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

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Abstract

In investigating the effects of algorithmic trading on stock market liquidity and commonality in liquidity in different market conditions in an electronic limit order market, we find algorithmic trading increases stock liquidity by narrowing quoted and effective bid–ask spreads. Furthermore, algorithmic trading decreases commonality in liquidity; this finding is robust across a variety of liquidity measures. We also find algorithmic trading narrows the quoted and effective spreads to a much lesser extent following extreme market conditions, particularly after large stock market declines. However, the effect of algorithmic trading on commonality in liquidity does not differ following large market declines.

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

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I. 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 understanding the impact of AT on an electronic limit order market by examining its effects on three dimensions, namely, (1) cross-sectional variations in 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, Jones and Menkveld 2011; Riordan and Storkenmaier 2012). Others emphasize the detrimental effects of AT on market quality, because algorithmic traders, through their ability to process information rapidly, can 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, Kang and Viswanathan 2010).

To investigate these issues, we consider an electronic limit order market, the Tokyo Stock Exchange (TSE), using data from 2007 to 2010. The TSE is a specifically suitable setting for this analysis for several reasons. First, it represents a large, well-developed electronic limit order 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. Second, the TSE adopted a new trading platform, Arrowhead, on 1 January 2010, specifically to cater to the high speed requirements of algorithmic traders, so it provides an ideal experimental setting. Third, the Japanese stock market experienced far fewer extreme market events during the sample period than did other developed markets, such as the U.S. and Europe, which bore the brunt of notable bankruptcies (e.g., Lehman Brothers) and a series of sovereign credit rating downgrades. Because the Japanese market was less affected by these extreme events, this setting should help us compare more clearly the effects of AT on liquidity in periods of normality and uncertainty.

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, Jones and Menkveld (2011) as an AT proxy on the U.S.

stock market; and Boehmer, Fong and Wu (2012) 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.

Our empirical analysis shows that AT is associated with lower quoted and effective bid–ask spreads but also lower market depth in some cases. When the effective spread is decomposed into realized spread and adverse selection costs, we find that the reduction in the effective spread is mainly due to decreases in the adverse selection cost. Furthermore, regardless of the liquidity measures employed, the association of individual stock liquidity with market-wide liquidity weakens in the presence of more AT. These findings are robust to the adoption of the Arrowhead trading platform as an instrumental variable.

Algorithmic traders also behave differently during periods associated with high levels of market uncertainty. Contrary to the results related to normal market conditions, the associations between AT and liquidity measures weaken after extreme market movements, particularly after market declines. In other words, AT improves spread-based liquidity less in the aftermath of extreme market conditions than it does during normal market times. However, we find no significant changes in the association between AT and liquidity commonality following extreme markets.

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, Jones and Menkveld 2011), international foreign exchange markets (e.g., Chaboud et al. 2011; Jovanovic and Menkveld 2012), or futures markets (Kirilenko et al. 2011). These studies assess the effects of AT on cross-sectional variations in market liquidity but have not considered commonality in liquidity. To the best of our knowledge, our study offers the first examination of the relation between AT and commonality in liquidity.

Moreover, our study deepens understanding of the effects of AT on liquidity after large market declines. To date, only a few studies examine AT in the presence of market uncertainty. Kirilenko et al. (2011) focus on AT behavior around a "flash crash" event on 6 May 2010. Rather than restricting their analysis to one extreme market event, Zhang (2010), Hasbrouck and Saar (2012), and Boehmer, Fong and Wu (2012) analyze a longer sample period and demonstrate the effects of AT or HFT on stock return volatility and liquidity in periods of market stress. We instead address the effects of AT immediately after large markets movements, when market participants and financial intermediaries must trade in the face of substantial information uncertainty. Particularly following large market declines, market liquidity may not be available because investors are eager to unwind their positions and financial intermediaries withdraw from providing liquidity (Brunnermeier and Pedersen 2009; Hameed, Kang and Viswanathan 2010). As we document in our findings, in uncertain market conditions the positive effects of AT on market liquidity are indeed moderated.

In Section II, we outline some existing literature and discuss our research questions. Section III contains a description of our data and research methods. In Section IV, we discuss the effect of AT on liquidity and analyze the effect of AT on commonality in stock liquidity in Section V. The analysis of the role of AT during extreme market conditions appears in Section VI, before we conclude with a discussion of implications in Section VII.

II. 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.

A. 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, Kadan and Kandel 2013).[1] In addition, algorithmic traders gather information 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 2010; Jovanovic and Menkveld 2012). Even if

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[1] In their model, Foucault, Kadan and Kandel (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.

ATs are uninformed, their automated liquidity provision likely increases competition among liquidity suppliers and reduces transaction costs (Cvitanic and Kirilenko 2010).

However, some theories highlight the negative externalities of algorithmic trading. 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, Foucault and Moinas (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 (2011) examine algorithmic trades on 30 DAX stocks traded on the Deutsche Boerse in January 2008 and find that the more efficient quotes that ATs place lead to more 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, but they contribute to only one-fourth of the book depth, compared with non-high frequency traders. Despite their insights about the actual trading strategies of algorithmic and high frequency traders, the analyses in these studies are limited to a selected sample of stocks and may not be representative of the market overall.

Another set of studies uses proxies to measure the extent of AT, which supports analyses of a greater cross-section of the market. For example, Hendershott, Jones and Menkveld (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 39 exchanges, Boehmer, Fong and Wu (2012) reach a similar conclusion. Hasbrouck and Saar (2012) 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, Jones and Menkveld (2011) as it enables us to examine all stocks listed on the TSE.

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).[2] 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, Kadan and Kandel 2013). Second, the implementation of the new trading platform by the TSE in 2010,

[2] Empirical evidence offered by Brogaard (2010) and Hendershott and Riordan (2011) confirms that high frequency traders can be either liquidity providers or demanders.

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 largely mitigate endogeneity concerns over the relationship between AT and market liquidity.

B. 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, Chung and Pérignon 2009; Chordia, Roll and Subrahmanyam 2000; Hasbrouck and Seppi 2001; Karolyi, Lee and van Dijk 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.

Motivated by the importance of liquidity co-movement, we explore the effects of AT on the commonality in liquidity. A priori, we propose that AT reduces commonality in liquidity in normal market conditions. Existing research (Brogaard 2010; Hendershott and Riordan 2011; Jovanovic and Menkveld 2012) suggests that algorithmic traders automate information gathering and processing and therefore are better informed than (slow) liquidity traders. A high level of private information acquisitions by algorithmic traders thus translates into low levels of co-movements with market-wide liquidity. Conceptually, this effect is similar to commonality (or lack of) in stock returns (i.e., stock price non-synchronicity). 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, Yeung and Yu 2000). Because information is a common driver of liquidity and stock returns,[3] algorithmic traders should promptly process and act on information, which decreases commonality in liquidity.

However, our prediction may be tempered by 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). In addition, Hendershott and Riordan (2011) find evidence of AT clustering in time in the 30 DAX stocks on the Deutsche Boerse. The correlated trading of algorithmic traders could increase commonality in liquidity. Thus, we investigate empirically how AT, on average, affects commonality in liquidity.

C. 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

[3] Karolyi, Lee and van Dijk (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.

