzes the trading behavior of 26 high frequency traders on 120 NASDAQ stocks and finds evidence that they provide the best bid and ask quotes for a significant portion of the day.

On the same sample, Carrion (2013) suggests that high frequency traders supply liquidity when it is scarce and consume liquidity when plentiful. Menkveld (2013) characterizes the cross-market trading strategy of one large high frequency trader and find that the trades of the high frequency trader are predominately passive which provide liquidity to other traders. Using data from NASDAQ-OMX Stockholm, Hagströmer and Nordén (2013) distinguish market-making HFT from opportunistic HFT and document that market makers constituent the majority (63%-72%) of HFT trading volume.

Another set of studies uses proxies to measure the extent of AT, which allows analyses of a greater cross-section of the market. For example, Hendershott et al. (2011) use the arrival rate of messages as a proxy for AT and find that AT narrows spreads and reduces adverse selection costs, particularly for large stocks. Using a broad sample of stocks across 42 stock exchanges, Boehmer et al. (2015) reach a similar conclusion. Hasbrouck and Saar (2013) use reference numbers supplied with NASDAQ transactions data to link each individual limit order with its subsequent cancellation or execution and propose a HFT measure based on "strategic runs". Their results suggest that the increased HFT activities lead to lower spreads and higher displayed depth in the limit order book. For our analysis, we use the AT proxy proposed by Hendershott et al. (2011) as it enables us to examine all stocks listed on the TSE. By design, this measure will capture both AT and an important subset of AT – HFT.

Compared with extant empirical studies, our research offers two new insights. First, we base our analysis on the TSE, an electronic limit order market. The effect of AT on market liquidity may differ from the influences documented using data from U.S. exchanges. Prior studies of electronic limit order markets suggest a possible blurring of the distinction between liquidity providers and liquidity demanders (Hasbrouck and Saar, 2009).[3] Because algorithmic traders can either demand or supply liquidity, the net effect of AT on the liquidity of an electronic limit order market is unclear and worthy of empirical research (Foucault et al., 2013). Second, the implementation of the new trading platform by the TSE in 2010, designed specifically to cater to the infrastructure requirements of AT, constitutes an exogenous event for the AT in our analysis. Through an event study, we mitigate endogeneity concerns over the relationship between AT and market liquidity.

2.2 EFFECT OF ALGORITHMIC TRADING ON COMMONALITY IN LIQUIDITY

As liquidity means more than an attribute of a single asset, many studies investigate how individual stock liquidity co-moves with market-wide liquidity, in terms of both spreads and depths. The phenomenon is not limited to U.S. markets; ample evidence suggests the existence of commonality in liquidity internationally (see for example, Brockman et al., 2009; Chordia et al., 2000; Hasbrouck and Seppi, 2001; Karolyi et al., 2012). Recognizing commonality in liquidity is inherently important, for at least two reasons. First, prior studies (Acharya and Pedersen, 2005; Lee, 2011) suggest that commonality in liquidity poses a systematic liquidity risk, with a significant bearing on asset pricing. Second, theoretical work on the funding constraints for liquidity provision (Brunnermeier and Pedersen, 2009; Kyle and Xiong, 2001) predicts that liquidity demand increases sharply and supply falls during market declines as investors seek to liquidate their positions and liquidity suppliers hit their funding constraints. In turn, commonality in liquidity should intensify during market turmoil.

[3] Empirical evidence offered by Brogaard (2010) and Hendershott and Riordan (2013) confirms that high frequency traders can either be liquidity providers or demanders.

Motivated by the importance of liquidity co-movement, we explore the effects of AT on commonality in liquidity. A priori, the relationship between AT and commonality in liquidity can be either positive or negative. On the one hand, AT reduces commonality in liquidity in normal market conditions. Existing research (Brogaard, 2010; Hendershott and Riordan, 2013; Jovanovic and Menkveld, 2012) suggests that algorithmic traders automate information gathering and processing and therefore are better informed than (slow) liquidity traders.[4] A high level of firm-specific information acquisitions by algorithmic traders thus translates into low levels of co-movements with market-wide liquidity. Conceptually, this effect is similar to stock price non-synchronicity (i.e., low commonality in stock returns). In the spirit of Grossman and Stiglitz (1980), information trading or a transparent information environment corresponds to a lower level of stock price commonality because private information gets incorporated quickly into stock prices (Morck et al., 2000). Because information is a common driver of liquidity and stock returns,[5] algorithmic traders should promptly process and act on information, which decreases commonality in liquidity.

On the other hand, AT may increase commonality in stock liquidity due to the correlated trading of algorithmic traders. That is, the strategies they adopt are more correlated than are those of non-algorithmic traders in the U.S. stock market (Brogaard, 2010) and foreign exchange markets (Chaboud et al., 2011). As support, Hendershott and Riordan (2013) find evidence of

[4] Brogaard (2010) empirically shows that HFT enhances stock price discovery on a sample of 120 Nasdaq stocks, in line with HFT's capacity for the rapid processing of private information. Hendershott and Riordan (2013) investigate the 30 DAX stocks listed on the Deutsche Boerse and find consistent results. Jovanovic and Menkveld (2012) theoretically demonstrate that HFT is able to quickly update quotes on firm-specific news, and the authors empirically show that HFT entry is associated with a 23% decline in adverse selection costs. In terms of the nature of their collection of firm-specific information, algorithmic traders could either automate firm-specific news updates via specialized news analytical data vendors such as the RavenPack database or rely on their proprietary algorithms and computational advantage to gather and process firm-specific news at faster speed than human traders.

[5] Karolyi et al. (2012) provide strong evidence that commonality in liquidity and commonality in stock returns are positively correlated over time in almost all 40 countries they study.

AT clustering in time in the 30 DAX stocks on the Deutsche Boerse. In addition, Coughenour and Saad (2004) document that commonality in stock liquidity tends to increase among stocks handled by the same market maker as a result of shared capital and information. Thus, we expect that commonality in stock liquidity increases with AT as previous evidence suggests that the market-making activity constitutes the lion's share of AT trading volume (Hagströmer and Nordén, 2013; Menkveld, 2013). Given the opposing views about the role of AT on liquidity commonality, we investigate empirically how AT, on average, affects commonality in liquidity.

2.3 LIQUIDITY EFFECT OF ALGORITHMIC TRADING IN EXTREME MARKET CONDITIONS

The recent dominance of AT in many stock exchanges has provided an impetus for researchers to attempt to understand its effect, particularly on liquidity during periods of market stress. Several studies report positive effects of AT on liquidity, but the joint CFTC/SEC report on the U.S. flash crash of 6 May 2010 conveys the regulator's concerns about the risk of AT when the market experiences high volatility.[6]

Prior literature offers few empirical insights into how algorithmic traders affect market liquidity during extreme market conditions. Kirilenko et al. (2011) examine HFT in the futures market around the flash crash of 6 May 2010 and find that although the traders did not trigger a crash, they exacerbated market volatility. Hasbrouck and Saar (2013) study the market impact of HFT in June 2008 following the fire sale of Bear Stearns in March. They document that HFT enhances market quality during stressful market times. Instead of restricting their analysis to brief periods of extreme market events, Boehmer et al. (2015) and Zhang (2010) examine

[6] See http://www.sec.gov/news/studies/2010/marketevents-report.pdf.

AT/HFT using a longer sample period with multiple market volatility episodes.[7] They indicate that HFT worsens market quality around the world.

We examine the AT behavior in TSE stocks during extreme market conditions, which we identify on the basis of the historic mean of the market index return (Hameed et al., 2010). However, unlike most prior research we use a longer sample period, rather than focus on specific events, to be representative of market conditions in general. We also analyze the effect of AT on commonality in liquidity during market stress whereby commonality in liquidity has been shown to increase.

3. SAMPLE AND DATA DESCRIPTION

3.1 INSTITUTIONAL BACKGROUND

According to annual statistics as at 2012, the TSE is the third largest exchange in terms of the total market capitalization of its listed firms at USD3,479 billion (World Federation of Exchanges, 2012). It thus ranks behind only the New York Stock Exchange at USD14,086 billion and the NASDAQ OMX at USD4,582 billion. It also is the largest exchange to operate as a pure electronic order–driven market, without market makers; its turnover in 2012 was USD3,214 billion. The TSE operates two trading sessions each day: a morning session from 9:00–11:00 am and an afternoon session from 12:30–3:00 pm. Similar to many order-driven markets with continuous trading, call auctions open and close trading for each session.

[7] Specifically, Zhang (2010) studies all stocks covered by CRSP and Thomson Reuters Institutional Holdings databases during 1995–2009 and finds that the positive correlation between HFT and market volatility increases with greater market uncertainty, on basis of the S&P 500 VIX implied volatility index. Boehmer et al. (2015) use the AT proxy from Hendershott et al. (2011) on an international sample of stocks from 39 exchanges from 2001 to 2009 and show that AT lessens market liquidity and worsens market volatility when market making is difficult.

The TSE introduced a new trading platform, Arrowhead, on 4 January 2010, with the specific aim of facilitating AT on the Japanese stock market. The Arrowhead trading system is built on an optical fiber ring network and has reduced latency (i.e., the time elapsed between order placement and order execution) to two milliseconds on average. The new trading speed is approximately one-thousandth of the time required under the previous trading system (Tokyo Stock Exchange, 2010) and is similar to that of the NYSE and the LSE. Depending on their physical distance from the TSE data center, market participants can experience additional latency. To minimize latency, participants can use the co-location service and install automatic order placement servers at the TSE data center, thus gaining even lower latency of less than one millisecond (Asia ETrading, 2014; Tokyo Stock Exchange, 2011).

The structure of the monthly access fee was changed when TSE implemented the new trading platform. Under the previous trading system, the monthly access fee for the trading platform was charged based on a tier system, beginning at 400 thousand yen for participants submitting fewer than 100,000 orders per month. The maximum monthly fee of 6,600 thousand yen was charged for a submission of 4 million orders or more. In anticipation of the larger number of order submissions under Arrowhead, the fee structure was amended, with the TSE no longer capping their monthly access fees. The TSE continues to use the tiered fee structure, but new tiers have been introduced. For instance, participants submitting between 5 million and 10 million orders per month are charged 7,100 thousand yen, and when participants submit more than 10 million orders, TSE now charges 500 thousand yen per 5 million orders.

Together with the implementation of the new trading platform, the TSE amended its trading rules. Of particular importance to our study is the change in the tick size structure; the introduction of more tick size intervals increased the number of intervals from 9 to 11 and decreased the tick size for stocks in these price zones.[8] For example, the tick size for stocks trading in the price range of 3,000 to 5,000 yen fell from 10 to 5 yen. This change may cause a decrease in the bid–ask spread for affected stocks; to ensure a clean sample, we exclude the affected stocks throughout the analysis.

3.2 SAMPLE SELECTION

We construct AT and stock liquidity measures using intraday transactions data obtained from the Nikkei Economic Electronic Database System. The database comprises real-time tick-by-tick data for all stocks listed on the TSE, where the transaction records are time-stamped to the nearest minute prior to January 2010 and to the nearest second after January 2010. Price, order flow, and volume information are available for a wide spectrum of common stocks in Japan. This detailed, comprehensive database is the best known trading data source on the Japan market and has been used widely in previous studies (e.g., Ahn et al., 2005; Ohta, 2006).

Due to the scarce AT activities in the years prior to 2010, our sample period runs from January 2007 to December 2012.[9] We focus on common stocks listed on the TSE and apply several filters to form the final sample. First, we exclude trading days without afternoon sessions

[8] Prior to 2010, the price (in JPY) and minimum tick size (in parentheses) were ≤2,000, (1); ≤3,000, (5); ≤30,000, (10); ≤50,000, (50); ≤300,000, (100); ≤3,000,000, (1000); ≤20,000,000, (10,000); ≤30,000,000, (50,000); and >30,000,000, (100,000). With the implementation of the Arrowhead trading platform, the price (in JPY) and minimum tick size (in parentheses) became ≤3,000, (1); ≤5,000, (5); ≤30,000, (10); ≤50,000, (50); ≤300,000, (100); ≤500,000, (500); ≤3,000,000, (1000); ≤5,000,000, (5000); ≤30,000,000, (10,000); ≤50,000,000, (50,000); and >50,000,000, (100,000).

[9] AT is an outcome of recent advances in technology. Chaboud et al. (2011) observe a very small portion of AT prior to 2006 in foreign exchange markets. Hendershott et al. (2011) also show a sharp increase in AT after January 2003, which coincided with the introduction of Autoquote on the NYSE, where new quotes are automatically disseminated when there was a relevant change to the limit order book. The TSE introduced Arrowhead on 4 January 2010 to boost automated trading in the Japanese market. Before then, AT was limited by trading platform capacity constraints.

to avoid the holiday effects.[10] Second, to mitigate bid–ask bounce concerns, we omit stocks with a price of less than 10 Japanese yen. Third, we exclude stock-day observations if the stock on a particular day has less than five trades executed in a continuous auction session with positive bid and ask prices. Fourth, we exclude the specific daily spread measure if its value on a particular day is greater than 20%. Fifth, we drop stocks that have experienced tick size reduction following the introduction of the Arrowhead trading platform. After applying these filters, our final sample consists of 1,572,355 stock-day observations from 1,302 unique stocks spanning 1,471 trading days.