U.S. flash crash of 6 May 2010 conveys the regulator's concerns about the risk of AT when the market experiences high volatility.[4]

Prior literature offers few empirical insights into how algorithmic traders affect market liquidity during extreme market conditions. Kirilenko et al. (2011) examine high frequency trading in the futures market around the flash crash of 6 May 2010 and find that though the traders did not trigger a crash, they exacerbated market volatility. Hasbrouck and Saar (2012) study the market impact of HFT in June 2008 following the fire sale of Bear Stearns in March. Their results conflict in that they conclude that HFT enhances market quality during stressful market times. Instead of restricting their analysis to brief periods of extreme market events, Boehmer, Fong and Wu (2012) and Zhang (2010) examine HFT using a longer sample period with multiple market volatility episodes.[5] 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, Kang and Viswanathan 2010). However, unlike most prior research we use a longer sample period, rather than focusing on specific events, to be representative of market conditions in general and generalize our results more widely. We also analyze the effect of AT on commonality in liquidity during market stress whereby commonality in liquidity has been shown to increase.

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

[5] 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, Fong, and Wu (2012) extend the analysis to an international sample of stocks from 39 exchanges from 2001 to 2009 and show that algorithmic trading lessens market liquidity and worsens market volatility when market making is difficult.

III. Sample and Data Description

A. Institutional Background

According to annual statistics, the TSE is the third largest exchange in terms of the total market capitalization of its listed firms at USD3,827 billion (World Federation of Exchanges 2010). It thus ranks behind only the New York Stock Exchange at USD13,394 billion and the NASDAQ OMX at USD3,889 billion. It also is the largest exchange to operate as a pure electronic order–driven market, without market makers; its trading volume in 2010 was USD3,793 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.

The TSE introduced a new trading platform, Arrowhead, on 1 January 2010, with the specific aim of facilitating AT on the Japanese stock market. It prompted a substantial increase in the number of orders placed on the exchange, with reports indicating an average daily increase from 6.72 million in 2009 to 8.24 million in 2010 (Tokyo Stock Exchange 2011). The turnaround time, from accepting the order at the participant's terminal to booking the order at the exchange server (i.e., order book entry latency) is approximately 2 milliseconds, similar to those reported for the fastest HFT system on the NASDAQ (Hasbrouck and Saar 2012).

Together with this 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.[6] The new

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[6] 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);

intervals then decreased the tick size for stocks in those price ranges. 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, a potential impact that we address in our robustness tests.

B. Sample Selection

We construct algorithm trading 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 2010.[7] 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

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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).

[7] Algorithmic trading is an outcome of recent advances in technology. Chaboud et al. (2011) observe a very small portion of algorithmic trading prior to 2006 in foreign exchange markets. Hendershott, Jones and Menkveld (2011) also show a sharp increase in algorithmic trading 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, algorithmic trading was limited by trading platform capacity constraints.

to avoid the holiday effects.[8] 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%. After applying these filters, our final sample consists of 1,564,988 stock-day observations from 1,837 unique stocks spanning 978 trading days.

C. 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, Jones and Menkveld (2011) to a U.S. sample and by Boehmer, Fong and Wu (2012) 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 the aggregate electronic message traffic on a given trading day and multiplying this ratio by –1.

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[8] 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.

A higher value of this proportional measure 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 the AT proxy, *ATrade*, increases steadily over our sample period. In particular, the mean value of *ATrade* increases from a low of –0.369 in 2007 to a high of –0.076 in 2010, and the median values exhibit similar upward patterns.

D. Liquidity Measures

The challenge associated with measuring stock liquidity is long standing (Goyenko, Holden and Trzcinka 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, Kang and Viswanathan (2010), though with one modification; that is, we include price zone dummies. The introduction of the Arrowhead trading system led to a change in the tick size for some stocks. Introducing price zone dummies addresses the effects of tick size changes. Specifically, we adjust our liquidity measures for stock *i* on day *t* as follows:

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

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 *j*th transaction can be computed as follows:

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

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,[9] the sample mean values of the quoted and effective spread measures are 0.0029 and 0.0023, respectively, largely comparable with their U.S. counterparts (Goyenko, Holden and Trzcinka 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 0.0035 in 2008, at the onset of the global financial crisis, and declines to 0.0027 in 2010 due to the resilient financial recovery (e.g., Campello, Graham and Harvey 2010; Ivashina and Scharfstein 2010; Lang and Maffett 2011).[10]

To investigate how AT affects stock liquidity, we decompose the 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

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

[10] 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, Graham and Harvey (2010), and Lang and Maffett (2011) identify 2008 as the year of the onset of the crisis.

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 *j*th transaction is defined as:

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

where $M_{i,j+5}$ refers to the midpoint of best quoted prices five minutes after the trade.[11] The adverse selection component of stock liquidity is measured as follows:

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

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.

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 -2010, for *Depth* and *Depth5* of 38.24 and 169.68, 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.

[11] Following Huang and Stoll (1996), we use the quote midpoint of the subsequent trade in the same trading session (i.e., morning or afternoon session) if a trade after five minutes is not available.

E. Control Variables

To ensure that observed relationships between the AT measure and stock liquidity are not driven by other stock characteristics, we control for four stock-level variables (see the Appendix): stock turnover (*Turn*), daily stock volatility (*Vol*), the inverse of stock price (*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, Roll and Subrahmanyam 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.

With all these variables winsorized at the top and bottom 0.05% of the full sample distribution, several interesting findings emerge from Table 1. The sample mean of *Turn* is 0.055, which indicates a liquid trading environment on the TSE. Stock volatility, *Vol*, exhibits the highest mean value of 488.486 and a standard deviation of 2911.342 in 2008 when the global financial crisis broke out.

IV. Algorithmic Trading and Stock Liquidity

During various liquidity cycles, algorithmic traders can act differently, as liquidity providers or liquidity demanders. Considering the dynamic nature of their trading algorithm, it remains unanswered whether and how algorithmic trading affects stock liquidity and commonality in liquidity on 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.

A. Main Regression Analysis

We first investigate the direct effect of AT on stock liquidity from 2007 to 2010 by regressing a wide range of stock liquidity measures on the AT variable and other stock characteristics in the following baseline ordinary least squares regression model:

$$Adj\_liq_{i,t} = ATrade_{i,t} + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t} \tag{5}$$

where $ATrade_{i,t}$ is the negative daily dollar trading volume scaled by the total number of quote updates for stock *i* on day *t*; and $Adj\_liq_{i,t}$ denotes various adjusted spread and depth measures. The list of control variables includes stock trading turnover (*Turn*), daily stock trading volatility (*Vol*), the inverse of stock price (*InvPrc*), and firm size (*Size*). We also include day dummies and adjust the standard errors for firm-level clustering and heteroskedasticity in the regression models.[12]

Table 2 contains the panel regression results from estimating Equation (5) with the full sample. Overall, we observe a significant positive effect of *ATrade* on various spread measures but a weak effect on market depth. In Models (1) and (2), the estimation results show the

[12] In regressions in which we use year dummies to denote the implementation of the new trading system, we do not include the day dummies.

coefficient on *ATrade* is –2.577 (*t*-statistic = –4.810) when the quoted spread is the proxy for stock liquidity, whereas the coefficient is –2.550 (*t*-statistic = –5.655) when the effective spread is the measure. From an economic perspective, a one standard deviation increase in *ATrade* leads to a 1.348 basis point decrease in the quoted spread and 1.334 basis point decrease in the effective spread. Because the mean of the quoted and effective spreads falls between 23 and 31 basis points, the impact of AT on stock liquidity is economically significant.

Turning to the components of stock liquidity (temporary inventory cost and adverse selection cost), the results of Models (5) and (6) suggest the reduction in adverse selection costs is the main source of the positive liquidity effect of AT. In Model (5), the coefficient on *ATrade* is –0.559 (*t*-statistic = –3.157) with realized spread as the measure of liquidity. In contrast, the coefficient on *ATrade* is markedly larger at –2.190 (*t*-statistic = –5.709) when liquidity is measured by adverse selection costs in Model (6). Although AT reduces both the temporary inventory and adverse selection costs, the main effect of AT on stock liquidity appears to be an improvement in the informational efficiency of stock transactions—consistent with the notion that algorithmic traders leverage their relative speed to gather and process information and thus improve information efficiency (Jovanovic and Menkveld 2012).

In sharp contrast with the results using spread-based variables, Models (3) and (4) show that AT has only weak effects on market depth. We observe an insignificant effect of *ATrade* on *Depth* and a marginally significant effect on *Depth*5. The results suggest that algorithmic traders' ability to modify or execute their orders instantaneously reduces the orders available in the market. Cartea and Penalva (2012) shed theoretical light on this trading surplus extraction by AT.

Our results also suggest a reliable control variable selection. When spread-based liquidity measures are used as dependent variables, all of the control variables are statistically significant, with the exception of stock turnover across all regression models; their signs are consistent with our expectations. Stock turnover relate negatively and significantly to quoted spread, in line with the clientele effect suggested by Amihud and Mendelson (1986), though it does not indicate any significant association with other liquidity measures. We also find that all spread-based (il)liquidity measures increase with stock volatility and the inverse of stock price but decrease with firm size. With regard to market depth proxies, the inverse of stock price (*InvPrc*) is the only statistically significant factor, suggesting a potential avenue for further research into the determinants of market depth.

B. Arrowhead Trading System Reform

While we have established the strong, significant relationship between AT and stock liquidity, our results still may be subject to endogeneity problems. The introduction of the Arrowhead trading system in January 2010 aims to improve the trading infrastructure and facilitate program trading, so it provides a perfect exogenous event for our analysis. When impediments due to limited access and speed are removed by the introduction of the new trading system, there should have been a substantial increase in AT activities.

To depict the direct impact of the upgrade of the trading system, in Figure 1 we plot the daily time series of the *ATrade* variable. In response to the system upgrade in 2010, we find a clear increase in the level of AT after January 2010. We also examine this impact by regressing the *ATrade* variable on the *Arrowhead* dummy variable in Model (1) of Table 3. After controlling for other stock characteristics, we find a significant increase in AT due to the introduction of the new trading system. The significant coefficient of 0.148 for the *Arrowhead* dummy variable indicates that the introduction of the new trading system leads to a 14.8% increase in AT for an average stock. Thus, the system upgrade has achieved its goal to boost AT on TSE.

A question that naturally follows is whether the increased AT also improves stock liquidity and market quality as a whole. To examine this issue, we incorporate into our baseline regression model the *Arrowhead* year dummy variable and its interaction with the *ATrade* variable. As we show in Table 3, we find strong evidence of a positive liquidity effect of the new trading system. For example, the *ATrade* coefficient is –2.428 (*t*-statistic = –4.478), after controlling for the *Arrowhead* dummy variable in Model (2), with quoted spread as the dependent variable. Meanwhile, we observe a significant, negative coefficient on the *Arrowhead* dummy variable, indicating an improvement in stock liquidity associated with this trading system reform. Regarding its marginal effect on stock liquidity, we interact the *Arrowhead* dummy variable with the *ATrade* variable. In Model (3), the *ATrade* coefficient is –2.742 (*t*-statistic = –4.720) after the inclusion of the interaction term, *ATrade*×*Arrowhead*. The significant coefficient of –22.714 on the interaction term confirms that the negative impact of AT on the quoted bid–ask spread is most pronounced after the implementation of the new trading system. This conclusion holds even when we substitute the quoted spread with effective spread as a measure of stock liquidity in Models (4) and (5).

The results in the last four columns of Table 3 show the *Arrowhead* effect on the components of stock transaction costs. The findings are consistent with the notion that algorithmic traders pocket the returns earned from providing liquidity in the short term and they improve market liquidity by dampening the information asymmetry faced by liquidity traders. In

Model (11), we find that though *ATrade* alone reduces the realized spread by a small economic magnitude (*ATrade* coefficient = –0.562), the coefficient for *ATrade*×*Arrowhead* (5.912) suggests AT widens the realized spread after the system introduction. The adoption of the Arrowhead trading platform thus gives algorithmic traders the market power to profit from the provision of liquidity. Clearly the cost of the Arrowhead trading platform is offset by its informational benefits. In Models (12) and (13), we note that AT eliminates information barriers in the trading process, after the implementation of the new trading system. With adverse selection costs as the dependent variable, the coefficient for *ATrade* is –2.362, and that for *ATrade*×*Arrowhead* is –22.491 in Model (13). Collectively, these results suggest that AT mitigates the information asymmetry problem; the effect grows stronger in 2010, when the new trading system increases the likelihood of more AT. However, we do not observe any significant changes in market depth. At best, we find a marginally significant coefficient of –3905.604 on *ATrade*×*Arrowhead* for *Depth5* in Model (9).

In summary, AT improves the liquidity of stocks listed on TSE, mainly due to AT's role in improving information efficiency. In terms of market depth, we observe only a marginally significant effect of AT on aggregated market depth at five price levels.

C. Additional Tests

Although the preceding analysis allays our endogeneity concerns, we remain cautious about other factors that may confound the relationship between stock liquidity and AT. We therefore conduct additional tests to address the endogeneity problem, driven by potentially missing control variables, as well as the simultaneous change in stock liquidity associated with the Arrowhead event.

In Panel A of Table 4, we control for the lagged dependent variable to exclude the possibility that we might not have considered time-invariant characteristics in stock liquidity. This research design is similar in spirit to a Granger causality test. In the expanded model, we find a strong autocorrelation in the spread and depth variables, with coefficients on the lagged value between 0.625 and 0.991. The coefficients on *ATrade* and *ATrade*×*Arrowhead* remain negative and significant for quoted and effective spread. The main difference in the results is with the coefficients on the *ATrade* variables for the market depth measures. In particular, the coefficients on *ATrade* and *ATrade*×*Arrowhead* are highly significant and negative in Models (7) and (8) when *Depth5* is used as the liquidity proxy.

Another concern is that stock liquidity and AT may be jointly determined by unobservable stock characteristics. To mitigate these concerns, we control for firm fixed effects in the baseline regression model (see Panel B of Table 4). The model with firm fixed effects yields qualitatively the same results: AT narrows quoted and effective spread while it lessens aggregated market depth at five price levels subsequent the introduction of the Arrowhead trading platform.