3.3 ALGORITHMIC TRADING MEASURE

Since we cannot differentiate orders placed by a computer from those placed by humans, in this study we use electronic message traffic as a proxy for AT. We define electronic message traffic as the sum of quote updates on a given trading day. This AT proxy has received strong support from existing literature. Biais and Weill (2009) provide theoretical support for this measure by demonstrating that the ratio of electronic messages to volume rises with the rate at which investors can contact the market. Empirically, this measure has been applied by Hendershott et al. (2011) to a U.S. sample and by Boehmer et al. (2015) to an international sample.

A caveat associated with the use of a raw electronic message traffic measure is that this measure rises with trading volume, even if AT remains stable (see Figure 1), leading to a spurious relationship between AT and electronic message traffic. To avoid misleading interpretations, we normalize electronic message traffic by dividing the dollar trading volume by

[10] In Japan, stock trading in the afternoon session was suspended the day prior to major national festivals, namely, in our sample, on 4 January 2007, 28 December 2007, 4 January 2008, 30 December 2008, and 5 January 2009. The implementation of the new trading system eliminated these half-holidays.

the aggregate electronic message traffic on a given trading day and multiplying this ratio by –1 and denote this variable as *ATrade*.[11] The theoretical boundary of *ATrade* is between negative infinity and zero. A higher value of *ATrade* indicates a higher level of AT. Table 1 summarizes our descriptive variable statistics; consistent with the time trend in Figure 1, the mean and median value of *ATrade* increases steadily over our sample period with a sharp jump from 2009 to 2010. The mean value of *ATrade* increases from a low of –0.27 in 2007 to a high of –0.06 in 2012, and the medians exhibit similar upward patterns.

3.4 LIQUIDITY MEASURES

The challenge associated with measuring stock liquidity is long standing (Goyenko et al., 2009; Korajczyk and Sadka, 2008). In an attempt to disentangle the effects of AT on various aspects of stock liquidity, we adopt six liquidity measures: quoted spread, effective spread, realized spread, adverse selection cost measure, market depth at the best bid/ask prices, and aggregated market depth at the first five price levels. Noting the persistence of seasonality effects across liquidity measures, we compute adjusted stock liquidity measures, similar to those used by Hameed et al. (2010), though with one modification; that is, we include price zone dummies. Specifically, we adjust our liquidity measures for stock *i* on day *t* as follows:

$$Liq_{i,t} = \sum_{j=1}^{4} d_j \, DAY_{i,t} + \sum_{j=1}^{11} m_j \, MONTH_{i,t} + \sum_{j=1}^{10} p_j \, PRICE_{i,t} + Adj\_liq_{i,t} \qquad (1)$$

[11] AT often manifests itself in active order submission, cancellation, and execution. Suppose AT activity has been stable but overall order executions have increased in response to positive news events, resulting in a higher value of both the raw electronic message measure and trading volume. In this case, the increased raw electronic message measure does not necessarily correspond to a rise in AT. This concern can be effectively alleviated using the electronic message measure adjusted for trading volume. Moreover, the adjusted message traffic measure normalized by trading volume also enables cross-sectional and time series comparisons. This is essential for our study which spans a long sample period from 2007 to 2012.

where $DAY_{i,t}$ is the day of the week dummy, $MONTH_{i,t}$ is the month dummy, and $PRICE_{i,t}$ denotes the price zone dummy. We run this regression model for each stock throughout the sample period and use the estimated residual, including the intercept, $Adj\_liq_{i,t}$, to measure stock liquidity in our subsequent empirical analyses.

The first two liquidity measures, quoted spread and effective spread, reflect aggregate stock liquidity. Quoted spread refers to the difference between the bid and ask price, scaled by the midpoint of bid and ask prices in each transaction. The effective spread for stock i on the jth transaction can be computed as follows:

$$ESpread_{i,j} = D_{i,j}(P_{i,j} - M_{i,j})/M_{i,j} \tag{2}$$

where $D_{i,j}$ equals 1 if the trade is buyer-initiated and –1 if seller-initiated; $P_{i,j}$ is the trade price; and $M_{i,j}$ refers to the midpoint of the bid and ask prices. Because the TSE is an order-driven market and all transactions occur at the best bid or ask prices, the initiator of a transaction can be identified with certainty. According to the summary statistics of these two spread measures in Table 1,[12] the sample mean values of the quoted and effective spread measures are 0.0033 and 0.0027, respectively, largely comparable with their U.S. counterparts (Goyenko et al., 2009). This indicates that the Japanese stock market is highly liquid and it thus serves as an appropriate environment for AT. Additionally, the time patterns of the two spread measures coincide with significant global and domestic financial events during the same period. For example, the mean quoted spread reaches its highest level of 0.0040 in 2008, at the onset of the global financial

[12] The spread measures in Table 1 are multiplied by 10^4 for presentation.

crisis, and declines to 0.0031 in 2012 due to the resilient financial recovery (e.g., Campello et al., 2010; Ivashina and Scharfstein, 2010; Lang and Maffett, 2011).[13]

To investigate how AT affects stock liquidity, we decompose effective spread into its inventory component (i.e., revenues for liquidity providers) and adverse selection component (i.e., gross losses to informed liquidity demanders). The former can be measured by the realized spread over the five-minute time interval; the latter is measured by the price impact of a trade over the same time interval. The realized spread, $RSpread$, for stock i on the jth transaction is defined as:

$$RSpread_{i,j} = D_{i,j}(P_{i,j} - M_{i,j+5})/M_{i,j} \quad (3)$$

where $M_{i,j+5}$ refers to the midpoint of the prevailing bid and ask prices at time of the subsequent trade five minutes after trade j.[14] The adverse selection component of stock liquidity is measured as follows:

$$ASel_{i,j} = D_{i,j}(M_{i,j+5} - M_{i,j})/M_{i,j} \quad (4)$$

For each spread measure for each stock on each day, we calculate the dollar volume weighted average across all trades that day. From Table 1, we observe a consistent pattern across the year subsamples. That is, the magnitude of the adverse selection component of stock liquidity is much higher than that of realized spread, which highlights the significance of information-based trading activities.

[13] The global financial crisis, stemming from the U.S. banking sector, spurs renewed interest in various finance and economics issues; most studies, including Ivashina and Scharfstein (2010), Campello et al. (2010), and Lang and Maffett (2011) identify 2008 as the year of the onset of the crisis.

[14] Following Huang and Stoll (1996), we use the prevailing best quotes for the first trade occurring five minutes after trade j in the same trading session (i.e., morning or afternoon session) if a trade is not available after five minutes. No realized spread is calculated if no subsequent trade exists in the same trading session.

Finally, we explore market depth at the best bid and ask prices and at the aggregated five-level market depth on the limit order book. We define market depth, *Depth*, as the total dollar value of shares available at the best bid/ask prices; the five-level market depth, *Depth5*, is the total dollar value of shares available at the best five levels of quoted prices. For each stock on each day, we calculate the average time-weighted market depth and express the measure in millions of Japanese yen. Table 1 reports means, for the entire sample period 2007-2012, for *Depth* and *Depth5* of 18.31 and 89.22, respectively. The finding that *Depth5* is less than five times the mean of *Depth* suggests greater market depth occurs at the best available quoted prices than at other levels. We plot the time-series of daily cross-sectional averages of our daily AT measure, *ATrade*, daily quoted spread (*QSpread*) and market depth (*Depth*) in Graph (a) of Figure 2. Together with the increase in AT activities from January 2010, we find that the cross-sectional average of daily quoted spread has declined and that of market depth has increased post the adoption of Arrowhead in 2010. We also note that the average quoted spread is relatively higher and more volatile during the global financial crisis period in 2008. The spike in market depth and quoted spread around March 2011 corresponds to the outbreak of the 9.0 magnitude earthquake on 11 March 2011.

3.5 CONTROL VARIABLES

To ensure that the observed relationships between the *ATrade* measure and stock liquidity are not driven by other stock characteristics and market-wide conditions, we control for four stock-level variables and three market-level variables; their detailed definitions are shown in the Appendix. The stock-level variables include stock turnover (*Turn*), daily stock volatility (*Vol*), the inverse of stock price multiplied by 100 (*InvPrc*), and the log of market capitalization (*Size*). Stock turnover refers to the number of shares traded, over the number of shares outstanding on a given trading day. Amihud and Mendelson (1986) show the bid–ask spread widens as the trading volume and number of shareholders decrease, which they attribute to a clientele effect. In controlling for stock turnover in our analysis, we expect this variable to be negatively associated with spread measures but positively related to market depth measures.

Substantial literature offers evidence of worsening stock liquidity during volatile stock markets. Therefore, we control for stock volatility, computed as the difference between high and low stock prices over a given trading day (Benston and Hagerman, 1974; Chordia et al., 2000). We predict that daily stock volatility has a negative relationship with stock liquidity measures. We further control for the inverse of stock price; Benston and Hagerman (1974) and Stoll (1978) report that stock transactions costs relate negatively to stock price. Finally, we account for firm size, measured by the natural log of market capitalization on a particular trading day.

The three control variables that proxy for market conditions are Japanese stock market return (*MRet*), realized market volatility (*MVol*) and expected future market volatility (*VXJ*).[15] In particular, expected stock market volatility is measured using the Volatility Index Japan index (*VXJ*) provided by the VXJ Research Group at the Center for the Study of Finance and Insurance from Osaka University. This measure is calculated on a daily basis following the VIX methodology as an index of market volatility implicit in the prices of Nikkei 225 options traded

[15] While we have controlled for several commonly used market variables, our results may still be driven by other unobservable time series variables. Because it is considerably challenging to find an appropriate control sample, we cannot completely resolve the endogeneity concern in our research setting.

at the Osaka Securities Exchange. We expect this index to capture the funding constraints for liquidity providers (Brunnermeier and Pedersen, 2009; Nagel, 2012).[16]

With all these variables winsorized at the top and bottom 0.05% of the full sample distribution, several interesting findings in Table 1 are noteworthy. The sample mean of daily stock turnover (i.e., *Turn* divided by 1,000) is 0.0039, consistent with TSE being a liquid stock market. Stock volatility, *Vol*, exhibits the highest mean value of 0.21 and a standard deviation of 1.96 in 2008 when the global financial crisis broke out.

4. ALGORITHMIC TRADING AND STOCK LIQUIDITY

Algorithmic traders can act differently, as either liquidity providers or liquidity demanders. Considering the dynamic nature of their algorithms, it remains unanswered whether and how algorithmic trading affects stock liquidity and commonality in liquidity in a limit order–driven market. We explore this research question in depth by analyzing the statistical and economic impact of AT on six different liquidity measures.

4.1 MAIN REGRESSION ANALYSIS

We first investigate the direct effect of AT on stock liquidity from 2007 to 2012 by estimating the following structural equations using the 2SLS regression method:

$$\begin{aligned} Adj\_liq_{i,t} = s_i + \alpha_1 ATrade_{i,t} + \alpha_2 Turn_{i,t} + \alpha_3 Vol_{i,t} + \alpha_4 InvPrc_{i,t} + \alpha_5 Size_{i,t} + \alpha_6 MRet_t + \\ \alpha_7 MVol_t + \alpha_8 VXJ_t + \varepsilon_{i,t} \end{aligned} \quad (5a)$$

$$\begin{aligned} ATrade_{i,t} = v_i + \beta_1 Arrowhead_t + \beta_2 Turn_{i,t} + \beta_3 Vol_{i,t} + \beta_4 InvPrc_{i,t} + \beta_5 Size_{i,t} + \\ \beta_6 MRet_t + \beta_7 MVol_t + \beta_8 VXJ_t + \theta_{i,t} \end{aligned} \quad (5b)$$

[16] The information about the VXJ index is obtained from the following website: http://www-csfi.sigmath.es.osaka-u.ac.jp/en/activity/vxj_method.php?id=3.

where $Adj\_liq_{i,t}$ denotes various adjusted spread and depth measures, and $ATrade_{i,t}$ is the negative daily dollar trading volume scaled by the total number of quote updates for stock i on day t. $Arrowhead_t$ is the instrumental variable in the first stage regression as specified by Equation (5b). This is a dummy variable that takes a value of one if the observation is on or after 4 January, 2010 and zero otherwise. The list of control variables includes stock trading turnover (*Turn*), daily stock trading volatility (*Vol*), the inverse of stock price (*InvPrc*), firm size (*Size*), stock market return (*MRet*), realized market volatility (*MVol*) and expected market volatility (*VXJ*). We also include firm fixed effects (i.e., s_i and v_i) to control for any omitted firm-level control variables.