In Panel C of Table 4, we examine the possibility that tick size changes may have confounded our findings. The introduction of the new trading system coincides with the TSE amending the tick sizes for a small group of stocks. Although the tick size reduction does not apply to all traded stocks, such changes inevitably would challenge our findings. To ensure the robustness of our results, we replicate our analysis for a sample of stocks that did not undergo tick size reduction. The results in Panel C affirm our previous conclusion: AT reduces transactions costs, measured by a variety of stock liquidity measures. Particularly, when we focus solely on stocks that experienced no tick size reduction, the relationship of AT with both the best available market depth and aggregated market depth at five price levels become significantly negative, highlighting impediments to market depth due to the presence of AT.

V. 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. This systematic liquidity risk is of particular concern during market downturns, when the commonality in liquidity tends to intensify. We therefore analyze whether AT plays a role in determining commonality in liquidity in Table 5. To start, we obtain a proxy for commonality in liquidity by estimating the following regression model on a monthly basis for each stock:

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

where $\Delta Liq_{i,t}$ is the change in individual stock liquidity for stock *i* on day *t*, and $\Delta MLiq_{,t}$ is the change in market liquidity, which is the simple average of the individual stock liquidity measure 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 logistically transform the measure by dividing R-squared by (1 – R-squared). We then use the following equation to investigate the effect of AT on commonality in liquidity:

(7) $$CLiq_{i,t} = ATrade_{i,t} + Size_{i,t} + Adj\_liq_{i,t} + \varepsilon_{i,t}$$

where *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 aggregated market depth at five price levels (*Depth5*).

Table 5 summarizes the results. Irrespective of the liquidity measures, we observe a consistently negative effect of *ATrade* on commonality in stock liquidity. In particular, the coefficient on *ATrade* ranges from –0.212 to –0.080 across the four models, with all of the coefficients significant at the 1% level. The results suggest that AT lessens individual stock liquidity co-movement with market liquidity, which might occur if algorithmic traders are experts in acquiring and trading firm-specific information. As such, AT improves the incorporation of firm-specific information into stock prices, which means that individual stock liquidity is influenced more by firm-specific information than by market-wide information. This conjecture is plausible as we previously observe a negative relationship between AT and adverse selection costs. Such a finding is also in line with the notion that algorithmic traders may engage in information-based trading, thus leading to the information efficiency in the marketplace.

To ensure that the observed relation between commonality in stock liquidity and AT is robust, we again rely on the implementation of the new trading system as an exogenous event. Operationally, we include the interaction term between the *Arrowhead* dummy variable and the *ATrade* variable, as well as the *Arrowhead* dummy variable, in Equation (7). The estimation results in Panel B are consistent with the conclusion drawn from Panel A. We continue to observe negative coefficients of the *ATrade* and *Arrowhead* variables and also find a significantly negative coefficient for the *ATrade*×*Arrowhead* interaction term. Therefore, commonality in liquidity appears lower with the implementation of the new trading system, especially for stocks associated with greater AT.

VI. 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 further 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.[13]

We conduct two additional analyses to understand the liquidity effects of AT in extreme market conditions. We first examine the changes of AT activities in extreme market conditions in Table 6, and then examine variations in the liquidity and liquidity commonality effects of AT in Tables 7 and 8. 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 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 Panel A of Table 6. We denote the days with highly positive (negative) market returns as *Up* (*Down*) market states. The highest number of extreme market increases and declines occurs in 2008, with 22 days of extremely high market returns and 32

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

days of extremely low market returns. This volatile stock market is clearly affected by the far-reaching 2008 global financial crisis. The year with the fewest days with highly positive market returns is 2010; the year with the fewest days with extremely low market returns is 2009, 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 0.068 and –0.070, respectively, which indicate the magnitude of the extreme market conditions.

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*). With the signs of the other control variables remain unchanged from the previous regression results, we note that the coefficient on |*MRet*| is 0.416 (*t*-statistic = 8.715). This suggests that on average, AT increases with market movement. Analyzing the extreme market conditions, however, offers a different message: The coefficients on *MRet*×*Up* and *MRet*×*Down* are –0.304 and 0.338, respectively. Considered together with the coefficient on |*MRet*|, these results suggest that algorithmic traders refrain from trading when the stock market shows large prior gains or losses.

We also ask how algorithmic traders affect individual stock liquidity and liquidity commonality during extreme market conditions. In Table 7, we regress the stock liquidity measures on *ATrade* and its interactions with *Up* and *Down* market state dummies. Although we consistently observe negative and significant coefficients on the *ATrade* variable, the coefficients on the interaction terms, *Up*×*ATrade* and *Down*×*ATrade*, reveal a different story. For example, with quoted spread and effective spread as liquidity proxies, we observe positive and statistically significant coefficients on *Up*×*ATrade* and *Down*×*ATrade*. Moreover, the magnitude of the coefficients on *Down*×*ATrade* is greater than that on *Up*×*ATrade*. Take Model (1) for example:

Compared with an *ATrade* coefficient of –3.720 in normal times, the coefficient on *ATrade* is –2.694 in the *Up* market state but only –0.541 in the *Down* market state. With regard to market depth measures, we observe no differential effect of *ATrade* in the *Up* market state but find positive coefficients for *Down*×*ATrade*. Together, these results suggest that AT continues to narrow the spreads but reduce market depths in extreme market conditions, though to a much lesser extent.

We examine the effect of AT on liquidity commonality for extreme market states in Table 8. 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 coefficients for *Up*×*ATrade*, such that the effect of *ATrade* on liquidity commonality is weaker in the *Up* market state. But the negative coefficient on *Up*×*ATrade* for the market depth commonality, as shown in Model (3), suggests that the association between *ATrade* and market depth is stronger in the *Up* market state.

Of particular interest are the coefficients on *Down*×*ATrade* across all the liquidity commonality proxies. Prior studies have shown that liquidity commonality tends to rise during down markets. However, our results do not indicate any strong changes in the association between AT and various liquidity in down market states. Rather, the coefficient on *Down*×*ATrade* is significant only when the quoted spread serves as the liquidity proxy in Model (1). In Model (1), the coefficient on *Down*×*ATrade* is 0.060 (*t*-statistic = 1.967), which means that AT reduces the commonality in the quoted spread to a lesser extent during down market conditions. For the rest of the estimation models, none of the *Down*×*ATrade* coefficients are statistically significant.

VII. 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 yields several interesting empirical findings. First, we show that the presence of AT significantly narrows the quoted and effective spread but decreases market depth. When decomposing the effective spread, we show that the main source of the spread-narrowing effect of AT stems from the reduction in the adverse selection cost. These findings are stronger after the introduction of the Arrowhead trading system. In addition, we find that AT reduces commonality in liquidity, regardless of how we measure stock liquidity. It is important to note that the liquidity improving effect of AT weakens following both bullish and bearish markets. Regarding liquidity commonality, we do not observe any robust changes in the associations between AT and liquidity commonality following down markets, except for the commonality in quoted spreads. Moreover, the negative association between AT and liquidity commonality, measured by either quoted or effective spread, weakens following bullish 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 transactions costs and mitigates individual stock liquidity co-movement with market-wide liquidity at normal times. However, regulators should be aware of the distinctive impact of AT in extreme market conditions. In particular, any effect of AT on market quality gets lessened during market declines, if not reversed. 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 (prevailing midpoint price minus the midpoint five minutes later 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 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).