Table 2 Panel A contains the 2SLS regression results from estimating Equations (5a) and (5b) with the full sample. We first check the validity of using the 2SLS regression methods by performing the Hausman test. The *p*-values of the Hausman tests are less than 5%, across all model specifications, suggesting the use of the 2SLS regression is more appropriate than the ordinary least squares (OLS) regression. In the first stage regressions, there is strong and consistent evidence across all the 2SLS estimations that the adoption of the Arrowhead trading platform has facilitated algorithmic trading activities. For example, in column (1), the coefficient of *Arrowhead* is 0.090 (*t*-statistic = 227.310), indicating that AT has increased substantially post the implementation of the new trading platform. In the second stage estimations, we observe significant coefficients on the *ATrad*e variable across four different stock liquidity measures. When quoted spread and effective spread are used as dependent variables in columns (2) and (4), the coefficients on *ATrade* are -14.298 (*t*-statistic = -35.750) and -3.089 (*t*-statistic = -10.792), respectively. From an economic perspective, a one standard deviation increase in *ATrade* leads to a 4.00 basis point decrease in quoted spread and a 0.86 basis point decrease in effective spread. Because the mean of the quoted and effective spreads falls between 27 and 32 basis points, the impact of AT on stock liquidity is economically significant. Consistent with the results using spread-based variables, columns (6) and (8) show that *ATrade* is positively and significantly associated with both of the market depth measures, suggesting an increased market depth with the rise of AT.

Our results also suggest a reliable control variable selection. When spread-based liquidity measures are used as dependent variables, all control variables are statistically significant, and the sign on the coefficients is consistent with our expectations. Stock turnover relates negatively to the spread-based illiquidity measure, in line with the clientele effect suggested by Amihud and Mendelson (1986). We also find that all spread-based illiquidity measures increase with stock volatility and the inverse of stock price but decrease with firm size. Finally, spreads narrow on days with high market returns and widen on days with high realized and expected market volatility. With regard to the model specifications, using market depth measures as dependent variables, the sign on the coefficients for *Size* and *VXJ* reverses, which is consistent with expectations for the level of market depth to be higher for large sized stocks and lower on days with high expected market volatility.

According to classic market microstructure models, information asymmetry and inventory risk are considered as major components of trading costs. Algorithmic traders' exposure to these two risks is likely to differ when compared to other traders. Their access to speed allows for more rapid (instantaneous) processing of public news (Biais et al., 2012; Jovanovic and Menkveld, 2012), and thereby reduces the risk of these traders being adversely selected. The ability to attenuate their adverse selection costs is likely to see AT improve liquidity through the submission of more aggressive limit orders. Inventory costs, a proxy for order execution costs after excluding adverse selection costs (Bessembinder, 2003; Huang and Stoll, 1996), may also decline with the rise of AT. The use of computerized trading enables algorithmic traders to quickly update their quotes and thus increase the competition among liquidity providers, shrinking the revenues from liquidity provision.

Using data for the entire time period, we evaluate the effects of AT on adverse selection and inventory costs in Table 2 Panel B. Our results show that the coefficients on *ATrade* are -2.293 (*t*-statistic = -5.403) for realized spread in column (2), and -1.501 (*t*-statistic = -3.518) for adverse selection cost in column (4). The magnitude of the *ATrade* coefficient for realized spread is much larger than the magnitude of that for the adverse selection cost, which is consistent with the findings in prior research that algorithmic traders are more likely to take on a market making role rather than exploit any informational advantages (Hagströmer and Nordén, 2013; Menkveld, 2013).

4.2 SOURCE OF THE EFFECTS OF AT ON STOCK LIQUIDITY

Among other possibilities, we attempt to explore one possible mechanism by which AT leads to an improvement in stock liquidity: the reduction in monitoring costs. AT could either automate the monitoring of stocks[17] or gather and process public available news instantaneously (Carrion, 2013), both of which markedly reduce the monitoring costs. We first use firm size as a proxy for the level of monitoring costs. It is argued that small stocks receive little investor attention (Hong

[17] Some databases provide real-time quantifiable assessments of firm-specific and market-wide news for algorithmic traders. As a prominent example, RavenPack News Analytics can analyze the news relevance and sentiment instantaneously to help their algorithmic customers predict liquidity, volatility, and directional market movements caused by news and assist to establish automated market-making strategies when there is a significant news impacting event on a particular stock. See RavenPack's website for more details: http://www.ravenpack.com/.

et al., 2000), have a lower quality of financial reporting (Dechow and Dichev, 2002)[18], release less public information, and have a lower extent of financial press coverage (Gadarowski, 2002).[19] Therefore, the monitoring costs of small stocks are expected to be higher than those of large stocks.

The 2SLS regression models involving interaction terms are more complicated empirically. Because *ATrade* is an endogenous predictor in the second-stage model, any interaction between this endogenous predictor and an exogenous variable such as *Size* is potentially endogenous. In cases where the second-stage model involves multiple endogenous predictors, it is important to satisfy the rank condition (Wooldridge, 2002, p.88) whereby there must be at least one instrument included for each endogenous predictor in the second stage. Following Murnane and Willett (2011), p.247, we use the *Arrowhead* dummy variable and the interaction between *Arrowhead* and *Size* as the instruments for *ATrade* and the interaction between *ATrade* and *Size.* Specifically, we regress *ATrade* and *ATrade*×*Size,* respectively, on *Arrowhead* and *Arrowhead*×*Size* together with other controls in the two first stage regressions. The predicted values of *ATrade and ATrade*×*Size* are used in the second stage.

The second stage results are summarized in Table 3 Panel A. We note that the coefficients on *ATrade*×*Size* are positive and significant at the 1% level for the spread measures in columns (1) and (2), and are negative and significant for the depth measures in columns (3) and (4). The

[18] Hong et al. (2000) suggest that private information travels faster for large stocks due to the fact that investors collecting private information are faced with the fixed costs of information acquisitions. As a result, they are more inclined to devote more efforts to stocks that can take strong positions. Another strand of the rich literature on financial accounting quality (e.g., Dechow and Dichev, 2002) supports the view that financial accounting quality is relatively high for large stocks.

[19] Analysts collect, filter and disseminate information about firms. They cover large stocks instead of small stocks because there is a high demand for analyst service from institutional investors who trade stocks that are in the index funds. They cover large stocks also because the cost of collecting non-public information is lower for large stocks. The relation between firm size and the level of analyst coverage is supported by the empirical findings of Bhushan (1989), Hong et al. (2000) and Rock et al. (2000).

evidence suggests that the effect of AT is most pronounced among small stocks that are likely to have high monitoring costs, which is in support of the idea that AT improves liquidity through reducing monitoring costs.

In addition to firm size, we also use two measures that are more direct proxies of monitoring costs: financial analyst coverage (Healy and Palepu, 2001) and the number of public news releases (Griffin et al., 2011); lower values of these two proxies represent higher levels of monitoring costs. We measure analyst coverage by the number of financial analyst forecasts in the three months prior to financial year end (denoted as *Analyst*) based on the information provided by the I/B/E/S database; to avoid unnecessary loss of data, we assign this variable the value of zero for stocks that are not included in the database. Consistent with prior results, we find in Panel B that after controlling for firm size, the liquidity effects of *ATrade* are significantly stronger for firms with low level of analyst coverage across all the liquidity measures. We capture firm-level public news events using the number of public news messages on a given trading day in the Thomson Reuters News database.[20] Again, the results in Panel C show that the effects of *ATrade* are more pronounced for firms with low level of public media coverage. The overall findings in this table suggest that the reduction of monitoring costs can be a potential explanation as to why AT improves stock liquidity.

At this juncture, it is necessary to review the size effect of AT activity documented in prior studies. Jain et al. (2012, Table 1) observe a more pronounced AT effect in improving liquidity in large-cap stocks from a simple univariate analysis using the TSE sample like us. At the first glance, our results seem to contradict their findings. However, a meaningful comparison is

[20] The number of news messages for the stock on day *t* includes news release from the previous day closing time to the closing on day *t*.

difficult due to several reasons. Jain et al. (2012) differs substantially from our study in terms of the liquidity measures, AT proxy, and estimation approach. Even without these differences, they do not test explicitly the size effect in their multivariate analysis.[21] The inference from their multivariate analysis is at best a positive relationship between AT and liquidity across all size groups, consistent with our findings.

The size effect on the AT-market quality relationship is also examined but not tabulated in Hasbrouck and Saar (2013, page 673). Although they do not observe any consistent pattern in the size quantiles during normal times (the 2007 sample), the authors report a stronger AT effect on volatility reduction in smaller stocks in the 2008 sample. They interpret the results as high volatility attracting AT in small-cap stocks. Considering our findings of a stronger AT effect in smaller stocks and informationally opaque stocks, our study extends Hasbrouck and Saar's findings by highlighting the reduction in monitoring costs as a potential economic channel for the stronger negative AT-volatility relationship in smaller stocks.

4.3 ALGORITHMIC TRADING AND COMMONALITY IN STOCK LIQUIDITY

Commonality in liquidity is another important dimension of stock liquidity. When individual stock liquidity moves together with market-wide liquidity and cannot be diversified away, systematic liquidity risk results. We analyze whether AT plays a role in determining commonality in liquidity in Table 4. To start, we obtain a proxy for commonality in liquidity by estimating the following regression model on a monthly basis for each stock:

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[21] While the magnitude of the Arrowhead variable does appear to decline from large-cap stocks to small-cap stocks in Table 3 of Jain et al. (2012) when regressing COI and LOB slope on the Arrowhead dummy variable, such a comparison is arbitrary without any statistical grounds. It is therefore no surprise that the authors did not remark on the size effect on the AT-liquidity relationship in their multivariate analysis at all.

$$\Delta Liq_{i,t} = \alpha_{i,t} + \beta_{i,t}\Delta MLiq_{-i,t} + \varepsilon_{i,t} \quad (6)$$

where $\Delta Liq_{i,t}$ is the change in individual stock liquidity for stock i on day t, and $\Delta MLiq_{-i,t}$ is the change in market liquidity, which is the simple average of the corresponding individual stock liquidity measure across all stocks except stock i on day t. The R-squared estimates from Equation (6) represent the co-movement of individual stock liquidity with market-wide liquidity. To ensure a reliable R-squared estimate, we exclude the monthly estimates from our subsequent analysis if there are less than 15 stock-day observations in a particular month. In addition, due to the bounded nature of R-square estimates, we divide R-squared by (1 – R-squared) and take the log of this ratio (Hameed et al., 2010; Karolyi et al., 2012).[22] To visualize the relationship between AT and commonality in liquidity, we plot the time series of the cross-sectional averages of monthly *ATrade,* commonality in quoted spread (*CQSpread*), and commonality in market depth (*CDepth*) in Graph (b) of Figure 2. We note that *CQSpread* and *CDepth* are relatively high during the global financial crisis in 2008 and the spike in March 2011 is due to the great earthquake in Japan. However, it is difficult to distinguish a clear pattern between *ATrade* and two commonality variables from the graph.

To investigate the effect of AT on commonality in liquidity, we then use the following 2SLS equations controlling for the endogeneity of AT:

[22] The mean values of the raw R-squared estimates range from 0.083 (*CDepth*) to 0.128 (*CQSpread*), and their medians are within a similar range. The mean values of the logistically transformed R-squared estimates are between -3.605 (*CDepth*) and -2.976 (*CQSpread*), and their median values are between -3.152 (*CDepth*) and -2.534 (*CQSpread*). For robustness, we also rerun our analyses using the original R-squared measures estimated from Equation (6) and our results continue to hold.

$$CLiq_{i,t} = s_i + \alpha_1 ATrade_{i,t} + \alpha_2 Liq_{i,t} + \alpha_3 Size_{i,t} + \alpha_4 MRet_t + \alpha_5 MVol_t + \alpha_6 VXJ_t + \varepsilon_{i,t} \tag{7a}$$

$$ATrade_{i,t} = v_i + \beta_1 Arrowhead_t + \beta_2 Liq_{i,t} + \beta_3 Size_{i,t} + \beta_4 MRet_t + \beta_5 MVol_t + \beta_6 VXJ_t + \theta_{i,t} \tag{7b}$$

where *CLiq* represents the logistically transformed monthly estimates of commonality from Equation (6) in four stock liquidity measures: quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), and aggregated market depth at five price levels (*Depth5*). All other variables in Equations (7a) and (7b) are the monthly averages of their daily measures defined in Equations (5a) and (5b).