*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, scaled by the number of shares outstanding.
Stock return volatility	*Vol*	Difference between the highest and lowest stock price on a given trading day.
Inverse of stock price	*InvPrc*	The inverse of the daily closing stock price.
Market capitalization	*Size*	Log of the market capitalization.
Market return	*MRet*	Daily market return, computed from the end-of-day value of TOPIX stock market index.

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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, and the stock-level control variables by year and for the full sample. The six daily stock liquidity measures are the 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 multiplied by 104. 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 (*InvPrc*), and the log of market capitalization (*Size*). *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.

Year	*NStocks*		*ATrade*	*QSpread*	*ESpread*	*RSpread*	*ASel*	*Depth*	*Depth5*	*Turn*	*Vol*	*InvPrc*	*Size*
2007	1735	Mean	-0.369	22.715	18.175	1.521	16.755	47.224	201.917	0.049	466.479	0.002	18.145
		Median	-0.132	16.740	13.413	0.177	13.032	5.185	25.781	0.002	21.000	0.001	17.929
		SD	0.741	21.324	16.677	14.001	15.340	545.513	1846.979	0.310	2814.852	0.003	1.533
2008	1710	Mean	-0.250	34.896	26.478	1.616	24.994	31.524	145.250	0.063	488.486	0.003	17.744
		Median	-0.079	23.243	17.664	-0.461	18.095	3.326	16.969	0.002	23.000	0.001	17.538
		SD	0.578	36.459	26.626	22.215	24.585	504.571	1731.699	0.401	2911.342	0.004	1.588
2009	1693	Mean	-0.175	32.329	26.138	3.049	23.192	34.125	154.049	0.052	237.399	0.003	17.560
		Median	-0.066	21.558	17.274	0.491	16.575	3.551	18.221	0.002	15.000	0.002	17.384
		SD	0.378	32.617	26.395	21.734	23.570	505.491	1737.573	0.343	1508.520	0.005	1.555
2010	1678	Mean	-0.076	26.594	22.751	3.772	19.007	39.883	176.765	0.053	177.657	0.003	17.606
		Median	-0.044	17.740	15.094	0.811	13.588	4.067	20.744	0.002	12.000	0.002	17.422
		SD	0.098	27.437	23.923	19.201	19.970	548.891	1802.568	0.356	1127.249	0.005	1.558
2007–2010	1837	Mean	-0.219	29.101	23.351	2.477	20.966	38.241	169.683	0.055	344.345	0.003	17.767
		Median	-0.073	19.493	15.729	0.272	15.160	4.011	20.345	0.002	17.000	0.001	17.570
		SD	0.523	30.348	23.945	19.554	21.402	526.664	1780.895	0.354	2247.003	0.004	1.576

TABLE 2 Impacts of Algorithmic Trading on Stock Liquidity

This table presents the results from the panel regressions of individual stock liquidity measures on stock-level algorithmic trading and control variables (day dummies are untabulated). The baseline regression model is

$$Adj\_liq_{i,t} = ATrade_{i,t} + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

In this model, *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 daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and log of market capitalization (*Size*). All the variables are defined in the Appendix. The *t*-statistics in parentheses are based on the standard errors, adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

	QSpread	*ESpread*	*Depth*	*Depth5*	*RSpread*	*ASel*
	(1)	(2)	(3)	(4)	(5)	(6)
ATrade	-2.577***	-2.550***	-278.122	-1,100.492*	-0.559***	-2.190***
	(-4.810)	(-5.655)	(-1.511)	(-1.784)	(-3.157)	(-5.709)
Turn	-2.080**	-0.030	-29.157	-103.117	-0.242	0.222
	(-2.411)	(-0.042)	(-1.406)	(-1.423)	(-0.743)	(0.329)
Vol	0.746***	0.633***	7.278	25.643	0.200***	0.419***
	(6.279)	(6.145)	(1.314)	(1.324)	(4.623)	(5.535)
InvPrc	3,225.064***	3,614.338***	2,424.159***	10,586.798***	1,925.923***	1,572.377***
	(24.632)	(31.477)	(4.326)	(5.015)	(18.554)	(12.886)
Size	-6.834***	-4.471***	1.891	21.520	-0.655***	-4.022***
	(-23.632)	(-22.683)	(0.161)	(0.544)	(-4.966)	(-22.474)
Constant	141.264***	92.425***	-63.591	-484.871	8.824***	87.617***
	(26.139)	(25.254)	(-0.353)	(-0.795)	(3.505)	(25.783)
N	1,564,962	1,564,986	1,564,988	1,564,988	1,564,864	1,564,862
$\overline{R^2}$	0.447	0.608	0.077	0.110	0.189	0.268

TABLE 3 Impacts of the Arrowhead Reform on Algorithmic Trading and Stock Liquidity

This table presents the panel regression results of the algorithmic trading or stock liquidity variables for the Arrowhead trading reform, together with other control variables. The baseline regression models are

(1) $$ATrade_{i,t} = Arrowhead_{i,t} + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

(2) $$Adj\_liq_{i,t} = ATrade_{i,t} + Arrowhead_{i,t} + ATrade_{i,t} \times Arrowhead_{i,t} + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

Here, *Arrowhead* is a dummy variable that takes a value of 1 if the particular trading day is on or after January 2010, and 0 otherwise. *Adj_liq* represents quoted spread (*QSpread*), effective spread (*ESpread*), realized spread (*RSpread*), adverse selection cost (*ASel*), market depth at best bid and ask prices (*Depth*), or market depth at five levels of stock prices (*Depth5*). The estimation of Equation (1) is shown in column (1); the estimations of Equation (2) are reported in columns (2)–(13). All liquidity measures are adjusted for monthly and weekly seasonality, as well as price zone variations. *ATrade* refers to the algorithmic trading measure. The daily control variables include stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and the log of market capitalization (*Size*). All the variables are defined in the Appendix. The *t*-statistics in parentheses are based on the standard errors, adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