Table 4 summarizes the results. Across all liquidity measures, we observe positive and significant coefficients on the *Arrowhead* dummy variable in the first-stage regressions. As for the second-stage model estimation, the coefficient on *ATrade* ranges from 2.997 to 4.302 across the four liquidity measures, with all coefficients significant at the 1% level. The results suggest that AT increases individual stock liquidity co-movement with market liquidity, which might occur if algorithmic traders are trading a basket of stocks when using correlated trading strategies (Brogaard, 2010; Menkveld, 2013). It is also possible if the majority of algorithmic traders act as new market makers. Each market maker provides liquidity for more than one stock; Coughenour and Saad (2004) document that stock liquidity co-move with the liquidity of other stocks handled by the same market maker because of shared capital and information. The signs on the coefficients for the control variables are mostly consistent with prior literature. We find the liquidity commonality measures increase with firm size (*Size*) and market volatility (*MVol*). There are, however, three control variables (*MRet, VXJ* and *QSpread)* that have coefficients with signs contrary to our expectations in some of the models. First, the coefficients on expected market volatility (*VXJ*) are negative and significant for the regressions examining commonality in quoted and effective spreads, and the coefficient on market return (*MRet*) is positive in the regression model examining commonality in market depth (*CDepth5*). This could be attributed to the multicollinearity problem arising from the high correlations between *VXJ* and *MRet/MVol* (the correlation coefficient between *VXJ* and *MRet* is -0.41; the correlation coefficient between *VXJ* and *MVol* is 0.60). In untabulated results, we find positive coefficients on *VXJ* when *MRet* and *MVol* are excluded; and more importantly, our primary results remain unaffected after excluding *VXJ* from the regression estimation. Second, we observe a negative coefficient on *QSpread* in column (2), which suggests that commonality in quoted spread decreases with quoted spread. The puzzling result for the coefficient on *QSpread* may be driven by small stocks that usually experience wide quoted spreads and low commonality in liquidity simultaneously (the correlation coefficient between *Size* and *QSpread* is -0.54). We run the model without controlling for *QSpread* and the untabulated results show that the sign and magnitude of the coefficient on *ATrade* remain similar.

To verify the robustness of our full sample results, we conduct an additional test and present the results in Panel B. We test whether our results hold when examining commonality in liquidity using intraday data. We investigate the effects of AT on intraday commonality measures for two reasons: (1) the inter-day findings may not extend to the intraday analysis if trading by algorithmic traders across different stocks occurs at different times of the day; (2) prior studies (see Huh, 2011; Jain et al., 2012) document evidence of positive associations between AT and intraday liquidity commonality and we are keen to verify these findings with our sample and measures. To examine whether the effect of AT holds for intraday liquidity co-movement, we re-estimate the four liquidity measures by using 1-minute snapshot data. The changes in the 1-minute liquidity measures are then regressed on the changes in the respective 1-minute market-level liquidity measure (excluding the own stock) based on Equation (6) for all liquidity measures within a given trading day. This allows us to generate intraday commonality in liquidity measures at a daily frequency. We then estimate Equations (7a) and (7b) based on daily observations. Summarizing the second-stage regression results in columns (1)-(4) in Table 4 Panel B, we note that the effects of AT on the intraday commonality in liquidity are positive and significant across all the intraday commonality measures, largely consistent with its effects on the low-frequency commonality in liquidity.

We further look at whether the reduction in monitoring costs leads to the positive effect of AT on liquidity commonality. If algorithmic traders are able to monitor firm-specific news more quickly and efficiently, we expect the effects of AT to be more pronounced for smaller firms and firms with fewer analyst following and lower media coverage as such firms often incur high monitoring costs. In other words, stocks that incur high monitoring costs are more likely to be included in the trading portfolio of algorithmic traders following the rise of AT, and therefore exhibit high commonality in liquidity. To test this effect, we introduce an interaction term between *ATrade* and the three proxies for monitoring costs (i.e., firm size, analyst and news coverage) in the baseline 2SLS regression models (Equations (7a) and (7b)). The second-stage regression results shown in Table 5 support this conjecture. The coefficients on *ATrade*×*Size, ATrade*×*Analyst, and ATrade*×*News* are negative and significant at conventional levels for all four liquidity commonality measures in Panels A, B and C, respectively. This suggests that stocks with high monitoring costs experience the most significant increase in liquidity commonality due to AT.

4.4 ALGORITHMIC TRADING AND STOCK LIQUIDITY IN EXTREME MARKET CONDITIONS

Noting the generally positive effect of AT on stock liquidity during normal market conditions, we investigate whether such effects persist in extreme market conditions. By many accounts, practitioners have unfavorable views of AT; the financial press often suggests that algorithmic traders take the same side on transactions in times of high market volatility and therefore exacerbate market quality.[23] Therefore, it is pertinent to explore the effects of AT during extreme market conditions.

We first examine the changes of AT activities in extreme market conditions in Table 6, and then investigate variations in the effects of AT on stock liquidity and liquidity commonality in extreme market conditions in Table 7. We use Hameed et al.'s (2010) criteria to identify extreme market conditions: A trading day is in an extreme market if the previous week's market return, proxied by the TOPIX market index, is more than 1.5 times the standard deviation above or below its unconditional mean. The unconditional mean and standard deviation of local market returns for a particular day are determined with a rolling window approach, which computes the basic statistics using 52 weekly historical market returns, prior to the particular trading day. By using a rolling window approach, we avoid an uneven distribution of extreme high and low market returns in certain calendar years, such as 2008.

The number of trading days with extreme market conditions in each year and over the full sample period is reported in Table 6 Panel A. We denote the days with highly positive (negative) market returns as *Up* (*Down*) market states. The highest number of extreme market increases and

[23] For example, "Algorithmic trades heighten volatility," *Financial Times*, December 4, 2008 (Gangahar, 2008).

declines occurs in 2008, with 22 days of extremely high market returns and 32 days of extremely low market returns. This volatile stock market is clearly affected by the far-reaching 2008 global financial crisis. The years 2010 and 2011 have the fewest days with highly positive market returns. The year with the fewest days with extremely low market returns is 2009, which is consistent with expectations associated with a gradual market recovery after the 2008 financial crisis. The average market returns for the *Up* and *Down* market states are 0.063 and –0.068, respectively, which indicate the magnitude of the extreme market conditions. More importantly, the *Down* dummy variable largely coincides with prominent negative events in global and Japanese stock markets. For instance, we find that *Down* days include 16 September 2008, following the overnight news that Lehman Brothers had filed for bankruptcy, as well as the 2-10 October 2008 period, when the global market plummeted in fear of a pervasive global financial crisis in the wake of the large investment bank's fall. The *Down* dummy variable is also equal to one for the 11-16 March 2011 period, during which the 9.0 magnitude earthquake occurred on 11 March and news of the nuclear plant accident was released on 14 March.

In Panel B, we explore whether AT activities change with market conditions by regressing *ATrade* on the absolute value of market returns, the interaction terms between local market returns and extreme market condition dummy variables (*Up* and *Down*). We note that the coefficient on $|MRet|$ is 0.102 (t-statistic = 7.629) after including the interactions terms, $MRet\times Up$ and $MRet\times Down$, in column (2). This suggests that on average, AT increases with market movement. Analyzing the extreme market conditions, however, offers a different message: The coefficients on $MRet\times Up$ and $MRet\times Down$ are –0.122 (t-statistic = -6.950) and 0.193 (t-statistic =10.404), respectively, suggesting a decrease in AT during extreme market conditions. To mitigate concerns that the results are driven by market returns having large outliers, we replace |*MRet*| with its rank values (denoted as *RAMRet*) and use the rank values in the interaction terms. With this specification, we continue to find that algorithmic traders curtail their trading when the market is under stress (i.e., during extreme down market conditions) but not when the market is performing well.

Next, we turn to ask how algorithmic traders affect individual stock liquidity and liquidity commonality during extreme market condition. Specifically, we regress the four liquidity measures and four commonality measures on the *Arrowhead* dummy variable and its interactions with the *Up* and *Down* dummies and report the results in Table 7. We note that the coefficients on *Arrowhead*×*Down* are 4.084 (*t*-statistic = 18.163) and 3.244 (*t*-statistic = 22.052) for *QSpread* and *ESpread*, respectively. Given the coefficients on *Arrowhead* are -1.650 for *QSpread* and -0.579 for *ESpread*, the collective evidence suggests that AT widens spreads when the stock market is under stress. The results for *Depth* and *Depth5* paint a similar picture. The coefficients on *Arrowhead*×*Down* are -4.149 (*t*-statistic = -2.847) and -15.972 (*t*-statistic = -5.146) for *Depth* and *Depth5*, respectively. Combined with the coefficients on *Arrowhead* (5.281 for *Depth* and 22.850 for *Depth5*), our results suggest that while AT is associated with improvement in market depth, their contribution to market depth is less so in down market conditions.

We examine the effect of AT on liquidity commonality for extreme market states in Table 7 Panel B. Because our liquidity commonality measures are computed monthly, we adjust the definitions of the *Up* and *Down* state dummies as follows: *Up* (*Down)* equals one if the monthly market return, proxied by the TOPIX index return, is 1.5 standard deviations above (below) the unconditional mean of the 12 monthly market returns in the past year, and zero otherwise. Using liquidity measured by quoted and effective spread, we note positive and statistically significant coefficients on the interaction terms *Arrowhead*×*Up* and *Arrowhead*×*Down* across all liquidity commonality measures. The results suggest that AT increases commonality in liquidity in both up and down market states. This is particularly worrisome for the down market states where market liquidity is typically scarce and commonality in liquidity intensifies.

4.5 DIFFERENTIAL EFFECT OF ARROWNET 2.0 TRADING NETWORK

On 25 June, 2012, the TSE rolled out an upgrade of the trading network – Arrownet Version 2.0. Using a Broadband-Line service, and through the consolidation of multiple lines using the network virtualization technology, the network is believed to be more reliable in connecting the trading participants and users to the TSE trading and market information systems. With this upgrade, a major goal achieved is the reduction in the latency of stock trading on the exchange. Specifically, the upgrade reduced the round-trip order response time from two milliseconds to less than one millisecond on average, and it was further reduced to less than 0.1 millisecond if the traders locate their servers in the co-location areas proximate to the exchange's trading systems.[24] In further analysis, we examine whether this technological advancement has any distinguishable effect on AT from the Arrowhead trading system adopted in January 2010.

To carry out the analysis, we re-define the *Arrowhead* dummy variable as follows: it takes a value of one if an observation is between 4 January, 2010 and 24 June, 2012 and zero otherwise. We also introduce a separate dummy variable, *Arrownet2*, which is equal to one if the observation is on or after 25 June, 2012 and zero otherwise. We replicate the previous results by using both dummy variables as instruments in the first stage.

[24] http://www.tse.or.jp/english/system/networkservices/arrownet.html

We document strong evidence that the upgrade to the Arrownet 2.0 realizes the policy expectation and further facilitates AT. We show the effects of the Arrowhead and Arrownet 2.0 on quoted spread in column (1) of Table 8 Panel A. The coefficient on *Arrowhead* is 0.088 (*t*-statistic = 221.073) while the coefficient on *Arrownet2* is 0.098 (*t*-statistic = 151.197), 11% larger than that of *Arrowhead*. The *p*-value of the Wald test confirms the statistical significance for the coefficient differences between these two dummy variables. The first-stage regression results are consistent across other liquidity measures and remain unchanged when we examine commonality in liquidity in Panel B. These results stress the importance of technological developments to AT. However, it is important to note that our second-stage estimation results are not affected even after controlling for *Arrownet2* in the first stage.

5. CONCLUSION

In response to increasing attention devoted to AT, this study has attempted to clarify the impact of AT on stock liquidity in a limit-order driven market. In particular, we investigate how AT affects spread-based and market depth–based liquidity and commonality in liquidity during both normal and extreme market conditions.

Our research based on the instrumental variable (2SLS) approach yields several interesting empirical findings. First, after controlling for the endogenous relationship between AT and liquidity, using the introduction of the Arrowhead trading system in 2010 as the exogenous event, we show that the presence of AT significantly narrows quoted and effective spread and increases market depth. When decomposing effective spread, we show that the main source of the decrease in spread stems from the reduction in realized spread (revenues for liquidity providers). In addition, we find that AT increases monthly and intraday commonality in liquidity, regardless of how we measure stock liquidity. Reduction of monitoring costs appears to explain the AT effects on liquidity and liquidity commonality. Finally, we find that the liquidity improving effect of AT weakens, but the positive effect of AT on liquidity commonality strengthens following bearish markets.

Our research carries significant implications for both researchers and policymakers, in relation to the surge of computer-driven trading activities in recent decades. In particular, we show that AT beneficially reduces spread-based transaction costs, but increases individual stock liquidity co-movement with market-wide liquidity at normal times. In addition, regulators should be aware of the effect of AT on liquidity and commonality in liquidity in extreme market conditions. In particular, the positive effects of AT on market quality are either weakened or reversed during market declines. Therefore, it is necessary to contemplate regulations and measures to oversee AT during times of financial stress.

Appendix: Variable Definitions

Variable	Acronym	Description
AT Proxy		
Algorithmic trading proxy	*ATrade*	Dollar amount of trading volume (millions of Japanese yen) divided by the total number of quote updates in a continuous auction on a given trading day, multiplied by –1.
*Daily Liquidity Measures**		
Quoted spread	*QSpread*	Quote time duration weighted average of the difference between bid and ask prices divided by the midpoint of bid and ask prices on a given trading day multiplied by 10,000. This measure is adjusted for seasonality based on Equation (1).
Effective spread	*ESpread*	Trading volume weighted average of the difference between trading price and the midpoint of bid and ask prices (trading price minus the midpoint for buyer-initiated trades, or midpoint minus trading price for seller-initiated trades), scaled by the midpoint on a given trading day, multiplied by 10,000. This measure is adjusted for seasonality based on Equation (1).
Realized spread	*RSpread*	Trading volume weighted average of the difference between trading price and the midpoint of bid and ask prices five minutes later (trading price minus the midpoint five minutes later for buyer-initiated trades, or midpoint five minutes later minus trading price for seller-initiated trades), scaled by the midpoint on a given trading day, multiplied by 10,000. This measure is adjusted for seasonality based on Equation (1).
Adverse selection cost	*ASel*	Trading volume weighted average of the difference between the midpoint of bid and ask prices five minutes after a particular trade and the midpoint of prevailing bid and ask prices of the trade (the midpoint five minutes later minus prevailing midpoint price for buyer-initiated trades, or midpoint five minutes later minus prevailing midpoint for seller-initiated trades), scaled by the midpoint on a given trading day, multiplied by 10,000. This measure is adjusted for seasonality based on Equation (1).
Market depth at best quoted prices	*Depth*	Quote time duration weighted average of dollar amount of order flows at the best bid and ask prices on a given trading day (millions of Japanese yen). This measure is adjusted for seasonality based on Equation (1).
Aggregated market depth at five levels of quoted prices	*Depth5*	Quote time duration weighted average of dollar amount of order flows at five levels of bid and ask prices on a given trading day (millions of Japanese yen). This measure is adjusted for seasonality based on Equation (1).

*All liquidity measures are adjusted for weekly and monthly seasonality and the change of minimum tick size, by regressing the measures on the day of week, month, and price zone dummies.

Liquidity Commonality Measures		
Commonality in quoted spread	*CQSpread*	Logistically transformed R^2 divided by $(1 – R^2)$, where R^2 is estimated monthly for each stock from the regression of the daily change of adjusted quoted spread on the daily change of the cross-sectional average of the adjusted quoted spreads of all stocks in the market.
Commonality in effective spread	*CESpread*	Logistically transformed R^2 divided by $(1 – R^2)$, where R^2 is estimated monthly for each stock from the regression of the daily change of adjusted effective spread on the daily change of the cross-sectional average of the adjusted effective spreads of all stocks in the market.
Commonality in market depth at best quoted prices	*CDepth*	Logistically transformed R^2 divided by $(1 – R^2)$, where R^2 is estimated monthly for each stock from the regression of the daily change of adjusted market depth on the daily change of the cross-sectional average of the adjusted market depth of all stocks in the market.
Commonality in aggregated market depth at five levels of quoted prices	*CDepth5*	Logistically transformed R^2 divided by $(1 – R^2)$, where R^2 is estimated monthly for each stock from the regression of the daily change of adjusted aggregated market depth at five levels of quoted prices on the daily change of the cross-sectional average of the corresponding market depth measure of all stocks in the market.
Control Variables		
Stock trading turnover	*Turn*	Daily number of shares traded in continuous auction, scaled by the number of shares outstanding, divided by 1,000.
Stock return volatility	*Vol*	Difference between the highest and lowest stock price on a given trading day, divided by 1,000.
Inverse of stock price	*InvPrc*	The inverse of the daily closing stock price multiplied by 100.
Market capitalization	*Size*	Log of the market capitalization in thousands of Japanese Yen.
Market return	*MRet*	Daily market return, computed from the end-of-day value of TOPIX stock market index.
Realized market volatility	*MVol*	The difference between the highest and lowest value of TOPIX market index.
Expected market volatility	*VXJ*	Volatility Index Japan sourced from the Center for the Study of Finance and Insurance from Osaka University.
Financial analyst coverage	*Analyst*	The number of financial analyst forecasts for the stock in the three months prior to financial year end month.
Media coverage	*News*	The number of news messages for the stock made during the period from the previous day closing time to the closing on a given trading day.

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Table 1. Summary statistics

This table reports the mean, median, and standard deviation (SD) of the algorithmic trading variable (*ATrade*), six different stock liquidity measures by year and for the full sample in Panel A and those of control variables by year and for the full sample in Panel B. The six daily stock liquidity measures are quoted spread (*QSpread*), effective spread (*ESpread*), realized spread (*RSpread*), adverse selection cost (*ASel*), market depth at best bid and ask prices (*Depth*), and market depth at five levels of stock prices (*Depth5*). The spread measures are expressed in basis points. All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. The control variables are daily measures of stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price multiplied by 100 (*InvPrc*), the log of market capitalization (*Size*), daily stock market return (*MRet*) expressed in percentage, realized market volatility (*MVol*) and expected market volatility (*VXJ*). *NStocks* refers to the number of stocks in each year and the full sample. All the variables are defined in the Appendix. We winsorize all variables at the top and bottom 0.05% distribution of the pooled sample.

Table 1 – Continued

Panel A: *ATrade* and liquidity variables

Year	*NStocks*		*ATrade*	*QSpread*	*ESpread*	*Depth*	*Depth5*	*RSpread*	*ASel*
2007	1185	Mean	-0.27	24.63	19.69	24.19	105.35	2.36	17.35
		Med	-0.11	18.73	14.28	4.13	20.53	0.43	13.11
		SD	0.49	22.19	18.38	245.32	660.47	15.46	16.20
2008	1177	Mean	-0.17	40.07	30.66	12.21	62.44	2.98	27.74
		Med	-0.07	28.26	21.61	2.47	12.37	-0.03	20.21
		SD	0.33	39.13	29.61	111.22	393.11	24.81	26.67
2009	1159	Mean	-0.13	37.66	30.81	13.46	66.78	4.59	26.27
		Med	-0.06	27.26	21.61	2.43	12.17	1.15	19.02
		SD	0.25	35.13	29.41	70.27	248.11	24.31	25.80
2010	1139	Mean	-0.07	31.88	27.61	23.43	107.76	5.77	21.83
		Med	-0.04	22.67	19.29	3.06	15.56	1.90	15.55
		SD	0.09	29.92	26.91	261.40	584.06	22.06	22.08
2011	1132	Mean	-0.06	31.61	27.87	18.04	94.65	5.18	22.66
		Med	-0.04	23.21	20.24	3.00	16.36	1.57	16.50
		SD	0.08	28.84	25.84	61.20	286.96	21.35	22.35
2012	1144	Mean	-0.06	31.22	27.83	18.51	98.87	5.32	22.37
		Med	-0.04	23.58	20.79	2.99	18.03	1.82	16.77
		SD	0.06	27.16	24.73	95.42	325.67	20.55	21.47
All	1302	Mean	-0.13	32.83	27.37	18.31	89.22	4.34	23.02
		Med	-0.06	23.66	19.47	3.00	15.71	1.10	16.70
		SD	0.28	31.30	26.33	163.38	446.29	21.66	22.92

Panel B: Stock- and market-level control variables

Year	*NStocks*		*Turn*	*Vol*	*InvPrc*	*Size*	*MRet(%)*	*MVol*	*VXJ*
2007	1,185	Mean	4.55	0.18	0.24	17.80	-0.05	20.68	21.80
		Med	2.12	0.01	0.16	17.55	0.02	18.44	19.73
		SD	15.44	1.86	0.33	1.40	1.22	9.97	5.77
2008	1,177	Mean	4.12	0.21	0.37	17.41	-0.22	26.37	40.89
		Med	1.80	0.01	0.23	17.18	-0.08	22.99	32.75
		SD	13.03	1.96	0.48	1.43	2.68	13.50	18.67
2009	1,159	Mean	3.57	0.12	0.43	17.24	0.02	13.09	34.68
		Med	1.30	0.01	0.28	17.05	0.03	11.91	30.33
		SD	15.10	1.11	0.52	1.41	1.54	5.64	10.82
2010	1,139	Mean	3.42	0.10	0.42	17.26	0.00	9.13	24.49
		Med	1.20	0.01	0.27	17.06	0.02	8.35	23.94
		SD	15.63	0.82	0.52	1.41	1.10	3.83	5.14
2011	1,132	Mean	3.76	0.15	0.41	17.26	-0.09	9.24	26.37
		Med	1.21	0.01	0.28	17.06	-0.01	7.65	24.43
		SD	15.56	1.37	0.46	1.38	1.44	8.25	8.30
2012	1,144	Mean	3.72	0.11	0.41	17.24	0.07	7.65	20.15
		Med	1.22	0.01	0.28	17.04	0.03	7.13	19.76
		SD	16.55	0.87	0.47	1.36	1.00	3.15	2.63
All	1,302	Mean	3.86	0.15	0.38	17.37	-0.05	14.35	28.04
		Med	1.45	0.01	0.25	17.17	0.01	10.98	24.99
		SD	15.25	1.42	0.47	1.42	1.60	10.72	12.41

Table 2. Effects of AT on stock liquidity

This table presents the results from the 2SLS regressions of individual stock liquidity measures on stock-level algorithmic trading and control variables. The baseline 2SLS regression models are:

$$\begin{aligned} Adj\_liq_{i,t} = {} & s_i + \alpha_1 ATrade_{i,t} + \alpha_2 Turn_{i,t} + \alpha_3 Vol_{i,t} + \alpha_4 InvPrc_{i,t} + \alpha_5 Size_{i,t} + \alpha_6 MRet_t + \\ & \alpha_7 MVol_t + \alpha_8 VXJ_t + \varepsilon_{i,t} \end{aligned} \quad \text{(Second-stage regression model)}$$

$$\begin{aligned} ATrade_{i,t} = {} & v_i + \beta_1 Arrowhead_t + \beta_2 Turn_{i,t} + \beta_3 Vol_{i,t} + \beta_4 InvPrc_{i,t} + \beta_5 Size_{i,t} + \\ & \beta_6 MRet_t + \beta_7 MVol_t + \beta_8 VXJ_t + \theta_{i,t} \end{aligned} \quad \text{(First-stage regression model)}$$

Arrowhead is the instrumental variable in the first stage regression, which is a dummy variable taking the value of one if the observation is on or after 4 January, 2010 and zero otherwise. *Adj_liq* is measured by quoted spread (*QSpread*), effective spread (*ESpread*), realized spread (*RSpread*), adverse selection cost (*ASel*), market depth at best bid and ask prices (*Depth*), and market depth at five levels of stock prices (*Depth5*). All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. *ATrade* refers to the algorithmic trading measure. The list of daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price multiplied by 100 (*InvPrc*), log of market capitalization (*Size*), daily stock market return (*MRet*), realized market volatility (*MVol*) and expected market volatility (*VXJ*). Firm fixed effects are also included. Panel A reports the effects of AT on a variety of stock liquidity measures including *QSpread*, *ESpread*, *Depth*, and *Depth5*, while Panel B presents the effects of *ATrade* on each component of *ESpread* (i.e., realized spread (*RSpread*) and adverse selection cost (*ASel*)). All the variables are defined in the Appendix. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-day observations. The last row reports the *p*-values of the Hausman test. The sample period is from January 2007 to December 2012.