	AT Proxy	**Liquidity Measures**											
	ATrade	*QSpread*		*ESpread*		*Depth*		*Depth5*		*RSpread*		*ASel*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ATrade		-2.428***	-2.742***	-2.503***	-2.714***	-274.708	-287.896	-1,086.087*	-1,140.035*	-0.644***	-0.562***	-2.051***	-2.362***
		(-4.478)	(-4.720)	(-5.602)	(-5.724)	(-1.515)	(-1.512)	(-1.787)	(-1.786)	(-3.730)	(-3.069)	(-5.404)	(-5.818)
Arrowhead	0.148***	-6.000***	-7.711***	-3.168***	-4.320***	54.797	-17.132	219.143*	-75.081	0.693***	1.138***	-3.891***	-5.586***
	(17.383)	(-21.819)	(-22.688)	(-17.509)	(-19.820)	(1.615)	(-0.918)	(1.920)	(-1.182)	(5.598)	(6.960)	(-24.456)	(-31.303)
ATrade× *Arrowhead*			-22.714***		-15.288***		-954.795		-3,905.604*		5.912***		-22.491***
			(-8.044)		(-7.284)		(-1.408)		(-1.705)		(4.136)		(-11.105)
Turn	0.086**	-2.139**	-2.206***	-0.055	-0.100	-28.584	-31.404	-100.566	-112.099	-0.250	-0.233	0.207	0.141
	(1.971)	(-2.507)	(-2.587)	(-0.077)	(-0.140)	(-1.408)	(-1.427)	(-1.417)	(-1.460)	(-0.773)	(-0.720)	(0.310)	(0.212)
Vol	-0.038***	0.811***	0.814***	0.662***	0.664***	7.140	7.242	25.088	25.506	0.179***	0.178***	0.470***	0.472***
	(-2.747)	(6.790)	(6.775)	(6.441)	(6.423)	(1.298)	(1.297)	(1.306)	(1.308)	(4.168)	(4.164)	(6.295)	(6.260)
InvPrc	-11.561***	3,274***	3,255***	3,635***	3,622***	2,804***	1,978***	12,174***	8,797***	1,902***	1,907***	1,619***	1,599***
	(-7.086)	(25.773)	(25.253)	(31.935)	(31.678)	(3.860)	(4.219)	(4.587)	(5.015)	(18.230)	(18.254)	(12.870)	(12.842)
Size	-0.191***	-6.935***	-7.245***	-4.520***	-4.729***	1.635	-11.391	20.423	-32.862	-0.608***	-0.527***	-4.120***	-4.427***
	(-17.426)	(-23.856)	(-22.957)	(-22.769)	(-21.966)	(0.137)	(-0.553)	(0.505)	(-0.475)	(-4.559)	(-3.663)	(-22.404)	(-22.328)
Constant	3.175***	144.414***	149.906***	94.028***	97.723***	-72.814	158.000	-520.489	423.662	7.868***	6.438**	90.206***	95.644***
	(16.646)	(26.566)	(25.569)	(25.516)	(24.605)	(-0.412)	(0.482)	(-0.869)	(0.385)	(3.095)	(2.358)	(25.861)	(25.651)
N	1,564,988	1,564,962	1,564,962	1,564,986	1,564,986	1,564,988	1,564,988	1,564,988	1,564,988	1,564,864	1,564,864	1,564,862	1,564,862
$\overline{R}^2$	0.367	0.426	0.427	0.597	0.598	0.077	0.084	0.109	0.119	0.181	0.181	0.241	0.243

TABLE 4 Robustness Tests on the Impact of Algorithmic Trading on Stock Liquidity

This table reports the results from a series of robustness tests on the impact of algorithmic trading on stock liquidity. The baseline regression model is

$$Adj\_liq_{i,t} = ATrade_{i,t} + Arrowhead_{i,t} + ATrade_{i,t} \times Arrowhead_{i,t} + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

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. *Arrowhead* is a dummy variable that takes a value of 1 if the particular trading day is on or after 4 January 2010 and 0 otherwise. The list of daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and log of market capitalization (*Size*). All the variables are defined in the Appendix. Panel A expands the baseline regression model by including the lagged dependent variable, y_{t-1}, and Panel B reports regression results, including firm fixed-effects. Panel C reports results based on a subsample of stocks that were not subject to the tick size reduction after the adoption of the Arrowhead trading system. The *t*-statistics in parentheses are based on the standard errors adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

Panel A: Lagged Dependent Variables								
	QSpread		*ESpread*		*Depth*		*Depth5*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
y_{t-1}	0.747***	0.744***	0.625***	0.621***	0.986***	0.986***	0.991***	0.991***
	(108.231)	(105.166)	(47.436)	(46.408)	(99.522)	(99.281)	(168.331)	(166.090)
ATrade	-0.655***	-0.494***	-1.027***	-0.931***	-6.596***	-7.139***	-20.471***	-22.515***
	(-4.727)	(-3.226)	(-5.927)	(-5.060)	(-7.123)	(-7.460)	(-8.170)	(-8.567)
Arrowhead		-1.851***		-1.582***		-0.488		-2.744***
		(-18.741)		(-16.547)		(-0.986)		(-3.285)
ATrade× Arrowhead		-4.401***		-5.345***		-21.877***		-84.323***
		(-6.051)		(-6.724)		(-3.352)		(-6.331)
Turn	-0.767***	-0.758***	-0.113	-0.106	1.579**	1.487**	5.129***	4.784***
	(-3.359)	(-3.312)	(-0.413)	(-0.386)	(2.126)	(2.006)	(2.791)	(2.583)
Vol	0.256***	0.255***	0.281***	0.280***	-0.509**	-0.501**	-1.680***	-1.651***
	(6.726)	(6.888)	(6.328)	(6.437)	(-2.390)	(-2.334)	(-3.219)	(-3.097)
InvPrc	835.477***	853.180***	1,371.345***	1,387.909***	15.960	-9.606	4.624	-87.448
	(21.317)	(21.370)	(19.600)	(19.514)	(0.673)	(-0.423)	(0.072)	(-1.461)
Size	-1.668***	-1.724***	-1.627***	-1.695***	-0.416**	-0.740***	-1.721***	-2.947***
	(-20.125)	(-19.165)	(-18.329)	(-17.700)	(-2.534)	(-4.495)	(-3.569)	(-6.542)
Constant	34.437***	35.904***	33.604***	35.158***	6.529**	11.959***	27.826***	48.586***
	(21.570)	(20.784)	(19.672)	(19.161)	(2.310)	(4.198)	(3.357)	(6.290)
N	1,540,094	1,540,094	1,540,137	1,540,137	1,540,140	1,540,140	1,540,140	1,540,140
$\overline{R}^2$	0.756	0.757	0.771	0.772	0.975	0.975	0.986	0.986

Panel B: Firm Fixed Effects								
	QSpread		*ESpread*		*Depth*		*Depth5*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade	-0.637***	0.022	-0.992***	-0.709***	-26.842	-37.998**	-109.510*	-165.473***
	(-3.913)	(0.109)	(-6.394)	(-4.659)	(-1.431)	(-2.248)	(-1.681)	(-2.802)
Arrowhead		-7.441***		-4.057***		0.174		-11.872
		(-24.218)		(-23.090)		(0.025)		(-0.488)
ATrade× Arrowhead		-14.174***		-8.775***		-151.235		-798.283**
		(-10.296)		(-9.893)		(-1.536)		(-2.282)
Turn	-3.397***	-3.395***	-2.308***	-2.314***	-9.741	-10.708	-43.482	-48.426
	(-5.602)	(-5.681)	(-4.666)	(-4.722)	(-0.715)	(-0.790)	(-0.980)	(-1.091)
Vol	0.638***	0.619***	0.561***	0.552***	1.325	1.446	7.573	8.160
	(8.163)	(8.953)	(7.774)	(8.245)	(0.259)	(0.282)	(0.475)	(0.508)
InvPrc	3,853.829***	3,883.919***	3,652.525***	3,668.540***	1,730.448*	1,670.804*	4,538.161*	4,284.589
	(20.273)	(20.734)	(20.977)	(21.156)	(1.825)	(1.789)	(1.654)	(1.574)
Size	-3.814***	-5.754***	-3.576***	-4.637***	8.947	8.539	26.036	20.619
	(-6.698)	(-9.778)	(-7.172)	(-9.124)	(1.053)	(0.948)	(0.982)	(0.736)
Constant	86.479***	122.576***	76.924***	96.623***	-131.117	-128.993	-329.140	-256.360
	(8.224)	(11.297)	(8.321)	(10.265)	(-0.869)	(-0.801)	(-0.702)	(-0.515)
N	1,564,962	1,564,962	1,564,986	1,564,986	1,564,988	1,564,988	1,564,988	1,564,988
$\overline{R}^2$	0.193	0.212	0.306	0.316	0.003	0.005	0.006	0.009