Table 2 – Continued

Panel A: Effects of *ATrade* on stock liquidity measures								
	ATrade	*QSpread*	*ATrade*	*ESpread*	*ATrade*	*Depth*	*ATrade*	*Depth5*
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade		-14.298***		-3.089***		54.319***		238.896***
		(-35.750)		(-10.792)		(17.650)		(30.583)
Arrowhead	0.090***		0.090***		0.090***		0.090***	
	(227.310)		(227.308)		(227.310)		(227.310)	
Turn	-0.002***	-0.078***	-0.002***	-0.029***	-0.002***	0.227***	-0.002***	1.351***
	(-238.149)	(-57.307)	(-238.149)	(-29.870)	(-238.149)	(21.801)	(-238.149)	(51.110)
Vol	-0.013***	0.156***	-0.013***	0.451***	-0.013***	7.238***	-0.013***	31.161***
	(-77.257)	(9.828)	(-77.257)	(39.689)	(-77.257)	(59.273)	(-77.257)	(100.533)
InvPrc	-0.073***	39.075***	-0.073***	37.426***	-0.073***	20.696***	-0.073***	63.765***
	(-87.480)	(480.803)	(-87.480)	(643.562)	(-87.480)	(33.096)	(-87.480)	(40.173)
Size	-0.183***	-6.188***	-0.183***	-5.331***	-0.183***	21.285***	-0.183***	79.499***
	(-276.512)	(-56.811)	(-276.512)	(-68.387)	(-276.512)	(25.395)	(-276.512)	(37.368)
MRet	0.012	-4.881***	0.012	-7.782***	0.012	-6.322	0.012	24.717
	(1.266)	(-5.611)	(1.267)	(-12.502)	(1.268)	(-0.944)	(1.268)	(1.455)
MVol	-0.001***	0.138***	-0.001***	0.082***	-0.001***	-0.009	-0.001***	-0.056
	(-43.903)	(74.281)	(-43.901)	(61.492)	(-43.903)	(-0.623)	(-43.903)	(-1.539)
VXJ	0.001***	0.283***	0.001***	0.130***	0.001***	-0.267***	0.001***	-1.289***
	(59.261)	(199.677)	(59.262)	(128.029)	(59.262)	(-24.449)	(59.262)	(-46.571)
N	1,572,347	1,572,347	1,572,350	1,572,350	1,572,355	1,572,355	1,572,355	1,572,355
p-value of Hausman Test		0.000		0.000		0.000		0.000

Table 2 – Continued

	Panel B: Effects of *ATrade* on *ESpread* components			
	ATrade	*RSpread*	*ATrade*	*ASel*
	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)
ATrade		-2.293***		-1.501***
		(-5.403)		(-3.518)
Arrowhead	0.090***		0.090***	
	(227.299)		(227.301)	
Turn	-0.002***	-0.070***	-0.002***	0.038***
	(-238.137)	(-48.497)	(-238.140)	(26.343)
Vol	-0.013***	-0.178***	-0.013***	0.630***
	(-77.255)	(-10.574)	(-77.253)	(37.188)
InvPrc	-0.073***	22.805***	-0.073***	12.533***
	(-87.481)	(264.423)	(-87.492)	(144.406)
Size	-0.183***	1.313***	-0.183***	-7.522***
	(-276.518)	(11.362)	(-276.508)	(-64.711)
MRet	0.012	-4.153***	0.012	-3.138***
	(1.272)	(-4.499)	(1.272)	(-3.380)
MVol	-0.001***	-0.078***	-0.001***	0.159***
	(-43.938)	(-39.362)	(-43.935)	(79.867)
VXJ	0.001***	-0.041***	0.001***	0.175***
	(59.258)	(-27.305)	(59.254)	(115.380)
N	1,572,238	1,572,238	1,572,237	1,572,237
p-value of Hausman test		0.002		0.000

Table 3. Effects of monitoring costs on the relation between AT and stock liquidity

This table reports the second stage regression results from regressing liquidity measures on *ATrade* and its interaction with three alternative measures of monitoring costs controlling for stock characteristics. The second stage regression model of the 2SLS baseline regression models is as below:

$$Adj\_liq_{i,t} = s_i + \alpha_1 ATrade_{i,t} + \alpha_2 ATrade_{i,t} \times MCost_{i,t} + \alpha_3 MCost_{i,t} + \alpha_4 Turn_{i,t} + \alpha_5 Vol_{i,t} + \alpha_6 InvPrc_{i,t} + \alpha_7 Size_{i,t} + \alpha_8 MRet_t + \alpha_9 MVol_t + \alpha_{10} VXJ_t + \varepsilon_{i,t},$$

where monitoring cost (*MCost*) is represented by firm size (*Size*), analyst coverage (*Analyst*) and media coverage (*News*) in Panels A, B, and C, respectively. In the first stage regression, we regress *ATrade* and *ATrade*×*MCost,* respectively, on *Arrowhead* and *Arrowhead*×*MCost* together with other controls in the first stage model where *Arrowhead* is a dummy variable that takes a value of one if the particular trading day is on or after January 4, 2010 and zero otherwise. The predicted values of *ATrade* and *ATrade*×*MCost* are used in the second stage model shown above. *Adj_liq* represents quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), or market depth at five levels of stock prices (*Depth5*). All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. *ATrade* refers to the algorithmic trading measure. The list of daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), log of market capitalization (*Size*), daily stock market return (*MRet*), realized market volatility (*MVol*) and expected market volatility (*VXJ*). Firm fixed effects are also included. All variables are defined in the Appendix. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-day observations. The sample period is from January 2007 to December 2012.

Panel A: *Size* as a proxy for monitoring costs				
	QSpread	*ESpread*	*Depth*	*Depth5*
	(1)	(2)	(3)	(4)
ATrade	-419.121***	-125.062***	417.786***	1,376.000***
	(-60.179)	(-26.382)	(8.417)	(11.005)
ATrade×Size	20.782***	6.262***	-18.659***	-58.374***
	(61.667)	(27.297)	(-7.769)	(-9.648)
Turn	-0.164***	-0.055***	0.305***	1.593***
	(-63.110)	(-31.082)	(16.456)	(34.182)
Vol	0.606***	0.586***	6.834***	29.897***
	(37.023)	(52.626)	(58.584)	(101.737)
InvPrc	41.775***	38.240***	18.272***	56.182***
	(504.860)	(678.959)	(30.984)	(37.819)
Size	-2.876***	-4.333***	18.312***	70.196***
	(-35.523)	(-78.616)	(31.734)	(48.290)
MRet	-4.418***	-7.643***	-6.737	23.417
	(-4.747)	(-12.064)	(-1.016)	(1.401)
MVol	0.156***	0.087***	-0.025*	-0.107***
	(82.951)	(68.084)	(-1.874)	(-3.156)
VXJ	0.278***	0.128***	-0.262***	-1.276***
	(183.103)	(124.170)	(-24.225)	(-46.771)
N	1,572,347	1,572,350	1,572,355	1,572,355

Table 3 - Continued

Panel B: *Analyst* as a proxy for monitoring costs				
	QSpread	*ESpread*	*Depth*	*Depth5*
	(1)	(2)	(3)	(4)
ATrade	-25.731***	-5.497***	104.209***	377.202***
	(-41.354)	(-12.471)	(22.151)	(31.757)
ATrade×Analyst	2.182***	0.468***	-6.554***	-20.472***
	(51.010)	(15.456)	(-20.267)	(-25.076)
Analyst	0.640***	0.110***	-11.411***	-24.940***
	(25.799)	(6.238)	(-60.803)	(-52.634)
Turn	-0.095***	-0.032***	0.309***	1.573***
	(-58.503)	(-28.373)	(25.323)	(50.989)
Vol	0.378***	0.499***	6.629***	29.193***
	(24.579)	(45.771)	(57.026)	(99.467)
InvPrc	39.395***	37.503***	22.538***	66.353***
	(486.776)	(654.129)	(36.832)	(42.949)
Size	-6.464***	-5.367***	29.731***	97.283***
	(-54.570)	(-63.965)	(33.198)	(43.025)
MRet	-4.827***	-7.773***	-7.298	22.585
	(-5.486)	(-12.470)	(-1.097)	(1.345)
MVol	0.139***	0.082***	-0.019	-0.079**
	(74.320)	(61.851)	(-1.329)	(-2.210)
VXJ	0.285***	0.130***	-0.253***	-1.268***
	(198.434)	(128.172)	(-23.308)	(-46.274)
N	1,572,347	1,572,350	1,572,355	1,572,355

Table 3 - Continued

Panel C: *News* as a proxy for monitoring costs				
	QSpread	*ESpread*	*Depth*	*Depth5*
	(1)	(2)	(3)	(4)
ATrade	-15.451***	-3.331***	57.102***	249.045***
	(-36.180)	(-10.917)	(17.419)	(29.957)
ATrade×News	0.450***	0.111***	-0.717***	-2.163***
	(35.608)	(12.269)	(-7.395)	(-8.801)
News	0.344***	0.123***	0.318***	2.561***
	(28.265)	(14.083)	(3.396)	(10.800)
Turn	-0.078***	-0.029***	0.221***	1.323***
	(-57.290)	(-30.140)	(21.220)	(49.989)
Vol	0.178***	0.455***	7.178***	30.934***
	(11.308)	(40.449)	(59.389)	(100.920)
InvPrc	39.093***	37.431***	20.682***	63.750***
	(481.065)	(644.664)	(33.157)	(40.300)
Size	-6.222***	-5.334***	21.449***	80.196***
	(-56.669)	(-67.995)	(25.451)	(37.524)
MRet	-4.792***	-7.755***	-6.341	24.885
	(-5.500)	(-12.458)	(-0.948)	(1.467)
MVol	0.138***	0.082***	-0.010	-0.061*
	(73.752)	(61.210)	(-0.677)	(-1.680)
VXJ	0.283***	0.130***	-0.266***	-1.286***
	(198.951)	(127.875)	(-24.374)	(-46.527)
N	1,572,347	1,572,350	1,572,355	1,572,355

Table 4. Effects of algorithmic trading on commonality in stock liquidity

Panel A of this table reports the results from the 2SLS regressions of monthly estimates of commonality in stock liquidity on the algorithmic trading variable and other control variables after controlling for the endogeneity of AT. The 2SLS baseline regression models are as below:

$$CLiq_{i,t} = s_i + \alpha_1 ATrade_{i,t} + \alpha_2 Liq_{i,t} + \alpha_3 Size_{i,t} + \alpha_4 MRet_t + \alpha_5 MVol_t + \alpha_6 VXJ_t + \varepsilon_{i,t} \qquad \text{(second-stage regression)}$$

$$ATrade_{i,t} = v_i + \beta_1 Arrowhead_t + \beta_2 Liq_{i,t} + \beta_3 Size_{i,t} + \beta_4 MRet_t + \beta_5 MVol_t + \beta_6 VXJ_t + \theta_{i,t} \qquad \text{(first-stage regression)}$$

In the first stage regression, the algorithmic trading variable (*ATrade*) is regressed on the *Arrowhead* dummy variable and other control variables. The *Arrowhead* dummy variable is equal to one if the particular trading month is on or after January 2010, and zero otherwise. In the second stage, we regress various monthly commonality in stock liquidity measures on the predicted value of *ATrade* estimated from the first stage, together with other controls. *CLiq* represents the monthly estimates of commonality in four stock liquidity measures: quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), and market depth at five levels of stock prices (*Depth5*). All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. *Size* is the monthly average of daily log of market capitalization. *MRet* is the monthly stock market return. *MVol* is the realized market volatility and *VXJ* is the expected market volatility. Firm fixed effects are also included. Panel B reports the 2SLS regression results of intraday commonality in liquidity measures on *ATrade* and other controls. The intraday commonality measures are logistically transformed R-squareds estimated daily from regressing the change in the 1-minute snapshot of each stock liquidity measure on the change in the corresponding market liquidity of the stock market portfolio (excluding the own stock). The first-stage estimation results are suppressed in Panels B and C. Firm fixed effects are also included. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-month observations. The sample period is from January 2007 to December 2012.

Table 4 – Continued

Panel A: 2SLS estimation of effects of *ATrade* on commonality in liquidity

	ATrade	*CQSpread*	*ATrade*	*CESpread*	*ATrade*	*CDepth*	*ATrade*	*CDepth5*
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade		3.862***		4.302***		2.997***		4.116***
		(12.981)		(13.866)		(10.134)		(14.030)
Arrowhead	0.085***		0.085***		0.086***		0.087***	
	(44.506)		(44.422)		(45.135)		(45.729)	
Size	-169.018***	848.006***	-189.572***	954.539***	-162.669***	572.205***	-162.028***	737.466***
	(-62.816)	(12.473)	(-66.489)	(12.336)	(-67.078)	(8.937)	(-66.985)	(11.598)
MRet	-0.748***	-17.253***	-0.834***	-39.615***	-0.688***	0.066	-0.642**	7.335**
	(-2.801)	(-4.786)	(-3.131)	(-10.551)	(-2.585)	(0.018)	(-2.419)	(2.027)
MVol	-1.829***	49.909***	-1.752***	51.606***	-1.876***	16.807***	-1.861***	28.637***
	(-12.780)	(22.346)	(-12.278)	(22.392)	(-13.175)	(7.475)	(-13.101)	(12.748)
VXJ	1.242***	-2.724**	1.295***	-4.707***	1.164***	7.514***	1.122***	1.291
	(15.595)	(-2.521)	(16.389)	(-4.202)	(14.791)	(7.025)	(14.290)	(1.207)
QSpread	-0.276***	-5.869***						
	(-5.005)	(-7.942)						
ESpread			-1.265***	2.028*				
			(-17.521)	(1.882)				
Depth					-0.108***	0.767***		
					(-20.417)	(9.944)		
Depth5							-0.059***	0.346***
							(-28.369)	(10.733)
N	74,092	74,092	74,076	74,076	74,096	74,096	74,096	74,096

Table 4 – Continued

	Panel B: Effects of *ATrade* on intraday liquidity commonality			
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	1.469***	0.865***	2.899***	8.845***
	(26.947)	(16.299)	(52.287)	(138.040)
Size	0.465***	-0.509***	0.249***	1.352***
	(34.583)	(-30.200)	(18.581)	(87.298)
MRet	0.807***	-0.361**	0.654***	-0.183
	(7.008)	(-2.540)	(5.560)	(-1.331)
MVol	1.080***	-8.417***	-5.907***	4.154***
	(4.348)	(-28.070)	(-23.302)	(14.017)
VXJ	0.551***	-7.670***	-1.437***	-12.068***
	(2.900)	(-32.410)	(-7.493)	(-53.854)
QSpread	1.190***			
	(11.859)			
ESpread		9.036***		
		(38.354)		
Depth			0.692***	
			(45.375)	
Depth5				0.573***
				(75.257)
N	1,559,235	1,216,585	1,572,311	1,570,965

Table 5. Effects of monitoring costs on the relation between AT and commonality in liquidity

This table reports the second stage regression results of commonality in stock liquidity on algorithmic trading variable, *ATrade,* and its interaction with three alternative measures of monitoring costs. The second stage baseline regression model is:

$$CLiq_{i,t} = s_i + \alpha_1 ATrade_{i,t} + \alpha_2 ATrade_{i,t} \times MCost_{i,t} + \alpha_3 MCost_{i,t} + \alpha_4 Adj\_liq_{i,t} + \alpha_5 Size_{i,t} + \alpha_6 M\,\mathrm{Re}t_t + \alpha_7 MVol_t + \alpha_8 VXJ_t + \varepsilon_{i,t},$$

where monitoring cost (*MCost*) is represented by firm size (*Size*), analyst coverage (*Analyst*) and media coverage (*News*) in Panels A, B, and C, respectively. In the first stage regression, we regress *ATrade* and *ATrade*×*MCost,* respectively on *Arrowhead* and *Arrowhead*×*MCost* together with other controls in the first stage model where *Arrowhead* is a dummy variable that takes a value of 1 if the particular trading month is on or after January 2010 and 0 otherwise. Then, the predicted values of *ATrade and ATrade*×*MCost* are used in the second stage. *CLiq* represents the monthly estimates of commonality in four stock liquidity measures: quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), and market depth at five levels of stock prices (*Depth5*). All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. *Adj_liq* is the monthly average of the four daily stock liquidity measures. *Size* is the monthly average of daily log of market capitalization. *MRet* is the monthly average of daily stock market return. *MVol* is the monthly average of daily realized market volatility. *VXJ* is the monthly average of the expected market volatility. Firm fixed effects are also included. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-month observations. The sample period is from January 2007 to December 2012.

Panel A: *Size* as a proxy for monitoring costs				
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	62.347***	68.552***	51.477***	66.955***
	(13.510)	(13.984)	(10.600)	(13.628)
ATrade×*Size*	-3,007.904***	-3,302.419***	-2,485.179***	-3,215.146***
	(-13.514)	(-13.960)	(-10.609)	(-13.576)
Size	429.272***	403.000***	382.435***	518.267***
	(9.194)	(7.966)	(7.485)	(9.980)
MRet	-15.557***	-37.633***	2.822	11.499***
	(-4.226)	(-9.791)	(0.751)	(3.044)
MVol	44.342***	45.411***	11.505***	22.173***
	(22.120)	(22.016)	(5.804)	(11.124)
VXJ	1.754*	-0.274	9.626***	3.421***
	(1.648)	(-0.249)	(9.060)	(3.210)
QSpread	-13.145***			
	(-15.367)			
ESpread		-10.734***		
		(-9.442)		
Depth			-0.286***	
			(-2.857)	
Depth5				-0.334***
				(-7.495)
N	74,092	74,076	74,096	74,096

Table 5 – Continued

Panel B: *Analyst* as a proxy for monitoring costs				
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	5.950***	6.669***	4.626***	6.297***
	(12.989)	(13.914)	(9.997)	(13.490)
ATrade×Analyst	-0.387***	-0.437***	-0.290***	-0.377***
	(-12.649)	(-13.648)	(-9.365)	(-12.082)
Analyst	-0.147***	-0.168***	-0.123***	-0.165***
	(-8.942)	(-9.763)	(-7.376)	(-9.829)
Size	925.270***	1,024.178***	671.701***	882.241***
	(12.452)	(12.320)	(9.157)	(11.930)
MRet	-16.753***	-39.021***	0.749	8.497**
	(-4.612)	(-10.295)	(0.205)	(2.315)
MVol	49.498***	51.119***	16.382***	28.250***
	(22.301)	(22.296)	(7.354)	(12.607)
VXJ	-2.456**	-4.497***	7.379***	0.856
	(-2.273)	(-4.006)	(6.850)	(0.789)
QSpread	-7.350***			
	(-9.995)			
ESpread		-0.643		
		(-0.623)		
Depth			0.316***	
			(4.254)	
Depth5				0.044
				(1.464)
N	74,092	74,076	74,096	74,096

Panel C: *News* as a proxy for monitoring costs				
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	4.669***	5.218***	3.616***	4.964***
	(13.042)	(13.969)	(10.039)	(13.816)
ATrade×News	-0.395***	-0.425***	-0.284***	-0.387***
	(-12.840)	(-13.250)	(-9.180)	(-12.502)
News	842.497***	944.457***	587.397***	762.775***
	(12.479)	(12.380)	(8.987)	(11.699)
Size	-0.213***	-0.193***	-0.143***	-0.216***
	(-11.345)	(-9.821)	(-7.523)	(-11.391)
MRet	-18.005***	-40.230***	-0.259	6.947*
	(-5.040)	(-10.820)	(-0.072)	(1.931)
MVol	49.898***	51.523***	16.737***	28.674***
	(22.482)	(22.518)	(7.477)	(12.823)
VXJ	-2.176**	-4.176***	7.705***	1.391
	(-2.040)	(-3.780)	(7.243)	(1.309)
QSpread	-6.719***			
	(-9.216)			
ESpread		0.688		
		(0.662)		
Depth			0.517***	
			(7.242)	
Depth5				0.173***
				(6.129)
N	74,092	74,076	74,096	74,096

Table 6. AT activities during extreme market conditions

Panel A of this table reports the distribution of extremely positive and negative weekly market returns by year and for the full sample, where a weekly market return is an extremely positive (negative) market return if the previous weekly market return is the 1.5 standard deviation above (below) the unconditional mean of 52 weekly market return in the past 250 trading days. *NDays* denotes the number of trading days in the given sample period. *Up* (*Down*) reports the number of extreme positive (negative) weekly market returns; Mean (*Up*) (Mean (*Down*)) reports the mean value of the *Up* (*Down*) dummy variable. Panel B presents the panel regression of *ATrade* on extreme market conditions as well as other control variables. The baseline OLS regression model is:

$$\begin{aligned} ATrade_{i,t} &= \mathrm{Re}\,turn_{t-1} + Up_{t-1} + Down_{t-1} + \mathrm{Re}\,turn_{t-1} \times Up_{t-1} \\ &+ \mathrm{Re}\,turn_{t-1} \times Down_{t-1} + Arrowhead_t + Turn_t + Vol_{i,t} \\ &+ Inv\,\mathrm{Pr}\,c_{i,t} + Size_{i,t} + MVol_{i,t} + VXJ_t + \varepsilon_{i,t} \end{aligned}$$

where *ATrade* is the algorithmic trading variable multiplied by 1,000, and *Return* alternatively represents the absolute value of the previous week market index return ($|MRet|$) or its rank values (*RAMRet*). The list of daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), the log of market capitalization (*Size*), daily realized market volatility (*MVol*) and expected market volatility (*VXJ*). All variables are defined in the Appendix. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-day observations. The sample period is from January 2007 to December 2012.

Panel A: Extreme Market Conditions					
Year	*NDays*	*Up*	Mean(*Up*)	*Down*	Mean(*Down*)
2007	245	14	0.0479	28	-0.0548
2008	245	22	0.0824	32	-0.0902
2009	243	14	0.0796	1	-0.1039
2010	245	8	0.0461	14	-0.0529
2011	245	8	0.0579	14	-0.0810
2012	248	19	0.0485	14	-0.0426
2007-2012	1,471	85	0.0630	103	-0.0680

Table 6 – Continued

Panel B: AT in Extreme Market Conditions				
	(1)	(2)	(3)	(4)
|*MRet*|	0.026***	0.102***		
	(2.743)	(7.629)		
RAMRet			0.004***	0.004***
			(7.848)	(8.033)
Up	-0.001	0.003***	-0.002***	-0.014*
	(-1.082)	(2.958)	(-3.006)	(-1.821)
Down	-0.004***	0.004***	-0.006***	0.028***
	(-4.061)	(3.349)	(-5.596)	(3.964)
MRet×Up		-0.122***		
		(-6.950)		
MRet×Down		0.193***		
		(10.404)		
RAMRet×Up				0.009
				(1.582)
RAMRet×Down				-0.025***
				(-4.956)
Arrowhead	0.090***	0.091***	0.090***	0.090***
	(15.351)	(15.414)	(15.362)	(15.387)
Turn	-0.002***	-0.002***	-0.002***	-0.002***
	(-7.337)	(-7.337)	(-7.337)	(-7.337)
Vol	-0.013**	-0.013**	-0.013**	-0.013**
	(-2.027)	(-2.028)	(-2.028)	(-2.028)
InvPrc	-0.073***	-0.072***	-0.073***	-0.073***
	(-6.196)	(-6.194)	(-6.195)	(-6.195)
Size	-0.183***	-0.183***	-0.183***	-0.183***
	(-11.017)	(-11.014)	(-11.013)	(-11.012)
MVol	-0.001***	-0.001***	-0.001***	-0.001***
	(-8.063)	(-7.751)	(-8.055)	(-7.931)
VXJ	0.001***	0.001***	0.001***	0.001***
	(7.941)	(7.966)	(7.794)	(7.924)
N	1,572,318	1,572,318	1,572,318	1,572,318
Adj. R^2	0.550	0.550	0.550	0.550

Table 7. Effects of AT on liquidity and commonality in liquidity following market declines

This table reports the OLS regression results of stock liquidity (Panel A)/commonality in stock liquidity (Panel B) on the adoption of Arrowhead dummy variable, *Arrowhead,* and its interactions with market condition dummy variables (*Up* and *Down*). *Arrowhead* is a dummy variable that takes a value of 1 if the particular trading month is on or after January 2010 and 0 otherwise. In Panel A, *Up* (*Down*) takes a value of one if the previous weekly market return is the 1.5 standard deviation above (below) the unconditional mean of 52 weekly market return in the past 250 trading days, and zero otherwise. The four daily liquidity measures are quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), or market depth at five levels of stock prices (*Depth5*). The unreported daily control variables used in Panel A are stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and the log of market capitalization (*Size*), daily stock market return (*MRet*), realized market volatility (*MVol*) and expected market volatility (*VXJ*). In Panel B, *Up* (*Down*) takes a value of one if the previous monthly market return is the 1.5 standard deviation above (below) the unconditional mean of 12 monthly market returns in the past year, and zero otherwise. The four commonality in liquidity measures are monthly estimates of commonality in four stock liquidity measures: quoted spread (*CQSpread*), effective spread (*CESpread*), market depth at best bid and ask prices (*CDepth*), and market depth at five levels of stock prices (*CDepth5*). *Adj_liq* is the monthly average of the respective daily stock liquidity measure. *Size* is the monthly average of daily log of market capitalization. *MRet* is the monthly average of daily stock market return. *MVol* is the monthly average of daily realized market volatility. *VXJ* is the monthly average of the expected market volatility. Firm fixed effects are also included in all estimations. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-month observations. The sample period is from January 2007 to December 2012.