Panel C: Subsample of Stocks Not Subjected to Tick Size Reductions								
	QSpread		*ESpread*		*Depth*		*Depth5*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATrade	-2.965***	-1.855**	-3.864***	-3.449***	-94.209**	-103.634**	-432.160***	-477.274***
	(-4.392)	(-2.332)	(-7.511)	(-6.662)	(-1.994)	(-2.162)	(-2.910)	(-3.168)
Arrowhead		-7.570***		-4.228***		-5.700		-40.662*
		(-19.172)		(-17.112)		(-0.910)		(-1.733)
ATrade× Arrowhead		-20.979***		-18.455***		-353.007***		-1,791.291***
		(-6.848)		(-9.265)		(-3.973)		(-5.360)
Turn	-4.799***	-4.608***	-2.123***	-2.040***	-31.611***	-32.634***	-114.913***	-119.694***
	(-7.136)	(-7.518)	(-5.427)	(-5.539)	(-2.755)	(-2.824)	(-2.643)	(-2.729)
Vol	1.112***	1.098***	0.951***	0.944***	8.502***	8.551***	31.036***	31.254***
	(8.624)	(8.807)	(9.120)	(9.277)	(3.170)	(3.221)	(3.098)	(3.171)
InvPrc	3,251.311***	3,276.012***	3,730.285***	3,737.761***	2,245.078***	1,947.220***	10,102.518***	8,659.914***
	(25.105)	(25.359)	(33.702)	(33.289)	(5.092)	(4.942)	(6.229)	(5.874)
Size	-8.220***	-8.359***	-5.678***	-5.848***	8.830***	4.091	40.241***	16.427*
	(-24.278)	(-23.249)	(-24.824)	(-24.361)	(2.740)	(1.557)	(3.927)	(1.907)
Constant	165.046***	169.048***	111.983***	115.706***	-160.668***	-83.169**	-728.853***	-336.574**
	(26.220)	(25.399)	(26.368)	(26.021)	(-3.034)	(-1.971)	(-4.305)	(-2.408)
N	1,083,380	1,083,380	1,083,383	1,083,383	1,083,385	1,083,385	1,083,385	1,083,385
$\overline{R}^2$	0.449	0.456	0.650	0.653	0.053	0.060	0.145	0.169

TABLE 5 Impacts of Algorithmic Trading on Commonality in Stock Liquidity

This table reports the results from the panel regressions of monthly estimates of commonality in stock liquidity on the algorithmic trading variable and other control variables. The baseline regression model is

$$CLiq_{i,t} = ATrade_{i,t} + Size_{i,t} + Adj\_liq_{i,t} + \varepsilon_{i,t}$$

where *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. We estimate the baseline regression equation in Panel A and augment this baseline equation by including the *Arrowhead* dummy variable and the interaction between *ATrade* and *Arrowhead* in Panel B. *ATrade* is the monthly average of daily algorithmic trading variable. *Size* is the monthly average of daily log of market capitalization, and *Adj_liq* is the monthly average of the four daily stock liquidity measures. All commonality measures are scaled downward by 1,000 in the coefficients. The *t*-statistics in parentheses are based on the standard errors adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

Panel A: Main Effects				
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	-0.086***	-0.080***	-0.163***	-0.212***
	(-3.981)	(-3.864)	(-6.759)	(-8.925)
Size	0.117***	0.080***	0.099***	0.097***
	(10.887)	(7.964)	(11.065)	(10.600)
QSpread	1.214**			
	(2.483)			
ESpread		4.089***		
		(5.602)		
Depth			0.059*	
			(1.819)	
Depth5				0.013
				(1.298)
Constant	-5.024***	-4.738***	-5.353***	-5.139***
	(-25.836)	(-25.759)	(-34.281)	(-32.242)
N	78,674	78,662	78,630	78,631
$\overline{R}^2$	0.046	0.039	0.020	0.029

Panel B: *Arrowhead* Effects				
	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	-0.124***	-0.118***	-0.165***	-0.235***
	(-5.111)	(-5.236)	(-7.116)	(-9.794)
Arrowhead	-0.098***	-0.221***	-0.163***	-0.065**
	(-3.924)	(-8.670)	(-6.966)	(-2.568)
ATrade× *Arrowhead*	-0.616***	-0.561***	-0.727***	-1.695***
	(-2.879)	(-2.917)	(-4.302)	(-7.645)
Size	0.107***	0.069***	0.084***	0.069***
	(9.475)	(6.446)	(9.126)	(7.284)
QSpread	0.995**			
	(2.071)			
ESpread		4.034***		
		(5.562)		
Depth			0.053*	
			(1.806)	
Depth5				0.008
				(1.057)
Constant	-4.832***	-4.506***	-5.060***	-4.663***
	(-23.702)	(-23.033)	(-31.557)	(-28.264)
N	78,674	78,662	78,630	78,631
$\overline{R}^2$	0.010	0.006	0.010	0.011

TABLE 6 Algorithmic Trading 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 the algorithmic trading on extreme market conditions as well as other control variables. The baseline regression model is:

$$ATrade_{i,t} = \left|MRet_{i,t-1}\right| + Up_{t-1} + Down_{t-1} + MRet_{i,t-1} \times Up_{t-1} + MRet_{i,t-1} \times Down_{t-1}$$
$$+ Arrowhead_t + Turn_{i,t} + Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

where *ATrade* is the algorithmic trading variable, and *MRet* is the previous week market index return. The list of daily control variables includes stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and the log of market capitalization (*Size*). All the variables are defined in the Appendix. The *t*-statistics in parentheses are based on the standard errors adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

TABLE 6 – continued

Panel A: Extreme Market Conditions					
Year	*NDays*	*Up*	Mean(*Up*)	*Down*	Mean(*Down*)
2007	245	14	0.0479	28	-0.0548
2008	245	22	0.0825	32	-0.0902
2009	243	14	0.0797	1	-0.1039
2010	245	8	0.0461	14	-0.0530
2007-2010	978	58	0.0684	75	-0.0702

Panel B: AT during Extreme Market Conditions		
	(1)	(2)
|*MRet*|	0.416***	0.577***
	(8.715)	(10.947)
Up	-0.016***	-0.003
	(-7.653)	(-1.384)
Down	-0.042***	-0.026***
	(-9.501)	(-6.686)
MRet×Up		-0.304***
		(-9.377)
MRet×Down		0.338***
		(9.267)
Arrowhead	0.150***	0.150***
	(17.694)	(17.706)
Turn	0.086**	0.086**
	(1.965)	(1.965)
Vol	-0.038***	-0.038***
	(-2.743)	(-2.742)
InvPrc	-11.626***	-11.622***
	(-7.097)	(-7.096)
Size	-0.191***	-0.191***
	(-17.390)	(-17.390)
Constant	3.162***	3.158***
	(16.531)	(16.521)
N	1,563,333	1,563,333
$\overline{R^2}$	0.367	0.367

TABLE 7 Impact of Algorithmic Trading on Stock Liquidity during Extreme Market Conditions