Table 7 – Continued

	Panel A: Liquidity effects in extreme markets				Panel B: Commonality effects in extreme markets			
	QSpread	*ESpread*	*Depth*	*Depth5*	*CQSpread*	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arrowhead	-1.650***	-0.579***	5.281	22.850**	0.342***	0.385***	0.280***	0.377***
	(-7.732)	(-4.520)	(1.217)	(2.049)	(13.834)	(15.447)	(10.928)	(14.831)
Arrowhead×Up	-0.005	0.223**	-0.868	0.384	0.228**	0.544***	0.288***	0.409***
	(-0.042)	(2.345)	(-1.059)	(0.152)	(2.376)	(5.323)	(2.791)	(4.339)
Arrowhead×Down	4.084***	3.244***	-4.149***	-15.972***	0.476***	0.657***	0.196***	0.215***
	(18.163)	(22.052)	(-2.847)	(-5.146)	(8.895)	(12.325)	(3.525)	(3.993)
Up	-1.004***	-0.826***	0.256	0.175	-0.293***	-0.440***	-0.255***	-0.177**
	(-8.847)	(-11.065)	(0.334)	(0.074)	(-4.371)	(-5.926)	(-3.510)	(-2.489)
Down	-0.303**	-0.250***	0.201	0.588	-0.292***	-0.474***	-0.192***	-0.189***
	(-2.242)	(-2.770)	(0.240)	(0.249)	(-8.822)	(-13.295)	(-5.310)	(-5.633)
N	1,572,310	1,572,313	1,572,318	1,572,318	72,821	72,805	72,825	72,825
Adj.R^2	0.709	0.783	0.356	0.459	0.052	0.042	0.028	0.054

Table 8. Differential effects of *Arrowhead* and *Arrownet 2.0* on AT

This table presents the 2SLS regression results of stock liquidity on AT activities in Panel A and of commonality in stock liquidity on AT activities in Panel B controlling for the differential effects of the implementation of Arrowhead and Arrownet 2.0 new trading systems in the first stage. *Arrowhead* takes a value of one if the observation is between January 4, 2010 and June 24, 2012, and zero otherwise; *Arrownet2* takes a value of one if the observation is on or after June 25, 2012, and zero otherwise. The four liquidity measures in Panel A are quoted spread (*QSpread*), effective spread (*ESpread*), market depth at best bid and ask prices (*Depth*), or market depth at five levels of stock prices (*Depth5*). The daily control variables used in Panel A are stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), the log of market capitalization (*Size*), daily stock market return (*MRet*), realized market volatility (*MVol*) and expected market volatility (*VXJ*). In Panel B, the four commonality in liquidity measures are monthly estimates of commonality in four stock liquidity measures: quoted spread (C*QSpread*), effective spread (C*ESpread*), market depth at best bid and ask prices (C*Depth*), and market depth at five levels of stock prices (C*Depth5*). *Adj_liq* is the monthly average of the respective daily stock liquidity measure. *Size* is the monthly average of daily log of market capitalization. *MRet* is the monthly average of daily stock market return. *MVol* is the monthly average of daily realized market volatility. *VXJ* is the monthly average of daily expected market volatility. Firm fixed effects are also included in all estimations. The last row presents the p-value of Wald test for the differences of the *Arrowhead* and *Arrownet2* coefficients. The *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *N* denotes the number of stock-month observations. The sample period is from January 2007 to December 2012.

Table 8 – Continued

	Panel A: *Arrownet* 2.0 and stock liquidity							
	ATrade	*QSpread*	*ATrade*	*ESpread*	*ATrade*	*Depth*	*ATrade*	*Depth5*
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade		-13.960***		-2.983***		53.688***		237.864***
		(-35.010)		(-10.449)		(17.490)		(30.528)
Arrowhead	0.088***		0.088***		0.088***		0.088***	
	(221.073)		(221.072)		(221.074)		(221.074)	
Arrownet2	0.098***		0.098***		0.098***		0.098***	
	(151.197)		(151.196)		(151.194)		(151.194)	
Turn	-0.002***	-0.077***	-0.002***	-0.029***	-0.002***	0.226***	-0.002***	1.349***
	(-238.146)	(-56.811)	(-238.147)	(-29.646)	(-238.147)	(21.684)	(-238.147)	(51.085)
Vol	-0.013***	0.160***	-0.013***	0.452***	-0.013***	7.230***	-0.013***	31.148***
	(-77.219)	(10.108)	(-77.219)	(39.820)	(-77.219)	(59.230)	(-77.219)	(100.528)
InvPrc	-0.073***	39.100***	-0.073***	37.434***	-0.073***	20.648***	-0.073***	63.687***
	(-87.627)	(481.598)	(-87.626)	(643.954)	(-87.626)	(33.035)	(-87.626)	(40.142)
Size	-0.182***	-6.110***	-0.182***	-5.306***	-0.182***	21.139***	-0.182***	79.260***
	(-274.176)	(-56.224)	(-274.176)	(-68.195)	(-274.176)	(25.268)	(-274.176)	(37.325)
MRet	0.011	-4.824***	0.011	-7.765***	0.011	-6.427	0.011	24.544
	(1.146)	(-5.550)	(1.147)	(-12.475)	(1.148)	(-0.960)	(1.148)	(1.445)
MVol	-0.001***	0.139***	-0.001***	0.082***	-0.001***	-0.010	-0.001***	-0.058
	(-44.639)	(74.760)	(-44.637)	(61.697)	(-44.638)	(-0.718)	(-44.638)	(-1.601)
VXJ	0.001***	0.283***	0.001***	0.130***	0.001***	-0.267***	0.001***	-1.289***
	(61.064)	(199.804)	(61.064)	(128.035)	(61.064)	(-24.451)	(61.064)	(-46.576)
N	1,572,347	1,572,347	1,572,350	1,572,350	1,572,355	1,572,355	1,572,355	1,572,355
p-value of Wald Test	0.000		0.000		0.000		0.000	

Table 8 – Continued

Panel B: *Arrownet* 2.0 and commonality in liquidity								
	ATrade	*CQSpread*	*ATrade*	*CESpread*	*ATrade*	*CDepth*	*ATrade*	*CDepth5*
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade		3.593***		4.041***		2.856***		4.017***
		(12.213)		(13.168)		(9.727)		(13.788)
Arrowhead	0.084***		0.084***		0.085***		0.086***	
	(43.095)		(43.016)		(43.728)		(44.306)	
Arrownet2	0.095***		0.095***		0.096***		0.097***	
	(32.632)		(32.563)		(32.990)		(33.420)	
Size	-167.784***	795.193***	-188.298***	897.910***	-161.402***	545.694***	-160.751***	718.818***
	(-62.044)	(11.812)	(-65.729)	(11.719)	(-66.110)	(8.573)	(-66.011)	(11.371)
MRet	-0.840***	-18.367***	-0.926***	-40.717***	-0.778***	-0.512	-0.733***	6.928*
	(-3.139)	(-5.129)	(-3.466)	(-10.916)	(-2.917)	(-0.142)	(-2.755)	(1.920)
MVol	-1.879***	48.505***	-1.802***	50.260***	-1.925***	16.057***	-1.910***	28.107***
	(-13.089)	(21.903)	(-12.591)	(21.992)	(-13.481)	(7.175)	(-13.411)	(12.569)
VXJ	1.299***	-2.488**	1.352***	-4.466***	1.220***	7.624***	1.179***	1.364
	(16.113)	(-2.317)	(16.897)	(-4.012)	(15.310)	(7.145)	(14.823)	(1.278)
QSpread	-0.279***	-5.969***						
	(-5.051)	(-8.127)						
ESpread			-1.266***	1.679				
			(-17.532)	(1.569)				
Depth					-0.108***	0.752***		
					(-20.414)	(9.783)		
Depth5							-0.059***	0.340***
							(-28.375)	(10.597)
N	74,092	74,092	74,076	74,076	74,096	74,096	74,096	74,096
p-value of Wald test	0.000		0.000		0.000		0.000	

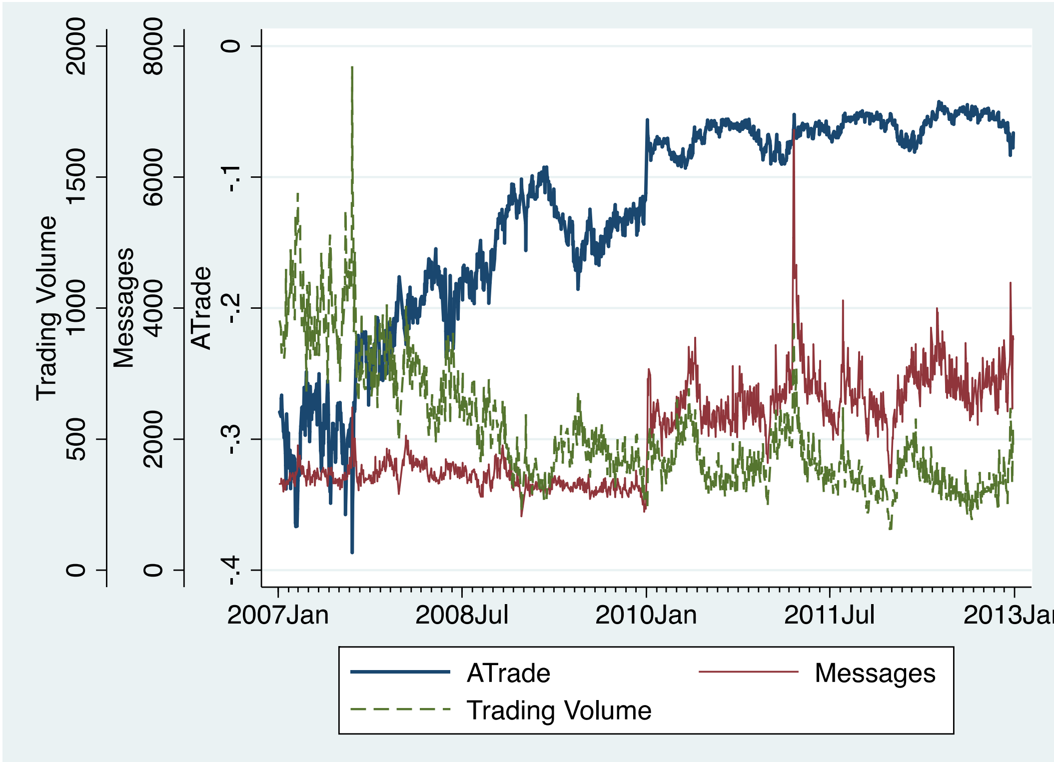
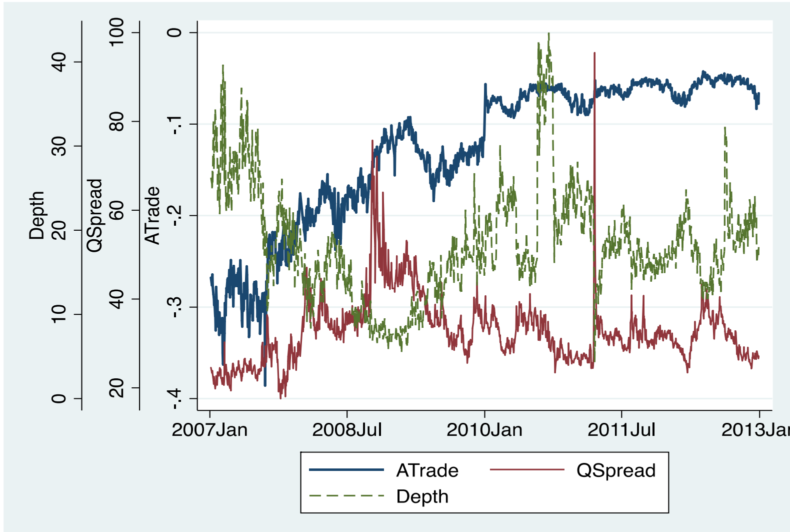
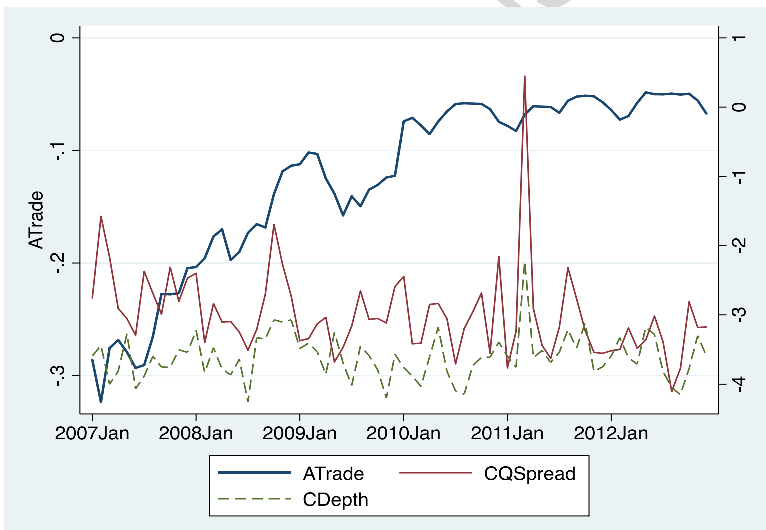


Figure 1. Time series of number of messages, trading volume, and algorithmic trading measures

This figure depicts the time series of the daily cross-sectional average of the number of traffic messages, stock trading volume, and algorithmic trading measure, *ATrade*, from January 2007 to December 2012, where the number of traffic messages is the number of quote price updates at five levels of quoted prices, trading volume is the dollar amount of shares traded, and the algorithmic trading measure (*ATrade*) is the trading volume divided by the number of traffic messages multiplied by –1.



Graph (a)



Graph (b)

Figure 2. Time series of cross-sectional averages of *ATrade* and liquidity/commonality measures

Graph (a) illustrates the time-series variations in the daily cross-sectional averages of *ATrade*, the quoted spread (*QSpread*), and the market depth (*Depth*), while Graph (b) presents the time-series variations in monthly cross-sectional averages of *ATrade*, the commonality in the quoted spread (*CQSpread*), and the commonality in market depth (*CDepth*) over the period from January 2007 to December 2012.