This table reports the panel regression of stock liquidity on algorithmic trading variable during extreme market conditions. The baseline regression model is:

$$Adj\_liq_{i,t} = ATrade_{i,t} + Up_{t-1} + Down_{t-1} + Up_{t-1} \times ATrade_{i,t} + Down_{t-1} \times ATrade_{i,t} + Turn_{i,t}$$
$$+ Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

In this model, *Adj_liq* alternatively represents 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. *ATrade* refers to the algorithmic trading measure. *Up* (*Down*) is a dummy variable equal to 1 if the previous weekly market return is 1.5 standard deviations above (below) the unconditional mean of 52 weekly market return in the past 250 trading days, and 0 otherwise. The *t*-statistics in parentheses are based on the standard errors adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

	QSpread	*Espread*	*Depth*	*Depth5*
	(1)	(2)	(3)	(4)
ATrade	-3.720***	-3.210***	-276.580	-1,092.218*
	(-6.925)	(-7.147)	(-1.546)	(-1.823)
Up	1.606***	0.526***	-3.686	-14.913
	(13.022)	(6.726)	(-0.487)	(-0.584)
Down	5.871***	3.069***	-2.157	-10.379
	(29.728)	(26.640)	(-0.541)	(-0.723)
Up×ATrade	1.026***	0.474***	20.196	77.035
	(6.520)	(3.785)	(0.731)	(0.821)
Down×ATrade	3.179***	1.896***	72.549**	284.204***
	(12.010)	(11.953)	(2.310)	(2.854)
Turn	-2.239***	-0.111	-28.429	-99.768
	(-2.613)	(-0.156)	(-1.437)	(-1.444)
Vol	0.823***	0.669***	7.210	25.316
	(6.664)	(6.361)	(1.341)	(1.350)
InvPrc	3,239.992***	3,617.372***	3,110.569***	13,403.516***
	(25.098)	(31.828)	(3.525)	(4.234)
Size	-7.053***	-4.584***	2.350	23.371
	(-24.136)	(-23.097)	(0.204)	(0.603)
Constant	144.373***	94.057***	-71.065	-514.812
	(26.495)	(25.552)	(-0.402)	(-0.861)
N	1,563,307	1,563,331	1,563,333	1,563,333
$\overline{R}^2$	0.421	0.595	0.076	0.107

TABLE 8 Impacts of Algorithmic Trading on Commonality in Stock Liquidity During Extreme Market Conditions

This table reports the panel regression of stock liquidity commonality on algorithmic trading variable during extreme market conditions. The baseline regression model is:

$$CLiq_{I,t} = ATrade_{i,t} + Up_{t-1} + Down_{t-1} + Up_{t-1} \times ATrade_{i,t} + Down_{t-1} \times ATrade_{i,t} + Turn_{i,t}$$
$$+Vol_{i,t} + InvPrc_{i,t} + Size_{i,t} + \varepsilon_{i,t}$$

Here, *CLiq* alternatively represents the monthly estimates of commonality in the following 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. *ATrade* refers to the algorithmic trading measure. *Up* (*Down*) is a dummy variable equal to 1 if the monthly market return is 1.5 standard deviations above (below) the unconditional mean of 12 monthly market returns in the past one year, and 0 otherwise. The list of control variables includes monthly average stock trading turnover (*Turn*), stock return volatility (*Vol*), the inverse of stock price (*InvPrc*), and the log of market capitalization (*Size*). The *t*-statistics in parentheses are based on the standard errors adjusted for firm-level clustering and robust to heteroskedasticity. ***, **, 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 2010.

	CQSpread	*CESpread*	*CDepth*	*CDepth5*
	(1)	(2)	(3)	(4)
ATrade	-0.164***	-0.171***	-0.186***	-0.208***
	(-5.680)	(-6.078)	(-6.284)	(-8.021)
Up	-0.084	-0.041	-0.087	-0.133**
	(-1.506)	(-0.659)	(-1.388)	(-2.267)
Down	0.226***	0.201***	0.120***	0.078***
	(9.203)	(8.166)	(4.860)	(3.176)
Up×ATrade	0.123*	0.418***	-0.209**	-0.117
	(1.709)	(3.676)	(-2.322)	(-1.410)
Down×ATrade	0.060**	-0.032	0.042	-0.011
	(1.967)	(-1.075)	(1.134)	(-0.322)
Size	0.112***	0.075***	0.095***	0.093***
	(10.195)	(7.242)	(10.522)	(10.170)
QSpread	0.893*			
	(1.854)			
ESpread		4.034***		
		(5.536)		
Depth			0.051*	
			(1.687)	
Depth5				0.017
				(1.584)
Constant	-4.967***	-4.690***	-5.282***	-5.067***
	(-25.086)	(-24.670)	(-33.858)	(-31.942)
N	77,011	76,998	76,966	76,967
$\overline{R^2}$	0.011	0.006	0.009	0.010

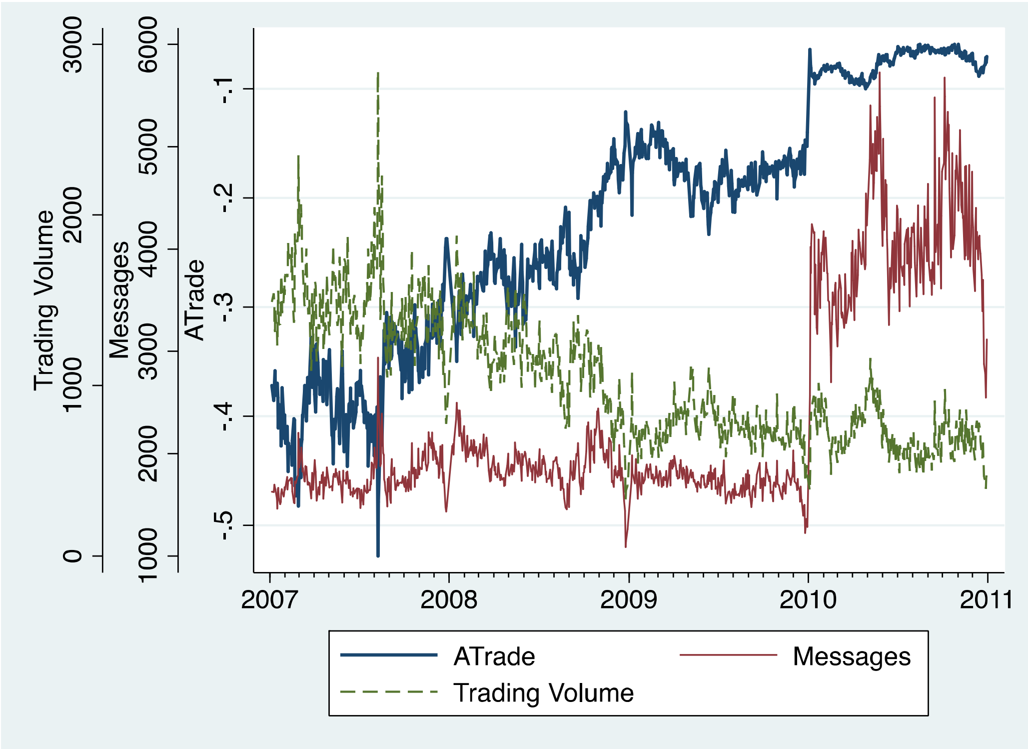

FIGURE 1

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 2010, 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.